Received: 28 February 2022 | Revised: 27 February 2023 | Accepted: 3 March 2023

DOI: 10.1002/hec.4679

RESEARCH ARTICLE

Health Economics WILEY

Cognitive activity at work and the risk of dementia

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Abstract

Dementia prevalence is projected to rise steeply in coming decades, producing tremendous burdens on families, and health and social services. Motivated by the need for further robust evidence on modifiable risk factors, we investigate the relationship between cognitive activity at work and later-life dementia. Using data from the US Health and Retirement Study matched to the O*NET occupational database, we find that a one standard deviation increase in the cognitive activity associated with one's longest held occupation is associated with a 0.9 percentage point reduction in (predicted) dementia, or a 24% reduction relative to the mean. This relationship is consistently found across model specifications and robustness tests. When controlling for individual fixed-effects we find that the association between dementia and work cognitive activity increases with age. Overall, our results provide some evidence in support of the inclusion of cognitive activity at work as a recognized modifiable risk factor for dementia.

KEYWORDS
cognition, dementia, HRS, O*NET, occupation, work

JEL CLASSIFICATION
I14, J11

1 | INTRODUCTION

Alzheimer's disease (AD) and other types of dementia are a huge burden on society. At least 50 million people worldwide have dementia, and the estimated total cost is US$1trillion (Patterson, 2018). The primary costs are due to complex care needs including home-based and institutional long-term care (Hurd et al., 2013; Kingston et al., 2018). Worryingly, the number of people living with dementia will significantly increase in the coming decades as younger-age mortality declines and the population ages (Livingston, 2020). There are currently around 10 million new cases every year, and by 2050 it is predicted that there will be 152 million people living with dementia (WHO, 2019). Given there is no known cure, considerable research effort is concentrated on identifying and understanding modifiable risk factors. While there is some doubt about the exact etiology of dementia, both genetic and lifestyle factors are thought to be drivers of the disease (Licher et al., 2019). There are currently 12 lifestyle-related risk factors identified in the 2020 report of the Lancet Commission on dementia prevention, intervention and care (Livingston et al., 2020): low education, hypertension, hearing impairment, smoking, obesity, depression, physical inactivity, low social contact, excessive alcohol consumption, traumatic brain injury, and air pollution. Taken together these preventable factors are thought to account for up to 40% of dementias (Licher et al., 2019; Livingston et al., 2020).

There is also growing evidence that another potentially modifiable risk factor for dementia (and cognitive decline more generally) is cognitive activity during the life course (Fisher et al., 2014; Lee et al., 2018; Salthouse, 2006). Specifically, a key hypothesis is that being cognitively active, and being in a stimulating environment, increases people's "cognitive reserve" by strengthening the functioning and plasticity of neural circuits (e.g., Kivipelto et al., 2018; Smart et al., 2014; Stern, 2012). Cognitive reserve has been proposed to account for the mismatch between the extent of brain damage and its clinical manifestation in the form of dementia, and is an important mechanism in promoting general cognitive resilience (Stern et al., 2012). Therefore, those with high cognitive reserve can sustain a higher level of neuropathology without experiencing cognitive impairment (Livingston, 2020). In contrast, people with low cognitive reserve develop dementia symptoms with fewer pathological changes (Brayne et al., 2010).

Empirical evidence suggests that cognitive activity at work might act to reduce cognitive decline and dementia (e.g., Andel et al., 2005; Boots et al., 2015; Fisher et al., 2014; Kroger et al., 2008; Smart et al., 2014). However, not all studies have found evidence in support of this mechanism. For example, Singh-Manoux et al. (2011) found a faster cognitive decline for those who worked in occupational positions with high administrative grades, and Staff et al. (2018) found no evidence that intellectual engagement influences the trajectory of age-related cognitive performance. While the Lancet Commission report recommends keeping cognitively active in middle and later life, it notes that there is little evidence in favor of any single specific activity.[1] However, it recognizes that, "Culture, poverty, and inequality are important obstacles to, and drivers of, the need for change to cognitive reserve. Those who are most deprived need these changes the most and will derive the highest benefit from them" (Livingston et al., 2020).

Uncertainty arises in the literature because many existing studies are based on small and selected samples, which makes it difficult to generalize results. Studies also measure work-based cognitive activity in different ways and control to varying extents for confounding pathways. Furthermore, we are unaware of any studies that have been able to establish causality between work cognitive activity and later life dementia risk. This is a particularly challenging task because of potentially complex non-random selection into occupations across the life course, with selection likely to be a function of many factors including parental socioeconomic characteristics, educational attainment, cognition, and past occupational choices.[2]

While we also cannot identify any plausible randomization into occupations, the high prevalence and increasing incidence of dementia, as well as the significant social and economic burdens, means that it is important to continue developing the literature on the potential association between work-based cognitive activity and dementia, even if causality cannot be established. That is the aim of this study using a large longitudinal survey from which the results should be more generalizable. We also contribute by controlling for many potential confounding factors using a range of econometric techniques. In addition, we explore the genetic dimension of dementia, assess the robustness of our findings against unobserved confounding factors, and analyze how the association between dementia and work cognitive activity evolves throughout the life cycle of individuals. The study serves as an initial step in health economics research on this topic and may help lay the foundation for future (possibly causal) studies.

Specifically, we use data from the US Health and Retirement Study (HRS), matched with occupational cognitive activity information from the Occupational Information Network (O*NET) database, to estimate the association between cognitive activity levels in a person's longest lifetime occupation and their incidence of (predicted) dementia. We also test the sensitivity of the estimated association to the inclusion of an extensive set of demographic, education, occupation, industry, work, and genetic controls. We find no evidence of genetic confounding or strong associations with placebo health outcomes, and we additionally find no significant association between an individual's work cognitive activity and spousal dementia. We also include individual fixed-effects and estimate how the cognitive activity coefficient varies with age.

More generally, our paper contributes to the small number of economic studies that have examined the importance of risk factors in explaining dementia, which includes estimated effects of education (Brent, 2018), income (Ayyagari & Frisvold, 2016), and pollution (Bishop et al., 2018). Economists have also explored the economic consequences of dementia on financial decision-making (Hsu & Willis, 2013), savings behavior (Shin et al., 2019), and household financial outcomes (Gresenz et al., 2020). Our paper also indirectly adds to an economics literature that more broadly explores the relationships between work activities and short- and long-term health outcomes, including self-assessed health (Fletcher et al., 2011; Ravesteijn et al., 2018; Schmitz, 2016), body mass index (Dang et al., 2019), mental health (Cottini & Lucifora, 2013), and blood pressure and cognition levels (Schmitz, 2016).

Our preferred estimate implies that a one standard deviation increase in lifetime occupational cognitive activity is associated with a 0.9% point reduction in predicted dementia (24% relative to the mean prevalence). Furthermore, the individual fixed-effects specification demonstrates that people with low work cognitive activity levels have a significantly steeper age-dementia gradient.

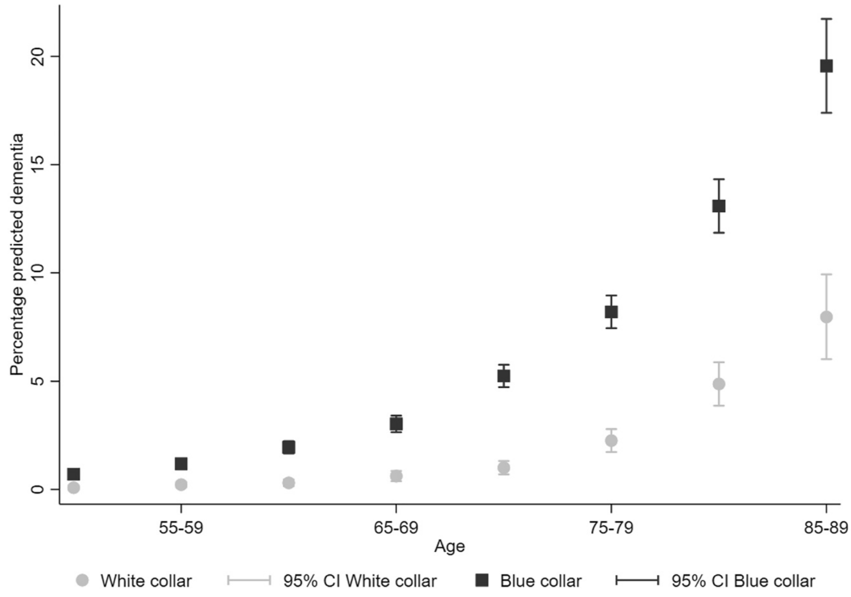

FIGURE 1 Percentage of health and retirement study Male Sample with (Predicted) Dementia by Age and Occupation. Sample restricted to males aged 60–85. The outcome is predicted dementia (binary). Collar color differentiates between blue-collar occupations involving agriculture, production, craft and repair, operators, fabricators and laborers, and white-collar occupations involving managers, professionals, technicians, or office and administration workers.

2 | BACKGROUND

It is widely known that there is a strong socioeconomic gradient in dementia risk, consistent with gradients in most of the 12 modifiable risk factors highlighted by the Lancet Commission (Livingston et al., 2020). To empirically motivate our study, Figure 1 shows the striking difference in the likelihood of experiencing consistently very low cognition levels (the definition used by Crimmins et al. (2011) to predict dementia; discussed further below) for blue- and white-collar male workers in the US using data from the HRS.[3] At age 50, we see very little difference between blue- and white-collar workers. However, the gap increases with age, and by age 80, those who worked in blue-collar occupations are more than twice as likely to experience dementia. Undoubtedly some of this strong association is caused by differences in background characteristics including education. Nevertheless, it is consistent with the cognitive reserve hypothesis that part of the association could be due to differences in the level of required cognitive activity between jobs.

Since early studies by Scherr et al. (1988), Dartigues et al. (1992), and Stern et al. (1995), there has been growing empirical evidence that working in occupations with more substantive complexity is linked to better cognitive outcomes later in life. Dartigues et al. (1992) using French community data found after controlling for education, that blue-collar workers had a much higher (odds ratio = 2.5) likelihood of suffering from cognitive impairment than those who had worked in "intellectual" occupations. They concluded that "occupational status should be taken into consideration when studying brain aging". Stern et al. (1995) identified a link between lifetime occupational activity, defined using the US Dictionary of Occupational Titles, and cognitive reserve for 51 Alzheimer's disease (AD) patients. They similarly concluded that "independent of education, aspects of occupational experience may provide a reserve that delays the clinical manifestations of AD". Since then studies have continued to examine the link between cognitive activity at work and cognitive impairment or dementia risk (see Alvares-Pereira et al., 2021). These studies are a combination of: (1) those that have used smaller samples (often <100 participants), but for whom data on the brain (e.g., hippocampal volume, brain atrophy) is combined with retrospective work activity information; (2) observational studies based on small and/or selected groups; and (3) studies that have used nationally-representative longitudinal surveys.[4]

Importantly, Fisher et al. (2014) also analyzed individuals ($N = 4182$) from the US HRS matched with occupation-level data from O*NET. Their focus was on examining if working in a mentally demanding occupation was associated with changes in episodic memory (their focus was not on dementia) before and after retirement, and they applied a variety of modeling approaches controlling for age, gender, years of schooling, self-reported health status, symptoms of depression, cardiovascular disease and income. The study found that individuals who worked in occupations with greater mental demands had better episodic memory before retirement, and slower declines after retirement, than those who worked in less demanding jobs.

Unlike Fisher et al. (2014), we explore predicted dementia, a more extreme outcome than episodic memory loss. Work activities may affect these outcomes differently, with episodic memory loss being highly dependent on crystallized intelligence, while dementia is a medical condition. The difference between both outcomes is reflected in our sample: 6296 (79.41%) individuals suffer an episode of memory loss—a lower cognition score from one wave to another—while only 766 individuals are ever classified to have dementia. As such, only 12.17% of the cases of episodic memory loss are classified as predicted dementia.

Our measure of work cognitive activity also differs from that used in Fisher et al. (2014). They take the average of all O*NET variables in the "Mental Processes" work activities category, while we run a factor analysis on all O*NET work activities variables (see Section 3.3). The variables with the highest loadings in our factor analysis mostly correspond to O*NET work activity categories other than "Mental Processes".[5]

Compared to the rest of the literature, this study includes a much richer set of work-activities and work context controls. Notably, we exploit variation in cognitive workplace activities within one-digit occupations and industries. Additionally, we explore how robust the results are to potentially unobserved confounding factors. Previous work has captured genetic information with co-twin designs and with the APOE4 protein, while we use the poly-genetic risk scores in the HRS, which capture the genetic predisposition of suffering several conditions related to dementia. Our longitudinal data also enable us to model within-individual changes in (predicted) dementia in order to better understand how the association with work cognitive activity varies as people age.

3 | DATA

Our sample is drawn from the US HRS and we have matched the lifetime occupations of respondents to information about work tasks in the Occupational Information Network database (O*NET).

3.1 | Health and retirement study

The HRS is a longitudinal study that has tracked financial, work, health, and family outcomes of over 37,000 older Americans (aged 50+) and their spouses. The first wave of interviews was undertaken in 1992 with a sample of 12,652 individuals aged 50–61, and respondents have been re-interviewed on a biennial basis since then. Baseline interviews were typically conducted face-to-face, in most cases at the home of the respondents, but also in nursing homes or in alternative places of residency.

Given that mapping work cognitive activity by longest lifetime occupation is central to our analysis, we focus only on males. For the female HRS sample, we found that 12% never worked (3% of males), 25% worked less than 10 years, and almost 50% worked less than 20 years[6] Females are also significantly more likely than men to have worked part-time. We are therefore concerned that our measure of work cognitive activity may poorly represent the lifetime cognitive activity levels of many females in this sample.

Our main sample then consists of males aged 60 to 85 drawn from the RAND HRS Longitudinal File 2014.[7] Each individual is observed between one and 12 times, depending on the cohort when they first participated in the survey and attrition. This provides a sample of 59,757 observations, which we further restrict by omitting observations with missing cognitive test score information (4.9%) and longest lifetime occupation (11.4%). The main reasons for the missing observations for longest lifetime occupation are: (1) not having worked at all (1.4%); (2) not having reported longest lifetime occupation, or not providing enough information from other questions to create a measure (7.8%); and (3) having an occupational code that we cannot match to the O*NET (2.1%). These restrictions leave us with a working sample of 9994 males aged 60–85 (50,357 observations) observed an average of 5.04 times, of which 82% are non-Hispanic white, 13% are non-Hispanic black and 4% are Hispanic.

3.2 | Predicted dementia

In this study, we are interested in the occurrence of dementia, rather than cognitive decline. We follow the approach outlined in Crimmins et al. (2011) to predict dementia for each respondent at each survey wave. The thresholds for dementia are derived from the correspondence of the specific test scores available in the HRS with detailed neuropsychiatric assessments from a subsample of 856 respondents (Crimmins et al., 2011).[8] This is based on the Langa-Weir Classification of Cognitive Function (Langa, 2020). Within economics, this classification approach has also been used by Hsu and Willis (2013) and Ayyagari and Frisvold (2016), and is preferred to using reported diagnosed dementia because of potentially high misclassification rates (Crowther et al., 2017). For example, a measure of "ever having been diagnosed with dementia" available in waves 10–12 of the HRS, indicates that only 1.9% of respondents have dementia. However, this statistic is many times lower than the estimated population prevalence reported in Hebert et al. (2013) for the year 2010: 3.0% for 65–74 olds, 17.6% for 75–84 olds, and 32.3% for people aged 85+. Wolters et al. (2020) report that 8.6% of individuals over the age of 65 develop dementia in the US.

Key to our analysis then are the HRS administered cognition tests. We use four of these tests to construct a measure of episodic memory, which is one of the major neurocognitive memory systems. According to Tulving (2002), it is "more vulnerable than other memory systems to neuronal dysfunction", and "makes possible mental time travel through subjective time, from the present to the past, thus allowing one to re-experience, through autonoetic awareness, one's own previous experiences". Poor episodic memory is thus a lead indicator of cognitive impairment (Fisher et al., 2014). These tests require each respondent to: immediately recall a list of 10 words (0–10 points); recall the same 10 words several minutes later (0–10 points); subtract

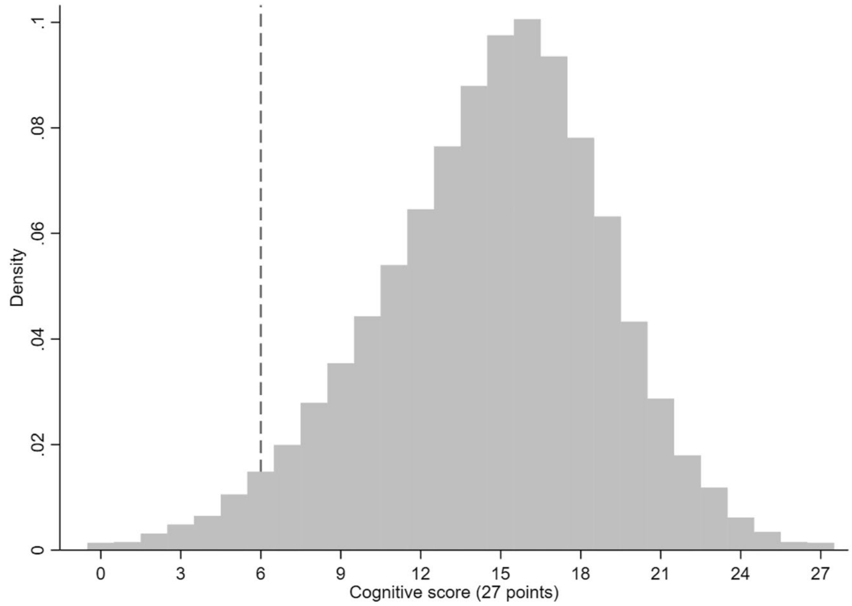

FIGURE 2 Histogram of Episodic Memory Test Score. Sample restricted to males aged 60–85. The vertical dotted line defines a threshold for predicted dementia and the left lower tail presents the proportion of individuals with dementia.

seven from 100 five times (0–5 points); and count backwards from 20 to 10 (0–2 points). Scores on these tests are combined to produce a scale ranging from zero to 27, increasing in cognitive ability. Figure 2 presents the distribution of scores in our estimation sample. The mean and standard deviation of scores in our sample of 60–85-year-old males equal 14.6 and 4.3, respectively.

Having (predicted) dementia at time *t* is based on two requirements. First, following Crimmins et al. (2011), is having an episodic memory test score at time *t* that is less than or equal to six. Scores between zero and six are over two standard deviations below the mean, representing the bottom 3.8% of test scores. Second, is having a mean score of all future tests that is less than or equal to six. Respondents complete episodic memory tests every wave and may move from below to above the cutoff, even though dementia is irreversible and progressive. For example, a low score in a particular wave may be due to a short-term illness that interrupts concentration. The second requirement ensures that they have consistently low scores across time, while still allowing for an occasional score that is slightly higher than the cutoff.

A complication with this definition is that around 6.6% of the sample required help from a proxy respondent due to communication problems and cognitive impairment, which are issues that are associated with dementia. For these people, we again follow Crimmins et al. (2011) and predict dementia based on the: (1) proxy's assessment of the respondent's memory (excellent to poor); (2) proxy's assessment of whether the respondent has problems with activities of daily living (e.g., using the phone, taking their medication); and (3) interviewer's assessment of the respondent's ability to answer survey questions (see Appendix for further details). Correspondingly, 11.11% of respondents who used a proxy are predicted to have dementia.

Figure 1 shows the proportions of males at different ages that are predicted to have dementia (by broad occupation type). Very few males at age 50 have predicted dementia (0.13% of the total sample), while almost 10% of males do so at age 80. This indicates that our constructed dementia variable is capturing significant declines in episodic memory as people age.

3.3 | Cognitive activity at work

The measure of longest lifetime occupation is based on a derived HRS variable, which is constructed from several questions, such as "What kind of work did you do most of your working life?". However, the questions are not consistently asked across survey years, and we follow the approach of Bugliari et al. (2019) to construct longest lifetime occupation. In a first step, the occupation with the longest job tenure is identified. In a second step, the occupation with the longest job tenure is set as the longest lifetime occupation. See Appendix for further details.

Following Autor and Dorn (2013), we then transform the 889 Census Occupational Categories recorded for our HRS sample into 330 occ1990dd occupational categories. Occupations in the O*NET are recorded following the Standard Occupation System codes, which are transformed to Census Occupational Categories, and to 330 occ1990dd occupational categories, to be merged with the HRS. Importantly, the O*NET contains expert ratings on hundreds of occupational characteristics, and these can be aggregated into six broad categories: abilities, interests, knowledge, skills, work activities, and work context. Most relevant for this study is the work activities category, which includes 41 variables divided into four sub-domains: (1) where and how required information is obtained (information input; five variables); (2) social interactions or supervisory

TABLE 1 Occupations that are ranked as having high and low cognitive activity Levels, grouped by six broad occupational groups.

Occupation groups	Three highest scores	Three lowest scores
Managers	Accountants and auditors (1.70); inspectors and compliance officers, outside (1.46); other financial specialists (1.18)	Buyers, wholesale and retail trade (−1.24); office supervisors (−0.93); business and promotion agents (−0.79)
Professionals	Mathematicians and statisticians (2.57); biological scientists (1.95); physicists and astronomers (1.91)	Athletes, sports instructors, and officials (−1.37); musicians and composers (−0.79); clergy and religious workers (−0.75)
Sales	Sales engineers (1.10); financial service sales occupations (1.01); insurance sales occupations (0.77)	Sales supervisors and proprietors (−1.69); door-to-door sales, street sales, and news vendors (−0.98); retail salespersons and sales clerks (−0.37)
Office and admin	Statistical clerks (1.87); computer and peripheral equipment operators (1.63); insurance adjusters, examiners, and investigators (1.54)	Office machine operators, n.e.c. (−1.03); mail carriers for postal service (−0.84); mail clerks, outside of post office (−0.55)
Production, craft and repair	Power plant operators (1.24); repairers of data processing equipment (1.19); elevator installers and repairers (1.08)	Other mining occupations (−2.02); painters, construction and maintenance (−1.93); glaziers (−1.89)
Operators, fabricators and laborers	Production checkers, graders, and sorters in (1.93); packers, fillers, and wrappers (0.52); forge and hammer operators (0.39)	Operating engineers of construction equipment (−2.05); excavating and loading machine operators (−1.86); parking lot attendants (−1,75)

Note: Mean cognitive activity levels for each occupation group are shown in brackets. The cognitive activity variable is standardized to mean zero and standard deviation one.

activities that occur (interacting with others; 17 variables); (3) physical activities performed, vehicles operated, and technical activities accomplished (work output; nine variables); and (4) processing, planning, problem-solving, decision-making, and innovating activities performed (mental processes; 10 variables). These 41 variables are listed in Appendix Table A1.

To summarize the data, we perform a factor analysis eliciting orthogonally rotated factors (see Table A1).[9] We label the first factor “Interaction with others”. It is most strongly associated with the activities “Coaching and developing others” and "Guiding, directing and motivating subordinates”. The second factor is our main variable of interest, and is labeled “Cognitive activity”. It is most strongly associated with “Processing information”, “analyzing data or information” and “Getting information”. Finally, the third factor is labeled “Working with machines”, and is associated with activities such as “Repairing and maintaining mechanical equipment” and “Operating vehicles, mechanized devices or equipment”. Each of the factors are standardized to have mean zero and standard deviation one.

Table 1 highlights occupations with high and low cognitive activity scores, within the six broad occupation groups covering 87% of our sample. The table demonstrates that our generated cognitive activity factor provides a sensible ranking of occupations: mathematicians and statisticians (mean cognitive activity score of 2.57), and biological scientists (1.95) are classified as high cognitive activity occupations, while operators of construction equipment (−2.05) and miners (−2.02) are classified as low cognitive activity occupations. It also clearly shows that there is considerable variation in cognitive activity levels even within these occupation groups (e.g., accountants and auditors (1.70) versus retail buyers and wholesalers (−1.24) within the “managers” group). This considerable variation highlights the need for an extensive set of covariates to be included in regressions to control for non-random selection into occupations.

We also conduct factor analyses using the variables in the O*NET work context category. Work context refers to physical attributes (e.g., sitting, standing, indoors, outdoors, hazardous conditions, repetitive motions) and social attributes (e.g., dealing with external customers, dealing with aggressive people) that influence the nature of work. Five factors are generated for the work context domain (eigenvalues greater than one), and these are included as covariates in some regressions.

4 | WORK COGNITIVE ACTIVITY AND PREDICTED DEMENTIA

4.1 | Main regression results

In this section, we explore the association between (predicted) dementia and work-related cognitive activity by estimating a series of regressions with increasingly larger covariate sets. Larger covariate sets will control for a greater proportion of the

TABLE 2 Estimated associations between work-related cognitive activity and (predicted) dementia.

	(1)	(2)	(3)	(4)	(5)
Work cognitive activity	−2.23***	−1.37***	−0.72***	−0.91***	−0.89***
	(0.364)	(0.253)	(0.204)	(0.310)	(0.296)
Demographics	×	✓	✓	✓	✓
Educational attainment	×	×	✓	✓	✓
O*Net factors variables	×	×	×	✓	✓
Occupation and industry	×	×	×	✓	✓
Wealth and employment	×	×	×	×	✓
Observations	50,357	50,357	50,357	50,357	50,357
R-squared	0.01	0.07	0.09	0.09	0.10

Note: Clustered standard errors at occupational level in parentheses. Sample restricted to males aged 60–85. The outcome in all regressions is a binary indicator of (predicted) dementia; however, all estimates have been multiplied by 100 for ease of interpretation (i.e., are in percentage point units). Work cognitive activity is standardized to have mean zero and standard deviation one. Demographic covariates: fixed effects for age, race/ethnicity, place of birth, being a proxy respondent and survey year, and years of parental education. Educational attainment covariates: no high school, GED, high school, some college, and college and above. O*NET factor variables: Factors 1 ("Interacting with others") and 3 ("Working with machines") and five work context factors. Occupation and industry: one-digit, 11 main occupations and 20 main industries. Wealth and employment covariates: retirement status, last year worked, years employed in paid work, and household wealth.
***p < 0.01; **p < 0.05; *p < 0.10.

non-random selection into different occupations and later life outcomes. Selection into longest lifetime occupation is likely a function of individual characteristics such as genetic factors, parental socioeconomic status, and educational attainment. It is also important to control for other job characteristics associated with work-related cognitive activity.

Table 2 shows the estimated regression coefficients on cognitive activity, in which the coefficients have been multiplied by 100 so that they are in percentage point units.[10] Column 1 is the estimated association from a univariate regression and equals −2.23 (p-value<0.001). This estimate implies that a one standard deviation increase in work cognitive activity decreases the probability of (predicted) dementia at time t by 2.23% points. In column (2) the regression includes survey year fixed-effects, and control variables representing exogenous and predetermined demographic characteristics: age, race/ethnicity, place of birth, and parental education. Given the strong non-linear relationship between age and dementia, the age relationship is controlled for with age fixed-effects. The estimated association reduces in magnitude by around 39% to −1.37 ($p < 0.001$. Additionally, controlling for own educational attainment, which often precedes occupational choice, further reduces (column 3) the association to −0.72 ($p < 0.001$). The substantial reduction in magnitude indicates that educational attainment is strongly associated with both cognitive activity levels required at work and the likelihood of (predicted) dementia in later life.

In Column (4), the regression additionally includes the interacting with others and working with machines factor variables, five physical and social work context factors, 11 one-digit occupation fixed-effects, and 20 one-digit industry fixed-effects, which partially control for unobserved determinants of occupational choice. In this regression, the estimated association between cognitive activity and (predicted) dementia is identified by variation in job work activities within occupation and industry categories. Despite these additional covariates, the estimated association in Column (4) raises in magnitude to −0.91 ($p = 0.004$) and remains statistically significant.[11] This estimate implies that the difference in required cognitive activity between insurance and retail sales occupations (1.14 standard deviations) is associated with a reduction in the likelihood of (predicted) dementia of around 1.0% points. This is a large reduction considering that the sample mean equals 3.8%.

In Column 5, we add contemporaneous economic controls: retirement status, last year worked, years in paid work, household wealth, and years employed in longest lifetime occupation.[12] Naturally, these individual characteristics will be partly determined by occupational choice, and may also be determined by cognitive decline, and therefore should be interpreted with caution. Nevertheless, we present these regression results to demonstrate that the significant association remains even when controlling for differences in the economic status between occupations.

The negative and significant association is robust to alternative modeling choices. First, if we instead use a logit or probit estimator to model (predicted) dementia the estimated marginal effects of a one standard deviation increase in work cognitive activity equal −1.01 ($p = 0.002$) and −1.04 ($p < 0.001$), as compared with −0.91 ($p = 0.004$) in Column (4). Second, a modeling assumption inherent in the Table 2 regressions is that the association between work cognitive activity and (predicted) dementia is linear. This assumption appears valid, because added quadratic and squared root functions of cognitive activity are statistically insignificant.

Third, the relationship is also robust to alternative approaches for predicting dementia. When the methods outlined in Hurd et al. (2013), the "expert" model in Gianattasio et al. (2020), and the "LASSO" model in Gianattasio et al. (2020) are used, the estimated association is even larger than shown in Table 2 (see Appendix Table A4).[13] Similarly, estimates are comparable if we use a more moderate definition that does not preclude "recoveries" (i.e., scoring below the dementia threshold in one wave and then above in subsequent waves) as our main outcome does (see Appendix Table A5). Estimates are also similar if we use a stricter definition that indicates dementia at time if individuals score less than or equal to six at time t and in all future waves. Table A5 also includes results from a purely cross-sectional regression where the outcome indicates whether the individual ever scored below the threshold of dementia. The coefficient estimate is larger from this specification, also when compared to its sample mean.

Fourth, we have explored the sensitivity of our results to using different measures of work cognitive activity, which are based on jobs held at different times of the individual's life (see Appendix Table A6). First, we use the work cognitive activity in the last occupation before retirement (column 2). We then disaggregate this measure based on the source of information for last occupation: prospective information from respondents who were employed when they joined the HRS (column 3), and retrospective information from respondents who were non-employed when they joined the HRS (column 4). Finally, we use the mean work cognitive activity across all occupation reported by the individual (column 5). The estimates in columns (2), (3) and (5) are similar to our main estimate, which is reported in column (1) for ease of interpretation. These consistent results are expected, given the high degree of stability in reported occupations among individuals: 70% report the same one-digit SOC code from one survey wave to the next. The estimate in column (4) is notably larger in magnitude (-1.84 with $p = 0.002$). This is likely driven by the fact that the sample who provide retrospective occupation information are older on average, and the estimated association between work cognitive activity and (predicted) dementia increases with age.

4.2 | Exploring the potential for genetic confounders

The results presented in Table 2 demonstrate that the estimated association between work cognitive activity levels and (predicted) dementia is strong, and cannot be "washed away" with the inclusion of demographic, education, occupation, and industry controls. However, it is still possible that there are omitted covariates that jointly influence occupation and dementia risk. One candidate is genetic factors that are not adequately controlled for with variables such as own and parental educational attainment. For example, genetic factors associated with high intelligence may increase work cognitive activity level (through occupation choice), and reduce the likelihood of dementia, even conditional on observed characteristics. In Table 3 we explore the potential for genetic confounding by using the HRS data on polygenic risk scores (PRS), which summarize the estimated impact of genetic variations on a person's phenotypes. These are available for a reduced sample of 4020 males with European ancestry, observed an average of 6.33 times.[14]

We begin by regressing (predicted) dementia on four PRS, representing individuals' genotype profiles for Alzheimer's disease (AD), general cognition, educational achievement, and coronary arterial disease (CAD). The CAD score is included because stroke and heart attack are associated with the occurrence of dementia (Deckers et al., 2017). Column (1) in Table 3 demonstrates that the AD and educational achievement scores are significantly associated with (predicted) dementia, while the cognition and CAD scores are not. After adding our main set of covariates—corresponding to column (4) in Table 2—the estimated associations with the AD and educational achievement scores shrink in magnitude and only the educational achievement PRS is still significantly different than zero (at the 10% level). Similarly, columns (3) and (4) present estimated associations between the PRS and work cognitive activity. In column (3) the AD score is negatively associated with work cognitive activity, while the education PRS is positively associated with it. The coefficients on the AD score and educational achievement score are reduced to near-zero once education, occupation, and industry covariates are added.

Based on the genetic information we have available, the results in Columns 1–4 indicate that genetic factors are unlikely to be confounding the estimated associations presented in Table 2. There is not an apparent relationship between a person's genotype (AD, intelligence, education, CAD) and both occupational choice and (predicted) dementia; particularly when an extensive set of covariates are added. This is confirmed by the results in Column (6). We add the PRS to the baseline dementia regression Column (5), using the smaller sample for whom this information is available, and find that the estimated coefficient on work cognitive activity on (predicted) dementia is similar to the baseline estimate and is statistically significant.

4.3 | Estimated associations between work cognitive activity and placebo health outcomes

We further explore the potential for omitted covariates that jointly influence occupation and dementia risk by estimating regressions with indicators of non-neurological disease as the outcomes. If omitted variables, such as lifestyle factors and background socioeconomic status, are confounding the estimated associations, it is likely that work cognitive activity will also

TABLE 3 Estimated associations between polygenic risk scores, work-related cognitive activity and (predicted) dementia.

	Predicted dementia		Work cognitive activities		Predicted dementia	
	(1)	(2)	(3)	(4)	(5)	(6)
Alzheimer's disease PRS	0.22*	0.15	−0.03*	−0.01	-	0.14
	(0.114)	(0.113)	(0.015)	(0.008)		(0.112)
General cognition PRS	0.09	0.09	0.02	0.00	-	0.09
	(0.122)	(0.119)	(0.016)	(0.009)		(0.119)
Coronary arterial disease PGS	−0.09	−0.03	−0.02	−0.00	-	−0.03
	(0.103)	(0.101)	(0.014)	(0.008)		(0.100)
Education PGS	−0.60***	−0.34*	0.11***	0.01	-	−0.33*
	(0.211)	(0.177)	(0.015)	(0.009)		(0.176)
Work cognitive activity	-	-	-	-	−0.87***	−0.78***
					(0.207)	(0.254)
Baseline covariates	×	✓	×	✓	×	✓
Observations	25,433	25,433	4020	4020	25,433	25,433
R-squared	0.00	0.06	0.03	0.74	0.06	0.05

Note: Clustered standard errors at the occupational level in parentheses. Sample restricted to males aged 60–85. The regression outcomes are given in the top row. The outcome in all regressions is a binary indicator of (predicted) dementia; however, all estimates have been multiplied by 100 for ease of interpretation (i.e., are in percentage point units). Work cognitive activity is standardized to have mean zero and standard deviation one. The polygenic risk scores (PRS) are defined by the genetic predisposition of suffering specific conditions. Each score has a mean of zero and a standard deviation of one. The Baseline set of covariates correspond to the set included in Column (4) of Table 2. This includes demographic covariates (fixed effects for age, race/ethnicity, place of birth, being a proxy respondent and survey year, and years of parental education), educational attainment covariates (no high school, GED, high school, some college, and college and above), O*NET factor variables (factor 1 (“Interacting with others”) and factor 3 (“Working with machines”) and five work context factors), and occupation and industry fixed-effects (one-digit, 11 main occupations and 20 main industries).

***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

be associated with health problems not normally linked with cognitive reserve and dementia. Specifically, we estimate the association between work cognitive activity and four common health problems—arthritis, cancer, lung disease, and diabetes—while again including all the control variables used in Column (4) of Table 2. Each of these conditions are known to have a strong socioeconomic gradient (Canizares et al., 2008; Merletti et al., 2011; Prescott et al., 1999), and to be impacted by lifestyle choices (Chehade et al., 2019; Demark-Wahnefried et al., 2008; Kispert et al., 2017).

In Column (1) of Table 4 we repeat our baseline (predicted) dementia regression using the sub-sample with non-missing information on arthritis, cancer, lung disease, and diabetes. This sub-sample is slightly older (mean of 73 vs. 71 years), and has a lower percentage of non-Hispanic black and Hispanic men, and those who worked in blue-collar occupations. In Columns (2) to (5) we present the estimated associations with the four health outcomes. The estimates for arthritis, cancer, and lung disease are relatively small (0.05%, 0.04%, 0.02% compared to the sample mean), indicating that work cognitive activity is not strongly associated with these conditions. The point estimate for diabetes is larger (though only slightly larger when compared to its sample mean), but imprecisely estimated. Moreover, the point estimate is the opposite sign to the (predicted) dementia estimate. Overall, these findings suggest that the association between work cognitive activity and (predicted) dementia is unlikely to be reflecting general SES or health lifestyle decisions.

We additionally explore whether own work cognitive activity is associated with spousal (predicted) dementia. This is not a pure placebo outcome as there may be a positive association if couples' assortative mate on occupation. However, there should not be any direct effect of own work cognitive activity on spousal dementia risk, and so any association for spouses should be much smaller than the main estimated association. For the married sample we find the main estimate for work cognitive activity equals −0.77 ($p = 0.024$), but the coefficient for male work cognitive activity on spousal (predicted) dementia is only −0.25 (and not statistically significant, $p = 0.325$).

4.4 | Further tests for robustness

One of the recognized modifiable risk factors identified in the Lancet Commission is physical inactivity (Livingston et al., 2020). We partly control for physical activity at work through the work activity factors and the five physical and social work context

TABLE 4 Estimated associations between work-related cognitive activity, placebo health conditions, and (predicted) dementia.

	Predicted dementia (1)	Arthritis (2)	Cancer (3)	Lung disease (4)	Diabetes (5)
Work cognitive activity	−0.81***	0.27	0.14	−0.16	1.67*
	(0.312)	(0.152)	(0.144)	(0.632)	(0.920)
% with condition	3.74	4.92	3.11	9.59	22.45
Observations	47,591	47,591	47,591	47,591	47,591
R-squared	0.09	0.01	0.00	0.02	0.03

Note: Clustered standard errors at occupational level in parentheses. Sample restricted to males aged 60–85. The outcomes in all regressions are a binary indicator of different health conditions, amongst others (predicted) dementia; however, all estimates have been multiplied by 100 for ease of interpretation (i.e., are in percentage point units). Work cognitive activity is standardized to have mean zero and standard deviation one. The Baseline set of covariates correspond to the set included in Column (4) of Table 2. This includes demographic covariates (fixed effects for age, race/ethnicity, place of birth, being a proxy respondent and survey year, and years of parental education), educational attainment covariates (no high school, GED, high school, some college, and college and above), O*NET factor variables (factor 1 ("Interacting with others") and factor 3 ("Working with machines") and five work context factors), and occupation and industry fixed-effects (one-digit, 11 main occupations and 20 main industries).

***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

factors. However, we go further by including additional physical activity at work variables (the respondents reported performing general physical activities), and physical activity at home variables (walking frequently and undertaking sports and exercise). In addition, being cognitively active at work could be a complement or substitute for cognitive activity at home. We therefore additionally control for the frequency of cognitive activity at home, captured by educational activities, reading, writing, doing crosswords, playing cards or chess, or using the computer. When we include all these additional variables our main work cognitive activity estimate is 0.90 ($p = 0.004$) compared to our main estimate of −0.91 ($p = 0.004$).

In addition to physical inactivity, the Lancet Commission highlighted another 11 recognized risk factors for dementia: low education, hypertension, hearing impairment, smoking, obesity, depression, low social contact, excessive alcohol consumption, traumatic brain injury, and air pollution (Livingston et al., 2020). Our main regression specification already controls for education, but we test whether the positive estimated association holds even when we control for these risk factors. In particular we control for hypertension (hypertension and high blood pressure), hearing impairment (using a hearing aid), being a smoker (currently smoker), obesity (BMI>30), depression (feeling depressed last week), social contact (feeling lonely last week), excessive alcohol consumption (consuming alcohol every day of the week), and traumatic head injury (ever having suffered a head or neck injury). The one risk factor for which we do not have a measure is exposure to air pollution. Interestingly, we find that these additional covariates leave our main estimate unchanged at −0.91 ($p = 0.003$).

Finally, we use the Cinelli and Hazlett (2020) method and the associated software (Cinelli et al., 2020) to evaluate the importance of unobserved confounding. The method involves quantifying the minimum strength of a potential unobserved confounder that would account for the estimated association between work cognitive activity and (predicted) dementia. To contextualize the minimum strength, we use the explanatory power of own educational attainment as a benchmark. The results in Table 2 demonstrated that of all the many included covariates, own educational attainment was the most important in terms of reducing the coefficient on work cognitive activity (from −1.37 in Column 2 to −0.72 in Column 3). This result is due to educational attainment having high explanatory power for both work cognitive activity and later-life (predicted) dementia.

The results from the Cinelli and Hazlett (2020) method indicate that the estimated work cognitive activity coefficient would roughly halve in magnitude, but retain statistical significance, if we added to our main regression covariate set an unobserved confounder (or group of confounders) that had the observed explanatory power of own educational attainment. Specifically, the estimate would decrease in magnitude from −0.89 to −0.54 (Appendix Table A7). To fully account for the observed estimated association, we would need to add a confounder with two to three times the explanatory power of own educational attainment.

4.5 | Heterogeneity in the relationship between work cognitive activity and dementia

The Lancet Commission noted that many risk factors for dementia cluster around poverty and inequalities, and that those who are most economically disadvantaged might derive the highest benefit from changes to cognitive reserve (Livingston et al., 2020). This motivates the heterogeneity analysis in this sub-section where we re-estimate our main regression specification for sub-groups defined by two indicators of childhood socioeconomic position. Although we do not have a comprehensive measure of childhood economic disadvantage, we distinguish between: (1) those whose mother had less than 10 years schooling

TABLE 5 Heterogeneity analysis by childhood socioeconomic indicators.

	(1)	(2)
Panel A: Mother years of education	≥10	<10
Work cognitive activity	−0.20	−1.99***
	(0.165)	(0.308)
Observations	21,714	23,213
R-squared	0.04	0.10
Panel B: Childhood financial background	About average or pretty well-off	Poor
Work cognitive activity	−0.46**	−1.89***
	(0.194)	(0.066)
Observations	31,957	17,327
R-squared	0.08	0.10

Note: Clustered standard errors at occupational level in parentheses. Sample restricted to males aged 60–85. The outcome in all regressions is a binary indicator of (predicted) dementia; however, all estimates have been multiplied by 100 for ease of interpretation (i.e., are in percentage point units). Work cognitive activity is standardized to have mean zero and standard deviation one. Demographic covariates: fixed effects for age, race/ethnicity, place of birth, being a proxy respondent and survey year, and years of parental education. Educational attainment covariates: no high school, GED, high school, some college, and college and above. O*NET factor variables: Factors 1 ("Interacting with others") and 3 ("Working with machines") and five work context factors. Occupation and industry: one-digit, 11 main occupations and 20 main industries. Wealth and employment covariates: retirement status, last year worked, years employed in paid work, and household wealth. Childhood financial status: Reporting that the family was "pretty well-off", "about average", or "poor" financially when growing up.

***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

(52%) compared to those with 10 or more years of schooling; and (2) those who report that their family was "poorly off" financially when they were growing up (35%) compared to those who report their family was "about average" or "pretty well off".

In Table 5 we demonstrate evidence of heterogeneity in the association between cognitive activity at work and dementia risk. The estimated work cognitive activity coefficients significantly differ across levels of maternal education ($p = 0.003$) and by whether the individual's family was poorly off financially ($p = 0.018$).[15] The results suggest that individuals from lower socioeconomic backgrounds benefit more from work cognitive activity in terms of lower (predicted) dementia.

4.6 | Modeling within-individual variation in dementia over time

An individual's age is the strongest predictor of dementia, and so we next explore whether work cognitive activity modifies the age-dementia relationship. In other words, we estimate whether people who worked in jobs with low work cognitive activity levels have a significantly steeper age-dementia gradient than people with high work cognitive activity levels. In this analysis we can extend our main specification by including individual fixed-effects in the regressions. Importantly, the "main" work cognitive activity coefficient is not identified in fixed-effects regressions and so in Table 6 we only report how it influences the association between (predicted) dementia and age.

The within-individual estimated association between age and (predicted) dementia equals 0.51 ($p = 0.043$) (Column 1). This implies that a 10-year increase in age raises the probability of (predicted) dementia by 5.1% points. In Column (2), interaction terms between age and work cognitive activity, education, and broad occupation type are added. The coefficient on the work cognitive activity interaction term equals −0.18 ($p < 0.001$). This value implies that a one standard deviation increase in work cognitive activity reduces the age-dementia gradient by 1.8% points. Column (2) also demonstrates that the age-dementia gradient is significantly lower if respondents have higher levels of education and white-collar occupations.

Age-squared terms are added to Column (3) to capture the non-linear relationship between age and (predicted) dementia. The statistically significant positive coefficient for "age squared" suggests that the marginal effect of age on dementia risk increases with age. Given the quadratic interaction terms in Column (3), it is difficult to interpret the importance of work cognitive activity on the age-dementia relationship, and so we have estimated marginal effects at different combinations of age and work cognitive activity.[16] Specifically, the estimated age marginal effects at ages 75, 80, and 85, for someone with mean work cognitive activity levels, equal 0.97, 1.44, and 1.91, respectively. In comparison, the estimated marginal effects for someone with work cognitive activity levels two standard deviations higher than the mean are substantially lower, equaling −0.03, 0.27,

TABLE 6 Estimates from individual fixed-effect regressions of (predicted) dementia.

	(1)	(2)	(3)
Age	0.51***	1.14***	−6.35**
	(0.043)	(0.104)	(1.892)
Work cognitive activity × Age		−0.18***	0.91**
		(0.043)	(0.510)
Age squared			0.05***
			(0.014)
Work cognitive activity × Age squared			−0.01**
			(0.004)
High educational attainment × Age		−0.33***	1.48*
		(0.047)	(0.767)
White collar × Age		−0.15**	−1.54
		(0.070)	(1.003)
High educational attainment × Age squared			−0.01**
			(0.006)
White collar × Age squared			0.01*
			(0.007)
Observations	50,357	50,357	50,357
Overall *R*-squared	0.03	0.04	0.05

Note: Clustered standard errors at occupational level in parentheses. Sample restricted to males aged 60–85. The outcome in all regressions is a binary indicator of (predicted) dementia; however, all estimates have been multiplied by 100 for ease of interpretation (i.e., are in percentage point units). Work cognitive activity is standardized to have a mean zero and a standard deviation of one. The set of covariates includes interactions between age and education (more than high school graduate), white-collar longest lifetime occupation, as well as factor 1 and factor 3 from the O*NET work activity factor analysis. Models 2 and 3 also include race/ethnicity-age interactions.

***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

and 0.57, respectively. It is therefore clear from these estimates that the age-dementia relationship is significantly reduced for men who worked in occupations with high cognitive activity.

5 | CONCLUSION

As well as being a major public health problem, dementia is an important economic issue given the high costs of complex care needs, including home-based and institutional long-term care (Hurd et al., 2013; Kingston et al., 2018). This issue will become even more crucial in the coming years, with 152 million people predicted to have dementia by 2050 (WHO, 2019). Consequently, providing additional evidence on potentially modifiable risk factors is important, despite the large literature that already exists on this topic.

Importantly, there remains uncertainty regarding the extent to which cognitive activity protects against dementia. The recent Lancet Commission report (2020) lists 12 modifiable risk factors, but cognitive activity does not make the list. In this paper, we focus on the link between a person's cognitive activity in their longest lifetime occupation—measured using the Occupational Information Network (O*NET) database—and their risk of dementia during older ages—measured in the US HRS. Work-related cognitive activity is important because over a 40-year full-time career a person could have worked around 70,000 h.

A key challenge in identifying the causal effect of work cognitive activity on dementia is the non-random selection into lifetime occupations. Even in a rare (hypothetical) situation where people could be quasi-randomly assigned to an initial occupation (through a natural experiment), it is inevitable that selection will occur over a lifetime. For instance, those with higher cognitive ability are likely to select into more cognitively intensive or demanding roles. Additionally, there are many potentially confounding pathways between cognitive activity and dementia that could inflate or negate the true relationship.

Our approach is to apply a modeling strategy that sequentially tests the robustness of our main estimate to the inclusion of increasing numbers of covariates. Each successive covariate set more comprehensively captures selection into occupation and other aspects of work that might be correlated with cognitive activity. We additionally perform a series of robustness exercises, including tests for whether there is evidence of genetic confounding and whether there are work cognitive activity associations with placebo health outcomes. In addition, we use the Cinelli and Hazlett (2020) method to estimate the explanatory power of potential confounders needed to account for the association between work cognitive activity and (predicted) dementia. Overall, we believe that we have more extensively explored the robustness of the relationship than previous studies. Our use of a large nationally representative longitudinal survey (HRS) also means that our results are more likely to be generalizable than studies with small or selected samples.

However, there are also some limitations. First is the practical limitation that we focus on males only. Second, we do not directly observe if an individual has clinically-defined dementia. Rather our measure is based on having very poor episodic memory across time, which is consistent with dementia. Third, we only explore overall dementia risk, and so we are unable to separately estimate associations with different types of dementia, such as Alzheimer's disease, vascular dementia, and dementia with Lewy bodies. Fourth, despite our comprehensive regression specifications and robustness tests, we do not provide a causal analysis and we cannot rule out residual confounding. Therefore, while we have shown a robust relationship between work cognitive activity and (predicted) dementia, we cannot make any causal claims. Finally, our measure of work cognitive activity does not capture changes in the work activities of occupations over time. For example, the cognitive activity required for some roles may have changed with the adoption and proliferation of computers.

Our main result is that the estimated relationship between work cognitive activity and (predicted) dementia risk is large and robust, and approximately 60% less than the raw correlation. Our preferred estimate indicates that a one standard deviation higher work cognitive activity in a person's longest lifetime occupation is associated with a 0.9% points lower likelihood of (predicted) dementia (24% lower relative to mean prevalence). We find evidence of significant heterogeneity in this relationship by measures of socioeconomic background, which is an important topic for future research. The individual fixed-effects regression results demonstrate that people with low work cognitive activity have a significantly steeper age-dementia gradient. Overall, our results provide some evidence in support of the inclusion of cognitive activity at work as a recognized modifiable risk factor for dementia.

ACKNOWLEDGMENTS

Open access publishing facilitated by Monash University, as part of the Wiley - Monash University agreement via the Council of Australian University Librarians.

CONFLICT OF INTEREST STATEMENT

The author declares that there is no conflict of interest that could be perceived as prejudicing the impartiality of the research reported.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the Health and Retirement Study. Restrictions apply to the availability of these data, which were used under license for this study.

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ENDNOTES

[1] In terms of the evidence that cognitive training for older adults reduces the risk of cognitive decline and/or dementia, the World Health Organization (WHO, 2019) currently classifies the quality of the evidence as "very low or low".

[2] It is difficult to think of any real-world randomisations into occupations; and even if there are examples of this for initial job tasks, selection into new tasks would inevitably occur over time. Arguably, such a long-term relationship (of up to 50 years) between work cognitive activities and later life dementia could also not be identified within either a laboratory-based or field experiment framework. Similarly, using a schooling reform that increased the minimum school leaving age as a natural experiment for example, while being useful to estimate the causal effect of education on dementia, would not have the specificity to determine selection into the occupations we use to define our work cognitive activity measure.

[3] Collar color is based on an individual's longest lifetime occupation and it differentiates between blue-collar occupations consisting of agriculture, production, craft and repair, operators, fabricators and labourers, and white-collar occupations consisting of managers, professionals, technicians, or office and administration workers. Longest lifetime occupation is defined in Section 3.3.

[4] In the epidemiological, psychology and medical literature, there are many studies that focus on smaller and specific samples. Examples include the analyses of 630 men and women from the Maastricht Aging Study (Bosma et al., 2003); 122 people with Alzheimer's Disease and 235 controls

in Cleveland (Smyth et al., 2004); 171 American patients with a confirmed Alzheimer's disease (Andel et al., 2006); 386 participants from the Swedish Panel Study of Living Conditions (Andel et al., 2007); 462 individuals in the longitudinal Swedish Adoption/Twin Study of Aging (Finkel et al., 2009); 1036 U.S. World War II veterans (Potter et al., 2008); 931 non-demented people, aged older or equal than 75 from the Kungsholmen Project, Stockholm (Karp et al., 2004, 2009); 1066 individuals from the Lothian 1936 Birth Cohort (Smart et al., 2014); 323 middle-age adults at risk of AD from the Wisconsin Registry for Alzheimer's Prevention (Boots et al., 2015); 498 volunteers who had taken part in the Scottish Mental Health Survey of 1947 (Staff et al., 2018); and 800 women in the Gothenburg H70 Birth Cohort Studies (Najar et al., 2019).

[5] There are 11 O*NET variables that load strongly on the work cognitive activity factor. Amongst these, four belong to the O*NET work activities category "Mental Processes", two to "Information Outcome", four to "Work Output", and one to "Interacting with Others". As such, the factor is a combination of the main O*NET work activities groups and differs notably from "mental processes", the explanatory variable considered in Fisher et al. (2014).

[6] The sample of females was restricted in an equivalent manner to the sample of males used for the baseline results (discussed below).

[7] Individuals younger than 60 have been excluded from the sample since, as illustrated in Figure 1, there are virtually no observations with predicted dementia at ages 50–59.

[8] Crimmins et al. (2011) conclude, "We have shown that in this large national sample of older people, results from the neuropsychological diagnostic approach on a limited subsample can be used to develop methods to classify people as having dementia based on the cognitive assessments available in large population studies. The overall levels of dementia and of CIND estimated using this approach can be made similar to those directly estimated from the neuropsychological study." Chen et al. (2019) further examined the correspondence between cognitive assessment of dementia in the HRS and linked Medicare claims. They found that 85% of respondents with predicted dementia measured by cognitive decline received a diagnosis or died within their study period (2000–2008).

[9] There were four factors with eigenvalues greater than one (See Appendix Table A1). However, the eigenvalue for Factor 4 is close to one so we have not retained it for our analysis. If we do include Factor 4 in our regressions the results for work cognitive activity are unchanged.

[10] We cluster the standard errors at the occupational level (308 clusters, with mean observations per cluster of 163.45). In Appendix Table A2 we present results clustering at the individual level. The standard error on the work cognitive activity estimate using our preferred specification (Table 2, Model 4) decreases from 0.310 to 0.288, with the estimate remaining statistically significant at a 1% confidence level ($p = 0.002$).

[11] We have examined the sensitivity of the estimated association to alternative measures of work cognitive activity (see Appendix Table A3). First, the "processing information" job attribute has the largest loading on the cognitive activity factor (factor 2). Using our preferred specification (Table 2, Column 4) and replacing our main cognitive activity measure with the "processing information" attribute gives an estimate of −0.88 ($p = 0.003$). Second, using a measure that averages only the job attributes that have loadings larger than 0.7 on Factor 2 (i.e., removes any physical attributes from the calculation) gives an estimate of −1.26 ($p = 0.002$). Third, an obliquely rotated (rather than orthogonally rotated) factor gives an estimate of −1.00 ($p = 0.007$).

[12] If we estimate the Table 2, Column 4 specification only using those who have worked greater than 20 years in their longest lifetime occupation then we get a coefficient on cognitive activity of −1.02 ($p = 0.007$) compared to −0.91 ($p = 0.004$). This could suggest that there is no additional "protection" after a large number of years. However, a difficulty with the interpretation is that the cognitive activity levels of a person's other occupations may be highly correlated with the levels in their longest occupation.

[13] The algorithms use different combinations of sociodemographic characteristics, health and physical functioning variables, social engagement indicators, and cognitive indicators to estimate (predicted) dementia probabilities, which are then used to classify dementia status using race/ethnicity-specific probability thresholds. The algorithms were trained and evaluated using a dataset linking HRS data and data from all four waves of the Aging, Demographics, and Memory Study (ADAMS).

[14] This data is a random subset of 26,000 total participants selected to participate in enhanced face-to-face interviews and saliva specimen collection (for DNA) in 2006, 2008, 2010, and 2012. We used the best-guess genotypic data that was imputed using approximately 21 million DNA variants from the 1000 Genomes Project, phase I (Ware et al., 2018). This provides individual polygenic risk scores for different traits and health conditions.

[15] If we estimate the Table 2, Column 4 specification adding these two indicators of childhood socioeconomic position, the coefficient of work cognitive activity raises to −1.06 ($p = 0.004$), compared to −0.91 ($p = 0.004$).

[16] The p-value for the hypothesis test that work cognitive activity × age and work cognitive activity × age squared are jointly equal to zero equals 0.038.

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How to cite this article: Martin-Bassols, N., de New, S. C., Johnston, D. W., & Shields, M. A. (2023). Cognitive activity at work and the risk of dementia. *Health Economics*, *32*(7), 1561–1580. https://doi.org/10.1002/hec.4679

APPENDIX

ADDITIONAL INFORMATION ON DERIVING DEMENTIA AND LONGEST LIFETIME OCCUPATION

Derivation of dementia for proxy respondents

Information is collected through proxy respondents for individuals with communication problems due to ill health, communication disorders, or psychiatric disorders. It is crucial to include these respondents since individuals who have dementia may not respond to the survey interview themselves. Having a proxy respondent cannot be directly used as a predictor of dementia since there are reasons other than cognitive impairment that may lead individuals to need assistance. However, based on Crimmins et al. (2011), it can be predicted if individuals using proxy respondents have dementia combining three tests: (1) Memory assessment, in which the proxy respondent rates the primary respondents' memory from excellent to poor (0–4 points); (2) An assessment of activities, in which the interviewer asks the proxy respondent if the main respondent has problems doing the groceries, preparing hot meals, using the phone, handling money and taking their medication (0–5 points); (3) The interviewer assessed the respondents' difficulty in answering the survey (0–2 points). These three items are added to generate a scale that ranges from zero to 11, with individuals being classified as suffering dementia if they score six to 11 points.

Longest lifetime occupation

Occupational histories are found in the HRS restricted data on industry and occupation. The approach of Bugliari et al. (2019) is followed to generate a measure of longest lifetime occupation across individuals, while losing as few observations as possible. In a first step the number of years worked at different occupations is identified. In a second step, the longest lifetime occupation is assigned to the occupation with the longest job tenure.

If longest job tenure cannot be found, a hierarchical combination of three different variables is imposed: (1) longest lifetime occupation; (2) last occupation; (3) current occupation. The hierarchical combination goes as follows. Longest lifetime occupation is the preferred measure, but this variable is not observed for some individuals. Last occupation is the second-best option and if neither of both variables are observed the current occupation of individuals is used. Note that only observing one of these measurements is sufficient to capture the longest lifetime occupation of individuals. In other words, if individuals reports at least once the longest lifetime occupation, last occupation or current occupation, they will be considered for the sample.

The HRS restricted data of industry and occupation is coded in three-digit Census Occupational Categories which are transformed into 330 occ1990dd occupational categories (Autor & Dorn, 2013). We use occupations coded in 1980, 2000, and 2010 Census Occupational Categories. Occupations in the O*NET are recorded following the Standard Occupation System codes (SOC). They are cross-walked to three-digit Census Occupational Categories, and also transformed to 330 occ1990dd occupational categories. This makes it possible to merge both databases. For each of the different occupations a score is assigned for the different work activities. The work activities scores are generated from the 2005 O*NET database, running a factor analysis.

ADDITIONAL TABLES

TABLE A1 Occupational activities sorted according to the rotated factors.

Occupational characteristics	Factor 1	Factor 2	Factor 3
Coaching and developing others	0.89	0.24	−0.01
Guiding directing and motivating subordinates	0.89	0.16	−0.07
Developing and building teams	0.89	0.29	−0.03
Scheduling work and activities	0.87	0.32	−0.05
Coordinating the work and activities of others	0.87	0.23	−0.05
Resolving conflicts and negotiating with others	0.86	0.30	−0.10
Training and teaching others	0.85	0.31	0.03
Establishing and maintaining interpersonal relationships	0.84	0.42	−0.13
Developing objectives and strategies	0.83	0.41	−0.09
Staffing organisational units	0.82	0.11	−0.14
Organizing planning and prioritizing work	0.76	0.47	−0.15
Monitoring and controlling resources	0.75	0.16	−0.06
Selling or influencing other	0.75	0.21	−0.11
Communicating with supervisors' peers or subordinates	0.74	0.51	−0.00
Performing for or working directly with the public	0.74	0.18	−0.02
Communicating with persons outside organization	0.72	0.46	−0.14
Assisting and caring for others	0.71	0.21	0.08
Provide consultation and advice to others	0.70	0.54	−0.10
Making decisions and solving problems	0.70	0.58	0.05
Thinking creatively	0.65	0.40	−0.12
Performing administrative activities	0.64	0.51	−0.20
Judging the qualities of things services or people	0.60	0.32	−0.01
Processing information	0.40	0.82	−0.15
Analyzing data or information	0.37	0.78	−0.10
Getting information	0.32	0.75	−0.06
Interacting with computers	0.44	0.74	−0.21
Documenting/recording information	0.49	0.71	0.01
Updating and using relevant knowledge	0.60	0.70	0.10
Performing general physical activities	−0.13	−0.67	0.51
Interpreting the meaning of information for others	0.64	0.65	−0.13
Identifying objects actions and events	0.36	0.65	0.20
Evaluating information to determine compliance with standards	0.27	0.61	0.13
Handling and moving objects	−0.49	−0.59	0.47
Repairing and maintaining mechanical equipment	−0.26	−0.24	0.79
Repairing and maintaining electronic equipment	−0.02	0.24	0.77
Inspecting equipment structures or material	−0.11	−0.12	0.76
Operating vehicles mechanized devices or equipment	0.25	−0.18	0.67
Controlling machines and processes	−0.47	−0.37	0.58
Monitor processes materials or surroundings	0.13	0.22	0.42
Drafting laying out and specifying technical devices	0.03	0.13	0.37
Estimating quantifiable characteristics of products or information	0.33	0.26	0.13
Eigenvalue	22.49	4.30	2.77

Note: Orthogonally rotated factors. Factors with eigenvalues greater than 1 retained.

TABLE A2 Estimated associations between work-related cognitive activity and (predicted) dementia clustering at the individual level.

	(1)	(2)	(3)	(4)	(5)
Work cognitive activity	−2.23***	−1.37***	−0.72***	−0.91***	−0.89***
	(0.173)	(0.158)	(0.157)	(0.288)	(0.287)
Demographics	×	✓	✓	✓	✓
Educational attainment	×	×	✓	✓	✓
O*Net factors variables	×	×	×	✓	✓
Occupation and industry	×	×	×	✓	✓
Wealth and employment	×	×	×	×	✓
Observations	50,357	50,357	50,357	50,357	50,357
R-squared	0.01	0.07	0.09	0.09	0.10

Note: Clustered standard errors at individual level in parentheses. Sample restricted to males aged 60–85. The outcome in all regressions is a binary indicator of (predicted) dementia; however, all estimates have been multiplied by 100 for ease of interpretation (i.e., are in percentage point units). Work cognitive activity is standardized to have mean zero and standard deviation one. Demographic covariates: fixed effects for age, race/ethnicity, place of birth, being a proxy respondent and survey year, and years of parental education. Educational attainment covariates: no high school, GED, high school, some college, and college and above. O*NET factor variables: Factors 1 (“Interacting with others”) and 3 (“Working with machines”) and five work context factors. Occupation and industry: one-digit, 11 main occupations and 20 main industries. Wealth and employment covariates: retirement status, last year worked, years employed in paid work, and household wealth.
***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

TABLE A3 Using alternative approaches for measuring work cognitive activity.

	(1)	(2)	(3)	(4)
Work cognitive activity orthogonal	−0.91***			
	(0.310)			
Processing information		−0.88***		
		(0.296)		
Average factors with loadings above 0.7			−1.26***	
			(0.404)	
Work cognitive activity oblique				−1.00***
				(0.371)
Baseline covariates	✓	✓	✓	✓
Observations	50,357	50,357	50,357	50,357
R-squared	0.08	0.08	0.08	0.08

Note: Clustered standard errors at occupational level in parentheses. Sample restricted to males aged 60–85. The outcome in all regressions is a binary indicator of (predicted) dementia; however, all estimates have been multiplied by 100 for ease of interpretation (i.e., are in percentage point units). Work cognitive activity is standardized to have mean zero and standard deviation one. Demographic covariates: fixed effects for age, race/ethnicity, place of birth, being a proxy respondent and survey year, and years of parental education. Educational attainment covariates: no high school, GED, high school, some college, and college and above. O*NET factor variables: Factors 1 (“Interacting with others”) and 3 (“Working with machines”) and five work context factors. Occupation and industry: one-digit, 11 main occupations and 20 main industries.
***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

TABLE A4 Using further alternative approaches for measuring dementia.

	(1)	(2)	(3)	(4)
	Main measure	**Hurd**	**Expert**	**Lasso**
Work cognitive activity	−1.57***	−2.08***	−2.17***	−1.29***
	(0.488)	(0.540)	(0.497)	(0.571)
Observations	18,700	18,700	18,700	18,700
R-squared	0.10	0.15	0.21	0.14

Note: Clustered standard errors at occupational level in parentheses. Sample restricted to males aged 60–85. The outcomes are the predicted dementia measure of Crimmins et al. (2011), Hurd et al. (2013), and Gianattasio et al. (2020). They are binary; however, all estimates have been multiplied by 100 for ease of interpretation (i.e., are in percentage point units). Work cognitive activity is standardized to have mean zero and standard deviation one. The Baseline set of covariates correspond to the set included in Column (4) of Table 2. Demographic covariates: fixed effects for age, race/ethnicity, place of birth, being a proxy respondent and survey year, and years of parental education. Educational attainment covariates: no high school, GED, high school, some college, and college and above. O*NET factor variables: Factors 1 (“Interacting with others”) and 3 (“Working with machines”) and five work context factors. Occupation and industry: one-digit, 11 main occupations and 20 main industries.
***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

TABLE A5 Using alternative approaches for measuring dementia.

	(1) Predicted dementia (main measure)	(2) Time changing dem. (can score below or above threshold in different waves)	(3) Always dem. after first dem. prediction	(4) Ever had dem. (One observation per individual)
Work cognitive activities	−0.91***	−0.69**	−0.60**	−2.35***
	(0.310)	(0.283)	(0.249)	(0.461)
Baseline covariates	✓	✓	✓	✓
Observations	50,357	50,357	50,357	8896
R-squared	0.09	0.11	0.09	0.08

Note: Clustered standard errors at occupational level in parentheses. Sample restricted to males aged 60–85. The outcome in column (1) is the baseline measure of predicted dementia. In column (2) dementia captures scoring below the dementia threshold in all subsequent waves after first being predicted to suffer dementia. In column (3) dementia captures having an average cognition score in the subsequent waves after first being predicted to suffer dementia below the dementia threshold. Individuals have to be classified as suffering dementia in one wave, and the average score in the subsequent waves must be below the dementia threshold. In column (4) the data is collapsed at an individual level and dementia captures ever having scored below the dementia threshold. The outcome measures are binary; however, all estimates have been multiplied by 100 for ease of interpretation (i.e., are in percentage point units). Work cognitive activity is standardized to have mean zero and standard deviation one. Demographic covariates: fixed effects for age, race/ethnicity, place of birth, being a proxy respondent and survey year, and years of parental education. Educational attainment covariates: no high school, GED, high school, some college, and college and above. O*NET factor variables: Factors 1 ("Interacting with others") and 3 ("Working with machines") and five work context factors. Occupation and industry: one-digit, 11 main occupations and 20 main industries.

***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

TABLE A6 Using alternative approaches for measuring occupation.

	(1) Longest lifetime occupation	(2) Last occupation before retirement	(3) Source prospective information (employed when joined HRS)	(4) Source retrospective information (non-employed when joined HRS)	(5) Average all occupations
Work cognitive activity	−0.91***	−0.88***	−0.87***	−1.84***	−1.17***
	(0.310)	(0.272)	(0.274)	(0.574)	(0.312)
Baseline covariates	✓	✓	✓	✓	✓
Observations	50,357	50,357	37,948	16,335	50,357
R-squared	0.09	0.09	0.07	0.12	0.09

Note: Clustered standard errors at occupational level in parentheses. Sample restricted to males aged 60–85. The outcome in all regressions is a binary indicator of (predicted) dementia; however, all estimates have been multiplied by 100 for ease of interpretation (i.e., are in percentage point units). Work cognitive activity in column (1) refers to the baseline measure of longest lifetime occupation, in column (2) it refers to the most currently reported occupation, and in column (3) to the average work cognitive activity across all ever-reported occupations. Work cognitive activity is standardized to have mean zero and standard deviation one. Demographic covariates: fixed effects for age, race/ethnicity, place of birth, being a proxy respondent and survey year, and years of parental education. Educational attainment covariates: no high school, GED, high school, some college, and college and above. O*NET factor variables: Factors 1 ("Interacting with others") and 3 ("Working with machines") and five work context factors. Occupation and industry: one-digit, 11 main occupations and 20 main industries.

***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

TABLE A7 Bounds on omitted variable bias.

Bound (1)	Share of residual variance of work cognitive activity (2)	Share of residual variance of work dementia (3)	Coef.	S.E.	Lower CI 95%	Upper CI 95%
1x	0.0078	0.0129	−0.54	0.17	−0.88	−0.20
2x	0.0157	0.0258	−0.14	0.17	−0.48	0.20
3x	0.0235	0.0387	0.26	0.17	−0.08	0.60

Note: Standard errors clustered at occupational level. (1) represents the extent of confounding. (2) represents R2dz.x (Cinelli & Hazlett, 2020), the share of residual variance of work cognitive activity explained by the omitted variable (benchmarked with educational attainment), after accounting for the remaining covariates. (3) represents R2yz.dx (Cinelli & Hazlett, 2020), the share of residual variance of predicted dementia explained by the omitted variable (benchmarked with educational attainment), after accounting for the treatment variable and the remaining covariates. Sample restricted to males aged 60–85. The outcome is a binary indicator of (predicted) dementia; however, all estimates have been multiplied by 100 for ease of interpretation (i.e., are in percentage point units). Work cognitive activity is standardized to have mean zero and standard deviation one. The Baseline set of covariates correspond to the set included in Column (4) of Table 2. This includes the following groups of covariates. Demographic covariates: fixed effects for age, race/ethnicity, place of birth, being a proxy respondent and survey year, and years of parental education. Educational attainment covariates: no high school, GED, high school, some college, and college and above. O*NET factor variables: Factors 1 ("Interacting with others") and 3 ("Working with machines") and five work context factors. Occupation and industry: one-digit, 11 main occupations and 20 main industries.