PhD-FHSE-2025-003
The Faculty of Humanities, Education and Social Sciences

DISSERTATION

Defence held on 30/01/2025 in Esch-sur-Alzette, Luxembourg

to obtain the degree of

DOCTEUR DE L'UNIVERSITÉ DU LUXEMBOURG

EN SCIENCES SOCIALES

by

Jung Hyun KIM
Born on 31 January 1994 in Daejeon, (Republic of Korea)

OLDER WORKERS, LABOR POLICY AND COGNITIVE HEALTH

Dissertation defence committee

Dr Anja Leist, dissertation supervisor
Professor, Université du Luxembourg

Dr Graciela Muniz-Terrera
Professor, Ohio University

Dr Louis Chauvel, Chairman
Professor, Université du Luxembourg

Dr Emilie Courtin
Assistant Professor, London School of Economics

Dr Rejko Krüger, Vice Chairman
Professor, Université du Luxembourg

Older Workers, Labor Policy and Cognitive Health

Jung Hyun Kim

Dissertation submitted in fulfillment of
the requirements for the degree of Doctor of Philosophy

University of Luxembourg
2025

Abstract

With the aging population, there has been growing attention on understanding the quality of life in later years. Cognitive functioning plays a vital role in the well-being of older adults, as it directly impacts their level of independence. Research has provided evidence of preventive measures that can slow or delay cognitive decline. Central to this understanding is the "use it or lose it" hypothesis, which suggests that intellectually stimulating activities can help protect against cognitive decline. One aspect of this hypothesis posits that participation in the labor force is cognitively stimulating, while withdrawal from the labor market may contribute to cognitive decline. Indeed, studies have consistently indicated that retirement can negatively affect cognitive function in older adults. However, little has been explored on the health effects of economic activities after the normative retirement age.

This thesis seeks to investigate late-life labor market participation as a potential social determinant of cognitive health. Chapter 1 examines how entering the labor market after the normative retirement age impacts the cognitive health of older adults. Chapters 2 and 3 explore the impact of labor policies, particularly minimum wage policies, on the cognitive health of older workers. Finally, Chapter 4 addresses the methodological challenges posed by small sample-sized populations when estimating dementia cases. Overall, this thesis explores the role of late-life labor market participation in the health of older adults through a causal lens and contributes to overcoming methodological challenges in dementia estimation for more accurate and equitable investigations.

Acknowledgments

I would like to thank my PhD advisor, Anja Leist for being an amazing mentor. It was especially during the moments of difficulty that her encouragement and guidance made me move forward. The lessons I have learned from Anja and the time together will be an irreplaceable asset throughout my path.

I am grateful to Graciela Muniz-Terrera (also as a collaborator) and Rejko Krüger for being part of my PhD committee. It has been a joy to work with and learn from them. I thank Emilie Courtin for agreeing to be a jury member, it is a true honor. I thank the chair of the jury, Louis Chauvel, for providing me with inspiring comments from which I have benefited immensely.

Incredible collaborators made this journey more exciting. I am grateful to Maria Glymour. From the first encounter, I knew that my research journey would not be the same. I am fortunate to have tried to find answers to the challenging issues in public health with her advice and direction. I thank Kenneth Langa for the encouragement with his warm words, which I have repeatedly read over and over again. I thank Marc Suhrcke, for his accurate comments and our exciting exchanges. I am grateful to Ichiro Kawachi for seeing my potential and giving me the opportunity to pursue the topics of my heart in a fantastic environment.

My thesis has benefited from the exchanges with Philippe Van Kerm, Conchita d'Ambrosio, Andrew Clark, Marianne Bitler, Mireille Jacobson, Susan Parker, William Dow, Christopher Lowenstein, and Ye Tian who have been generous with their time and energy.

I thank my wonderful colleagues and friends, with whom I have been fortunate to interact. It is through their humility and brilliance I can find hope and joy in pursuing research. Beyond the academic community, I have been blessed to be surrounded by caring friends who have stood by my side. My gratitude will be conveyed individually.

I am eternally grateful to my family for challenging me to see what's not seen and to hear what's not heard. It was the discussion in the park with my father that led me to pursue this topic. They have been the source of my inspiration and provided me with meaning in this journey.

My last word of gratitude goes to my best friend Friedo, who has been the first reader of my work from my bachelor's thesis to this one, and whose steadfast love and support have shaped me into a better person.

"Research is a service we give back to society", is the word that I have been keeping throughout this path. If there is anything I can give back to society, it must be the gift of life that I have received from every encounter and the light found between them.

Statement of conjoint work

Part of the chapters of this thesis has been published or is under review in peer-reviewed academic journals.

Below is the list of conjoint work with Professor Graciela Muniz-Terrera from Ohio university and the University of Edinburgh, Professor M. Maria Glymour from Boston University, Professor Kenneth M. Langa from University of Michigan, Professor Marc Suhrcke from the Luxembourg Institute of Socio-Economic Research and University of York, and Professor Anja K. Leist from the University of Luxembourg.

For these studies, I conceptualized and designed the study, obtained and analyzed the data, interpreted the results, and drafted the paper. All co-authors advised on the statistical analysis, interpretation, provided feedback on the draft, and read and approved the final version of the manuscript.

Chapter 1. Kim JH, Muniz-Terrera G, Leist AK (2023), "Does (re-)entering the labour market at advanced ages protect against cognitive decline? A matching difference-in-differences approach" *Journal of Epidemiology and Community Health*: 77:663-669.

Chapter 2. Kim JH, Suhrcke M, Leist AK (2024), "The unintended effects of a large minimum wage increase on health: Evidence from South Korea" *Social Science*

& Medicine: 365.

Chapter 3. This chapter is based on a single-authored work:
Kim JH (2024), "Minimum wages and health of older workers".

Chapter 4. Kim JH, Glymour MM, Langa KM, Leist AK (2024), "Improving accuracy in the estimation of probable dementia in racially and ethnically diverse groups with penalized regression and transfer learning" *Forthcoming at American Journal of Epidemiology.*

Contents

List of Tables

List of Figures

General Introduction

Cognitive aging and its determinants

How we perceive, remember, and reason is critically impacted by cognitive function. Consequences of cognitive decline include the loss of autonomy, which is integral to the dignity of one's life. Severe cognitive impairment is a major symptom of dementia, characterized by a decline in memory and other cognitive functions, impeding independence in daily functioning (American Psychiatric Association 1994). Among individuals aged 65 and older, 10% were diagnosed with dementia, and 22% were identified as having mild cognitive impairment in the United States (Manly et al. 2022). The prevalence of dementia is expected to rise rapidly in North Africa, the Middle East, and Eastern Sub-Saharan Africa due to population growth and aging (Nichols et al. 2022b).

Beyond the individuals experiencing symptoms, cognitive impairment and dementia concern families and society, as they require resource-intensive care. In aging societies, neurodegenerative diseases accompanied by cognitive impairment represent one of the most costly public health challenges. Specifically, dementia alone affects 55 million people worldwide, with related costs amounting to $1.313 billion (Wimo et al. 2023). While potential treatments for cognitive impairment and dementia are beginning to show progress (Budd Haeberlein et al. 2022; van Dyck et al. 2023), the cost of treatment remains unattainable for the public due to limited availability (Chandra et al. 2023). This is why careful causal inference studies to identify potential risk factors for cognitive impairment and dementia are an urgent public health priority. Despite growing awareness and an increasing number of research studies, several unanswered questions remain, especially regarding the social and economic determinants of cognitive health.

Livingston et al. (2024) claimed that by modifying 14 risk factors (including less education, head injury, physical inactivity, smoking, excessive alcohol consumption, hypertension, obesity, diabetes, hearing loss, depression, infrequent social contact, air pollution, vision loss, and high LDL cholesterol), we might be able to prevent or delay almost half of dementia cases. The mechanisms for preventing or delaying dementia include reducing vascular damage and lowering neuropathological damage. Vascular damage is associated with stroke and vascular dementia, while neuropathological damage involves the accumulation of β-amyloid and tau proteins, which are linked to Alzheimer's disease.

Individuals with higher educational and occupational attainments have been found to experience delayed onset of cognitive decline, although the rate of decline accelerates after its onset (Andel et al. 2006). The capacity to remain resilient against brain damage and pathology is referred to as *cognitive reserve*. There are two types of reserve, distinguished by their level of activeness: the process of actively compensating for brain damage is termed cognitive reserve, while the ability to delay the onset of cognitive decline until a certain threshold is called brain reserve (Stern 2002). For instance, education formed in early stage of life is thought to build brain reserve by delaying the onset of dementia, rather than actively compensating for damage itself (Lövdén et al. 2020; Muniz-Terrera et al. 2009), whereas a healthy diet and physical and social activities in later life may be more related to building cognitive reserve.

Due to the urgency and high prevalence of cognitive impairment and dementia, extensive lifestyle interventions, such as dietary guidance, physical exercise, cognitively stimulating activities, health advice, and monitoring, have been explored (Kivipelto et al. 2018, for the summary review). The Finnish Geriatric Intervention Study to Prevent Cognitive Impairment and Disability (FINGER) provided evidence that interventions targeting multiple lifestyle domains were effective in preventing cognitive decline in older adults (Ngandu et al. 2015). However, findings from intervention studies do not fully address the fundamental social causes that lead to less healthy lifestyle choices. This has led to a growing focus on the *social determinants* of cognitive impairment and dementia (Berkman et al. 2014; Chauvel and Leist 2015). Social and economic factors, such as lower education, income, unemployment, or health-hazardous occupations, reflect unequal opportunities to maintain health and develop cognitive functioning. These factors may increase neuropathological damage or reduce the potential to build cognitive reserve.

Further investigations into policies and actions aimed at reducing social disadvantage, from early childhood to late adulthood, are warranted to address cognitive health challenges (Rossor and Knapp 2015; Adler et al. 2016; Saunders et al. 2017). To achieve this, a life-course approach (Shanahan 2000; Elder Jr. and Shanahan 2007) has been suggested to study the socioeconomic risk factors for cognitive decline across different life stages (Glymour and Manly 2008). Research on social determinants of cognitive health includes, but is not limited to, studies on adverse childhood experiences (Kobayashi 2024), structural racism (Adkins-Jackson et al. 2024), education (Lee et al. 2003; Courtin et al. 2019; Seblova et al. 2020), mid-life labor market experiences (Virtanen et al. 2009; Andel et al. 2011; Leist et al. 2013, 2014), retirement (Bonsang et al. 2012), living arrangements (Mazzuco et al. 2017), social isolation (Okamoto and Kobayashi 2020), and additional income (Rosenberg et al. 2024) in late life.

An important area with potential for cognitive development that has surprisingly received little attention is *late-life labor market experiences*. The “use it or lose it” hypothesis for cognitive health suggests that engaging in intellectually stimulating activities might help build cognitive reserve (Hultsch et al. 1999b; Salthouse 2006). Examples of cognitively stimulating activities include learning, reading, playing music or games, or participating in cultural activities (Mitchell et al. 2012). However, it remains uncertain how older adults with limited means to engage in such activities can protect themselves from both cognitive decline and financial strain. For those without sufficient resources, involvement in economic activities in late life might be more relevant for maintaining cognitive health. Late-life labor market experiences may affect cognitive health through changes in income and consumption, time allocation, cognitive stimulation, and social interactions, but also through job strain and physical demands. One study showed that older retirement ages were associated with lower dementia risk, supporting the“use it or lose it” hypothesis (Dufouil et al. 2014). However, the causal impact of late-life labor market experiences on cognitive function remains unclear, as establishing causality is challenging due to the difficulty of conducting randomized control trials with potential risk factors.

This thesis explores the social determinants of cognitive impairment through a causal lens, with a focus on late-life labor market experiences beyond the normative retirement age.

Research questions and outline

This thesis focuses on late-life labor market experiences as a potential social determinant of cognitive health in older adults. The central question addressed is: *What is the impact of labor market experiences after retirement age on the cognitive health of older adults?*

The thesis begins by challenging the prevailing assumption of a defined "working age." In fact, in South Korea, more than one in three adults aged 65 and older is engaged in paid work, while in the US, the figure is one in five (OECD 2024). These substantial percentages highlight the need to reconsider traditional views on working age and demonstrate the importance of studying social determinants of health within the labor market context for older adults. In Chapter 1, I investigate the impact of entering the labor market at age 65+ on cognitive health by comparing South Korea and the US. Drawing upon data from the Health and Retirement Study (HRS) and its sister study in Korea, the Korean Longitudinal Study of Aging (KLoSA), I use the matching difference-in-differences method to estimate the impacts on health. The findings reveal that in South Korea, older workers benefit positively from labor market participation, whereas in the US, no significant effects are observed. Differences in contextual factors and the financial situations of older adults in South Korea and the US may explain these variations.

While some individuals may experience positive, neutral, or negative health outcomes from working beyond the normative retirement age, the health implications are highly dependent on the socioeconomic status and circumstances of older workers. As a result, the focus shifts to lower-income older workers, who may experience the most pronounced health impacts from labor market participation.

The next two chapters focus on the impact of minimum wage policy on cognitive health. In Chapter 2, I analyze the impact of a significant minimum wage increase that occurred in South Korea in 2018. I use KLoSA data and exploit the quasi-randomness of minimum wage increases, applying two-way fixed effects to study the causal effects. Surprisingly, I find that this increase led to a decline in cognitive functioning among lower-wage older workers. No effects were observed among slightly higher-wage older workers, indicating that the cognitive decline was specific to the target group of the minimum wage policy. This decline in cognitive function may be linked to a significant reduction in working hours, caused by tight labor market conditions affecting lower-wage older workers.

Chapter 3 continues the investigation into the health effects of minimum wage policies. Using HRS data, I leverage state-level variation in minimum wage increases and employ modern difference-in-differences methods that are robust to staggered treatment timings and heterogeneous effects. I find negative health effects related to self-reported health, but not cognitive function. I observed an increase in the frequency of alcohol consumption among older workers without college degrees following minimum wage increases. These negative health effects were not found among college-educated workers. The rise in alcohol consumption may explain the unintended negative health consequences experienced by non-college-educated older workers in the US. The health effects of minimum wage policies vary by wage and education levels, and future research could explore how these health implications differ across racial and ethnic groups, considering potential societal barriers.

Chapter 4 addresses a methodological issue to enhance the quality of future studies on the determinants and consequences of dementia. It focuses on improving dementia classification algorithms, particularly for non-Hispanic Black and Hispanic populations. By applying a transfer learning approach from machine learning, I demonstrate improved accuracy in dementia classifications for these demographic groups. More precise dementia classifications can lead to more accurate answers to questions concerning the social determinants of cognitive health in diverse populations. This final empirical chapter introduces new statistical methods to address the challenge of small sample sizes in cognitive health and dementia research.

The thesis concludes by summarizing the findings across chapters, elaborating on their contributions and limitations, and outlining future research directions in Chapter 5.

Chapter 1

Employment at advanced ages and cognitive function

A version of this study is published in the *Journal of Epidemiology and Community Health* (Kim, Muniz-Terrera, Leist, 2023).

1.1 Introduction

An increase in advanced-age labor force participation, specifically beyond ages 65 and older, has been observed across industrialized economies over the last decade (Taylor et al. 2016; Bureau of Labor Statistics 2019; Eurostat 2020; Oshio et al. 2020). South Korea makes itself an interesting case study with the highest labor force participation rate of older adults, accounting for 36% of the individuals aged 65+ in 2021 (OECD 2023b).

In this chapter, I examine the impacts of the late-life labor market "entry and exit" on cognitive function in South Korea and compare the causal effects with results from the US, a country whose older population has marked cultural and socioeconomic characteristics with South Korea's.

The main interest is cognitive function. Poor cognitive function is a growing public health concern for aging societies (Anderson and McConnell 2007). A decline in cognitive function is negatively associated with the deprivation of one's physical and mental autonomy and imposes a financial burden on the family and society due to the high cost of health and social care (Lin and Neumann 2013). Due to such reasons, exiting or remaining in the labor force at later adulthood on cognitive function has received public health and economic attention (Bonsang et al. 2012; Xue et al. 2018; Atalay et al. 2019; Rohwedder and Willis 2010; Schwingel et al. 2009; Wickrama et al. 2013; Dufouil et al. 2014). Yet, very few studies have examined the impacts of late-life labor market participation beyond age sixty-five, and the evidence has been restricted to a few countries.

This chapter uses population-based data from South Korea and the United States. Investigating and comparing causal effects with more than one population is challenging with age-nonrelated policy change as an instrument unless such changes occur in parallel. To overcome these limitations, I use the matching difference-in-differences from the potential outcomes framework (Imai et al. 2023). This approach shares the reasoning of trial emulation in epidemiology which mimics randomized controlled trials (García-Albéniz et al. 2017; Hernán and Robins 2016).

This method matches the confounders and the employment histories prior to the exposure. Past work history is an important confounder affecting future employment status (Dingemans and Möhring 2019) and cognitive health (Leist et al. 2013). By matching according to the employment history, I may capture further unobserved time-varying confounders such as work attitude, desire to work, or job insecurity.

In line with the 'use it or lose it' hypothesis (Hultsch et al. 1999), that intellectually stimulating activities can protect against cognitive decline in later life, I expect labor market entry to have positive effects on cognitive functioning and labor market exits to have negative effects, similar across countries. I explored putative moderators, sex/gender, education, and socioeconomic status without directed hypotheses.

Late-life financial conditions in South Korea and the US

Earnings from work as a source of income account for more than half of the total income of older adults aged 65+ in Korea (OECD 2021a). The share of public transfers on total income at ages 65+ is only slightly above 25% in Korea, while public transfers contribute to 57% of incomes in the advanced economies (In Korea, the pension age was 60 in 2007 and 62 in 2020). Moreover, a low percentage of private occupation-related pensions as a source of income excludes the possibility of private pensions substituting the lack of public transfers. This suggests that the maturing of the public pension system has not yet fully managed to keep pace with the country's earning growth. With few alternative income sources to compensate for insufficient public transfers, many Korean older adults (re-)enters the labor market at advanced ages. However, there is still a significant generational income gap between the current working-age population and the population aged 65+.

In the US, earnings from work account for around 35% of income sources of older adults. More than 40% of the total income is covered by public transfers. Retirees on average have around 94% of the average total income of the total population. The labor force participation of older adults in the US age 65 and above was slightly less than 20% in 2020. Overall, older adults in the US are better financially than the average older adults in advanced economies. However, an alarming amount of income inequality measured by the Gini coefficient implies that the favorable conditions of older adults are disproportionately shared (OECD 2023b, 2021a).

1.2 Data: Health and Retirement Study and Korean Longitudinal Study of Aging

Data came from the Korean Longitudinal Study of Aging (KLoSA), which is a sister study of the Health Retirement Study (HRS). It started data collection in 2006 and it is designed to be nationally representative of Korean households. It is a biennial survey on approximately 10,000 individuals on demographics, family composition, health, employment, and financial status for adults over age 45 who reside in South Korea (excluding Jeju Island). Further information can be found on the KLoSA website (http://survey.keis.or.kr). I used data from 2006 to 2020 for this study (Figure 1.1).

For the US analysis, I used the HRS, a nationally representative sample of private households with members aged 51 years and older in the US since 1992. It is a biennial follow-up data on more than 43,000 individuals on demographics, family structure, health, and economic resources. Further information is available elsewhere (Sonnega et al. 2014). I used from year 2006 to 2018 of the RAND HRS Longitudinal File 2018 (V2) and the HRS 2020 Core Early Release (Version 2.0) (Figure 1.2).

Employment status transitions at late life

To reduce possible selection into entering or exiting the labor market, I employ a difference-in-differences (DID) design to compare participants with and without exposure after several steps of reducing possible confounding. Using the terminology of the DID method, the so-called 'treatment' "entering the labor market" captures employment transitions from being non-employed at wave $t-1$ to employed at wave t. I compare individuals entering the labor market to the 'control' group of individuals who remain inactive, i.e., out of the labor market from wave $t-1$ to wave t. Likewise, "exiting the labor market" identifies employment transitions from being employed at wave $t-1$ to non-employed at wave t. I compare individuals who exit the labor market to the 'control' group of individuals who stay in the labor market from wave $t-1$ to wave t. I restrict the treatment years from 2012 to 2018.

Covariates

Following the established definitions, I call all methods that balance the covariates between the treated and control groups "matching" (Stuart 2010). I match the

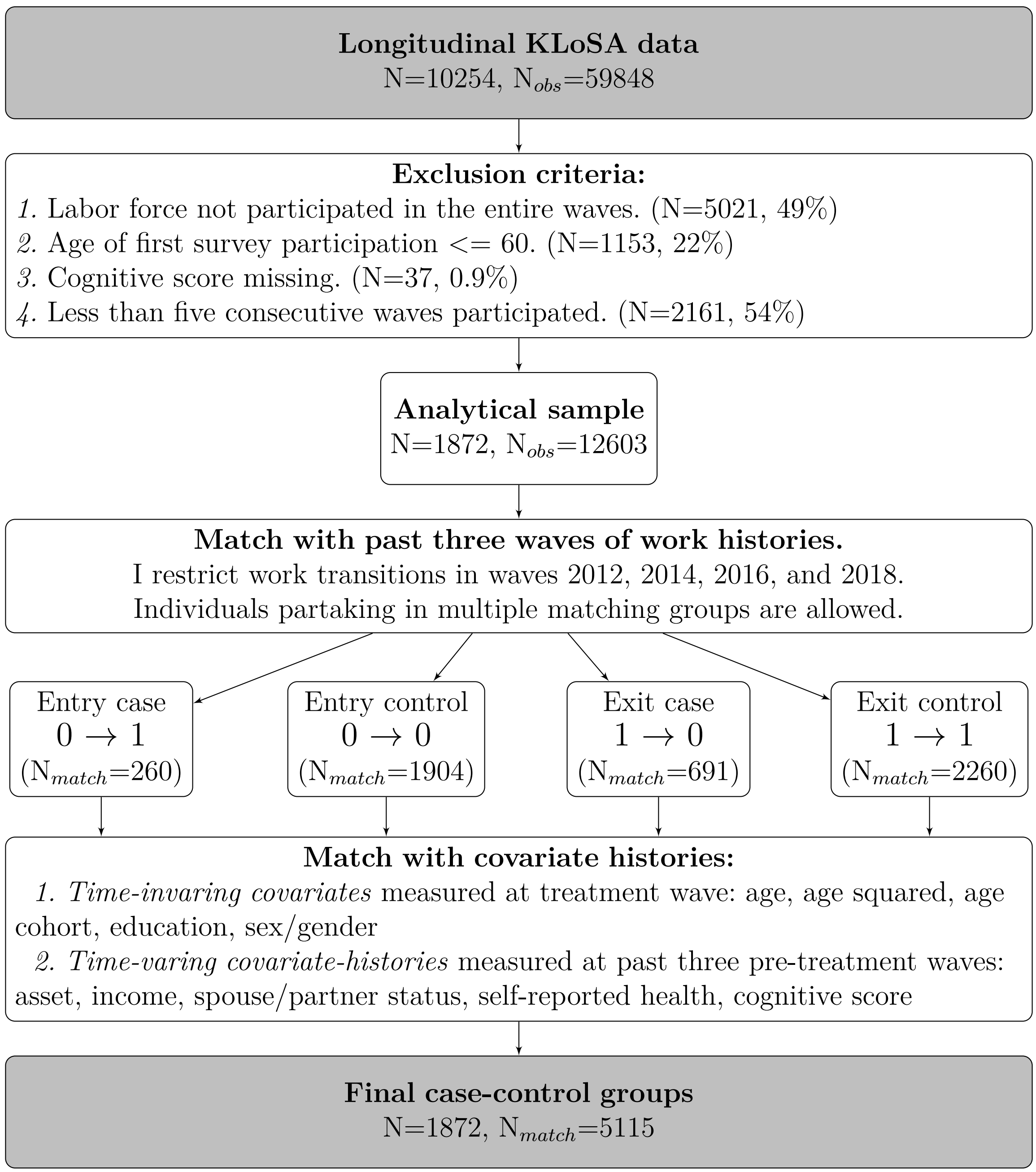


Figure 1.1: **Flowchart of KLoSA sample** This flowchart summarizes matching steps and how I arrive at our final sample size. N is the number of individuals, N_{obs} is the number of observations, and N_{match} is the number of matched observations.

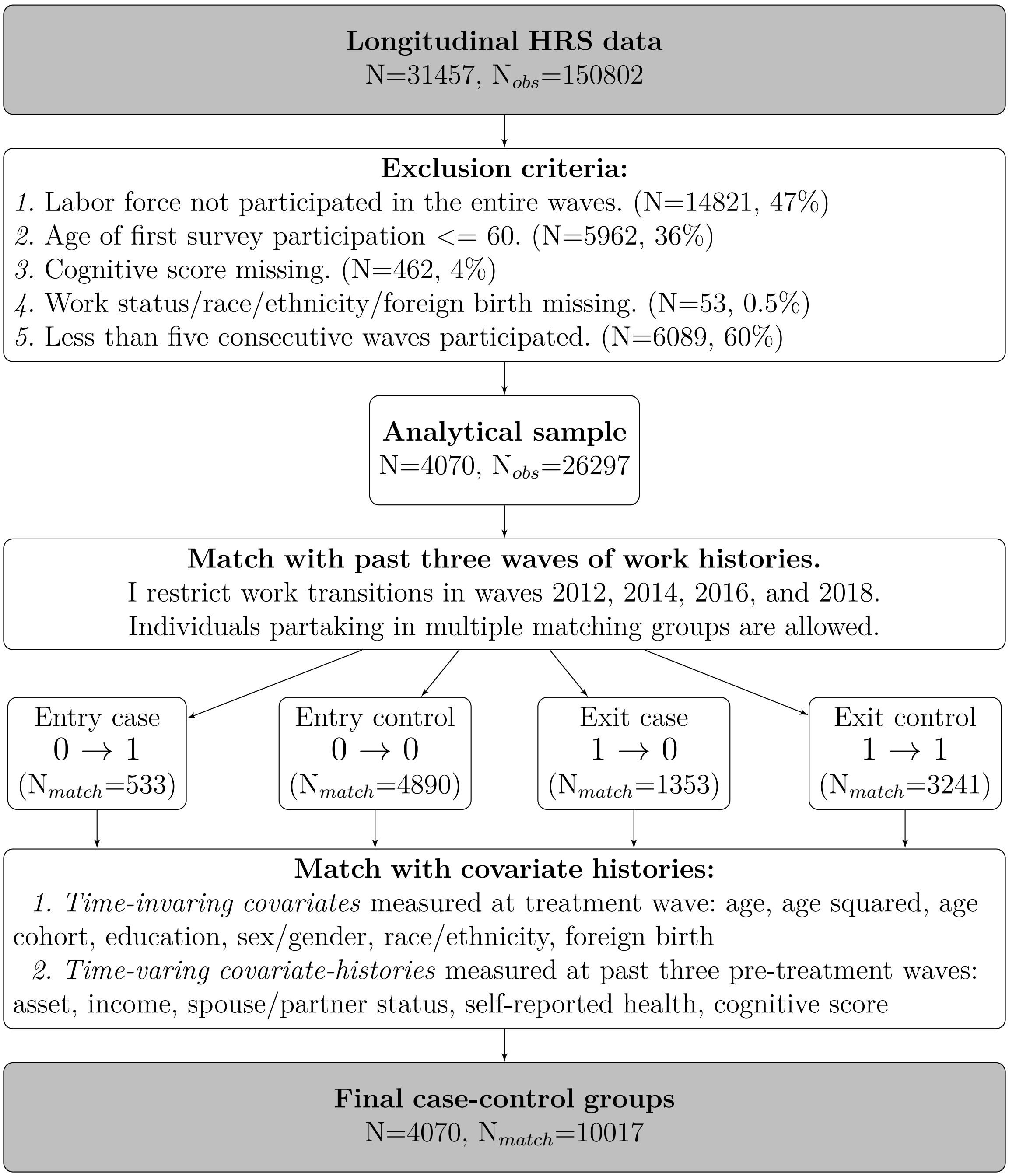


Figure 1.2: **Flowchart of a HRS sample** This flowchart summarizes matching steps and how I arrive at our final sample size. N is the number of individuals, N_{obs} is the number of observations (period-person), and N_{match} is the number of matched observations.

following variables; age, age squared, sex/gender, education, household net income, household net asset, occupation level, living with a spouse/partner, self-reported health, a birth year before 1945 and cognitive scores. For HRS, I additionally match race/ethnicity and foreign birth for its availability in the data. Time-invariant variables are measured at the treatment year, and the time-varying variables are measured throughout the last three waves prior to the transitions to capture the trajectories. I classified occupations based on the skill levels following the International Standard Classification of Occupations (International Labour Organization 2022). Financial values such as asset and income are harmonized into USD in thousands adjusted for purchasing power parity (PPP) (World Bank 2022b) and inflation (World Bank 2022a). In the analyses, I transformed asset and income values to tertiles as proxies for relative economic status. Covariates with missing values are handled by creating indicator variables of partially observed variables with values 0 for the missing values and 1 for the non-missing values. Table 1.1 describes the baseline characteristics of each of the analytical samples used. Tables A1.2 and A1.3 in appendix show the descriptive statistics by entry to or exit from the labor market for both datasets.

Table 1.1: Descriptive statistics of HRS and KLoSA.

	HRS N=4070	KLoSA N=1872	*P value*	N
Cognitive Function	16.6 (3.88)	25.9 (4.06)	0.000	5942
(HRS: TICS, KLoSA: MMSE)				
Age	65.5 (4.94)	65.0 (4.58)	<0.001	5942
Birth Year<=1945	2596 (63.8%)	1151 (61.5%)	0.094	5942
Female	2194 (53.9%)	816 (43.6%)	<0.001	5942
Education:			0.000	5932
Up to Primary	122 (3.00%)	1038 (55.4%)		
Secondary	209 (5.15%)	306 (16.3%)		
High School	1565 (38.5%)	392 (20.9%)		
Above High School	2164 (53.3%)	136 (7.26%)		
Spouse/Partner	2885 (70.9%)	1572 (84.0%)	<0.001	5941
Household Asset	547.3 (1205.8)	163.0 (263.0)	<0.001	4860
Annual Income	78.4 (143.6)	14.0 (15.1)	<0.001	5888
Occupation Level:			<0.001	4023
Elementary	325 (11.2%)	303 (27.2%)		
Service/Skilled-Manual	1629 (56.0%)	728 (65.4%)		
Managerial/Professional	956 (32.9%)	82 (7.37%)		
Self-Reported Health:			<0.001	5940
Very Bad	67 (1.65%)	385 (20.6%)		
Bad	535 (13.2%)	595 (31.8%)		
Fair	1351 (33.2%)	724 (38.7%)		
Good	1495 (36.8%)	139 (7.43%)		
Very Good	620 (15.2%)	29 (1.55%)		
Race/Ethnicity:			.	4070
Non-Hispanic white	2964 (72.8%)	. (.)		
Non-Hispanic black	642 (15.8%)	. (.)		

continued on next page

Table 1.1 – *continued from previous page*

	HRS N=4070	KLoSA N=1872	*P value*	N
Hispanic	362 (8.89%)	. (.)		
Non-Hispanic others	102 (2.51%)	. (.)		
Foreign Birth	417 (10.2%)	. (.)	.	4070

Notes: All covariates are measured at the study entry regardless of waves. Listed values are mean (± standard deviation) or total number (%). Cognitive functions are measured by HRS: HRS-TICS, KLoSA: K-MMSE. HRS sample uses education year to calculate each category; -6, 7−9, 10−12, >12 yrs. Asset/income are harmonized into thousands USD with inflation/PPP adjustment. Occupation level is calculated with last observation due to high missingness. Race/ethnicity and foreign birth are not asked in the KLoSA survey.

Source: HRS 2006-2020, KLoSA 2006-2020 own calculations.

1.3 Matching Difference-in-Differences Approach

I apply the matching DID method (Imai et al. 2023). It first matches control observations with identical employment histories in the same period as the treatment group. Borrowing from Imai et al. (2023), I refer to the set of matched control observations as a *matched set* (Imai et al. 2023). Appendix Figure A1.3 presents a graphical illustration of matching across individuals and waves. Then, it refines the matched sets via weighting using pre-treatment covariate histories up to three past waves prior to the transitions. Finally, it computes the DID estimators among refined matched sets.

I chose the number of lags to be three to include more than one wave of past treatment history while balancing against the need for a sufficient sample size of the matched set. I set the number of leads to be one to have enough individuals in the matched set and to avoid effects from interference coming from the lead period. I present a separate sensitivity analysis with two waves of past histories of treatment in appendix Figure A1.2.

Covariate balancing using pre-treatment covariate trajectories

I first match individuals by their employment histories and build a matched set. Subsequently, I balance the covariates of the control and the treatment group. This is done by giving higher weights to individuals in the matched set with similarity in terms of covariate history to the treatment group. I tested several covariate balancing methods, such as Mahalanobis distance matching (Rubin 1980), propensity score matching (Rosenbaum and Rubin 1983), propensity score weighting, and covariate balancing propensity score (CBPS, Imai and Ratkovic 2014), and CBPS weighting method best adjusted the covariates (appendix Figure A1.1).

Assumptions

Following the covariate balancing, three assumptions need to be satisfied. The most challenging one is the *parallel trend assumption*, which needs to be met to ensure that the effect is driven by the treatment and not by possible unobserved confounding in the pre-treated period. Visual inspections (appendix Figures A1.4 and A1.5) indicate that the parallel assumption might be valid, as the standardized mean difference in cognitive score of the pre-exposed period after balancing was close to zero.

The second assumption is the absence of *spillover effects*, which means that one's employment status transition should not affect others' cognitive function. I cannot rule out the possibility of spillover effects as I do not have information on the connectedness of individuals through living in close geographical proximity or sharing the work environment etc. However, I believe that the amount is trivial.

Lastly, although this method allows the investigation of *carry-over effects* by deciding the number of lags to consider, I must assume that the potential outcome is independent of the treatment history beyond the number of lags, three waves. I believe that employment histories of up to three waves (six years) are enough to capture unobserved confounders related to employment status.

Model estimation

I present the empirical DID estimation according to Imai et al. (2023). Briefly, $DID_{Ent}(F, 3)$ is the average causal effect measured at wave F after entering the labor market, assuming that the cognitive function depends on the work history up to three waves back. This study focuses on the causal quantity measured in the treatment wave and one wave after, $DID(0, 3)$ and $DID(1, 3)$.

Specifically, in equation (1), i is a case observation, i' is a control observation, and t is time. M_{it} is the number of observations in the matched set. $w_{it}^{i'}$ is the non-negative weight constructed from matched set constituting the control group with CBPS weighting. Ent_{it} is an indicator function that has value 1 if the individual entered the labor market and has any positive number of individuals from the matched set. N is the number of observations.

$$\widehat{DID}_{Ent}(F,3) = \frac{1}{\sum_{i=1}^{N}\sum_{t=4}^{T-F} Ent_{it}} Ent_{it}[(H_{i,t+F} - H_{i,t-1}) - \sum_{i' \in M_{it}} w_{it}^{i'}(H_{i',t+F} - H_{i',t-1})] \tag{1}$$

where $H_{i,t+F} - H_{i,t-1}$ is the difference in the health outcome (cognitive score) between time $t-1$ and $t+F$ for the case observations that entered the labor market. Whereas $w_{it}^{i'}(H_{i',t+F} - H_{i',t-1})$ is the counterfactual, the weighted difference in cognitive scores for the control observations who are out of labor market but sharing identical past employment history with the case observations. Likewise, I build separate matched sets for the exit case, $\widehat{DID}_{Exit}$ where $Exit_{it}$ becomes the exposure.

Standard errors of the estimator from equation (1) are calculated with 1000 repetitions of the weighted block bootstrap procedures (Imai et al. 2023; Otsu and Rai 2017). The method described above was implemented using an open-source statistical software package *PanelMatch* (Kim et al. 2018) in R version 4.2.1 (R Foundation for Statistical Computing, Vienna, Austria). Stata version 17.0 (StataCorp LLC, College Station, TX) was used for data preparation.

1.4 Results

Sample characteristics

The final samples include 1872 Korean individuals and 4070 US individuals (Figures 1.1 and 1.2). I present descriptive statistics comparing Korea and US in table 1.1. US participants reported higher assets and incomes than Korean participants. A noticeable difference between the two samples was that the share of education above the high school level was more than seven times higher in the US sample. While only 7% of the Korean sample had managerial or professional occupations, 33% of US participants belonged to this category of occupation group. Descriptive statistics according to the transition status are provided in the appendix Tables A1.2 and A1.3.

Estimated effects of entering and exiting the labor market

Figure 1.3 shows the estimated effects of entering the labor market and exiting on cognitive functioning for immediate and the wave following the transition in the Korean and the US sample. The effects of entering the labor market were positive during the transition wave in the Korean sample, but such effects were not found in the US sample. Meanwhile, I found negative effects in both samples.

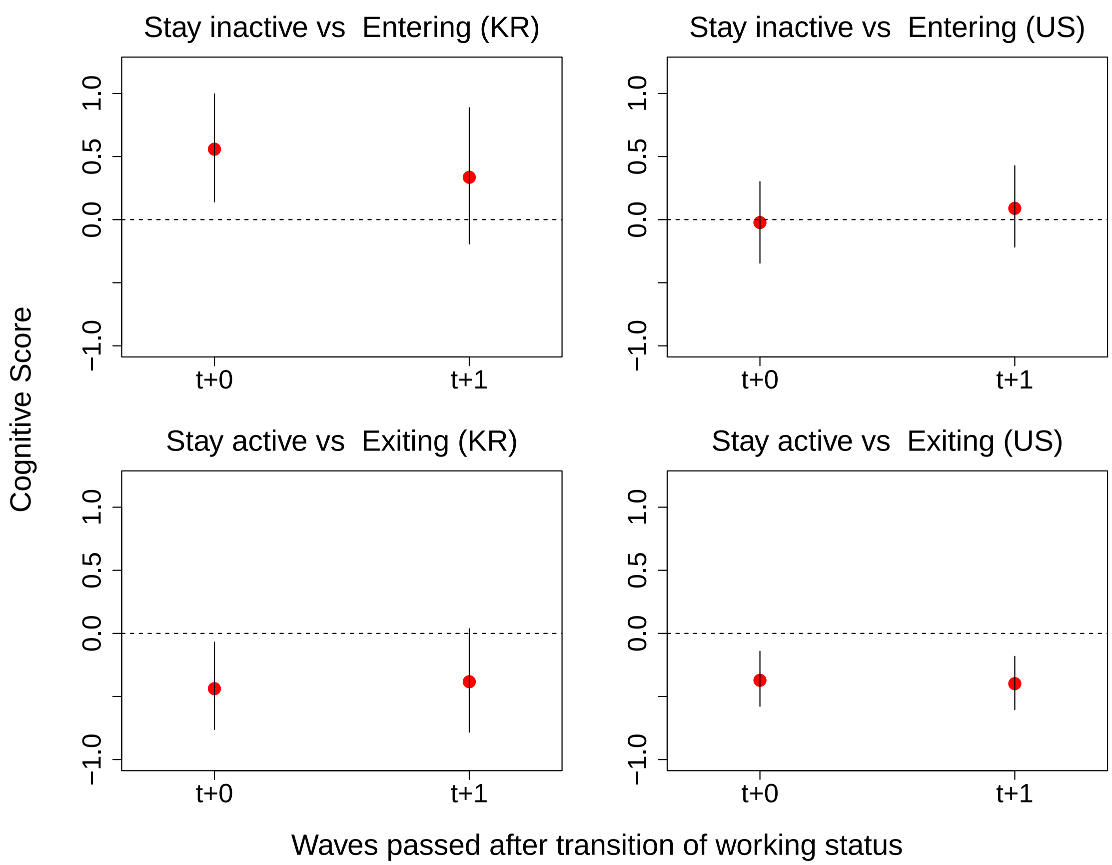


Figure 1.3: **Estimated effects of entry to and exit from the late-life labor market** The estimation results are obtained after matching according to treatment history and covariate balancing propensity score (CBPS) weighting with covariate histories during the three waves before the treatment. The left panel indicates the results from the Korean sample and the right panel is from the US sample. The estimates for the average effects of entering the labor market (upper panel) and exiting (bottom panel) are shown for the period of immediate and one wave after the transition, with 95% asymptotic confidence intervals as vertical bars. CBPS weighting is chosen for its best performance in adjustment.

Table 1.2: Estimated effects of late-life labor transitions on cognitive function.

	Cognitive Function							
	Unadjusted				Adjusted			
	DID	S.E.	2.5%	97.5%	DID	S.E.	2.5%	97.5%
Entering								
Korea at $t+0$	0.920*	0.242	0.462	1.390	0.653*	0.251	0.167	1.133
Korea at $t+1$	0.828*	0.315	0.224	1.484	0.504	0.331	-0.144	1.146
US at $t+0$	0.213	0.178	-0.143	0.551	0.049	0.180	-0.262	0.431
US at $t+1$	0.318	0.176	-0.021	0.671	0.108	0.171	-0.230	0.446
Exiting								
Korea at $t+0$	-0.456*	0.197	-0.857	-0.070	-0.438*	0.173	-0.770	-0.088
Korea at $t+1$	-0.418	0.209	-0.833	0.033	-0.383	0.190	-0.741	0.002
US at $t+0$	-0.473*	0.129	-0.718	-0.208	-0.432*	0.137	-0.698	-0.165
US at $t+1$	-0.466*	0.126	-0.717	-0.218	-0.390*	0.132	-0.627	-0.116

Notes: DID: difference-in-differences; estimation of the average effects of labor transition on cognition. Adjustment: Covariates are measured prior to the transitions; age, age squared, sex/gender, education, household net income, household net asset, occupation level, living with a spouse/partner, self-reported health, a birth year before 1945, and past cognitive scores. For US study, I include race/ethnicity and foreign birth for the data availability.
S.E., Weighted bootstrapped standard errors. 2.5%, 97.5%., 95% asymptotic confidence intervals, *$P <$ *0.05*.

Table 1.2 compares the unadjusted and adjusted estimation results. The magnitude of the positive effects of entering the labor market in Korea was reduced but remained positive after covariate balancing. I observe a negative effect of exiting in both samples before and after the covariate balancing. I show that the main results are robust to the matching with shorter lags in the appendix Figure A1.2.

Subgroup analyses by socioeconomic status and sex/gender

I show the DID estimates based on subgroup analyses by median asset level measured at the study entry wave, education level, and sex/gender (appendix Figures 1.6, 1.7, and 1.8). Due to its relatively large sample size, I conduct subgroup analyses solely with HRS data. I found individuals with below-median baseline asset level, low education, and men experienced more noticeable negative effects from exiting the labor market. I did not observe such differences for the entry into the late-life labor market.

Potential mechanisms

Heterogeneous late-life work motivation in the US

The findings of positive effects of entering the labor market moderated by the asset level in the US data might be related to different incentives and motivations to work, and thus different opportunities to choose an occupation and work tasks. For individuals with above-median levels of assets, working at very advanced ages might not be directly related to their necessities. Motivation for work related to social connections and personal growth might be more relevant in individuals with above-median asset levels than for individuals with below-median asset levels, which in contrast may choose a job based on what they expect to earn (Fasbender et al. 2016). Therefore, individuals may select the type of occupation differently based on the level of their assets. These effects, however, were only immediate and did not last.

The negative effects of exiting the labor market moderated by asset level in US data might be related to different willingness to exit based on the financial situation. For individuals with below-median assets, the income at very advanced ages might more directly serve their necessities. Thus, there is a higher probability that external reasons such as job displacement or care obligations might have caused the exit from the labor market (Szinovacz and Davey 2005). These external push factors plus the reduced earnings may lead to more stressful challenges during exiting work, which might result in a decline in cognitive functioning.

Financial conditions and work attachment in South Korea

In the Korean sample, I found positive immediate and lasting effects of entering the labor market on cognition, regardless of the level of assets. These general effects observed in the Korean sample might be due to several reasons.

First, there is heterogeneity in both cognitive and socioeconomic levels of individuals entering the labor market at very advanced older ages between Korea and the US. In this study, individuals entering the labor market after retirement age in Korea had both a lower cognitive score and socioeconomic status compared to individuals that did not enter the labor market. In Korea, people with lower education and occupational class were more likely to work after retirement (Cho et al. 2016, Lee and Yeung 2020).

Several reasons may be put forward to explain the cognitive benefits of individuals who participate in the labor market for financial reasons, regardless of initial low cognitive scores. One study in Korea argued that parents' beliefs to take full economic responsibility for their children might derive retirees from taking whatever jobs were available (Cho et al. 2016). Motivation driven to support their children financially might lead to a sense of control and purpose by taking up work and guide to general positive effects of entering the post-retirement labor market regardless of occupation level. Several studies evidenced that having a greater purpose in life reduced the risks of Alzheimer's disease and mild cognitive impairment (Boyle et al. 2010; Lewis et al. 2016).

Secondly, the positive effects of entering the labor market in the Korean sample might be due to general psychological benefits from working in this cultural context. Studies from geographically and culturally close countries provide relevant evidence. One study from Singapore showed that participants who continued working after retirement had fewer depressive symptoms than those exiting the labor market permanently (Schwingel et al. 2009). Another study found that Japanese men who started working at post-retirement ages had fewer depressive symptoms (Shiba et al. 2017). It is known that retirees who experienced severe work identity loss were significantly more likely to intend to reenter the labor force (Feldman 1994; Armstrong-Stassen et al. 2012). Self-identity strongly tied to work might explain the roots of the benefit beyond monetary ones.

1.5 Discussion

An increase in advanced-age labor force participation in aging countries calls for the need to understand better the impacts of labor market participation and withdrawal at ages beyond 65 years on cognitive functioning. The present study examines labor market "entry and exit" effects on cognitive functioning using data from two large population representative studies, HRS and its sister Korean study KLoSA.

Using the matching difference-in-differences that follows the idea of trial emulation (Imai et al. 2023; Hernán and Robins 2016; García-Albéniz et al. 2017), I find that the effects of employment transitions at age 65+ on cognitive function are heterogeneous in country contexts. The estimated effects of entering the labor market were positive in Korea, while I did not find such positive effects in the US. On the other hand, I found negative effects from exiting the labor market in both datasets. To understand the magnitude of the positive effects from the Korean study, I compare our result to a study that investigated the effects of receiving social pension for 5 years on cognitive functioning using the same data and cognitive assessment (Hwang and Lee 2022). They found a positive effect of 1.309 points while in our study estimated a positive effect of 0.653 points for entering the late-life labor market, roughly half the size of the cognitive benefit from long-term social pension.

Our results add support to the 'use it or lose it' hypothesis in late-life labor force participation (Hultsch et al. 1999) and are in line with previous studies of the positive associations of labor market participation at advanced ages and cognitive functioning (Schwingel et al. 2009; Wickrama et al. 2013; Dufouil et al. 2014). However, our findings suggest that the general positive effects are country-specific. In the Korean sample, we found positive effects of entering the labor market on cognitive function. These general effects observed uniquely in the Korean sample might be due to several reasons.

First, KLoSA participants have lower education, income, and asset level compared to the HRS respondents. Moreover, it is individuals with lower cognitive scores and socioeconomic status within the country enter the late-life labor market. In Korea, people with lower education and occupational class were more likely to work after retirement (Cho et al. 2016; Lee and Yeung 2020). The cognitive gain might be related to the absence of cognitively stimulating activities outside of the workplace due to insufficient financial means that create a relative cognitive benefit at the workplace.

Secondly, the positive effects of entering the labor market in the Korean sample might be due to general psychological benefits from working in this cultural context. Studies from geographically and culturally close countries provide relevant evidence. One study from Singapore showed that participants who continued working after retirement had fewer depressive symptoms than those exiting the labor market permanently (Schwingel et al. 2009). Another study found that Japanese men who started working at post-retirement ages had fewer depressive symptoms (Shiba et al. 2017). It is known that retirees who experienced severe work identity loss were more likely to intend to reenter the labor force (Feldman 1994; Armstrong-Stassen et al. 2012). Self-identity culturally strongly tied to work might explain the roots of the benefit beyond monetary ones.

Concerning the well-established detrimental effects of labor market withdrawal (Bonsang et al. 2012; Xue et al. 2018; Atalay et al. 2019), our study comes to the same conclusion as previous studies by using a different causal identification strategy.

I add to this body of literature by extending the study population from retirees to anyone exiting the labor market exit at 65+, potentially including post-retirement work. Furthermore, I show that negative effects are more pronounced in groups with low socioeconomic status and in men.

There are limitations to this study. First, the sample size of the Korean study is relatively small. And the treated group in our analysis represents a rather small portion of individuals who transitioned into or out of work in Korea and the US. Concerning the possibility of reverse causality, I present the appendix Tables A1.2 and A1.3, which measured cognitive function one wave before the transitions. I observe that in both countries, individuals who enter the labor force are not positively selected in terms of better cognitive functioning. Rather they have the second lowest cognitive functioning, contrary to the reverse causality argument. Second, I remove a large share of observations (US: 60%; Korea: 54%) due to the criterion of five consecutive participation in the survey. This exclusion is crucial to match individuals with past three employment histories and investigate the effects up to one follow-up wave. I report the descriptive statistics by the exclusion criterion in the appendix Tables 1.4 and 1.5. A sensitivity analysis relaxing this criterion from five to four waves of consecutive participation by matching on past two waves led to similar result patterns (appendix Figure A1.2). Third, the two cognitive measurements in each data set are overlapping in some dimensions but are not identical (appendix Table A1.1). Compared to the US data, the distribution in Korean data is more skewed to the right (see appendix Figure A1.3). While I believe some of the concerns are relieved by using the *change* score of cognitive functioning instead of the score itself, I suggest restraining from making direct comparisons in the magnitude of the effects until further harmonization of cognitive assessment becomes available. Fourth, our analytical strategy is subject to unobserved time-varying confounders that might influence the labor force transition and cognitive functioning such as somatic disorders which are not easily captured. Fifth, both cognitive scores measure global cognition and thus might not capture the subtle cognitive functioning change.

Despite these limitations, our contribution to the knowledge of employment status transitions at advanced ages and cognitive functioning is analyzing the transition effects with a rigorous modeling strategy and a cross-country perspective from South Korea, where one out of three is participating in the labor market at 65+ (OECD 2023b), and the US, with growing inequality among older adults in labor participation (Bosworth et al. 2016). Estimating identical data-analytic models with multiple datasets is useful for the external validity of findings by ensuring replicability and reproducibility of the research design (Hofer and Piccinin 2009; Graham et al. 2017). This is promising with a growing attempt to harmonize better cognitive aging data from different countries (Langa et al. 2020; Kobayashi et al. 2021).

Future research should add by testing more potential pathways and confounders of effects of labor market entry and exit by assessing possible effect differences in more fine-grained types of occupation and psychosocial work characteristics, health conditions, and racial and ethnic groups.

Chapter 2

The unintended effects of a large minimum wage increase on health

A version of this study is published in the *Social Science & Medicine* (Kim, Suhrcke, Leist, 2024).

2.1 Introduction

Minimum wages have long been a highly debated policy measure because of their seemingly complex and ambiguous impacts on wages, employment, and labour productivity. Some argue that minimum wages lead to a decline in working hours and employment for low-waged workers (Neumark et al. 2004), while others claim that it raises the employment probability of low-wage earners as the increased minimum wage is passed on to consumers (Card and Krueger 1994). While the largest share of existing economic research on minimum wages focuses on labour market effects, for a more comprehensive assessment of the welfare consequences of the policy, it is important to consider other potentially significant social consequences, such as health (Leigh et al. 2019).

In this chapter, I seek to contribute to the growing but still limited international evidence base on the impact of minimum wages on health. Previous research explored various dimensions of health, including psychological and physical ones (see Leigh et al. 2019 for a review). However, the evidence remains inconsistent, possibly because of varying study designs (Leigh 2021; Neumark 2024b), data sources, and differences in minimum wage policies. Previous research has also mainly focused on the U.S. and the UK, with insufficient attention given to countries with different economic contexts (Leigh 2021).

One key aspect that has rarely been studied is the extent to which the size of the increase in the minimum wage matters. For example, a substantial increase in the minimum wage, exceeding 10% in real terms, might have different effects on health outcomes than more modest increases. Maxwell et al. (2022) have most recently compared the health effects of UK minimum wage increases of varying magnitudes across time periods. Their findings indicate that even a sizable minimum wage increase in 2016 (9% in real terms) did not lead to any discernible impact on mental health, aligning with the insignificant effects of the smaller increases. However, it is important to consider that this observed lack of impact might be attributable to the relatively modest increase and that a more substantial wage increase might yield more pronounced effects on health outcomes. The present study aims to fill this research gap by investigating the health impacts of a "large" minimum wage increase on older workers, and specifically for changes in their cognitive functioning and self-reported health. I do so by capitalising on the minimum wage hike in South Korea, which experienced a 16.4% increase (approximately 14.7% of the real growth rate) in 2018. The magnitude of this increase has not been observed in the last two decades in South Korea, and the pace of minimum wage growth has been substantial compared with other countries (Doh and Van der Meer 2023). This significant minimum wage hike was a promise of the new government that came into power in 2017, although the magnitude of this increase was unanticipated (Doh et al. 2022).

The health implications of the minimum wage are contingent upon its impact on economic factors such as employment, working hours, and earnings. According to Azar et al. (2023), empirical evidence reveals that the labour market effects of the minimum wage vary depending on the concentration of labour. In a monopsonistic setting, where the wage is set below marginal productivity, an increase in the minimum wage does not yield negative employment consequences. In this scenario, the minimum wage signifies an increase in earnings without a decrease in other job-related conditions. Consequently, we may anticipate positive health effects through improved job satisfaction and, thus, better psychological health, at least for those receiving the minimum wage. Nevertheless, some conditions may have adverse health effects, as previous research has demonstrated that increased earnings through the Earned Income Tax Credit (EITC), in the absence of adjusted labour market conditions, results in higher cigarette consumption among lower-income smokers (Kenkel et al. 2014). Conversely, in a labour market where the wages are already set equal to or higher than the marginal productivity, firms might respond by implementing structural changes to offset potential losses, as associated with the minimum wage increase. In this context, an increase in the minimum wage may lead to adverse employment outcomes, a reduction in working hours, or a substantial increase in workload. Consequently, these structural changes in the workplace may lead to a heightened risk of stress, which in turn may lead to adverse health effects.

Research on the economic impacts of the 2018 South Korean minimum wage hike indicates that the increased minimum wage led to a reduction in total employment (Doh et al. 2022) and gross output (Seok and You 2022), and an increase in short-term workers who are exempt from social insurance mandates (Kim et al. 2023a). According to Doh et al. (2022), firms responded to a minimum wage increase through layoffs, plant closures, and substitution between labourers of different skill levels. The labour market dynamics in South Korea before the 2018 minimum wage increase resembled a scenario in which wages were already established at levels that did not fall below marginal productivity. In this context, our research aims to investigate how large increases in the minimum wage translate into health outcomes of older workers.

Minimum wage policies are likely to have a greater impact on the health of vulnerable individuals, such as those of advanced ages. In the South Korean context, one in three older adults participates in the labour market after the age of 65, mainly due to a lack of sufficient other income sources (OECD 2021b). In this chapter, I focus on older adults who continue to work and examine the impact of the minimum wage hike on their physical health and cognitive functioning. I included cognitive functioning as our main health outcome because it is the centre of control of the human body and influences every aspect of life, including an individual's well-being, development, and productivity. Furthermore, maintaining sound cognitive functioning is essential for effective financial decision-making, which tends to decline after the age of 60 (Finke et al. 2017).

I utilised data from the Korean Longitudinal Study on Aging, which is a sister study of the Health and Retirement Study in the United States. To estimate the impact of the minimum wage increase, I applied a difference-in-differences design. In line with the empirical strategies used in previous studies, our intervention group included individuals whose pre-intervention hourly wages were below the minimum wage, and I compared this group with those whose hourly wages were slightly above the minimum wage (Reeves et al. 2017; Kronenberg et al. 2017; Maxwell et al. 2022).

Unexpectedly, our findings suggest that the minimum wage hike negatively impacted the cognitive functioning of older adults in South Korea, with cognitive function decreasing by 0.704 points during the year of the hike. I did not find statistically significant effects on self-reported health. Between 2014 and 2016, a period during which a modest minimum wage increase was implemented, no negative health effects were found. This suggests that the estimated negative effects are specifically linked to the presence of a larger increase in the minimum wage but not necessarily to smaller increases.

This chapter builds on previous research exploring the impact of minimum wage on health outcomes, specifically using longitudinal data and a difference-in-differences design to assign intervention groups based on hourly wages (Reeves et al. 2017; Lenhart 2017; Kronenberg et al. 2017; Maxwell et al. 2022). While some previous studies found positive effects on mental and self-reported health, respectively (Reeves et al. 2017; Lenhart 2017), others found insignificant results on mental health (Kronenberg et al. 2017) or on both mental and self-reported physical health (Maxwell et al. 2022). Our findings similarly suggest insignificant effects on self-reported health but negative effects on cognitive health for the first time.

This chapter contributes to the literature in at least three ways. First, I examine the health impact of a minimum wage *hike*. Previous research on minimum wage hikes has focused on economic outcomes, such as unemployment, labour productivity, and gross output (Harasztosi and Lindner 2019; Doh et al. 2022; Seok and You 2022; Jardim et al. 2022), but not on health outcomes. Second, I present evidence from South Korea, which is yet to be investigated in the context of the health effects of the minimum wage. Despite being a high-income country, South Korea's work environment and corporate culture may differ significantly from those of the U.S., the UK, and Western Europe. Following years of substantial economic growth, the Asian financial crisis of the late 1990s, brought about considerable structural changes and a notable surge in job insecurity (Khang et al. 2005). These significant economic fluctuations within a period of robust growth likely exerted a lasting influence on aspects of both labour supply and demand aspects, such as mandatory early retirement and active labour participation at older ages (OECD 2018, 2021b). Therefore, evidence from South Korea has the potential to critically enrich the global evidence on the relationship between the minimum wage and health.Third, I focused on older workers and investigated their cognitive functioning and self-reported health as the main outcomes. Understanding the policy impacts on older workers is particularly important in ageing economies with increasing retirement ages.

Minimum wage and older workers in South Korea

The Minimum Wage Act in South Korea was established in December 1986 and implemented in January 1988 to improve the standard of living of employees, enhance the quality of the labour force, and contribute to the overall development of the national economy (as stated in Article 1 of the Minimum Wage Act). Notably, the minimum wage in South Korea is national and uniform across all industries and business sizes (Jung 2011), with minor exceptions (as outlined in Article 3 of the Minimum Wage Act). Significant punishment is foreseen for employers who fail to comply with these regulations, such as imprisonment, labour for up to three years, or a fine of up to 20 million Korean won (equivalent to 24,989 USD, adjusted for 2023 Purchasing Power Parities (PPP) according to the World Bank (2024)).

The 2018 minimum wage hike in South Korea was a significant policy change that aimed to improve the standard of living for low-income earners and drive consumption-led economic growth. This increase was the largest since 2001 (Seok and You 2022), affecting a large part of the population, an estimated 4.6 million individuals, representing 24% of all wage earners in the country (Ministry of Employment and Labor 2023). Figure 2.1 shows the annual growth evolution of the South Korean minimum wage in an international context, comparing it with that of the UK and the U.S. This comparison was made after harmonisation using PPP to account for differences in the cost of living among OECD countries OECD (2023a). South Korea stands out because of its significant increase, particularly in 2018, which was the episode I intend to focus on our evaluation. According to Doh and Van der Meer 2023, the pace of minimum wage growth in South Korea was exceptional compared with other countries, when judged based on the ratio of minimum to mean wages.

South Korea has the highest relative poverty rate among older adults among OECD countries, and the majority of Korean older workers have precarious jobs

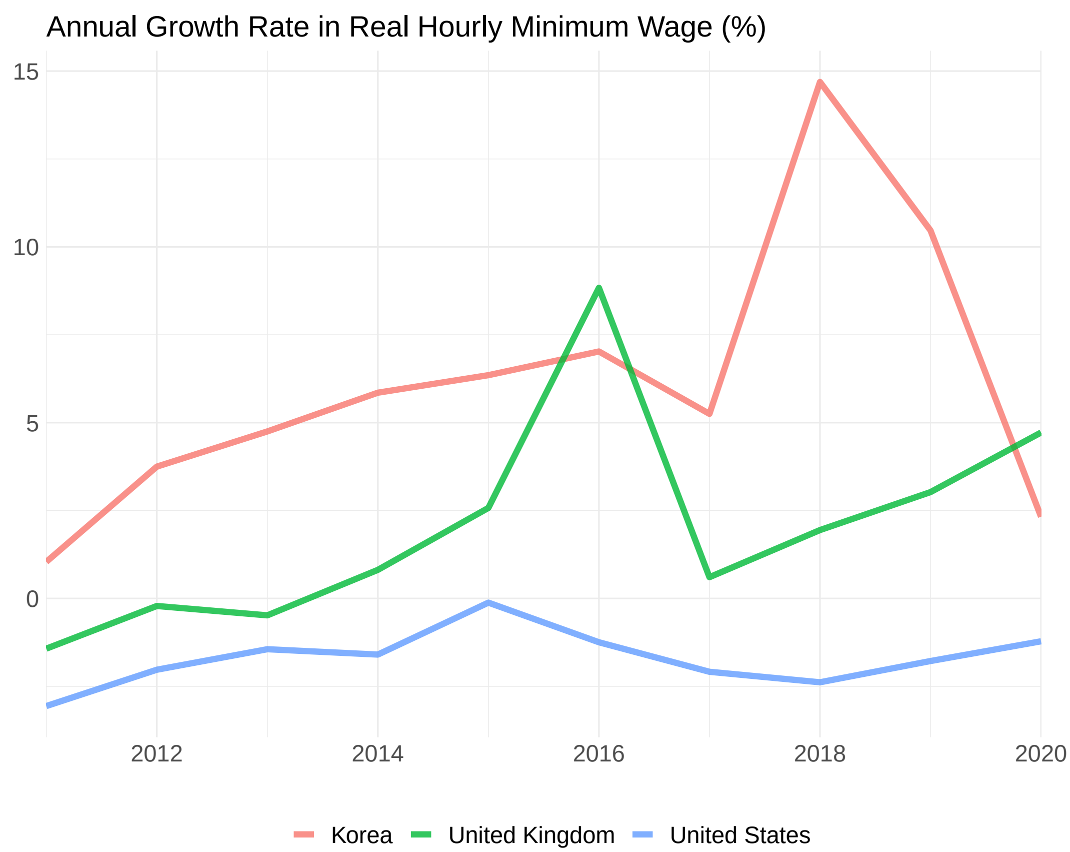


Figure 2.1: **Annual growth rate in real hourly minimum wages year 2011-2020.** The figure displays international comparisons of the annual growth rate in real hourly minimum wages from 2011 to 2020. As per OECD (2023a), real hourly minimum wages are derived by initially deflating the series using the Consumer Price Index, with 2021 serving as the base year. Subsequently, these values are converted into a common currency unit (USD) using Purchasing Power Parities (PPP) for the year 2021. The annual growth levels are then calculated based on these adjusted values.

with non-permanent positions due to mandatory early retirement, which is used to curtail labour costs from the hiring side (OECD 2021b, 2018). The labour force participation rate of individuals aged 65+ years in South Korea has consistently been greater than 30% from 2012 onwards and was 36% in 2021 (OECD 2023b), the highest among OECD countries. Many individuals re-enter the labour market after the nominal retirement age because of the low percentage of private occupation-related pensions and insufficient public transfers (Kim et al. 2023b). Kim (2018) demonstrates that older workers constitute one of the demographic groups most likely to be minimum-wage earners in the South Korean labour market. Among older workers aged 60 and above, 35.1% were estimated to receive wages close to the minimum wage, based on the 2022 national statistics (Korea Minimum Wage Commission 2023). The within-age group share of minimum wage workers aged 60 and above was the second largest among all age groups, behind only the age group 19 and below.

2.2 Data: Korean Longitudinal Study of Aging

This chapter utilises data from the Korean Longitudinal Study on Aging (KLoSA), a nationally representative longitudinal survey of over 10,000 individuals aged 45 or older in Korea. Conducted biennially since 2006, the KLoSA has been comparable to the Health and Retirement Study in the U.S. and the English Longitudinal Survey of Aging in the UK (Smith 2021), providing a valuable dataset for investigating the impact of social and economic policies on older adults. For This chapter, I focused on waves 2016 and 2018, collected from September to December, as our pre- and post-intervention periods, respectively. One significant advantage of the KLoSA data is the availability of objective measurements of cognitive functioning, enabling us to explore the impact of the minimum wage policy on cognitive health, an crucial factor that has not been investigated. It also provides detailed information on employment types, distinguishing between working for payment, working non-financially, and self-employment. This level of specificity allows us to exclude employment forms that may not be directly affected by minimum wage policies. Moreover, the KLoSA data provides detailed information about the types of pensions individuals receive, which allows for the effective removal of the potential confounding effects of pension benefit status on health.

Intervention and control group assignment

Similar to numerous datasets that offer comprehensive health outcome information, the KLoSA data does not provide precise hourly wage data. Consequently, an approximation is necessary to define the 'likely' intervention group, which closely follows the previous research (Reeves et al. 2017; Kronenberg et al. 2017). The selection of the intervention and control groups was based on the derived hourly wage, which was calculated from the self-reported monthly income divided by the number of hours worked (Arulampalam et al. 2004; Reeves et al. 2017; Kronenberg et al. 2017; Bai et al. 2023). A summary of previous studies and the intervention assignments of This chapter are provided in Table 2.1.

Individuals with pre-intervention hourly wages below the 2018 minimum wage (7530 Korean Won, equivalent to 8.76 USD when adjusted for 2016 PPP) were assigned to the *intervention group*. In the sensitivity analysis, I put further restrictions on the amount of the wage increase for the intervention group to exclude potentially large wage increases unrelated to the minimum wage policy, which is in line with Reeves et al. 2017.

Individuals with pre-intervention hourly wages between 100-150% of the 2018 minimum wage are assigned to the *control group*. I conduct sensitivity analyses by varying the upper bound of the pre-intervention hourly wages for the control group in the Table 2.5. As the derived hourly wages might overestimate the actual hourly wages owing to the lack of information on excess hours, further spillover effects from individuals with slightly higher wages were not considered.

Table 2.1: Comparisons of intervention assignment.

Studies	**Intervention Group**	**Control Group**	**N**
Reeves et al. (2017)	(1) $Wage_{pre}$<MW (2) MW$\leq Wage_{post} \leq 1.1\times MW$	MW$\leq Wage_{pre} \leq 1.1\times MW$	170
Kronenberg et al. (2017)	$Wage_{pre}<$ MW	MW$<Wage_{pre}<1.4\times MW$	1433
Maxwell et al. (2022)	(1) $Wage_{pre}<$ MW (2) MW$\leq Wage_{post}$	MW $\leq Wage_{pre} \leq 1.2\times MW$	803
Current study	$Wage_{pre}<$ MW	MW $\leq Wage_{pre} \leq 1.5\times MW$	462

Note. MW is the national minimum wage for the year. N denotes the number of participants. For the Kronenberg et al. (2017), a wage-based group is used. For the Maxwell et al. (2022), the study sample with the 2016 minimum wage policy is included.

Several selection criteria were applied to the samples. First, the sample was limited to individuals who were not self-employed or non-paid labourers during the pre-intervention survey year of 2016. Second, individuals with missing data on the main health outcome were excluded. Third, to create similar characteristics between the intervention and control groups, individuals whose hourly wages were above 150% of the minimum wage were excluded. Fourth, individuals who were not employed during the post-intervention survey year of 2018 were excluded to eliminate the potential unemployment effects. This criterion is in line with the previous research (Reeves et al. 2017; Kronenberg et al. 2017; Maxwell et al. 2022); nevertheless, I also provide the estimation results including unemployed individuals subsequent to the minimum wage hike in the Table 2.6. Finally, individuals with observations available in both survey years were selected. After applying these selection criteria, a balanced panel of 462 individuals and 924 observations were used to represent the final analytical sample (see Figure 2.2).

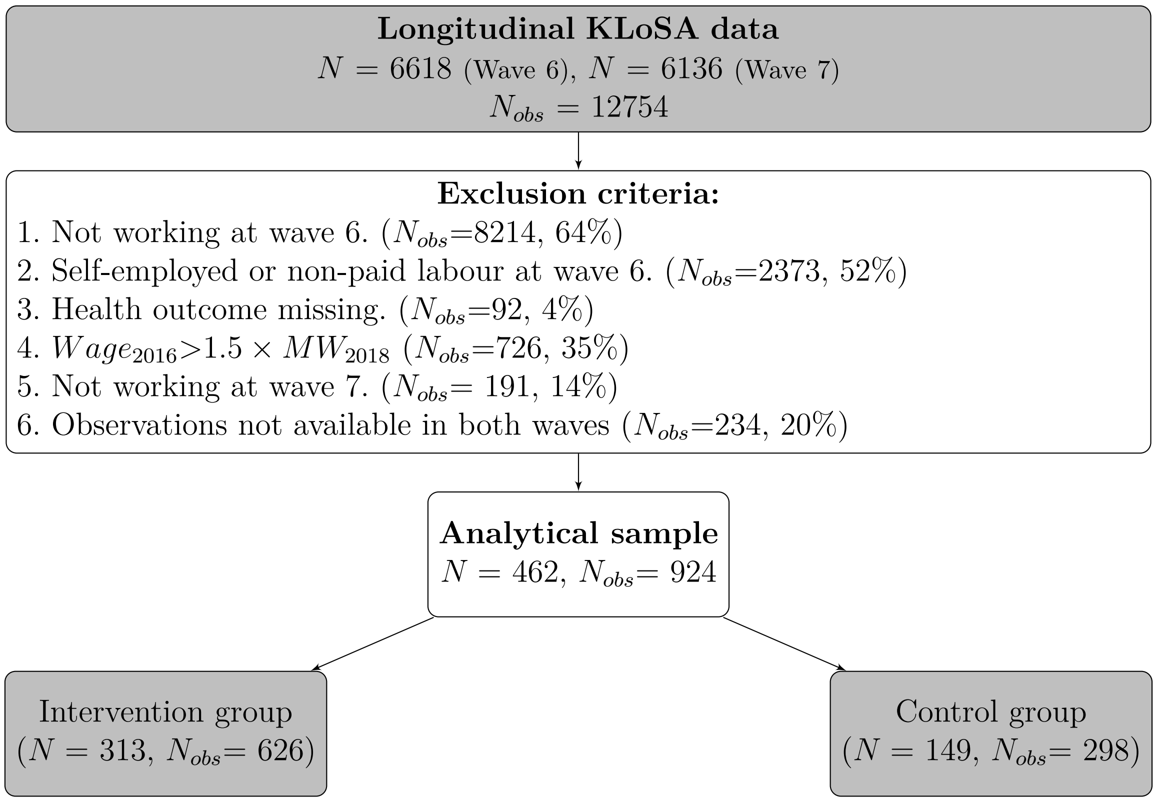


Figure 2.2: **Flowchart of the final analytical sample** This flowchart summarises the implementation of exclusion criteria to arrive at the final sample. N is the number of individuals; N_{obs} is the number of observations. The intervention group was defined by participants reporting hourly wages below the minimum wage. Participants reporting hourly wages equal to 100-150% of minimum wage were chosen as a control group. I also provide estimation results relaxing criterion 5 to include the unemployed individuals in the sensitivity analysis.

Cognitive functioning and self-rated health outcomes

The primary health outcomes were cognitive functioning and self-reported health status. Cognitive functioning was measured using the Korean version of Mini-Mental State Examination (K-MMSE), a clinically validated tool to measure general cognitive functioning among older adults in Korea (Kang et al. 1997). Scores on the K-MMSE range from 0 to 30, with higher scores indicating better cognitive function. For self-reported health, participants were asked to rate their physical health on a scale of 1 to 5, with higher values indicating better physical health. I also investigated the binary version of self-reported health in appendix Table A2.1. We refrained from dichotomising the K-MMSE score due to a lack of a scientific consensus in favour of a specific optimal cut-off across characteristics (Han et al. 2008; Kim et al. 2016).

2.3 Two Way Fixed Effects Regression

This chapter investigated the effects of a minimum wage hike on cognitive functioning and self-reported health. I build on the empirical approach of previous studies that used longitudinal data to assign intervention and control groups based on hourly wages (Reeves et al. 2017; Kronenberg et al. 2017; Maxwell et al. 2022). Specifically, I use two-way fixed effects regressions, which produce the same estimation results as the canonical difference-in-differences approach, with two units and two periods (Roth et al. 2023a). The adaptation of the two-period difference-in-differences method to study the health impacts of a specific minimum wage policy, based on hourly wage to design the intervention, aligns with the approach used by Maxwell et al. (2022). The regression equation was as follows:

$$Y_{i,t} = \alpha_i + \lambda_t + \phi X_{i,t} + (\mathbb{1}[t = 2018] \cdot D_i)\beta + \epsilon_{i,t}$$

where $Y_{i,t}$ represents the health outcomes (cognitive functioning and self-reported health) at time t. α_i and λ_t are individual- and time-fixed effects, respectively, controlling for time trends in the health outcomes common across individuals. $X_{i,t}$ is a time-varying covariate vector at the individual level, including 5-year interval age dummies to control for non-linear age effects on cognitive and physical health. I also include a dummy variable for marital status and whether individuals receive any of the pensions, including national, specific corporate, or basic pensions. $\mathbb{1}[t = 2018]$ is a post-intervention indicator, and D_i is the intervention or control group assignment based on the calculated hourly wage before the policy change. Our model specification includes both individual and time-fixed effects. Variables such as education and gender are not included, as they are already accounted for in the individual-fixed effects. Other time-varying factors that apply equally to both the control and intervention groups are also excluded, as they are included in the time-fixed effects. $\epsilon_{i,t}$ is the time-varying error term. Our parameter of interest is $\hat{\beta}$, which measures the average health effect of the minimum wage hike for the intervention group.

Our identification strategy relies on two assumptions: no anticipatory effect and parallel trends. The government announced the new minimum wage in August 2017, which came into effect on 1 January 2018. I assumed that any anticipation of a wage increase or subsequent unemployment would not cause significant changes in work, consumption, or health behaviour, eventually affecting cognitive or self-reported health outcomes before the policy change. The second assumption is that there is a parallel trend in the average health outcomes between the intervention and control groups in the periods preceding the minimum wage hike. Thus, I conducted placebo tests using survey data from 2014 to 2016 to check for pre-existing health impacts on the intervention group before the minimum wage hike.

2.4 Results

Descriptive statistics before the policy change

Table 2.2 summarises the characteristics of the intervention and control groups measured in 2016, prior to the minimum wage hike. I did not observe any significant differences in cognitive functioning between the two groups. Nevertheless, some variables, such as age, education level, self-reported health, working hours, and monthly income, differed. While the difference in monthly income aligns with the intentional design of the intervention allocation, differences in other pre-intervention characteristics might potentially introduce bias. To mitigate this problem, I conducted a propensity score weighting with regard to age, gender, marital status, education level, self-reported health, working hours, and working days to balance the two groups (Imai and Ratkovic 2013). After applying the propensity score weights, I failed to detect statistically significant differences in any of these characteristics, except for the monthly income.

I present the characteristics of all individuals below the 2018 minimum wage in 2016 and compare the differences in their subsequent employment statuses in appendix Table A2.2. Individuals who were out of the labour market following the minimum wage increase were more likely to be women, older, less educated, report lower levels of health, and perform worse on the cognitive test than those who remained in the labour market.

General effects of the minimum wage hike

This section provides causal evidence of the impact of a minimum wage hike on cognitive functioning and physical health. Results obtained after covariate balancing through propensity score weighting provide the least biased estimates. The minimum wage hike had an adverse effect on cognitive functioning at a statistically significant level of $p < 0.05$ level but no significant effect on self-reported health as shown in Table 2.3. With a large minimum wage increase from 2016 to 2018, the workers earning less than the 2018 minimum wage before the policy change experienced an average decline of 0.704 point in cognitive functioning. To understand the size of the impact, obtaining a 5-year consecutive social pension led to a 1.301 point increase in cognitive functioning among older Korean adults using an identical survey and health outcomes to ours (Hwang and Lee 2022).

Table 2.2: Descriptive statistics at pre-intervention assessment

Variable	Before weighting: Intervention group N=313	Before weighting: Control group N=149	p-value	After weighting: Intervention Group N=313	After weighting: Control group N=149	p-value
Health						
Cognitive function (K-MMSE)	27.36 (2.70)	27.56 (2.96)	0.5	27.50 (2.61)	27.03 (3.30)	0.2
Self-Reported Health:			0.002			0.12
Bad	9.6	2.7		8.3	4.1	
Normal	41	33		39	41	
Good	43	56		45	50	
Very Good	6.1	6.0		7.5	3.6	
Best	0.3	2.0		0.5	1.1	
Demographics						
Age	63.90 (6.55)	60.96 (5.39)	<0.001	63.11 (6.45)	62.74 (6.69)	0.7
Female	55	48	0.13	54	56	0.6
Married	83	84	0.9	85	81	0.5
Education:			0.002			>0.9
$\leq$ Elementary school	32	20		28	30	
Middle school	26	19		25	23	
High school	35	48		39	39	
$\geq$ College/University	6.7	13		8.4	8.3	
Work characteristics						
Working hours (week)	43.14 (17.98)	40.42 (11.30)	0.048	41.95 (17.22)	40.09 (13.63)	0.3
Working days (week)	4.87 (1.11)	5.01 (0.99)	0.2	4.87 (1.09)	4.94 (1.12)	0.6
Monthly Income (10,000KRW)	101.88 (42.80)	157.23 (45.96)	<0.001	101.20 (42.75)	154.95 (54.26)	<0.001

Notes: Listed values are the mean (SD) for continuous variables; otherwise, they are %. This table describes the means of the observable characteristics when comparing the intervention and control groups. The intervention group comprised participants who reported hourly wages below the minimum wage. Participants reporting hourly wages equal to 100-150% of the minimum wage were selected as the control group. Listed values are mean (standard deviation) for continuous variables and percentages otherwise. Propensity score weights were applied to weighted group. P-values indicate whether statistical differences exist between the two groups. All values were measured in 2016, prior to the large minimum wage increase. 10,000KRW in 2016 is equivalent to 11.64 USD when adjusted for 2016 PPP. K-MMSE: Korean version of the Mini-Mental State Examination.

Table 2.3: Minimum wage and health.

	Before weighting		After weighting	
Dependent variable:	Cognitive function	SR Health	Cognitive function	SR Health
MW increase	−0.672	−0.001	−0.704*	−0.057
	(0.343)	(0.076)	(0.289)	(0.067)
Observations	924	924	924	924

Notes: This table presents an estimate of the impact of the 2016 to 2018 minimum wage increase on health outcomes. The intervention group comprised participants who reported hourly wages below the minimum wage. Participants reporting hourly wages equal to 100-150% of the minimum wage were selected as the control group. Cognitive scores range from 0 to 30, and self-rated health from 1 to 5. Columns 2-3 report the unadjusted estimation results. Columns 4-5 show propensity-weighted estimation results. All specifications used time-varying variables such as pension status, marital status and 5-year age categorisation. The standard errors are reported in parentheses. *p<0.05, **: p<0.01, ***: p<0.001.

Sensitivity analysis

Parallel trends assumption and event study results

To assess the validity of the parallel trends assumption, I conducted placebo tests using data from 2014 to 2016, when the minimum wage increased modestly, compared with the large minimum wage increase from 2016 to 2018. In contrast with the reform period, the placebo test showed positive effects on cognitive health and null effects on self-reported health. The findings from the placebo tests suggest that the negative health impacts on cognitive functioning exist only with a considerable increase in the minimum wage (see Table 2.4). I provide the trends in mean cognitive functioning and self-reported health for both the intervention and control groups in appendix Figures A2.1 and A2.2. This provides confidence that the parallel trends hold and that the

Table 2.4: Minimum wage and health - Placebo group.

	Before weighting		After weighting	
Dependent variable:	Cognitive function	SR health	Cognitive function	SR health
MW increase	0.282	0.129	0.494*	0.004
	(0.257)	(0.071)	(0.250)	(0.072)
Observations	990	990	990	990

Notes: This table presents an estimate of the impact of the minimum wage on health outcomes of a modest increase from 2014 to 2016, which served as a placebo test. The intervention group comprised participants who reported hourly wages below the minimum wage. Participants reporting hourly wages equal to 100-150% of the minimum wage were selected as the control group. Cognitive scores range from 0 to 30, and self-rated health from 1 to 5. Columns 2-3 report unadjusted estimation results. Columns 4-5 show propensity-weighted estimation results. All specifications used time-varying variables such as pension status, marital status and 5-year age categorisation. The standard errors are reported in parentheses. *$p<0.05$, **: $p<0.01$, ***: $p<0.001$.

decline is only observed in cognitive functioning, not in self-reported health.

Furthermore, we show the event study results of the minimum wage effects on cognitive functioning in Figure 2.3 and on self-reported health in appendix Figure A2.3. For the event study plot, we included one additional prior wave, from the year 2014. We used the 2016 wage to categorize the treatment and control groups. In this process, 16 individuals who did not participate in 2014 were removed, giving us a balanced panel of 446 individuals and 1338 observations. Due to the potential bias from heterogeneous effects coming from the negative weights (Sun and Abraham 2021), we used the two-stage difference-in-differences estimator(Gardner et al. 2024) alongside the traditional TWFE. We observe that the results are significant on the year of minimum wage hike and not appearing before. The results from event study strengthen the main results.

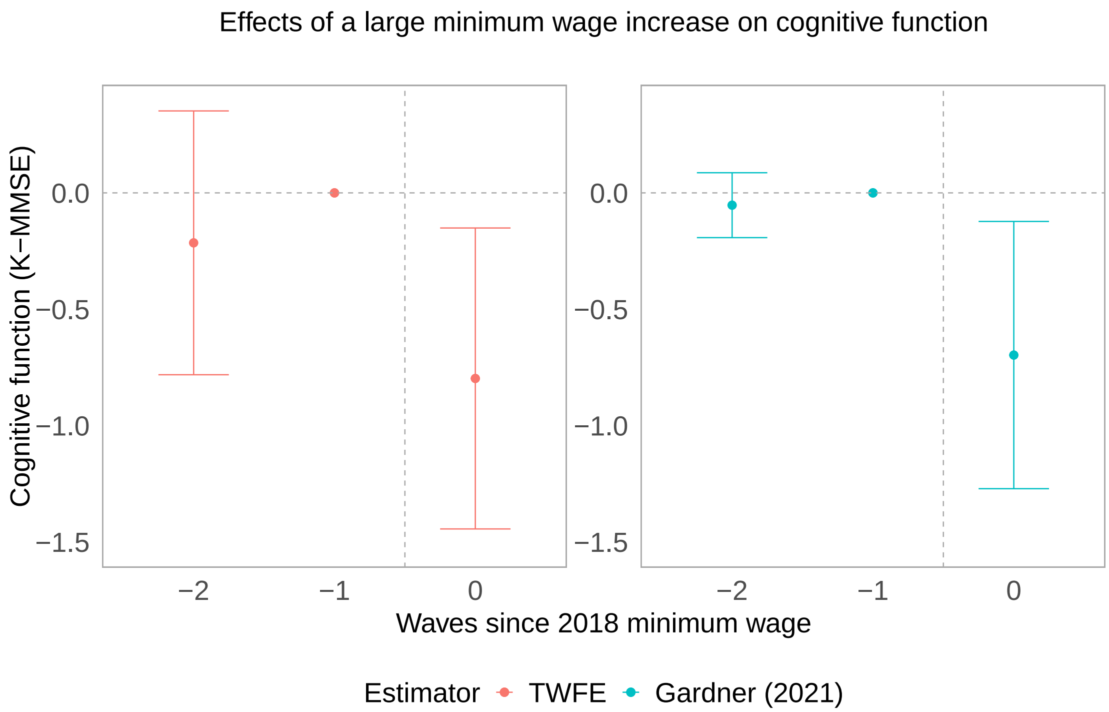


Figure 2.3: **Event study results regarding cognitive functioning** These figures present the dynamic effects of the large minimum wage increase from 2016 to 2018 on cognitive functioning. The left panel shows the results from using a two-way fixed effects estimator, while the right panel displays the results from the two-stage difference-in-differences estimator. Cognitive function was measured by the Korean version of Mini-Mental State Examination (K-MMSE). K-MMSE ranges from 0 to 30. The intervention group comprised participants whose reported hourly wages in 2016 were below the new minimum wage. The control group included participants whose hourly wages in 2016 were between 100-150% of the new minimum wage.

Alternative definitions of control groups

As noted in Maxwell et al. (2022), there is a trade-off between the size of the control group and the upper limit of the hourly wage used for the selection. To balance the number of individuals in the two groups in our main analysis, I set the upper limit to 150%. However, reducing the upper limit would have resulted in a more similar control group, albeit with a smaller sample size. To test the sensitivity of our results, I lowered the limit stepwise by 10% and found statistically significant negative effects on cognitive functioning across all upper limits (between 150% and 120%) except the lowest (110%). I provide the results in Table 2.5. While the smaller sample size of the control group in these scenarios comes with the benefit of greater similarity to the intervention group, our findings suggest that the negative effects on cognitive functioning remain robust across a range of upper limits.

Table 2.5: Alternative definitions of control groups.

Dependent variable	Cognitive functioning				
Control group upper limit:	150%	140%	130%	120%	110%
MW increase	-0.704^{*}	-0.884^{***}	-0.862^{**}	-0.625^{*}	-0.532
	(0.289)	(0.266)	(0.272)	(0.271)	(0.275)
Observations	924	908	866	790	704

Notes: This table presents an estimate of the impact of the minimum wage increase from 2016 to 2018 on cognitive functioning. The intervention group comprised participants who reported hourly wages below minimum wage. Participants reporting hourly wages equal to 100-150% of the minimum wage were selected as the control group. Propensity score weights were then applied. Column 2-6 show a decrease in the control group's upper limit of 10% of the minimum wage. Column 6 is the smallest control group with individuals with hourly wages from 100-110% of the minimum wage, and column 2 is the largest one with 100-150%. All specifications used time-varying variables such as pension status, marital status and 5-year age categorisation. The standard errors are reported in parentheses. *$p<0.05$, **: $p<0.01$, ***: $p<0.001$.

Alternative definitions of intervention groups

I conducted two sensitivity analyses using different definitions for the intervention groups. The first employs a stringent definition by imposing an additional constraint on the magnitude of the wage increase for the intervention group to rule out a substantial wage increase unrelated to the minimum wage policy. This additional constraint is consistent with Reeves et al. 2017. The intervention group was limited to individuals whose new hourly wage after the policy change was between 100-120% of the new minimum wage and whose pre-intervention hourly wages were below the new minimum wage (see appendix Table A2.4 for the descriptive statistics). appendix Table A2.5 demonstrates that these results align with the main findings and, in fact, exhibit even greater strength.

A second sensitivity analysis was conducted, including unemployed individuals, after the minimum wage increase. I relaxed the Exclusion Criterion 5 (Figure 2.2) and included individuals who exited the labour force. Skipping the exclusion criterion 5 and subsequently removing observations not available in both waves (N_{obs} = 75, 6%) resulted in an analytical sample of N=637 and N_{obs}=1274 where the intervention group had a sample size of N=436 and the control group N=201. Table 2.6 presents our findings. When I included individuals outside the labour force, I observed negative effects on cognitive functioning solely in the sample with a significant minimum wage increase. Even in the presence of negative impacts of unemployment, the findings are consistent with the main results.

Potential mechanisms

A significant increase in the minimum wage may impact health outcomes through two channels: structural changes in the workplace and increases in income. Regarding the first mechanism, it is important to consider not only the increase in the net value of hourly wage but also the associated structural changes (Clemens 2021). Evidence from Korean data investigating a minimum wage hike founds that there was a substitution

Table 2.6: Minimum wage and health - Including unemployed.

	Original sample		Placebo test	
Dependent variable:	Cognitive function	SR health	Cognitive function	SR health
MW increase	-0.573^{*}	-0.019	0.311	0.044
	(0.241)	(0.059)	(0.244)	(0.061)
Observations	1274	1274	1344	1344

Notes: This table presents an estimate of the impact of the minimum wage increase on health outcomes. The intervention group was defined as participants reporting hourly wages below the minimum wage, regardless of their subsequent employment status. Participants reporting hourly wages equal to 100-150% of the minimum wage were selected as the control group. Propensity score weights were then applied. Cognitive scores range from 0 to 30, and self-rated health from 1 to 5. Columns 2-3 report large minimum wage increase from 2016 to 2018. Columns 4-5 show a modest increase from 2014 to 2016, which served as a placebo test. All specifications used time-varying variables such as pension status, marital status and 5-year age categorisation. Standard errors are reported in parentheses. *$p<0.05$, **: $p<0.01$, ***: $p<0.001$.

between labour at different skill levels (Doh et al. 2022). Similarly, another study from Hungary showed that substantial minimum wage increases led to the substitution of labour with capital (Harasztosi and Lindner 2019). These findings suggest that a minimum wage hike may trigger structural changes in the labour market, which may have affected job characteristics and work demand. Such a substitution might lead to reduced working hours for low-skilled/inexperienced minimum wage workers and increased cognitive load at work for high-skilled/experienced minimum wage earners. Based on our data, after applying propensity score weighting, I found a statistically significant decrease in working hours by 4.06 hours per week for the intervention group compared to the control group after the minimum wage hike (in appendix Table A2.3). I investigated other potential mechanisms, including changes in job satisfaction and job security, but found no significant effects. Decreases in working hours may have led to decreases in cognitive or social stimulation at work, but the exact pathways cannot be tested in this dataset, and thus they remain unclear. Future research can empirically test the changes in non-wage-related aspects, although objective measurements of work environment, work-related stress, working conditions, or fringe benefits are often lacking (Clemens 2021).

Regarding the second proposed mechanism, I observed an increase in monthly income of 174,600 KRW (equivalent to 204 USD when adjusted for 2018 PPP) for the intervention group compared to the control group after the minimum wage hike (in appendix Table A2.3). Between 2016 and 2018, when the nominal minimum wage increased by 25%, the intervention group experienced a 34% increase in monthly income, while the control group saw a 12% increase. Some studies argue that an increase in income from a rise in the minimum wage leads to unhealthy behaviours, such as an increase in cigarette smoking and a decrease in fruit and vegetable consumption (Huang et al. 2021; Bai et al. 2023; Andreyeva and Ukert 2018). Using the South Korean 2018 minimum wage increase as a natural experiment, one study showed that a large minimum wage increase led to an increase in smoking behaviour among working age (19–64 years) study participants (Bai et al. 2023). However, in our analyses adjusted for confounders, I did not observe any statistically significant change in smoking or drinking status within our sample (appendix Table A2.3). However, I may have missed more fine-grained changes in the number of cigarettes smoked or units of alcohol consumed due to a lack of information in this dataset. Another study examining the impact of continually receiving social pensions on South Korean older adults, using the same survey and health outcomes as ours concluded that there were positive effects (Hwang and Lee 2022). Therefore, the pathway through consumption requires further investigation.

I conclude that based on the information and reasoning presented above, the negative effects I found might be driven by changes in non-wage-related job attributes (e.g., change in working hours) from firms actively compensating for the presumed economic losses due to the significant increase in the minimum wage.

2.5 Discussion

This chapter investigates the impact of a substantive minimum wage increase on the cognitive functioning and self-reported health of older workers in South Korea using substantive and given the magnitude of unexpected minimum wage policy changes as a natural experiment. By analysing nationally representative longitudinal individual-level data, I found that the minimum wage hike had a negative impact on cognitive functioning, with a decrease of 0.704 points compared with the unaffected group, while I did not observe significant effects on self-reported health. The magnitude of the cognitive decline is sizable when compared to a study that investigated the health effects of continuous receipt of social pensions among South Korean older adults using the same survey and cognitive measurements, which found a 1.301 points benefit. I also tested for placebo effects by examining the impact of a modest minimum wage increase from 2014 to 2016, and found no negative effects on self-reported health and positive effects on cognitive health. In periods with modest wage increases, individuals earning the minimum wage may experience improved living standards due to additional income, without facing significant negative changes in their working conditions. However, during periods of drastic minimum wage hikes, the advantages of extra income may become less significant when weighed against potential substantial alterations in working conditions. Additional analyses that invalidate possible competing pathways suggest that changes in non-wage-related job attributes, such as decreases in working hours, may have driven the the negative impacts. Overall, our study provides important insights into the potentially negative health consequences of a large minimum wage increase. I investigated the hypotheses proposed by Kronenberg et al. (2017); Maxwell et al. (2022) to determine whether significant minimum wage increases have more pronounced impacts on health outcomes than smaller ones. Our findings suggest that a minimum wage hike may have a negative impact on the cognitive functioning of older workers, whereas modest increases have positive effects. While I attribute these negative impacts to a significant decrease in the working hours of low-wage individuals upon the implementation of the minimum wage hike, the relationship between reduced working hours and cognitive decline requires further investigation. Further research is needed to empirically examine the changes in non-wage aspects due to substantial minimum wage increases, using objective measurements (Clemens 2021). Although no study has examined the effect of a minimum wage hike on health outcomes, This chapter adds to the existing literature on the recent minimum wage spike in South Korea and its negative consequences on employment and workers (Doh et al. 2022; Seok and You 2022; Kim et al. 2023a).

Our study has several limitations that should be considered. First, I need to assume parallel trends between the intervention and control groups. To mitigate potential bias, I used propensity score weighting with pre-intervention characteristics. In addition, a visual inspection of the trends in mean cognitive function for the intervention and control groups (see appendix Figure A2.1) and event-study plot in Figure 2.3 suggest that the parallel trends assumption is likely to hold.

Second, our sample size was small due to the assignment of intervention groups based on hourly wages, which is less biased but has more variance than other criteria, such as education attainment cutoffs. Due to the limited sample size and, consequently, a lack of power, I refrained from further analyses to test heterogeneous effects, e.g., by gender, which may be relevant to consider in future studies. However, these limitations are not unique to our study and apply equally to the previous studies (Reeves et al. 2017; Maxwell et al. 2022). Third, there may have been measurement errors in our calculated hourly wages based on self-reported working hours and income. Our data did not provide information on overtime, which could have resulted in a slight overestimation of hourly wages. Four, there might be wage spillover effects on our control group. Lee and Park (2023) demonstrated the presence of wage spillover effects of minimum wage policy in the Korean labour market up to two times the new minimum wage, affecting 0.3 to 0.5 percentage points of the wage growth rate. Therefore, our estimation results of the minimum wage effects on health might be underestimated. This limitation applies to the previous studies with similar intervention designs (Reeves et al. 2017; Kronenberg et al. 2017; Maxwell et al. 2022). Finally, I cannot rule out that other unobserved time-varying factors (e.g., concurrent economic policies or social changes) may have affected the health of older workers in the intervention and control groups differentially despite their similarities.

Further research could explore the long-term effects of substantial minimum wage increases on health outcomes; however, it is important to consider that current minimum wage policies are not independent of past decisions. When a country experiences a rapid increase in the minimum wage, it may subsequently decrease the minimum wage growth rate in subsequent years, which can confound the long-term health outcomes. Thus, investigating the long-term effects of rapid minimum wage increases can be challenging. Future studies should also confirm the generalisability of our findings by exploring the experiences of other countries that have experienced or are currently facing similar significant minimum wage increases. For instance, Spain, Mexico, and Germany have recently experienced substantial real minimum wage increases. Comparing the impacts of significant minimum wage increases on health outcomes across different countries in varying economic contexts can provide valuable insights and help generalise the findings. The health effects of minimum wage increases are partly dependent on the economic context and need to be considered in cross-national and period-specific changes in minimum wage policies.

Our results cannot be generalised to younger age groups or countries with different economic contexts. Moreover, I cannot assume that the negative health impacts of the minimum wage hike observed in South Korea will continue. Despite these limitations, I advise that caution is necessary when implementing sudden and significant minimum wage increases, as these may have immediate negative effects on older workers' cognitive functioning through structural changes in the labour market.

Chapter 3

Minimum wages and health of older workers

3.1 Introduction

Among older adults working at age 65 in the United States, one in five earn wages close to the minimum wage. This proportion increases to 30% among those working at age 70 (Hampton and Totty 2023). While recent studies investigate the minimum wage impact on employability of the older adults near retirement age (Fang and Gunderson 2009; Borgschulte and Cho 2020; Hampton and Totty 2023), the health effects are yet to be investigated. In this chapter, I examine the health implications of state-level minimum wage increases on workers aged near and beyond the normal retirement age.

This study draws upon the restricted version of the individual level panel data provided by the Health and Retirement Study (HRS), including information on the state of residency, sociodemographic characteristics, economic activities, and health outcomes. HRS offers a unique opportunity to evaluate the impact of minimum wage on health in older workers due to its availability on cognitive function measures—an important outcome that has not been studied in the context of US minimum wage policy and health. This study also examines other health outcomes including self-reported health, depressive symptoms, and health-related behaviors. The empirical strategy is to leverage the exogenous variation across states and time of the minimum wage policy and employ difference-in-difference methods. I focus on the health implications for the older workers who did not attend college, as they are most likely to be affected by the minimum wage policy. I provide placebo regressions with individuals with a bachelor's degree or higher.

I find that increases in the minimum wage result in a decline in the self-reported health while not affecting cognitive function among older, non-college-educated workers. With regards to parallel pre-trends, individuals residing in states with minimum wage increases do not show notably different trends in all health outcomes compared to their counterparts, and I observe a sudden drop in self-reported health at the minimum wage increase year. I do not find any effects on cognitive function and self-reported health and among college-educated older workers.

To potentially pinpoint the targeted group of minimum wage policy, I supplement the analysis using hourly wage instead of education level as a proxy for exposure to the minimum wage despite the reduced sample size of the analysis. I compare the results of individuals earning an hourly wage near minimum wage with those earning a higher hourly wage. The results are consistent with the main findings that the targeted group reports decreased self-reported health whereas cognitive health is not impacted. Both health outcomes have valid parallel pre-trends.

While the findings of the minimum wage impact on health have been mixed (see Leigh et al. 2019; Neumark 2024c for a review), the results on reduced self-reported health on non-college-educated workers following the minimum wage increases are in line with prior research on working-wage workers (Horn et al. 2017). Despite the absence of comparisons with existing literature on the impact of the US minimum wage on cognitive function[1], the null findings in this study relate to the previous research on labor market experiences in late adulthood and their insignificant impact on cognitive functioning within the context of the United States (Kim et al. 2023b). This study is also related to the recent studies investigating the impacts on employability with a focus on older adults near retirement age (Borgschulte and Cho 2020; Hampton and Totty 2023). In line with these previous findings, this study also do not observe negative impacts on employability contrary to the prediction of traditional economic theory.

Exploring potential pathways, including psychological effects and health behaviors, I find that drinking frequency increases among non-college-educated older workers, while such associations are not observed among college-educated older workers. I suggest that the negative effects on self-reported health found in non-college-educated older workers, might be associated with increased drinking frequency linked to the minimum wage increases. This study contributes to the literature on minimum wage and health by introducing the evidence with older workers.

It is important to specifically investigate the health effects of the minimum wage policy on older workers for the following reasons. First, the share of older workers is going to increase over time as long as the life expectancy continues to increase and the real wage growth is low (Scott 2021). Figure 3.1 illustrates the trend in the proportion of older workers over time and the demographic makeup of the labor force by age groups. Over time, there is a noticeable rise in the proportion of older

[1] A recent study finds a decrease in cognitive function following a large minimum wage increase in South Korea (Kim et al. 2025).

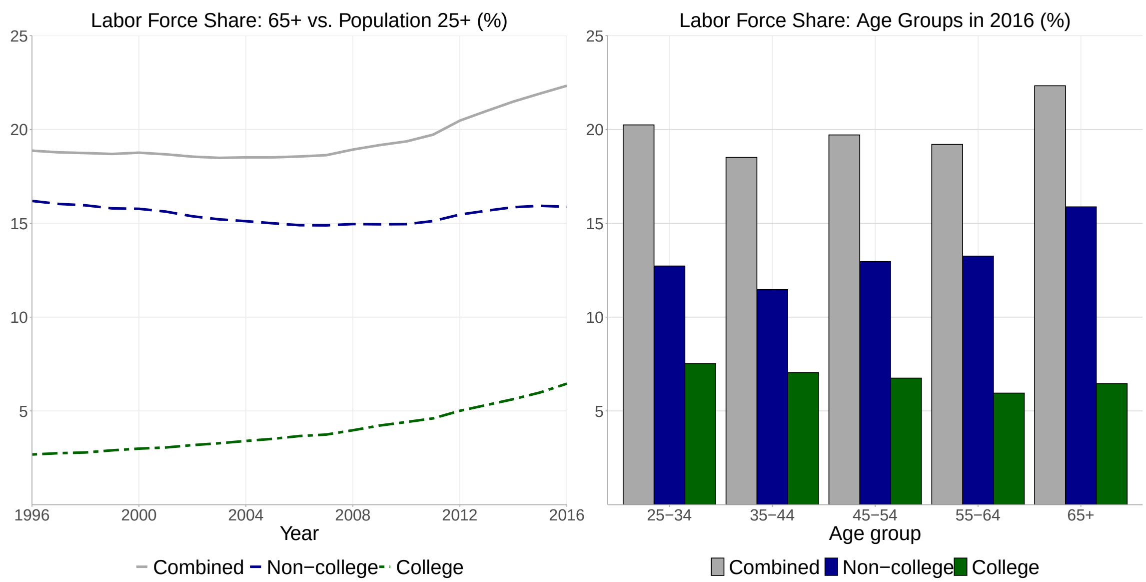


Figure 3.1: **Demographic composition of the labor force.** The right figure illustrates the proportion of workers divided by age groups relative to the overall workforce aged 25 and above using 2016 data. The left figure displays the trend of the share of older workers relative to the each year's overall workforce aged 25 and above. *Source:* Current Population Survey 1996-2016

workers in the labor force. On the right-hand side, I observe that individuals aged 65 and above constitute the largest share of employment among all age groups, with a significant portion without college degrees. Therefore, with the increasing presence of older workers in the labor market, designing policies to promote the participation of older adults can better obtain sustainability through incorporating cognitive and physical health effects. Second, although age-friendly jobs characterized as those that are performed in offices, not physically demanding, and requiring social and communication skills, are increasing in the US economy, these jobs are concentrated on older college-educated workers (Acemoglu et al. 2022). As non-college-educated older workers are less likely to have an age-friendly work environment, it is worth investigating whether a minimum wage policy can compensate for some of the unfavorable job conditions. Third, the motivation for labor might differ by age. There are age-specific benefits in social security systems including access to public health insurance and pension that impact the employment decision at late life (French and Jones 2011; Yu 2024). With these benefits, older workers might be more flexible in negotiating their financial remunerations as they are already or soon to be the beneficiaries of the social security system. On the other hand, older workers might face more financially challenging situations compared to younger groups, as they need to work for income despite facing greater health risks from labor. As such, it is not straightforward to make an inference about older adults from the results deriving from younger age groups.

Background

Labor market for non-college-educated older workers

The number of older adults working at age 65 and above surged from 3.6 million to 8.7 million between 1996 and 2016 according to the Current Population Survey. Over two-thirds of older workers do not have a college degree and this demographic group constitutes over 15% of the total labor force aged 25 and above (see Figure 3.1).

With regards to job characteristics and industries for the American older workers, Acemoglu et al. (2022) show that male non-college-educated older workers are more likely to be in physically demanding jobs with harsh working conditions, higher job hazards, and reduced autonomy and flexibility. The main industries for this demographic group include manufacturing and construction. Similarly, female non-college-educated older workers exhibit comparable job characteristics, although the contrast between male and female graduates is less pronounced, and a large proportion of them are engaged in the professional and retail sectors.

Motivation and barriers for late-life employment

There are several motivations for engaging in economic activities in late life. The first is the financial reward. For example, working at a later age allows individuals to delay claiming social security income, resulting in a higher pension (Hampton and Totty 2023). Another reason is to smooth consumption. Individuals accustomed to a certain lifestyle may find their pension insufficient to maintain their quality of life, encouraging them to choose to work in their late 60s and beyond. The second motivation is to maintain physical activity and social contact. Volunteering is found to have positive causal effects on cognitive functioning (Gupta 2018), similar to the benefits observed in populations engaging in prolonged work life (Dufouil et al. 2014;

Kim et al. 2023b). The link between productive activities and cognitive functioning can be traced back to the theory of the“use it or lose it” hypothesis (Hultsch et al. 1999a), which suggests that engaging in cognitively stimulating activities may protect against cognitive decline in later life.

In the meantime, obstacles to engaging in late-life employment exist. A study documents that these barriers to late-life economic activities begin well before individuals reach age 60 (Berkman and Truesdale 2023). The barriers include poor health, challenging working conditions, and caregiving responsibilities. Additionally, age discrimination practices have been shown to have negative effects on the hiring process of older workers (Neumark 2024a).

Therefore, the motivations and barriers surrounding participation in the labor market beyond the normal retirement age, especially for those with low-wage jobs, emphasize the importance of older workers' financial circumstances, health status, working conditions, and fairness in the hiring process in shaping their decision-making processes.

Minimum wages and health

According to Neumark (2024c), the predicted health response to minimum wage in the following way: $\partial H/\partial MW = p_I(\partial H/\partial I) * \Delta I_{MW} - (1-p_I) * (\partial H/\partial I) * c * \Delta I_{MW}$. p_I is the probability of keeping the jobs and $1-p_I$ is losing the jobs. H is the health, MW denotes minimum wage, and I is the income. c is the wage that individuals would have received if they were able to keep their jobs. The above framework applies when the non-wage related benefits, which might affect the health, remain intact. This is the case when the employment elasticity is positive and the p is close to 1, meaning that most of the workers can keep their jobs, ceteris paribus.

However, the minimum wage can affect fringe benefits and other non-wage conditions in the competitive market (Clemens et al. 2018). After a minimum wage increase, if employers cannot adjust compensation, they might reduce working hours or non-wage benefits such as employer health benefit (Meiselbach and Abraham 2023). Conversely, for those who become unemployed due to a minimum wage increase, eliminating work-related stress and other job-related penalties might have positive health effects. However, the exact changes in non-wage-related characteristics require further study.

For example, if non-wage benefits are reduced for employed individuals and non-wage penalties are reduced for unemployed individuals, the framework is modified as follows: $\partial H/\partial MW = p_I(\partial H/\partial I * \Delta I_{MW} - \partial H/\partial NWB * \Delta NWB_{NWB}) - (1 - p_I) * (\partial H/\partial I * c * \Delta I_{MW} + \partial H/\partial NWP * \Delta NWP_{NWP})$ with the appearance of effects of change in non-wage related characteristics in either employed or unemployed cases, where NWB stands for non-wage related benefits and NWP for non-wage related penalties. Therefore, while the original framework is useful to decompose the effects of minimum wage policy, non-negligible parts are accounted for by changes in characteristics that are not directly related to income changes, when the wages are already set in equilibrium.

It is not surprising to find mixed evidence on the health effects of minimum wage increases. This is potentially due to heterogeneous minimum wage-employment elasticity, income responsiveness of health (Neumark 2024c), and the responsiveness of non-wage-related characteristics. Previous studies find that the relationship between the minimum wage and employment is positive for near-retirement age workers (Borgschulte and Cho 2020; Hampton and Totty 2023). This signifies that the health effects of minimum wage policy for older workers might depend on the income responsiveness of health rather than changes in employability or non-wage related characteristics, as the labor market is not tight. Studies show positive health effects of social pensions for older adults (Aguila et al. 2015; Hessel et al. 2018; Hwang and Lee 2022). Aguila et al. (2015) explains that the Mexican older adults who received extra income spent it in health-favoring ways, including on food, medical appointments, and the purchase of medications. However, unlike social pensions, the minimum wage policy might have different implications on income responsiveness of health as it is contingent on working status.

3.2 Data: Health and Retirement Study

To investigate the impact of minimum wage increases on older workers, I use the Health and Retirement Study (HRS). It is a population-representative longitudinal study collected biennially since 1992 with questionnaires on demographics, economic status, family composition, and self-rated health and cognitive function of individuals aged 50 years or older residing in the United States. Data on the state residence of the participants, which is a key information for the identification strategy, is acquired under a restricted data agreement for the HRS.

The advantage of HRS data is its rich information of economic activities and various health outcomes. Having data on education and self-employment status can effectively remove individuals who are not likely to be affected by the minimum wage. While I use education as a proxy for the exposure in the main analysis, the HRS contains data on hourly wage, providing another ways to assign the intervention and control groups. Regarding health outcomes, this study assesses cognitive functioning and self-reported health, making it the first study to investigate the impact of minimum wage on cognitive functioning for workers in the US. Additionally, data on health behaviors including frequency of drinking and physical activity, smoking status, and depressive symptoms, allow the exploration of the potential mechanisms in a concrete way. Nevertheless, the advantages of using HRS, which contains rich information on economic activities and health outcomes, comes with the caveat of a limited sample size.

To control for state-specific macroeconomic trends, I use the welfare data from the University of Kentucky Center on Poverty Research (UKCPR 2023). Following the previous literature on minimum wage and deaths of despair (Dow et al. 2020), I include state GDP, the population share receiving social security income, state population, and Affordable Care Act (ACA) Medicaid expansion, which might affect the health of older workers independent of minimum wage policy. The geographic information of the participants is matched with the state-level minimum wage data obtained from Vaghul and Zipperer (2022). Wage, earnings, and minimum wage are adjusted for inflation to 2016 dollars using IMF inflation indicator. From 1996 to 2016, there were 344 cases of yearly state-level real minimum wage increases, with 15 of these cases involving increases of more than one dollar. During the observed period, federal minimum wage was raised five times (1996, 1997, 2007, 2008, 2009). Each state experienced an average of 6.7 cases of state-level minimum wage increases, with 0.3 of these being the *first* increase of more than one dollar. In our sample which was collected biennially, individuals experienced an average of 2.1 cases of state-level real minimum wage increases, with 0.5 of these being the first increase of more than one dollar between survey waves.

Sample selection

The focal group of this study is older adults, who are working in non-self-employed jobs at the baseline. I do not impose further restrictions on subsequent employment status to capture health effects across individuals, whether employed, unemployed, or not in the labor force subsequent to the minimum wage increases. I include individuals aged 65 and above. I define the baseline year as the first wave of participation between waves 1996 and 2016. I then select individuals who were employed in non-self-employed jobs at the baseline and drop those without information on self-reported health or education, gender, race/ethnicity, working status, and state residency, which results in 3,333 individuals and 16,964 observations. The restriction on the baseline employment status is consistent with many studies on older workers to isolate economically inactive individuals due to retirement or caregiving obligations (Boyle et al. 2010; Hampton and Totty 2023). This final analytical sample accounts for 14% of all participants aged 65 and above, a proportion comparable to the employment — population ratio of individuals in the same age group in 1996, which is 12%, according to the Current Population Survey.

I focus on non-college-educated workers who are most likely to be affected by minimum wage policies, specifically those with a high school education or less, resulting in 9314 observations. This identification approach for determining the minimum wage target group aligns with previous studies (Horn et al. 2017; Dow et al. 2020; Sigaud et al. 2022). To assess potential heterogeneous effects between men and women, I conduct separate analyses for each gender. To examine placebo effects, I run the analysis only with individuals holding a bachelor's degree or higher. Additionally, to investigate effects at the population level, I conduct the analysis including both low-wage and higher-wage workers.

Lastly, I construct an alternative way of identifying the low-wage group by using hourly wage. Hourly wage information in the HRS dataset is obtained either directly or derived from weekly, monthly, or annual wages through scaling down, excluding overtime wages. Therefore, while hourly wage data is a more precise measure to define the target group, it still remains a self-reported and derived one. I include individuals with a baseline hourly wage below the prevailing minimum wage plus two dollars to capture the potential spill over effects in the US labor market (Hampton and Totty 2023). For the placebo sample, I select participants whose hourly wage rate falls between two dollars more than and twice the prevailing minimum wage.

Table 3.1: Summary statistics by gender and educational attainment

Gender	Women		Men	
Education	HS or less	BA or higher	HS or less	BA or higher
Age	72.1	71.0	72.1	71.3
	(5.4)	(5.3)	(5.4)	(5.4)
Observations	4945	3813	4369	3837
Non-white	17%	16%	24%	11%
Observations	4945	3813	4369	3837
Poor health (Y/N)	24%	12%	27%	15%
Observations	4945	3813	4369	3837
Cognitive score (0-35)	22.6	24.9	21.2	24.2
	(4.7)	(4.2)	(4.4)	(3.9)
Observations	4768	3706	3910	3647
Smoking (Y/N)	14%	6%	13%	7%
Observations	4916	3794	4438	3811
Drinking (Y/N)	24%	38%	33%	52%
Observations	4938	3804	4352	3831
Depressive symtoms (Y/N)	21%	13%	15%	10%
Observations	4783	3734	3921	3659
Continue working (Y/N)	48%	61%	52%	62%
Observations	4945	3813	4369	3837
Annual income	9452	22415	14408	35575
	(18285)	(34493)	(30517)	(60643)
Observations	4945	3813	4369	3837

Notes: Table describes the summary statistics of the sample of older workers aged 65 and above, covering years 1996-2016. Values in parentheses the standard deviations. Survey weights are applied. Poor health is defined by answering yes to 'poor' among five-scale self-reported health. Depression refers to binary indicator of scoring more than 3 out of 8 on the Center for Epidemiologic Studies Depression Scale. Drinking is a binary variable of drinking more than one day in a week. Smoking is a binary variable of the smoking status.

Table 3.1 presents the summary statistics of the sample categorized by gender and educational attainment. I observe a higher prevalence of poor health and smoking and lower cognitive scores, among non-graduate older workers compared to graduate counterparts. Frequent drinking is observed the most in male, graduate older workers followed by female graduate older workers. State-level macroeconomic variables including GDP, population, and share of individuals receiving social security income, appear similar across gender and educational attainment (appendix Table A3.1).

Main health outcomes

The HRS data contains a five-point scale of self-reported health; "excellent", "very good", "good", "fair", or "poor". I use the five-point scale to capture the full range of changes in health. Self-reported health has been proven as a consistent and validated measure to assess health status (Idler and Benyamini 1997). Previous research on minimum wage and health use self-reported health as their primary outcome (Horn et al. 2017; Buszkiewicz et al. 2020; Sigaud et al. 2022). Nonetheless, there is the inherent nature of subjectivity in self-assessed health measures. Dowd and Zajacova (2007) show that individuals' report on health might depend on socioeconomic status, with more accurate self-evaluation of health for individuals with higher education and income. Despite this limitation, the widely used self-assessment of health allows us to compare the results with other studies and it is an easily accessible measure that is independent of healthcare access.

I investigate the cognitive function of older adults as another main outcome of this study. Cognitive function includes attention, memory, and language (Craik and Salthouse 2008). Tymula et al. (2013) show the impact of cognitive function on decision making and reasoning including the decline in choice consistency and risk appetite. Maintaining cognitive function is essential for individual autonomy, and its decline can result in substantial long-term care costs. Due to its integral role in the health and well-being of individuals and society, special attention is called to optimize the brain health of older adults (World Health Organization 2022). The HRS cognitive test for individuals above 65 years old is a 35-point scale capturing global cognitive functioning with simple questionnaires suitable for large-scale surveys (McArdle et al. 2009). The cognitive tests in HRS have been shown to effectively measure individuals' cognitive status (Crimmins et al. 2011).

3.3 Two-way fixed effects and imputation difference-in-differences approach

Two-way fixed effects approach

This study investigates the health effects of minimum wage on older adults aged 65 and above who are working in paid, non-self-employed jobs at baseline. The outcome of interest is $Health_{ist}$ for individual i in state s at year t. I run the analysis for self-reported health and cognitive function respectively. The treatment variable is the log value of the minimum wage increases. The two-way fixed effects (TWFE) estimation approach has been most commonly used to examine the relationship between health outcomes and the minimum wage while accounting for state and year effects in the previous research (see e.g., Horn et al. 2017; Buszkiewicz et al. 2020; Sigaud et al. 2022; Dow et al. 2020). In our study, I use the individual as the unit instead of the state because the same individuals are repeatedly present in the survey, this way of design is in line with Regmi (2020) that uses individual-level panel data to study the the minimum wage impact on children's math and reading test scores. I include individual fixed effects, year fixed effects, and the treatment variable. I assume that changes in other time-varying unobserved variables that are correlated with the minimum wage increase do not affect individuals' health outcomes, after controlling for individual and time-fixed effects and individual and state-level time-varying covariates:

$$Health_{ist} = \beta(\log MW_{st}) + X_{ist}\psi + \alpha_i + \lambda_t + u_{ist} \tag{2}$$

where X_{ist} is a vector for time-varying state-level economic trends (shared uninsured, log state GDP, log population share receiving Social Security Income (SSI), log state population, ACA medicaid expansion) and individual characteristics (age in 5-year categories). α_i is the individual fixed effects and λ_t is the time fixed effects. β denotes the change in health outcomes for each year following a percent change in minimum wage. There are two assumptions to obtain valid estimator for β. The first is the parallel trends that the gaps of health outcomes between treated and control groups are constant over time so that any health changes subsequent to minimum wage increase is due to the exposure to the policy. The second is that the treatment effects are homogeneous between individuals and across time.

Imputation difference-in-differences methods

When the treatment occurs at different times and there are heterogeneous treatment effects across individuals and over time within those individuals, the assumption is likely to be violated resulting in a biased estimator (Goodman-Bacon 2021). Meeting the constant treatment condition is especially challenging, for example, if the health effects of a minimum wage increase are larger in the immediate year and the effect size decreases over time (Sun and Abraham 2021). If the assumption is violated and negative weights are generated, then the results might even turn the direction of the causal effects opposite to that of the true ones. Therefore, I use the recent difference-in-differences model that is robust in the presence of the staggered treatment and heterogeneous effects. To do so, I convert the exposure variable to binary, non-reversible, and not reoccurring. The recoding of the exposure might introduce left censoring issues if there has already been a dollar increase prior to the sample period, 1996 - 2016. However, I verify that no participants in the sample experienced a dollar increase in state-level minimum wage prior to 1996. Therefore, I believe that the left censoring issues are not critical in my analyses. I present the TWFE with the binary treatment event, that is, the first prominent minimum wage increase of at least one dollar.

$$Health_{ist} = \underbrace{\sum_{k=-L}^{-2} \beta^k D_{st}^k}_{\text{Pre-trend}} + \underbrace{\sum_{k=0}^{K} \beta^k D_{st}^k}_{\text{Post-trend}} + X_{ist}\psi + \alpha_i + \lambda_t + u_{ist} \tag{3}$$

where D_{st}^k is the indicator of whether state s at year t experienced at least one dollar minimum wage increase. k denotes the lag and lead of treatment from the treatment year. β_k is the coefficient of the interest, and it is the weighted average of all β regardless of the treatment timing.

Recent literature on difference-in-differences poses questions on the validity of traditional two-way fixed effect facing issues coming from heterogeneous treatment effects with staggered treatment timing (see de Chaisemartin and D'Haultfœuille 2022; Roth et al. 2023b, for review). Following the previous literature looking into state-level minimum wage impacts on worker's welfare (Clemens 2021) and retirement decision (Hampton and Totty 2023), I use the imputation approach by Borusyak et al. (2024) within the recent difference-in-differences literature for its simplicity and intuitiveness.

Imputation approach estimates Equation (3) only with not-yet-treated observations. The parameters obtained from the first stage estimation using the control group provide the counterfactual outcome for the treated group. Then, the contrast between the observed health outcomes and imputed potential outcomes gives an estimate of the treatment effect. Borrowing the explanation from Roth et al. (2023b), the imputation estimator defines $ATT(t, g)$ as the average treatment effect for the time period t and the group treated in time g:

$$ATT(t, g) = \underbrace{(\overline{Health}_{t,g} - \overline{Health}_{t,\infty})}_{\text{Difference at time t}} - \underbrace{(\overline{Health}_{pre,g} - \overline{Health}_{pre,\infty})}_{\text{Difference in pre-periods}} \tag{4}$$

where the first contrast is the difference in health outcomes between the treated and never-treated units at time t, and the second contrast is the difference in health outcomes during the pre-treatment periods between the treated and never-treated units. I provide the event study results using the imputation estimator and verify the parallel trends assumption and the dynamic effects that unfold over time in Figure 3.2.

3.4 Results

Two-way fixed effects approach

I show the traditional TWFE results of the log value of minimum wage increases on self-reported health and cognitive function from Equation 2 in Table 3.2. Panel A presents the results for the older workers without college degrees and Panel B shows the results for the older workers with college degrees. I observe the negative impacts on self-reported health among the older workers without college degrees, while such effects do not show for the college-educated older workers. Cognitive functions are not impacted in both demographics. When aggregated regardless of the education level, Panel C shows the negative impacts on self-reported health. I further look into the non-college-educated older workers by gender. Panel D shows the results for the non-graduate women and Panel D for the non-graduate men. While the negative effects on self-reported health are larger for men compared to women, I do not observe significant effects on both self-reported health and cognitive function.

Table 3.2: Effects of minimum wage increases on self-reported health and cognitive function

	(1)	(2)	(3)	(4)
	Self-reported health		Cognitive function	
Panel A: High school or less				
Log Minimum Wage	-0.334*	-0.325*	-0.086	0.055
	(0.143)	(0.145)	(0.629)	(0.635)
Observations	9314	9314	8678	8678
Panel B: BA or higher				
Log Minimum Wage	-0.132	-0.122	-0.257	0.016
	(0.142)	(0.145)	(0.678)	(0.693)
Observations	7650	7650	7353	7353
Panel C: All older workers				
Log Minimum Wage	-0.243*	-0.239*	-0.159	0.019
	(0.101)	(0.103)	(0.461)	(0.467)
Observations	16964	16964	16031	16031
Panel D: Women, HS or less				
Log Minimum Wage	-0.283	-0.291	-0.135	0.133
	(0.189)	(0.191)	(0.876)	(0.885)
Observations	4945	4945	4768	4768
Panel E: Men, HS or less				
Log Minimum Wage	-0.391	-0.378	0.082	0.033
	(0.218)	(0.220)	(0.899)	(0.906)
Observations	4369	4369	3910	3910
Covariates	No	Yes	No	Yes

Notes: Self-reported health ranges from 0 to 5 and the cognitive function from 0 to 35, both with higher values indicating better health and cognitive function, respectively. Covariates include 5-year age categorization dummies, log state GDP, log social security income recipients, log population, and affordable care act expansion. All the models include individual and year fixed effects. Standard errors in parentheses clustered at the individual level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Imputation difference-in-differences methods

Due to the potential violation of assumptions using traditional TWFE, I show the recent difference-in-differences methods that are robust to the staggered treatment timings using the imputation approach (Borusyak et al. 2024). Figure 3.2 demonstrates the estimation results of the first large increase, at least a dollar (in 2016), instead of the continuous minimum wage increases. The event studies provide visual evidence for parallel pre-trends and show how the effects unfold over time on health outcomes. The results from the imputation difference-in-differences are in line with the main findings. I observe constant and significant negative effects among non-college-educated older workers except for the period one wave after the prominent minimum wage increase, while for the college-educated older workers any meaningful health impacts are not found. Combining both non-college and college-educated older workers, I observe negative effects on self-reported health unfolding over time and null effects on cognitive function.

Robustness

I run three sets of robustness checks. First, I redefine the health outcomes. Instead of using the 5-point full scale of self-reported health, I dichotomize the outcome; the responses ‘‘excellent’’, ‘‘very good’’, and ‘‘good’’ are given the value 1, and ‘‘fair’’, or ‘‘poor’’ receives the value 0. This re-coding of self-reported health measures is useful to minimize concerns related to the potential biases inherent in self-reported health measures (Horn et al. 2017; Sigaud et al. 2022). For the cognitive function, due to the potential ceiling effects, that the summary score of the cognitive function might be concentrated in the highest values, I use the assessment of episodic memory measured by the summed score of immediate and delayed recall of 10 words (Bonsang

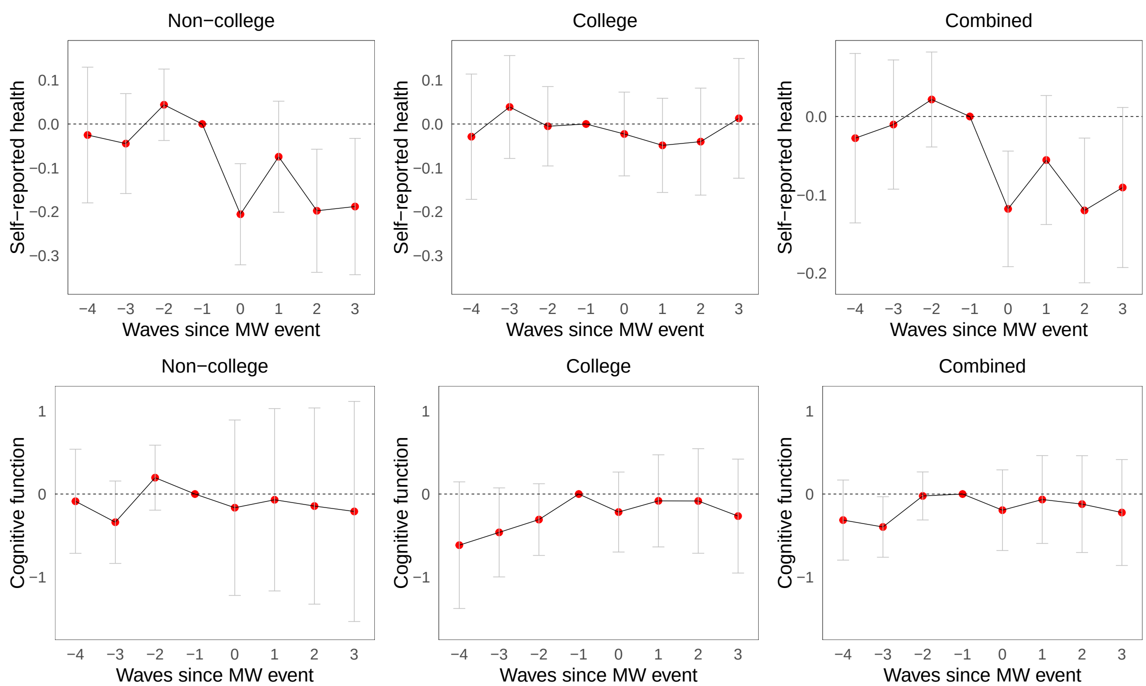


Figure 3.2: **Minimum wage effects on health outcomes.** The upper panels illustrate the minimum wage effects on self-reported health by the education levels and the bottom panels show the impacts on cognitive function. *Source:* Health and Retirement Study 1996-2016

et al. 2012). Appendix Figure A3.1 shows the negative impact on the binary measure of self-reported health among non-college-educated older workers while significant effects are not found among college-educated older workers. For the cognitive function measured by episodic memory, I observe null effects regardless of the education level. The results with alternative health outcomes are consistent with the main findings.

Second, instead of using education to assign the treatment group, I use the baseline hourly wage to allocate the treatment and the control group. While using wage is more suitable to precisely identify the target population of the minimum wage policy, the reduced sample size might hinder the generalization of these findings to estimate the broader population. I define the low wage group as individuals whose baseline hourly wages are between the prevailing minimum wage plus two dollars and the higher wage group are individuals whose baseline hourly wages fall between the minimum wage plus two dollars and double the minimum wage. I show the results using recent difference-in-differences in appendix Figure A3.2 and traditional TWFE with continuous minimum wage increases in appendix Table A3.2. The findings are consistent with the main results.

Lastly, I consider potential birth cohort effects by accommodating the Social Security pension eligibility age. Instead of including individuals aged 65 at the baseline across different birth cohorts, I set the sample age criteria to 65 for individuals born before 1943, 66 for individuals born between 1943 and 1959, and 67 for individuals born in 1960 and later. The findings are similar to the main results (appendix Table A3.3).

Potential mechanisms

Leigh et al. (2019) suggest three major potential pathways for the link between minimum wage and health: affordability, psychosocial effects, and worker and firm decision making. The HRS has the strength to investigate these potential pathways through the self-reported responses of the participants. I explore the following outcomes: affordability through drinking and smoking behavior, psychosocial effects through depressive symptoms, and worker and firm decision making through changes in mild physical activity and employability. I also investigate changes in income and working hours among older workers.

Table 3.3 shows that the drinking frequency is increased following the minimum wage increases among non-college-educated older workers while such effects are not found in college-educated older workers and female non-college-educated older workers. The increased drinking frequency might be related to the affordability hypothesis. As expected, I find increases in income among non-college-educated older workers, especially among men (appendix Table A3.4). I find insignificant impact on smoking status. Other pathways including depressive symptoms, physical activity, and employability do not show significant effects. I observe insignificant changes in working hours, except among male, non-college-educated older workers (appendix Table A3.4). The non-negative impacts on employment following the minimum wage increases for older adults near retirement age are in line with the previous research (Borgschulte and Cho 2020; Hampton and Totty 2023).

These results suggest that the negative impacts on self-reported health among non-college-educated older workers might be associated with the increased frequency of drinking. However, due to a lack of quality data on workload, work environment, and job characteristics, and other fringe benefits, there is a limitation in exploring the pathways related to firm decision making. Further research is needed to empirically measure the changes within the workplace and fringe benefits following the minimum wage increases, which might impact the health of older workers.

Lastly, I present the health implications by the change in employment status in appendix Table A3.5. I find that older workers' experiences of minimum wage increases and becoming unemployed have a negative impact on self-reported health and null impact on cognitive function regardless of educational attainment. The impacts on self-reported health are larger among non-college-educated older workers. Older workers who are continuously employed do not experience the negative impacts on health. These results indicate that unemployment associated with minimum wage increases has harmful effects on health, with this having a larger impact on non-graduate older workers.

Table 3.3: Effects of minimum wage increases on depression, drinking, smoking, physical activity and employability

	(1) Depression	(2) Drinking	(3) Smoking	(4) Sports	(5) Emp
Panel A: High school or less					
Log Minimum Wage	-0.072	0.584**	-0.015	-0.167	0.061
	(0.069)	(0.219)	(0.031)	(0.204)	(0.072)
Observations	8704	9290	9254	7438	9314
Panel B: BA or higher					
Log Minimum Wage	-0.121	-0.201	-0.006	0.349	-0.006
	(0.064)	(0.278)	(0.028)	(0.218)	(0.082)
Observations	7393	7635	7605	6374	7650
Panel C: All older workers					
Log Minimum Wage	-0.090	0.241	-0.010	0.065	0.031
	(0.048)	(0.173)	(0.021)	(0.149)	(0.054)
Observations	16097	16925	16859	13812	16964
Panel D: Women, HS or less					
Log Minimum Wage	-0.089	0.358	-0.027	0.008	-0.003
	(0.100)	(0.243)	(0.043)	(0.254)	(0.097)
Observations	4783	4938	4916	4054	4945
Panel E: Men, HS or less					
Log Minimum Wage	-0.048	0.882*	0.002	-0.388	0.136
	(0.095)	(0.379)	(0.046)	(0.329)	(0.107)
Observations	3921	4352	4338	3384	4369
Covariates	Yes	Yes	Yes	Yes	Yes

Notes: Covariates include 5-year age categorization dummies, log state GDP, log social security income recipients, log population, and affordable care act expansion. All the models include individual and year fixed effects. Depression refers to binary indicator of scoring more than 3 out of 8 Center for Epidemiologic Studies Depression Scale. Drinking refers to the frequency of drinking days per week. Smoking is a binary variable of the smoking status. Sports is the frequency of the mild physical activity. Standard errors in parentheses clustered at the individual level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

3.5 Discussion

This study examines the health implications of the minimum wage policy for older workers. With increasing life expectancy and stagnating real wages, the number of older workers is expected to grow. The majority of the older workforce are individuals without college degrees, more likely to be the target of the minimum wage policy. Despite the importance of minimum wage policy implications on older workers, no study has focused on the health effects of older workers near and beyond normative retirement age.

Using difference-in-difference methods with Health and Retirement Study data from 1996 to 2016, I find that minimum wage increases do not impact the cognitive function but have a negative effect on self-reported health, especially among older workers who did not attend college. These results are consistent using the recent difference-in-differences method that is robust to the staggered treatment timings. The negative impacts on self-reported health might be associated with the increased frequency of drinking observed solely among non-college-educated older workers, noticeably among men. I do not observe meaningful results in other pathways such as change in employability, smoking status, physical activity, and psychological effects.

The negative effects of minimum wage increases on self-reported health among non-graduate workers are in line with the previous findings of Horn et al. (2017) on working-age population; 10% of minimum wage increases is associated with a 0.4-percentage point decrease in a 5-point self-reported health scale among working-age men and a decline of 0.5 among working-age women. I find a larger impact on health among older workers: a 10% increase in minimum wages leads to a 3-percentage point decrease in a 5-point self-reported health scale. Regarding the heterogeneous effects by gender, while previous studies have identified gender differences in the health implications of minimum wages (Horn et al. 2017; Sigaud et al. 2022), with noticeable negative effects among men, I do not observe a significant difference between men and women. In sum, the health impacts are larger among older workers compared to the working-age population.

For the results on cognitive function, this chapter provides the first evidence of impacts of minimum wage, making comparisons with previous findings challenging. However, Bonsang et al. (2012) show that experiencing retirement leads to a 1-point decline in cognitive score using the same data and cognitive measurement (20-point episodic memory), which is about a 10% decrease in cognitive score. This study demonstrates that the 10% increase in the minimum wage leads to a 0.1 percentage point decline[2] in the cognitive score, corresponding to a 0.01% decrease compared to the sample average among non-college-educated older workers. Therefore, the magnitudes of the cognitive decline from minimum wage increases appear trivial and not statistically significant. With regards to previous findings on economic consequences of minimum wage increases on older workers, previous studies report non-negative impacts on employability (Borgschulte and Cho 2020; Hampton and Totty 2023), and this chapter also does not observe any negative effects on employability among older workers.

Several limitations are worth mentioning. First, the findings from this chapter may not apply to older adults who are unable to participate in the labor market at advanced ages due to health issues or who choose not to engage in economic activities for other reasons. Therefore, it is important to acknowledge that the results are restricted to older adults who are in paid labor at age 65 or older at the baseline wave. While the selection was intentional to evaluate the impact of minimum wage

[2]The estimation results presented in this section utilize 20-point episodic memory score identical to the outcome used in Bonsang et al. (2012), with log value of the minimum wage increases. The event study results with a prominent minimum wage increase are provided in appendix Figure A3.1.

policies among older workers, the sample selection prevents us from generalizing the findings to older adults. Second, I use an intent-to-treat approach with an assumption that non-graduate workers are likely to be targeted by the minimum wage policy. There might be a non-negligible share of older workers without college degrees earning significantly higher than the minimum wage. To address issues of including groups that are not relevant to minimum wage policy, I provide additional analysis where hourly wages are used to assign the intervention and the control group and the results are consistent with the main findings. Third, the sample size is small thus making it difficult to consider further analysis by race and ethnicity, which is important due to the potentially different job characteristics of older workers. While the HRS provides a variety of questionnaires that allow us to explore health outcomes and potential pathways of older adults, the findings might overly represent the health implications of mainly white older workers. While previous research does not detect heterogeneity in minimum wage impact on suicides between white non-Hispanics and the other groups (Dow et al. 2020), Averett et al. (2018) study focuses specifically on the minimum wage health impacts in a sample of Hispanic women. More investigation is needed to understand the potential heterogeneous health effects by race and ethnicity.

This chapter contributes to the literature on minimum wage and health by focusing on older workers near and beyond the normative retirement age — a sizable and growing population in the labor market that has not yet been studied. This chapter demonstrates that the minimum wage increases have a negative impact on the health of older workers, noticeably those without college degrees, while not affecting the cognitive function. The negative effects on self-reported health might be associated with the increased frequency of alcohol consumption among non-college-educated older workers.

The findings of this chapter may offer evidence of how the effects of "deaths of despair" (Case and Deaton 2020, 2022) persist into advanced age. Workers without college degrees who struggle to secure good jobs and supportive communities may experience a reduced sense of belonging and purpose. Despite income gains from policy changes, this could lead to increased reliance on drugs or alcohol for self-soothing. While minimum wage policies aim to increase the well-being of workers at the low-wage distribution, these findings raise questions about the effectiveness of past policies in improving the well-being of older workers and warn about the unintended health consequences for older workers without college degrees.

Chapter 4

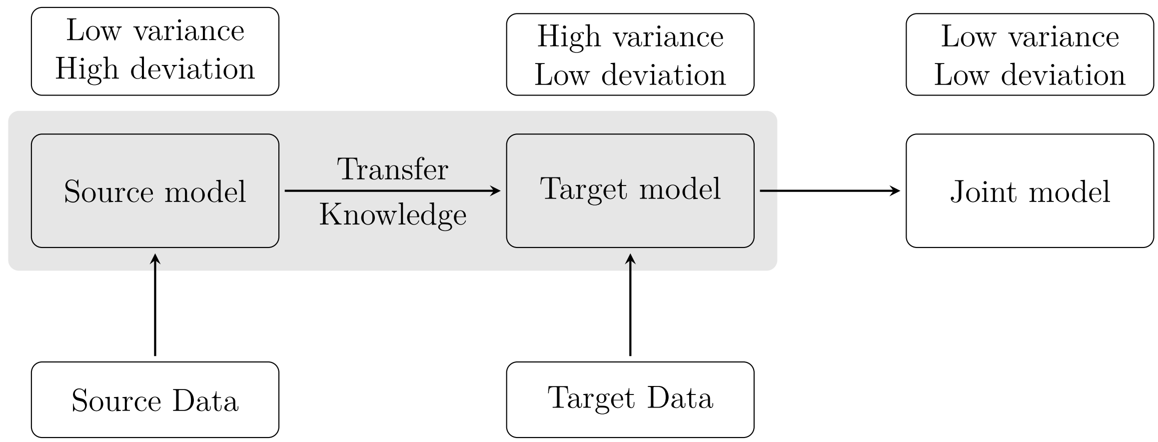
Improving the estimation of dementia in racially and ethnically diverse groups

4.1 Introduction

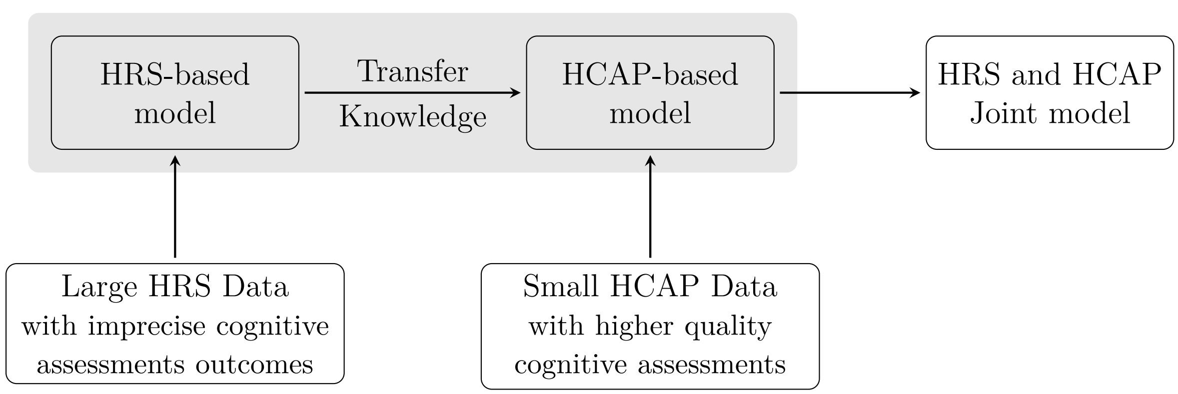
Dementia affected 57 million people worldwide in 2019 (Nichols et al. 2022b), with and estimated prevalence of 10% among United States residents individuals aged 65+ years. Dementia inequalities are well documented: African Americans face the highest risk of dementia compared to other racial and ethnic groups (Mayeda et al. 2016) and are nearly twice as likely to have dementia than non-Hispanic White individuals in the United States (Manly et al. 2022). Non-White individuals are routinely underrepresented in dementia research studies, however. Large community-based surveys are valuable resources for studying dementia risk factors due to their comprehensive data on demographics, socioeconomic factors, and health. Such surveys typically collect brief cognitive assessments that can be used to estimate dementia status. However, accurately estimating dementia status for non-Hispanic Black and Hispanic adults using the brief cognitive assessments is challenging due to the small share of data collected from these groups (Gianattasio et al. 2019). Improvement of estimation algorithm accuracy for underrepresented racial and ethnic groups is crucial for the advancement of epidemiological modeling and research on dementia, and for understanding potential racial disparities in dementia risk and outcomes.

Recent efforts have been made to address this challenge by developing algorithms that are sensitive to racial and ethnic information using a subset of population-representative data that received a clinical assessment of dementia (Gianattasio et al. 2020; Hudomiet et al. 2022). A study incorporated race and ethnicity information and its interactions with some of the predictors to estimate the status of dementia and set different cutoff values for classification to achieve similar model performance across racial and ethnic groups (Gianattasio et al. 2020). Another study estimated the status of dementia using a longitudinal, latent-variable model of unobserved cognitive ability and observed predictors such as age, race and ethnicity, and education (Hudomiet et al. 2022). These studies offer valuable insight into building dementia estimation models when there is only a single dataset for model construction. However, when additional data containing higher-quality, detailed cognitive assessments is available, the accuracy of the dementia-status model can be further improved by combining knowledge coming from models trained on the new data with those trained on the old data instead of solely using either the old or the new data.

In this chapter, the objective is to improve the estimation of dementia status for racially and ethnically diverse groups using a transfer learning method with brief cognitive assessments, applicable to large survey data. Transfer learning is a method that leverages large data from a source population with imprecisely measured



(a) Conceptual Framework of Transfer Learning Method



(b) Application of Transfer Learning Method in Study Context

Figure 4.1: **Illustration of Transfer Learning: (a) Conceptual framework and (b) Study-Specific Application** Figure (a) illustrates the conceptual framework, whereas Figure (b) demonstrates the application of the transfer learning method within the context of this chapter . *Abbreviation.* HCAP, Harmonized Cognitive Assessment Protocol; HRS, Health and Retirement Study.

outcomes to improve estimations for a target population with higher quality outcome assessments (see Figure 4.1a). The target estimator, i.e., the algorithm trained on the target dataset, contains high variance due to the small sample size, whereas the source estimator, although more deviated, has low variance. Therefore, jointly using the source and the target data helps solve the deviation-variance tradeoff, resulting in improved estimation (Pan and Yang 2010; Bastani 2021). Transfer learning improves the estimation accuracy when there are predictor differences between the target and source data, particularly when these differences have *sparse structure* (Bastani 2021). This means that comparing the coefficients of the predictors from the two models, only a small subset of predictors differs between the two datasets. Intuitively speaking, when there are few differences between the source and target predictors, LASSO regression focuses only on the important differences, resulting in a reduction in the estimation error.

The idea of transfer learning is closely related to the concepts of transportability and generalizability in epidemiological risk estimation modeling but focuses specifically on improving the measurement of the outcome (Vergouwe et al. 2010; Steingrimsson et al. 2022). For example, small hospitals rely on risk scores that are based on large hospitals' patients. In this case, the target outcome of interest is the small-hospital patients' risk score, and the source outcome is the one based on large-hospital patient cohorts. However, there may be systematic differences in the predictor-outcome associations between source and target data. Although certain predictors might be highly predictive in large-hospital patients, they might be less predictive in small-hospital patients due to differences in physician prescribing patterns or encoding of the medical record, even when there is no true difference in patient characteristics. The transfer learning method first learns the predictor-outcome associations from the large hospital data. Subsequently, to address potential deviation between the estimator built from the large hospital data and that from the small hospital data, the method employs so-called regularization techniques by introducing a penalty term, effectively selecting predictors, and thereby preventing overfitting while minimizing error (for definition see Friedman et al. 2001; Leist et al. 2022). In this study, these techniques are used to effectively capture and minimize the deviation between the source and target estimators while obtaining the minimum error of the final estimator. As a result, the final estimator shows reduced deviation compared to one built from large hospital data and decreased variance compared to the one built from small hospital data. A study found that the highest medical risk performance was achieved by jointly using small and large hospital data rather than using them separately (Bastani 2021).

In this study, I use a large community-based survey as our *source data*, which provides estimated probabilities of dementia using previously introduced algorithms. The source data contains outcomes that are imprecise estimations of dementia status, but data large sample. Our *target data* is a recently collected subsample with detailed cognitive assessments and dementia classifications, but small sample size. While I might readily construct dementia status estimation models using this new sample, the ongoing challenge is to develop a robust model specifically for Black and Latino participants, who comprise less than 30% of an already small-sized dataset. Thus, transporting knowledge of predictor-outcome associations from the large source data, might improve the quality of the outcome classifications in the target data despite potential differences between the samples (see Figure 4.1b).

Transfer learning has been used in clinical decision models to mitigate disparities in model performance for small subgroups (Gao and Cui 2020). Ultimately, I demonstrate the improvement of dementia status estimation model performance by addressing the deviation-variance tradeoff through the joint usage of source and target data.

4.2 Data: Health and Retirement Study and Harmonized Cognitive Assessment Protocol

The Health and Retirement Study (HRS) is a population-based longitudinal study that tracks economic status, family composition, physical health, and cognitive function (randomly assigned either in person or by telephone) of individuals aged 50 years or older living in the United States. The study began in 1992 and has since collected data on more than 43,000 individuals (Sonnega et al. 2014).

The Harmonized Cognitive Assessment Protocol (HCAP) was fielded as a cost-effective method to measure the cognitive function of individuals aged 65 years or older with the aim of facilitating international harmonization (Langa et al. 2020). The HRS-HCAP sample (henceforth HCAP) was a randomly selected subset of the 2016 HRS respondents stratified by household composition. With an eligible sample size of 4,425 and a response rate of 80%, the final sample consisted of 3,496 individuals; respondents were demographically similar to non-residents (Langa et al. 2020).

The HCAP sample received an in-depth cognitive function assessment through 1 hour of computer-assisted personal interview that included five cognitive domains: memory, executive functioning, language, visuospatial, and orientation. Individuals were assigned to one of three categories: normal cognition, cognitive impairment, or dementia. The HCAP dementia diagnosis allows the expected scores for cognitive performance on the battery to vary by age, sex, education, race, and ethnicity using a robust normative sample. Therefore, it can classify dementia cases more effectively, potentially identifying cases that might have been overlooked if the participants were to be compared to distant demographic groups in terms of the characteristics (Manly et al. 2022).

I utilized the 2016 HRS interview data for the joint analysis of HRS and HCAP data, including scores of cognitive changes between 2016 and 2014, thus largely following a cross-sectional design. Throughout this paper, I used the term predictor to signify covariates to estimate and classify prevalent dementia status.

Participants

Several criteria were applied to the HRS and HCAP data to obtain the final analytical sample (Figure 4.2). Individuals under 70 years of age were excluded from the model development as most of the previously developed dementia classification algorithms included only people ages 70 and older (Hurd et al. 2013; Gianattasio et al. 2020). I trained the model on data of participants aged 70 and older in line with earlier studies (N = 880, 25%). Subsequently, those without race and ethnicity information or who identified themselves as other than non-Hispanic White, non-Hispanic Black or Hispanic were excluded (N = 59, 2%). Individuals without estimated dementia probabilities due to missingness in the cognitive elements were excluded (N = 169, 7%). I provide the summary statistics in appendix Table 4.2 for this criterion. Participants with missing cognitive items were on average older, more likely to be female, and having a higher degree of functional limitations. The final analytical sample with cognitive status included 2,388 participants, of which 1,835 identified as non-Hispanic White, 343 as non-Hispanic Black, and 210 as Hispanic individuals, selected from HCAP.

Similarly, for the source sample (HRS), individuals under 70 years of age were excluded (N = 2637, 26%), as well as those without race and ethnicity information or those who identified themselves as other than non-Hispanic White, non-Hispanic Black, or Hispanic (N = 170, 2%). Participants whose estimated dementia probabilities were unknown due to missing data in the cognitive items were excluded (N = 557, 8%, see appendix Table 4.3). The final analytical source sample with cognitive status included 6,630 HRS participants, of whom 5,078 were identified as non-Hispanic White, 955 as non-Hispanic Black, and 597 as Hispanic individuals.

In cases where individuals were unable to respond directly, due to cognitive impairments or other limitations, either a family member, caregiver, or friends, was designated to respond on behalf of the individual. The proxy respondent answered questionnaires based on behavioral symptoms to assess cognitive function. Among the final sample of the HCAP data, 6% (N = 150) had proxy respondents, and for the HRS data, 8% (N = 505) of the final sample comprised proxy respondents.

Existing dementia status estimation algorithms

Several dementia status estimation algorithms embedded in HRS were previously developed based on data from the Aging, Demographics, and Memory Study (ADAMS). ADAMS was a substudy of the HRS that included detailed in-person clinical cognitive assessments of 856 participants aged 70 years or older. ADAMS was conducted from 2001 to 2008 and established dementia status for each participant (Langa et al. 2005). Algorithms trained on the ADAMS data aimed to estimate the clinical diagnosis of dementia based on a set of predictors available in the main HRS questionnaire, including demographics, a brief cognitive function assessment, activities of daily living, and instrumental activities of daily living.

For proxy respondents, to accommodate the distinct predictor set required, various approaches were used, including the missing indicator method, interaction terms with proxy status, or separate models for proxy respondents. Predictors specifically for the proxy respondents included the 16-item Informant Questionnaire on Cognitive Decline

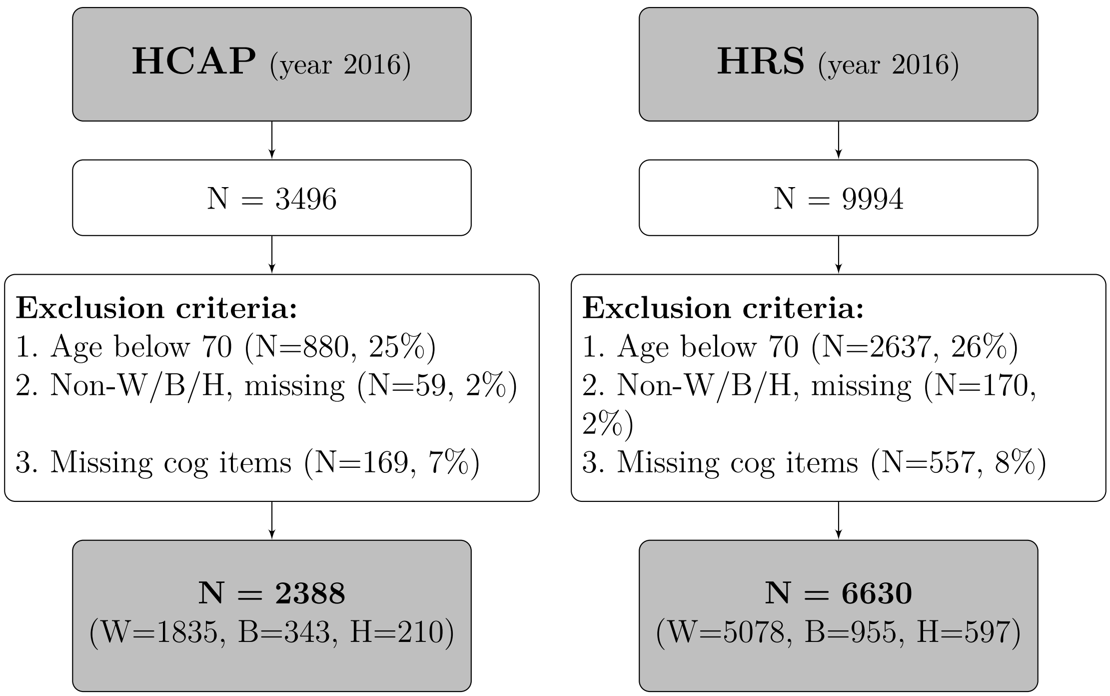


Figure 4.2: **Flowchart of HRS and HCAP samples** This flowchart summarizes how I arrive at our final sample size. We require the criterion 1 to 3 to conform to the existing dementia status estimation algorithms. *Abbreviation*. B, non-Hispanic Black; H, Hispanic; HCAP, Harmonized Cognitive Assessment Protocol; HRS, Health and Retirement Study; Missing cog items, missing in cognitive items; W, non-Hispanic White.

in the Elderly (Jorm IQCODE), a five-scale proxy-rated memory assessment, and a summary score of Jorm symptoms of cognitive impairment (Jorm and Jacomb 1989; Jorm 1994; Gianattasio et al. 2019).

For our transfer learning analysis, I used four published estimated dementia probabilities accessible on the HRS website `https://hrs.isr.umich.edu/data-products/cognition-data`. The four dementia probabilities were obtained through algorithms including the Expert model, a logistic model that uses predictors selected by experts and their interactions; the Lasso model, a model that uses numerous predictors and interacts them with race and ethnicity; the Hurd model, a probit model that uses predictors including demographic and cognitive items and the changes in cognitive items (Hurd et al. 2013; Gianattasio et al. 2020); and the Latent model, based on a latent-variable model of cognitive function using demographics and cognitive items (Hudomiet et al. 2022). Similar to the dementia diagnosis in HCAP, the HRS dementia ascertainment algorithms were designed to estimate and classify prevalent dementia status.

Predictors used in the transfer learning model

I adopted the predictors used in the original Hurd model (Hurd et al. 2013). These predictors included age (categorized in 5-year intervals), education, sex/gender, and cognitive function items, which I provided in detail in appendix A. The model also included assessments of limitations in activities of daily living (ADLs), instrumental activities of daily living (IADLs), and changes in cognitive item scores during the past two waves. For the education predictor, instead of using three categories proposed by the Hurd model, I expanded it to five groups: below 6 years of education, 6 to 8 years, 9 to 11 years, 12 years, and above 12 years of education.

For participants who provided answers through proxy respondents, predictors for measuring cognitive functioning were replaced with IQCODE (see appendix A for further information) and its changes during the past two waves. Additionally, the self-response status from the previous survey wave was included. For self-respondents in previous years, cognitive scores from the prior wave were included.

All other listed predictors, except changes in IQCODE and cognitive items from previous wave, had less than 5% of missingness; I utilized the R package *missForest* (Stekhoven and Bühlmann 2011) to handle any missing values through random forest imputation. Imputations were performed separately based on the response status by self-report or proxy.

4.3 Penalized regression and Transfer Learning

Statistical analysis

I employed a transfer learning based on the works of Bastani Bastani (2021) and Tian and Feng (2022b). Throughout this paper, I refer to the HRS with algorithmic dementia probability using the Hurd model as the *source data* and the HCAP with in-depth cognitive status classification as the *target data*.

If the target and source outcomes are not relevant, then transferring knowledge from the source data might be harmful, which is called *negative transfer* (Torrey and Shavlik 2010). Therefore, it is necessary to test the relevance between the target and source data to avoid negative transfer. I established the validity of the transferability of the source data through an algorithm with the software package *glmtrans* provided by Tian and Feng (2022a), which allowed us to distinguish if the source data was informative for transfer learning.

The transfer learning method consists of two main steps: gaining knowledge and correcting the deviation. I provide the graphical abstract of the method in the Figure 4.1. The code for this paper is available on the Digital repository: `https://github.com/TL-dementia/Code`.

Step 1: Gaining knowledge from the source data

Risk score algorithms have typically used single datasets to make estimations. Instead of obtaining predictor-outcome associations solely from individual datasets, transfer learning involves the joint use of both source and target data. The first step of the analysis is a standard lasso regression (Tibshirani 1996) to obtain knowledge from the source data, as seen in the following.

$$\hat{\beta}_{source}(\lambda) = \arg\min_{\beta}\left\{\frac{1}{n_{source}}\sum_{i=1}^{n_{source}} \ell\left(\beta;\quad \mathbf{X}^{(i)}, Y_{source}^{(i)}\right) + \lambda\|\beta\|_1\right\} \tag{5}$$

Here, Y_{source} is the algorithmic dementia probability, $\mathbf{X}$ is the matrices of the predictor set, and n_{source} is the number of samples in the source data. I dichotomized Y_{source} with an arbitrary threshold value, 0.5, to estimate with a logistic lasso regression. Experimenting with different thresholds, including 0.25 and 0.75, showed that the performance results were similar to those with a threshold of 0.5, across race and ethnic groups. The term $\lambda\|\beta\|_1$ represents the regularization to prevent overfitting, where λ controls the strength of the penalty and was chosen to minimize 10 K-fold cross-validation error, and $\|\beta\|_1$ is the magnitude of the coefficient vector. The result, denoted as $\hat{\beta}_{source}$, is the transferred knowledge, which is the set of coefficients that best fit the lasso regression model in HRS. The function $\ell\left(\beta;\quad \mathbf{X}^{(i)}, Y_{source}^{(i)}\right)$ is the standard loss function for a logistic regression for a single sample represented by

$(\mathbf{X}^{(i)}, Y^{(i)}_{source})$. It is obtained through the negative log-likelihood function as follows;

$$\ell\ (\beta;\ \ \mathbf{X}^{(i)}, Y^{(i)}_{source}) = -\left[Y^{(i)}_{source}\log\left(\frac{1}{1+e^{-\mathbf{X}^{(i)\top}\beta}}\right) + (1-Y^{(i)}_{source})\log\left(\frac{e^{-\mathbf{X}^{(i)\top}\beta}}{1+e^{-\mathbf{X}^{(i)\top}\beta}}\right)\right]$$

Step 2: Correcting the deviation in the target data

In this second step, the goal is to update the coefficients by minimizing the loss function on the target data. For this reason, our model requires some overlap in the collection of the predictor set because the purpose of using transfer learning is to fine-tune the parameters learned from the source data with the target data. I incorporated regularization term that penalizes the difference between the coefficients of the target and the source data. The objective function is as follows:

$$\hat{\beta}_{TL}(\lambda) = \arg\min_{\beta}\left\{\frac{1}{n_{target}}\sum_{i=1}^{n_{target}}\ell\ (\beta;\ \ \mathbf{X}^{(i)}, Y^{(i)}_{target}) + \lambda\|\beta - \hat{\beta}_{source}\|_1\right\} \tag{6}$$

Here, Y_{target} is the detailed cognitive assessment, $\mathbf{X}$ is the matrices of the predictor set, and n_{target} is the number of samples in the target data. $\hat{\beta}_{source}$ is the coefficient vector from the source data. $\ell\ (\beta;\ \ \mathbf{X}^{(i)}, Y^{(i)}_{target})$ is the standard loss function for logistic regression, which remains the same as used in Equation 5, but now applied to the target data. The term $\lambda\|\beta - \hat{\beta}_{source}\|_1$ represents the regularization, where λ controls the strength of the penalty and was chosen to minimize 10 K-fold cross-validation error. $\beta - \hat{\beta}_{source}$ is the difference between the coefficient for the predictor in the source and target data (Bastani 2021). Therefore, when λ is close to 1, it sets the coefficients closer to 0 if the deviations between target and source β are small. This regularization allows us to select only predictors with larger deviations between the target and the source predictor coefficients. Our final estimate is $\hat{\beta}_{TL}$, which is the coefficient vector adjusted to reduce the difference between the target and source data. I guide the readers interested in the proof and more detailed information on this method to the following study (Bastani 2021; Tian and Feng 2022b).

Validation and assessment of model performance

Subsequently, I used internal validation with bootstrapping to evaluate the performance of the model. In a simulation study, researchers demonstrated that when the sample size is small, internal validation with bootstrapping is preferred to external validation by keeping the sample complete while correcting for optimism with resampling methods (Steyerberg and Harrell 2016). Thus, I built a training set by random sampling with replacement from the target data, while the original target data served as a test set. I repeated the entire procedure from the variable selection to model estimation 1,000 times and provided an asymptotic standard deviation.

Performances were evaluated by the following metrics (Steyerberg et al. 2010; Leist et al. 2022) ; *overall performance* according to the Brier score (Rufibach 2010), *discriminative ability* by area under the receiver operator characteristic curves (AUC) (Janssens and Martens 2020), and area under the precision-recall curve (AUPRC) (Davis and Goadrich 2006), and *goodness-of-fit* by calibration slope and intercept (Collins et al. 2015; Van Calster et al. 2019; Stevens and Poppe 2020). These measures are briefly summarized in Table 4.1 and we explained in detail in the appendix B.

Although overall performance is the summary score, research has suggested that discriminative ability and calibration should be reported in the prediction model as one is not sufficient to represent the different aspects of the model performance (Steyerberg et al. 2010).

The method described above was implemented using an open-source statistical software package *glmtrans* (Tian and Feng 2022a) in R version 4.3.0 (R Foundation for Statistical Computing, Vienna, Austria), and Stata version 17.0 (StataCorp LLC, College Station, TX) was used for data preparation.

Table 4.1: Description of the performance measures.

Category	Measure	Description
(1)	Brier	Mean squared error between predictions and actual outcome
(2)	Intercept	Intercept of the predicted probabilities on observed outcome
	Slope	Slope of the predicted probabilities on observed outcome
(3)	AUC	Aggregated area of a curve between sensitivity and specificity
	AUPRC	Aggregated area of a curve between precision and recall

(1): Overall performance, (2): Calibration, (3) Discriminative ability. *Abbreviation.* AUC, Area under the receiver operator characteristic curves; AUPRC, Area under the precision-recall curve.

Table 4.2: Distributions of the characteristics of the analytical sample of HCAP 2016, stratified by dementia status, racial and ethnic identity, and self/proxy response status

	Dementia status							
	No Dementia				**Dementia**			
Proxy status	Self-respondents			Proxy respondents	Self-respondents			Proxy respondents
race and ethnicity	**White**	**Black**	**Hispanic**	**Any race**	**White**	**Black**	**Hispanic**	**Any race**
	N = 1578	N = 292	N = 172	N = 53	N = 155	N = 23	N = 18	N = 97
	Mean (SD) or %				Mean (SD) or %			
Age, years								
70-74	40%	43%	46%	36%	11%	18%	8.9%	8.7%
75-79	27%	28%	30%	17%	22%	25%	33%	16%
80-84	18%	19%	11%	13%	26%	18%	34%	20%
85-89	8.9%	7.4%	8%	14%	24%	8.6%	24%	21%
>89	6.3%	3.8%	4.7%	21%	17%	30%	0%	34%
Female, sex	54%	67%	67%	37%	57%	71%	74%	65%
Schooling, years								
<6	0.2%	2.4%	19%	4.7%	1.3%	7%	2.8%	11%
6-8	3.2%	7.8%	24%	18%	3.7%	17%	37%	19%
9-11	9.0%	20%	17%	12%	11%	6.9%	25%	6.4%
12	36%	32%	21%	18%	26%	33%	6.2%	35%

>12	34%	37%	19%	40%	32%	51%	29%	28%
Cognitive assessment								
Date orientation	3.72 (0.57)	3.70 (0.57)	3.50 (0.86)		2.82 (1.26)	2.21 (1.37)	2.21 (1.49)	
Immediate recall	5.23 (1.58)	4.58 (1.62)	4.35 (1.91)		3.37 (1.56)	2.66 (1.66)	2.67 (1.66)	
Delayed recall	4.26 (1.87)	3.50 (1.85)	3.43 (2.04)		1.93 (1.76)	1.11 (1.31)	2.00 (1.85)	
Serial 7	3.84 (1.45)	2.40 (1.81)	2.66 (1.92)		2.34 (1.81)	1.54 (1.98)	1.08 (1.14)	
Backward count	95%	86%	86%		83%	73%	76%	
Name (scissors)	99%	98%	97%		95%	96%	98%	
Name (cactus)	98%	82%	91%		80%	42%	77%	
Name (president)	98%	98%	93%		84%	76%	78%	
IQCODE				3.24 (0.39)				4.20 (0.73)
Difficulties in ADL	0.29 (0.80)	0.42 (0.96)	0.59 (1.19)	0.85 (1.57)	0.93 (1.49)	1.57 (1.70)	0.65 (1.52)	3.48 (1.71)
Difficulties in IADL	0.22 (0.64)	0.28 (0.67)	0.60 (1.19)	0.96 (1.49)	1.25 (1.54)	1.71 (1.67)	1.24 (1.71)	4.25 (1.22)

Abbreviation. ADL, Activities of Daily Living; HCAP, Harmonized Cognitive Assessment Protocol; IADL, Instrumental Activities of Daily Living; IQCODE, Informant Questionnaire on Cognitive Decline in the Elderly; SD, Standard Deviation. *Note.* The percentages show the shares of the full sample or the completion rates of the cognitive tests, respectively. Survey weight is applied. Date recall (0-4), immediate recall (0-10), delayed recall (0-10), serial 7 subtraction (0-5), difficulties in ADL/IADL (0-5, higher number worse condition), and IQCODE (0-5, higher number worse condition). The cognitive assessment for proxy respondents was conducted using the IQCODE.

4.4 Results

Sample characteristics

I compared the characteristics of HCAP participants by dementia status and self-response status in Table 4.2. HCAP and HRS data have an almost identical distribution of the survey items (appendix Table 4.1).

Model development

For self-respondents, analyses were stratified by race and ethnicity in the source and target data. For proxy respondents, I created a separate model and used the race and ethnicity combined sample with 505 participants from the source data and 150 participants from the target data. The source data was utilized in the transfer learning step to train the model. The model was then debiased using bootstrapped target data, and its performance was assessed using the original target data.

Model performance

Table 4.3 compares the performance of the four existing models, the re-estimated the Hurd model with the original predictor set using HCAP data (Hurd-HCAP model) and the transfer learning model. For the non-Hispanic Black sample, the Brier score, which measures the overall accuracy, was the best with the transfer learning model compared to the previous four models and the Hurd-HCAP model. Additionally, the transfer learning obtained the calibration intercept closest to zero, meaning that this model contains the least systematic deviation compared to the target estimator (Steyerberg and Vergouwe 2014). Discriminative ability was also the highest in the transfer learning model. It is important to note that the performance was evaluated to estimate prevalent dementia, which differs from detecting incident dementia (Nichols et al. 2022a).

For Hispanic participants, the calibration intercept and slope largely improved despite large standard deviations using the transfer learning model. Overall, I observed that the accuracy and discriminative ability were moderately better than the existing models.

For the non-Hispanic White sample, the overall accuracy of the transfer learning model was similar to that of the other best-performing existing models. The Hurd-HCAP model outperformed the transfer learning model in terms of calibration, whereas the transfer learning model showed a marginal improvement in discriminative ability.

For proxy respondents, the overall accuracy and the calibration of the transfer learning model were better than the existing models, while the discriminative ability remained almost unchanged. The low-performance gain with non-Hispanic White sample and proxy respondents reflects the small systematic deviation of the existing algorithms in these groups compared to the target estimator.

Table 4.3: Performance comparisons of various models with HCAP data, using internal validation with bootstrap

Model	**Overall accuracy**	**Calibration**		**Discriminative ability**	
	Brier score	Intercept	Slope	AUC	AUPRC
	(Numbers in the subscript are the standard deviations.)				
Self-respondents					
Black, non-Hispanic					
Hurd	0.064	−1.23	0.65	0.81	0.46
Expert	0.102	−1.79	0.48	0.80	0.33
Lasso	0.066	−1.22	**0.77**	0.82	0.43
Latent	0.070	−1.58	0.13	0.81	0.37
Hurd-HCAP	$0.061_{0.009}$	$-1.31_{0.37}$	$0.29_{0.19}$	$0.81_{0.05}$	$0.39_{0.08}$
TL	$\mathbf{0.049}_{0.003}$	$\mathbf{-0.39}_{0.29}$	$0.70_{0.11}$	$\mathbf{0.84}_{0.02}$	$\mathbf{0.52}_{0.04}$
Hispanic					
Hurd	0.075	−1.15	0.62	0.86	0.41
Expert	0.091	−1.27	0.49	0.85	0.35
Lasso	0.088	−1.35	0.66	0.83	0.41
Latent	0.099	−1.21	0.19	0.83	0.38
Hurd-HCAP	$0.056_{0.015}$	$-1.19_{0.34}$	$0.08_{0.01}$	$0.87_{0.05}$	$0.56_{0.10}$
TL	$\mathbf{0.052}_{0.008}$	$\mathbf{-0.07}_{0.60}$	$\mathbf{0.87}_{0.31}$	$\mathbf{0.89}_{0.03}$	$\mathbf{0.61}_{0.08}$
White, non-Hispanic					
Hurd	0.060	**−0.15**	0.76	0.87	0.50
Expert	0.070	−0.76	0.60	0.86	0.45
Lasso	0.062	−0.48	0.81	0.86	0.49
Latent	0.069	−0.61	0.24	0.85	0.44

continued on next page

Table 4.3 – *continued from previous page*

Model	Overall accuracy	Calibration		Discriminative ability	
	Brier score	Intercept	Slope	AUC	AUPRC
Hurd-HCAP	0.057 0.001	−0.21 0.14	**0.87** 0.07	0.87 0.01	0.54 0.01
TL	**0.056** 0.001	−0.20 0.11	0.82 0.04	**0.88** 0.00	**0.56** 0.01
Proxy respondents					
Hurd	0.124	0.15	0.22	0.88	0.91
Expert	0.137	−0.56	**0.67**	0.88	0.92
Lasso	0.132	−0.49	0.66	0.88	0.89
Latent	0.156	−0.21	0.23	0.87	0.92
Hurd-HCAP	0.118 0.015	0.10 0.22	0.41 0.24	**0.90** 0.02	**0.94** 0.02
TL	**0.105** 0.008	**−0.04** 0.22	0.65 0.13	**0.90** 0.01	0.93 0.01

Abbreviation. AUC, area under the receiver operator characteristic curves; AUPRC, Area under the precision-recall curve; HCAP, Harmonized Cognitive Assessment Protocol; Hurd-HCAP, Hurd model developed with HCAP data; TL, transfer learning. *Note.* The best model performances are in bold letters. Brier score: the lower, the better. Calibration intercept: the closer to 0, the better. Calibration slope: the closer to 1, the better. AUC/AUPRC: the higher, the better. By using published dementia probability for Hurd, Expert, Lasso, and Latent models, I do not engage in model development; thus, the standard deviation is not provided.

Predictor deviations

I present the predictor deviations between target and source estimator in Figure 4.3 for the case of self-respondents. Here, the deviation refers to the difference between the coefficient for the predictor in the source data (HRS) to the target data (HCAP). Our analysis focused on significant deviations, determined at the 95% confidence level, and was detected more than 500 times out of 1,000 runs. The list of deviations provided is somewhat analysis-specific and may exhibit moderate variations due to the inherent randomness associated with the variable selection process of l_1 penalized regression, which I employed for deviation detection. However, our findings indicated a consistent pattern in which the magnitude of each deviation tends to be higher for the non-Hispanic Black sample, followed by the Hispanic sample, when compared to the non-Hispanic White sample. I refrain from further stratification by sex/gender due to the limited sample size.

4.5 Discussion

Although algorithmic dementia status estimations are widely used in research, developing algorithms that are valid and reliable for racial and ethnic groups with small samples in existing surveys remains a challenge. Our work aimed to improve accuracy of group-specific dementia status estimation, with previously reported algorithms as benchmark performance. I employed the transfer learning method, which combines knowledge gained from modeling of large source data with less precise assessment of the outcome and modeling of small target data with more precise assessment of the outcome. An important step in the modeling process is the regularization, which detects and reduces discrepancies (deviations) in estimated coefficients of the two models, similar to the concept of priors or penalties in other

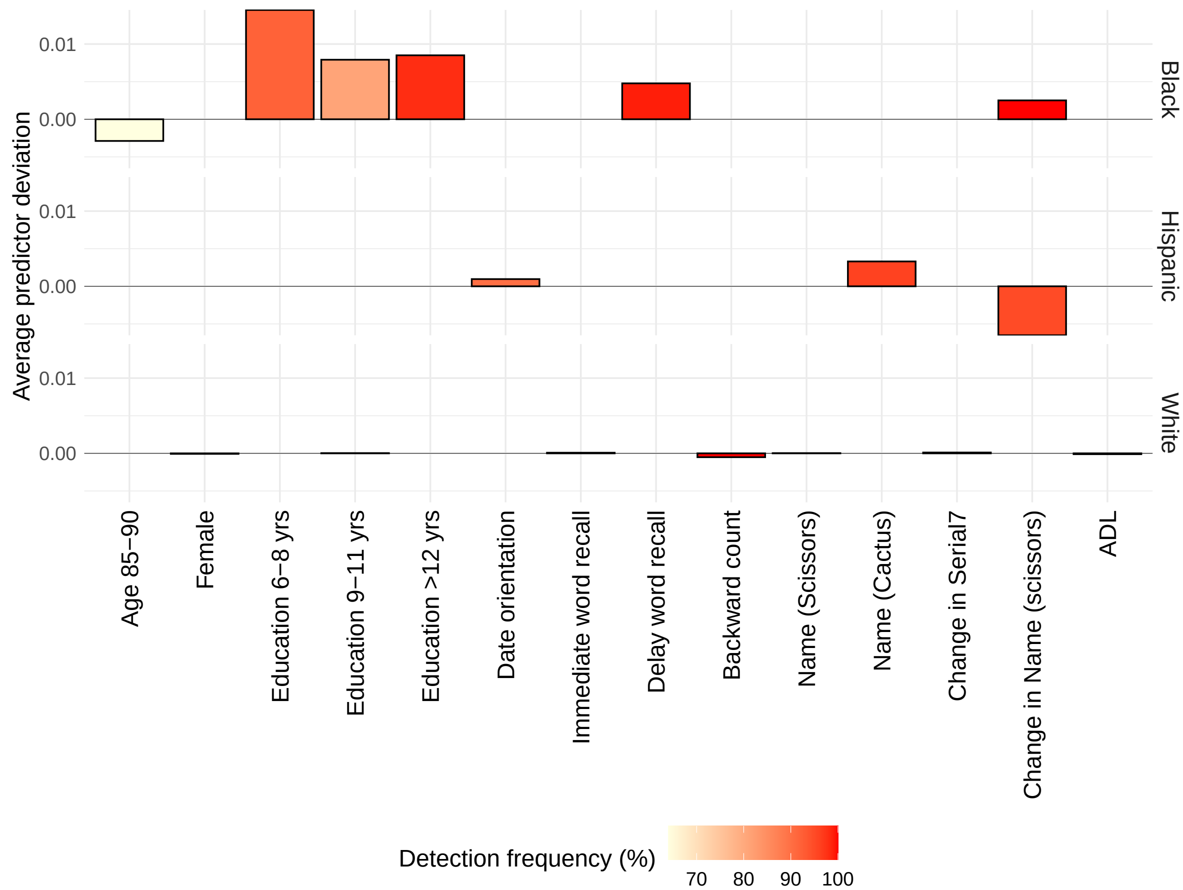


Figure 4.3: **One example of predictor deviation for non-Hispanic Black (panel on top), Hispanic (middle panel) and White (lower panel) participants** This figure illustrates the race and ethnicity-specific deviation between the estimator from HRS (source) data and the estimator from HCAP (target) data. Here, I list the deviations that are significant at the 95% level and detected in at least 50% of 1,000 runs. *Abbreviation.* ADL, activities of daily living; Backward, backward counting; Black, non-Hispanic Black; White, non-Hispanic White; Delay, delay word recall; HCAP, Harmonized Cognitive Assessment Protocol; HRS, Health and Retirement Study; IADL, instrumental activities of daily living; Immediate, immediate word recall; Name(.), name test; Serial7, serial 7 subtraction.

modeling strategies.

Transfer learning led to improved performance of the 'probable dementia' algorithm in the non-Hispanic Black sample, as indicated by an 20% increase in the Brier score, a 4% increase in the AUC, a 33% increase in the AUPRC, and improved calibration of the model compared to the best previously reported. For the Hispanic sample, I observed a 7% increase in the Brier score, a 2% increase in the AUC, a 9% increase in the AUPRC, and improved calibration of the model compared to the best previously reported.

I built upon the works of previous algorithmic dementia status estimations (Hurd et al. 2013; Gianattasio et al. 2020; Hudomiet et al. 2022) and showed further improvement in group-specific performance compared to these models in overall precision, discriminative ability, and calibration. Our adoption of the transfer learning approach aligns with the concepts of transportability and generalizability in epidemiology (Vergouwe et al. 2010; Steingrimsson et al. 2022). The new method overcomes limitations of earlier studies, in which responses to cognitive items were suspected to be differently informative across racial and ethnic groups, by training models on data of different racial and ethnic groups separately.

There are several limitations. First, although I employed the transfer learning method, which effectively used source and target data to mitigate concerns arising from the small sample size, the HCAP data may still be too small to build robust models for each racial and ethnic group. Nonetheless, the HCAP data offers a distinct advantage by being less susceptible to missed or misdiagnosed conditions due to heterogeneous levels of healthcare access, a concern particularly relevant to underrepresented groups.

Second, the model assumed that there were no measurement errors in the diagnosis of HCAP dementia. However, dementia diagnoses in actual clinical settings is based on comprehensive in-person assessments or consensus among multiple experts. In contrast, the HCAP dementia assessment was grounded in a systematic classification that reflects a robust norm sample with similar demographic characteristics. However, an extensive assessment has made misclassification less likely.

Third, this study did not consider the variation within the same racial and ethnic group, which could differ according to factors such as country of birth or skin color, as these aspects are intertwined with experiences of racial discrimination. I also lacked data to develop algorithms for smaller ethnic minority populations, such as Alaskan Native Americans or Asian Americans. While our study was able to establish race-specific estimation, a more comprehensive approach would involve a thorough inclusion of variables that fully capture the racialized experience, as I discuss in appendix C.

Despite these limitations, this chapter demonstrated that transfer learning can detect and address deviations between the source and target estimators in existing dementia status estimation models. Our approach combines the advantages of a larger sample in the source data – reducing variance in model parameters due to small samples – with the advantages of higher quality outcome assessments in the target data – reducing bias in model parameters. Transfer learning improved the estimation performance particularly for non-Hispanic Black and Hispanic participants, with the transfer-learned algorithm performing better than previously reported algorithms.

Transfer learning is widely applicable in epidemiological research. For example, self-reported responses, which are simple to collect, can serve as the source data. The target data could be responses obtained from a subsample of participants that received gold-standard assessments, such as biomarkers from blood or spinal fluid, structural or functional brain measures, or in-depth neuropsychiatric assessment. We can anticipate a more accurate estimation of the disease status by jointly using the target and source data compared to using a single dataset. Still, to create a dementia status estimation model that truly represents the population, we require large, high-quality data sets that capture various demographic characteristics of underrepresented groups.

Chapter 5

Discussion

The objective of this thesis was to understand how labor market experiences in late adulthood impact the health of older adults. Labor market experience combines various aspects, such as income, job characteristics, job-related stress, physical demand, and social interactions, through which the health of older adults can be impacted. I focused on two types of labor market experience: first, entering/exiting the labor market after the retirement age, and second, experiencing minimum wage policies as an older worker.

5.1 Summary of findings and contributions

Chapter 1 asked "How does entering/exiting the labor market after retirement age affect cognitive health?". I compared two countries: South Korea, where there was the highest share of older adults returning to labor after retirement and the US where more and more older adults were participating in labor activities due to the polarizing economy. While there is ongoing population aging and a growing number of older adults in the labor market, how entering or exiting post-retirement age affects health was not studied before. The main challenge lies in disentangling the causal direction as participating or exiting the labor market is non-random. I contribute to the literature of social determinants of health for older adults by answering the post-retirement labor market participation effects on health with the causal lens. Specifically, using the population-representative data from the US and South Korea, I employed the matching technique that were developed to study the impact of transitioning from autocracy to democracy on economic growth (Imai et al. 2023). I created matching sets where the individuals shared a similar trajectory including health, and employment status, so that the transition to entering or exiting the labor market would be almost a random event. With the matching difference-in-difference method, I found that entering the labor market at an age past the normative retirement ages in South Korea was beneficial for the cognitive health while it was insignificant for older adults in US. Exiting the labor market at age 65+ was negative on cognitive health for both US and South Korea. The findings from Chapter 1 partially confirm the 'use it or lose it' hypothesis where engaging activities at later ages are beneficial for cognitive health. In the meanwhile, the different findings by the country with heterogeneous labor market conditions and older adults' circumstances including health and financial situations caution against the generalization of the cognitive benefits from working post-retirement ages.

While Chapter 1 examined all older workers across different levels of socioeconomic conditions, Chapters 2 and 3 narrowed the focus to the older workers with less education or lower income, who are more likely to be susceptible to the health impacts from the labor market experiences. The main questions was "How does minimum wage policies impact the health of older workers". I exploited the quasi-randomness of the minimum wage policy that occurs independently of older adults' health. While minimum wage and health is a widely investigated topic, the studies have limited the sample to working age population. However, older workers are one of the largest growing demographic groups in the labor market in aging economy. Moreover, the health impacts are likely to be more salient as their health risks are higher than younger workers. I contribute to the literature of minimum wage health by focusing on the impacts on older adults, which has not been investigated despite its importance.

Chapter 2 examined the 2018 Korean large minimum wage increase which marked as the largest during the last two decades within the country, with a 16% of increase with the newly launched government. Drawing upon the 2016 to 2018 year of the large population-representative data, KLoSA, I created the exposed and the control group by the hourly wage older adults received prior to the large increase of the minimum wage, so that both exposed and control groups shared similar characteristics despite slightly different hourly wages which distinguished their exposure to the minimum wage policy. Using the large minimum wage increase as a quasi-random experiment, I calculated the difference in differences between exposed and control groups before and after the large minimum wage increase. Difference-in-differences method with two periods and two groups is equivalent to the canonical two-way fixed effects estimator where the individual and time-specific components are captured. Using an additional prior wave from 2014, I showed that the parallel trends assumption is likely to hold that the difference in health outcomes post-intervention was solely attributable to the policy intervention. I found that the older workers within the exposure group experienced a cognitive decline compared to the control group who were similar otherwise but received slightly higher hourly wages. A reduction in working hours experienced by the exposure group might explain the negative health findings. While unintended, the large minimum wage policy could trigger the employer to actively compensate for their loss. The findings from the large South Korean minimum wage increase present evidence to be cautious about the level of minimum wage increase as there might be a reaction from the cost side as the amount might be unexpectedly large to prepare for the loss of profits.

Chapter 3 investigated the health impacts of state-level minimum wage increases experienced by older adults in the US. While previous studies provided evidence on the minimum wage impacts specific to certain demographics including parents with young children and Hispanic women (Godøy et al. 2021; Averett et al. 2018), the health implications focusing older workers have not been studied. The expected heterogeneous effects are due to the different labor market conditions, bargaining powers, and other obligations such as the care-taking roles of the employees pertinent to the demographic groups. I contribute to the literature on minimum wage and health by adding evidence with older adults in the US.

Using the Health and Retirement Study from 1996 to 2016, I leveraged the state-level variations of the minimum wage increases. The treatment group was assigned to the individuals who resided in the states with the increases in the minimum wages and the control group comprised of individuals residing in the states where the minimum wages did not increase during the same periods. I first employed the traditional difference-in-differences with the continuous value of minimum wage increase. I then showed the event study results of a minimum wage increase of at least a dollar using the modern difference-in-differences estimator that is robust to the staggered treatment timings and the heterogeneous treatment effects. As the state-level minimum wage policies are associated with other concurrent state-level policies and the demographic and economic circumstances, I controlled for time-varying state-level variables that might be associated with minimum wage policy. The analytical sample comprised older workers defined by those who were in the labor market at the baseline wave of the survey regardless of their subsequent employment status. The findings suggest that the minimum wage increases had negative impacts on the self-reported health of the older workers without college degrees while the college degree holders did not experience such effects. I did not find any impact on the cognitive functioning of the older workers. I explained the findings with the increased frequency of drinking among the less educated older workers residing in the states with minimum wage increases. Although the HRS did not contain fine-grained data on the job characteristics and workload of the employees, further studies are warranted to investigate whether a more taxing workload might have led to increased alcohol consumption despite the income gain.

Chapter 4 presented a parenthesis, an excursus on a new method to improve the available large-scale aging studies to inform and improve future studies on health outcomes for older adults with an equity lens. Due to the focus on cognitive health, the decision was made to improve equitable detection of probable dementia. Chapters 1 to 3 used a large population-representative study to investigate the health impacts of the labor market experiences. While large population-representative data such as Health and Retirement Study serves as an appropriate source to investigate the social determinants of cognitive health or estimate an prevalence of dementia, there remains a challenge with investigating with a population of small sample size. It is difficult to provide a robust estimation with the limited sample of older adults at the lower end of the distribution of socioeconomic status or racially or ethnically diverse groups. Demographics with smaller sample sizes require more careful attention as they face higher risks for health hazards from the less advantageous socioeconomic circumstances. Chapter 4 contributes methodologically by bringing tools from the machine learning literature (Pan and Yang 2010; Bastani 2021; Tian and Feng 2022b) aiming to partially overcome the low sample size issues to more accurately estimate the prevalent dementia case, especially for racially and ethnically diverse populations. I used a transfer learning method that combines the benefits of jointly using large data with less precise outcomes and small data with higher precision in the outcome. Transfer learning first learns the relationship between the predictors and the outcome with large data and then fine-tunes the estimator using the precise outcome with small data. I use HRS and HCAP, each representing large data with less precise outcomes and smaller data with more precise outcomes, separately. I showed that compared to using a single data source to build prevalent dementia algorithms, the accuracy was improved especially for African Americans and Latino older adults using both HRS and HCAP data jointly through the transfer learning method. I showed that the small sample size issues were partially overcome through the implementation of a transfer learning method with improved prevalent dementia classification algorithms. Chapter 4 invites further utilization of transfer learning methods to epidemiological and public health research where the setting of having large survey data but less precise outcome data and smaller but highly precise outcomes (e.g., biomarkers or image data) is common.

5.2 Implication for policy

The empirical findings in this thesis have policy implications based on the evidence regarding the labor market experiences and health of older adults. I suggest two main policy implications outlined below.

Job opportunities and work environment

Findings from Chapter 1 suggest that creating more job opportunities for older adults post-normative retirement ages in South Korea has potential health benefits. Socializing and becoming involved in society again through labor market participation after the retirement age might help older adults delay their cognitive declines.

However, the health benefits observed in South Korea may be a specific case, as job conditions and workers' characteristics vary significantly across countries. The less favorable socioeconomic circumstances of older South Korean workers, compared to those in the US, may reflect that participation in the labor force is their only viable option for social engagement as opposed to leisure or voluntary activities

For the US labor market, special considerations are needed to design the job opportunities and work environment that could lead to health benefits of older adults. Schedule flexibility and autonomy at workplace (Maestas et al. 2023) are found to be important components to consider in creating job opportunities that might bring health benefits for older adults while providing them the stage to be actively involved in society with financial rewards.

Toward optimal policy intervention

Chapters 2 and 3 provide evidence that careful calculation and consideration are essential in designing optimal minimum wage policy, especially for the older workers. It is important to understand the hiring side of the minimum wage policy, e.g., how the employer would react to the minimum wage increases, as they are relevant to the potential changes in employment, working hours, job characteristics, working load, job flexibility, and other job amenities. Chapter 2 calls for an optimal design of the minimum wage increase level. While a large minimum wage increase might have unintended effects on the health of workers, a modest but gradual increase that reflects current economic circumstances may achieve the objective of enhancing employee well-being without forcing employers to make drastic cost cuts.

The state-level minimum wage policy serves as a tool to bring justice to the wage system. Nevertheless, it might not be sufficient to compensate for the unfavorable work conditions faced by older workers with less education. Even with the appropriate levels of minimum wage increases, the income gain from the policy change might not lead to health-promoting consumption due to potential job insecurities or despair of the prospects with increasing economic uncertainties and inaccessible health care. The minimum wage policy touches upon the surface of the disparity in the wage while not being able to tackle the systemic barriers to healthcare access. Combining changes in government-provided or employer-based health insurance—such as a commitment to provide accessible and effective treatments for the leading causes of death—could be promising for achieving health equity among older workers in the US, as it addresses the core of systemic health inequalities by lowering obstacles to healthcare access.

5.3 Limitations

The first limitation relates to the different measurements of the same health outcome. In Chapter 1, I compared the impact of entering or exiting the labor market post-normative retirement ages between US and South Korea. Cognitive function was measured using different sets of questions in the HRS and KLoSA data, making the results not entirely comparable. While KLoSA data uses the K-MMSE to measure cognitive function, the HRS uses TICS questionnaires. Although there are overlapping components, ideal comparisons can only be made using the exact same questionnaires.

The second limitation involves the time intervals between data collection. In Chapter 2, I investigated the large impact of minimum wage increases on the health of older adults. KLoSA data is collected biennially, meaning the year 2017, which immediately preceded the significant minimum wage increase, was not observed. I built exposed and control assignments using data from 2016, the most recent wave prior to 2018, but the ideal case would be to use the data from the 2017 so that any changes between 2016 and 2017 would not affect the treatment designs. The same limitation applies to Chapter 3, where I investigated the health implications of state-level minimum wage policies for older adults using the biennial HRS. The number of available waves in the data posed a limitation in Chapter 4 as well, where I used HCAP data with dementia classifications available only for 2016. This limits the study's ability to generalize the predictor-dementia association to future waves of data. For instance, the predictor-dementia link may change over time due to shifts in population definitions or disease characteristics.

The third limitation concerns the focus of the sample. In Chapters 1 to 3, I purposefully focused on older adults who were at least partially involved in the labor market at baseline to examine the health implications of their labor market experiences. However, this selection introduces bias, as older adults with unfavorable health conditions or disabilities may not be included in the sample. Likewise, older adults who no longer need additional social interaction from workplace or financial resources might choose different activities, such as leisure or volunteering, rather than engaging in the labor market. Therefore, the findings apply to older adults who are able, willing, or required to participate in economic activities for various reasons. It is important to acknowledge this selection bias when interpreting the findings.

5.4 Direction for future research

This thesis provided evidence of the health implications of labor market experiences for older adults, a social determinant of health that has been largely understudied. In this section, I discuss a future research agenda that extends beyond the scope of the four chapters.

The first suggestion is to investigate the characteristics of employers with a higher share of older workers to reveal where market equilibrium exists and understand what the current labor market is able to provide to engage older workers.

The second suggestion is to identify the gap between the work environment employees need for their health and well-being and the one that is being provided. While income is an important reward from labor market activities, other key factors including job security, flexible work schedules, autonomy, and a cooperative work atmosphere with social interactions, are found to be essential for workers' health, especially for older adults. By comparing the current work environment provided for older adults with the desired work environment, we would be able to identify which job characteristics or work conditions could be improved for employees' health and well-being.

The third suggestion relates to the role of the government in promoting older adults' engagement in society while protecting their health and well-being, especially for less-educated or less-skilled older adults. This agenda aims to identify policy-induced incentives that influence older workers' labor market engagement and employers' willingness to hire or retain them. Careful consideration in policy design is warranted, as these policies may have health implications for older adults.

Bibliography

Acemoglu, Daron, Nicolaj Søndergaard Mühlbach, and Andrew J. Scott (2022) "The rise of age-friendly jobs," *The Journal of the Economics of Ageing*, 23, 100416, 10.1016/j.jeoa.2022.100416.

Adkins-Jackson, Paris B., Boeun Kim, César Higgins Tejera et al. (2024) ""Hang Ups, Let Downs, Bad Breaks, Setbacks": Impact of Structural Socioeconomic Racism and Resilience on Cognitive Change Over Time for Persons Racialized as Black," *Health Equity*, 8 (1), 254–268, 10.1089/heq.2023.0151.

Adler, Nancy E., M. Maria Glymour, and Jonathan Fielding (2016) "Addressing Social Determinants of Health and Health Inequalities," *JAMA*, 316 (16), 1641–1642, 10.1001/jama.2016.14058.

Aguila, Emma, Arie Kapteyn, and James P. Smith (2015) "Effects of income supplementation on health of the poor elderly: The case of Mexico," *Proceedings of the National Academy of Sciences*, 112 (1), 70–75, 10.1073/pnas.1414453112.

American Psychiatric Association (1994) *Diagnostic and Statistical Manual of Mental Disorders*, Washington, D.C.: American Psychiatric Association, fourth edition edition.

Andel, Ross, Michael Crowe, Ingemar Kåreholt, Jonas Wastesson, and Marti G. Parker (2011) "Indicators of Job Strain at Midlife and Cognitive Functioning in Advanced Old Age," *The Journals of Gerontology: Series B*, 66B (3), 287–291, 10.1093/geronb/gbq105.

Andel, Ross, Cheryl Vigen, Wendy J. Mack, Linda J. Clark, and Margaret Gatz (2006) "The effect of education and occupational complexity on rate of cognitive decline in Alzheimer's patients," *Journal of the International Neuropsychological Society*, 12 (1), 147–152, 10.1017/S1355617706060206.

Anderson, Lynda A. and Stephen R. McConnell (2007) "Cognitive health: An emerging public health issue," *Alzheimer's & Dementia*, 3 (2S), S70–S73, 10.1016/j.jalz.2007.01.018.

Andreyeva, Elena and Benjamin Ukert (2018) "The impact of the minimum wage on health," *International Journal of Health Economics and Management*, 18 (4), 337–375, 10.1007/s10754-018-9237-0.

Armstrong-Stassen, Marjorie, Francine Schlosser, and Deborah Zinni (2012) "Seeking resources: Predicting retirees' return to their workplace.," *Journal of Managerial Psychology*, 27 (6), 615–635, 10.1108/02683941211252455, Place: United Kingdom Publisher: Emerald Group Publishing Limited.

Arulampalam, Wiji, Alison L. Booth, and Mark L. Bryan (2004) "Training and the New Minimum Wage," *The Economic Journal*, 114 (494), C87–C94, 10.1111/j.0013-0133.2003.00197.x.

Atalay, Kadir, Garry F. Barrett, and Anita Staneva (2019) "The effect of retirement on elderly cognitive functioning," *Journal of Health Economics*, 66, 37–53, 10.1016/j.jhealeco.2019.04.006.

Averett, Susan L., Julie K. Smith, and Yang Wang (2018) "Minimum Wages and the Health of Hispanic Women," *Journal of Economics, Race, and Policy*, 1 (4), 217–239, 10.1007/s41996-018-0019-3.

Azar, José, Emiliano Huet-Vaughn, Ioana Marinescu, Bledi Taska, and Till von Wachter (2023) "Minimum Wage Employment Effects and Labour Market Concentration," *The Review of Economic Studies*, rdad091, 10.1093/restud/rdad091.

Bai, Yihong, Chungah Kim, and Antony Chum (2023) "Impact of the minimum wage increase on smoking behaviour: A quasi-experimental study in South Korea," *Social Science & Medicine*, 333, 116135, 10.1016/j.socscimed.2023.116135.

Bastani, Hamsa (2021) "Predicting with Proxies: Transfer Learning in High Dimension," *Management Science*, 67 (5), 2964–2984, 10.1287/mnsc.2020.3729.

Berkman, L.F., I. Kawachi, and M.M. Glymour (2014) *Social Epidemiology*: Oxford University Press.

Berkman, Lisa F. and Beth C. Truesdale (2023) "Working longer and population aging in the U.S.: Why delayed retirement isn't a practical solution for many," *The Journal of the Economics of Ageing*, 24, 100438, 10.1016/j.jeoa.2022.100438.

Bonsang, Eric, Stéphane Adam, and Sergio Perelman (2012) "Does retirement affect cognitive functioning?" *Journal of Health Economics*, 31 (3), 490–501, 10.1016/j.jhealeco.2012.03.005.

Borgschulte, Mark and Heepyung Cho (2020) "Minimum Wages and Retirement," *ILR Review*, 73 (1), 153–177, 10.1177/0019793919845861.

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess (2024) "Revisiting Event-Study Designs: Robust and Efficient Estimation," *The Review of Economic Studies*, rdae007, 10.1093/restud/rdae007.

Bosworth, B, G Burtless, and K Zhang (2016) "Later retirement, inequality in old age, and the growing gap in longevity between rich and poor,"Technical report, `https://www.brookings.edu/wp-content/uploads/2016/02/BosworthBurtlessZhang_retirementinequalitylongevity_012815.pdf`.

Boyle, Patricia A., Aron S. Buchman, Lisa L. Barnes, and David A. Bennett (2010) "Effect of a Purpose in Life on Risk of Incident Alzheimer Disease and Mild Cognitive Impairment in Community-Dwelling Older Persons," *Archives of General Psychiatry*, 67 (3), 304–310, 10.1001/archgenpsychiatry.2009.208.

Brickman, Adam M., Raquel Cabo, and Jennifer J. Manly (2006) "Ethical issues in cross-cultural neuropsychology," *Applied Neuropsychology*, 13 (2), 91–100, 10.1207/s15324826an1302_4.

Budd Haeberlein, Samantha, P.S. Aisen, F. Barkhof et al. (2022) "Two Randomized Phase 3 Studies of Aducanumab in Early Alzheimer's Disease," *The Journal of Prevention of Alzheimer's Disease*, 9 (2), 197–210, 10.14283/jpad.2022.30.

Buszkiewicz, James H, Heather D Hill, and Jennifer J Otten (2020) "Association of State Minimum Wage Rates and Health in Working-Age Adults Using the National Health Interview Survey," *American Journal of Epidemiology*, 190 (1), 21–30, 10.1093/aje/kwaa018.

Card, David and Alan B. Krueger (1994) "Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania," *American Economic Review*, 84 (4), 772–793.

Case, Anne and Angus Deaton (2020) *Deaths of Despair and the Future of Capitalism*: Princeton University Press.

——— (2022) "The Great Divide: Education, Despair, and Death," *Annual Review of Economics*, 14 (Volume 14, 2022), 1–21, 10.1146/annurev-economics-051520-015607.

Cerdeña, Jessica P, Marie V Plaisime, and Jennifer Tsai (2020) "From race-based to race-conscious medicine: How anti-racist uprisings call us to act," *The Lancet*, 396 (10257), 1125–1128, 10.1016/s0140-6736(20)32076-6.

Chandra, Amitabh, Courtney Coile, and Corina Mommaerts (2023) "What Can Economics Say about Alzheimer's Disease?" *Journal of Economic Literature*, 61 (2), 428–70, 10.1257/jel.20211660.

Chauvel, Louis and Anja Leist (2015) "Social epidemiology," in *International Encyclopedia of the Social and Behavioral Sciences*, FNR - Fonds National de la Recherche [LU]: Elsevier, 10.1016/B978-0-08-097086-8.14039-5.

Chin, Alexander L., Selamawit Negash, and Roy Hamilton (2011) "Diversity and Disparity in Dementia: The Impact of Ethnoracial Differences in Alzheimer Disease," *Alzheimer Disease & Associated Disorders*, 25 (3), 10.1097/WAD.0b013e318211c6c9.

Cho, Joonmo, Ayoung Lee, and Kwangho Woo (2016) "A Comparative Study on Retirement Process in Korea, Germany, and the United States: Identifying Determinants of Retirement Process," *The International Journal of Aging and Human Development*, 83 (4), 441–467, 10.1177/0091415016657556, Publisher: SAGE Publications Inc.

Clemens, Jeffrey (2021) "How Do Firms Respond to Minimum Wage Increases? Understanding the Relevance of Non-employment Margins," *Journal of Economic Perspectives*, 35 (1), 51–72, 10.1257/jep.35.1.51.

Clemens, Jeffrey, Lisa B Kahn, and Jonathan Meer (2018) "The Minimum Wage, Fringe Benefits, and Worker Welfare," Working Paper 24635, National Bureau of Economic Research, 10.3386/w24635.

Collins, G S, J B Reitsma, D G Altman, and K G M Moons (2015) "Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD): The TRIPOD statement," *British Journal of Cancer*, 112 (2), 251–259, 10.1038/bjc.2014.639.

Courtin, Emilie, Vahe Nafilyan, Maria Glymour, Marcel Goldberg, Claudine Berr, Lisa F Berkman, Marie Zins, and Mauricio Avendano (2019) "Long-term effects of compulsory schooling on physical, mental and cognitive ageing: a natural experiment," *Journal of Epidemiology & Community Health*, 73 (4), 370–376, 10.1136/jech-2018-211746.

Craik, Fergus I. M. and Timothy A. Salthouse eds. (2008) *The Handbook of Aging and Cognition*: Psychology Press, 3rd edition.

Crimmins, Eileen M., Jung Ki Kim, Kenneth M. Langa, and David R. Weir (2011) "Assessment of Cognition Using Surveys and Neuropsychological Assessment: The Health and Retirement Study and the Aging, Demographics, and Memory Study," *The Journals of Gerontology: Series B*, 66B (suppl1), i162–i171, 10.1093/geronb/gbr048.

Davis, Jesse and Mark Goadrich (2006) "The relationship between precision-recall and ROC curves," *Proceedings of the 23rd international conference on Machine learning - ICML '06*, 10.1145/1143844.1143874.

de Chaisemartin, Clément and Xavier D'Haultfœuille (2022) "Two-way fixed effects and differences-in-differences with heterogeneous treatment effects: a survey," *The Econometrics Journal*, 26 (3), C1–C30, 10.1093/ectj/utac017.

Dingemans, Ellen and Katja Möhring (2019) "A life course perspective on working after retirement: What role does the work history play?" *Advances in Life Course Research*, 39, 23–33, 10.1016/j.alcr.2019.02.004.

Doh, Taeyoung, Kyoo il Kim, Sungil Kim, Hwanoong Lee, and Kyungho Song (2022) "The economic effects of a rapid increase in the minimum wage: Evidence from South Korea experiments," *SSRN Electronic Journal*, 10.2139/ssrn.4292238.

Doh, Taeyoung and Luca Van der Meer (2023) "The Employment Effect of an Increase in the National Minimum Wage: Review of International Evidence," *Economic Review*, 108 (2), 10.18651/ER/v108n2DohVanderMeer.

Dow, William H., Anna Godøy, Christopher Lowenstein, and Michael Reich (2020) "Can Labor Market Policies Reduce Deaths of Despair?" *Journal of Health Economics*, 74, 102372, 10.1016/j.jhealeco.2020.102372.

Dowd, Jennifer Beam and Anna Zajacova (2007) "Does the predictive power of self-rated health for subsequent mortality risk vary by socioeconomic status in the US?," *International Journal of Epidemiology*, 36 (6), 1214–1221, 10.1093/ije/dym214.

Dufouil, Carole, Edwige Pereira, Geneviève Chêne et al. (2014) "Older age at retirement is associated with decreased risk of dementia," *European Journal of Epidemiology*, 29 (5), 353–361, 10.1007/s10654-014-9906-3.

van Dyck, Christopher H., Chad J. Swanson, Paul Aisen et al. (2023) "Lecanemab in Early Alzheimer's Disease," *New England Journal of Medicine*, 388 (1), 9–21, 10.1056/NEJMoa2212948.

Elder Jr., Glen H. and Michael J. Shanahan (2007) *The Life Course and Human Development*, Chap. 12: John Wiley & Sons, Ltd, https://doi.org/10.1002/9780470147658.chpsy0112.

Eurostat (2020) "Ageing Europe - looking at the lives of older people in the EU," November, `https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Ageing_Europe_-_looking_at_the_lives_of_older_people_in_the_EU`.

Fang, Tony and Morley Gunderson (2009) "Minimum Wage Impacts on Older Workers: Longitudinal Estimates from Canada," *British Journal of Industrial Relations*, 47 (2), 371–387, 10.1111/j.1467-8543.2009.00724.x.

Fasbender, Ulrike, Mo Wang, Jan-Bennet Voltmer, and Jürgen Deller (2016) "The Meaning of Work for Post-retirement Employment Decisions," *Work, Aging and Retirement*, 2 (1), 12–23, 10.1093/workar/wav015.

Feldman, Daniel C. (1994) "The Decision to Retire Early: A Review and Conceptualization," *Academy of Management Review*, 19 (2), 285–311, 10.5465/amr.1994.9410210751, Publisher: Academy of Management.

Finke, Michael S., John S. Howe, and Sandra J. Huston (2017) "Old Age and the Decline in Financial Literacy," *Management Science*, 63 (1), 213–230, 10.1287/mnsc.2015.2293.

French, Eric and John Bailey Jones (2011) "The effects of health insurance and self-insurance on retirement behavior," *Econometrica*, 79 (3), 693–732.

Friedman, Jerome, Trevor Hastie, and Robert Tibshirani (2001) *The Elements of Statistical Learning*, 1: Springer Series in Statistics, New York.

Gao, Yan and Yan Cui (2020) "Deep transfer learning for reducing health care disparities arising from biomedical data inequality," *Nature Communications*, 11 (1), 5131, 10.1038/s41467-020-18918-3.

García-Albéniz, Xabier, John Hsu, and Miguel A. Hernán (2017) "The value of explicitly emulating a target trial when using real world evidence: an application to colorectal cancer screening," *European Journal of Epidemiology*, 32 (6), 495–500, 10.1007/s10654-017-0287-2.

Gardner, John, Neil Thakral, Linh T. Tô, and Luther Yap (2024) "Two-Stage Differences in Differences," working paper, `https://linh.to/files/papers/2sdd.pdf`.

Gianattasio, Kan Z, Adam Ciarleglio, and Melinda C Power (2020) "Development of Algorithmic Dementia Ascertainment for Racial/Ethnic Disparities Research in the US Health and Retirement Study," *Epidemiology (Cambridge, Mass.)*, 31 (1), 126–133, 10.1097/EDE.0000000000001101.

Gianattasio, Kan Z., Qiong Wu, M. Maria Glymour, and Melinda C. Power (2019) "Comparison of Methods for Algorithmic Classification of Dementia Status in the Health and Retirement Study," *Epidemiology*, 30 (2).

Glymour, M. Maria and Jennifer J. Manly (2008) "Lifecourse Social Conditions and Racial and Ethnic Patterns of Cognitive Aging," *Neuropsychology Review*, 18 (3), 223–254, 10.1007/s11065-008-9064-z.

Godøy, Anna, Michael Reich, Jesse Wursten, and Sylvia Allegretto (2021) "Parental Labor Supply: Evidence from Minimum Wage Changes," *Journal of Human Resources*, 10.3368/jhr.1119-10540R2.

Goodman-Bacon, Andrew (2021) “Difference-in-differences with variation in treatment timing,” *Journal of Econometrics*, 225 (2), 254–277, 10.1016/j.jeconom.2021.03.014, Themed Issue: Treatment Effect 1.

Graham, Eileen K., Joshua P. Rutsohn, Nicholas A. Turiano et al. (2017) “Personality predicts mortality risk: An integrative data analysis of 15 international longitudinal studies,” *Journal of Research in Personality*, 70, 174–186, 10.1016/j.jrp.2017.07.005.

Gupta, Sumedha (2018) “Impact of volunteering on cognitive decline of the elderly,” *The Journal of the Economics of Ageing*, 12, 46–60, 10.1016/j.jeoa.2018.01.002.

Hampton, Matt and Evan Totty (2023) “Minimum wages, retirement timing, and labor supply,” *Journal of Public Economics*, 224, 104924, 10.1016/j.jpubeco.2023.104924.

Han, Changsu, Sangmee Ahn Jo, Inho Jo, Eunkyung Kim, Moon Ho Park, and Yeonwook Kang (2008) “An adaptation of the Korean mini-mental state examination (K-MMSE) in elderly Koreans: Demographic influence and population-based norms (the AGE study),” *Archives of Gerontology and Geriatrics*, 47 (3), 302–310, 10.1016/j.archger.2007.08.012.

Harasztosi, Peter and Attila Lindner (2019) “Who Pays for the Minimum Wage?” *American Economic Review*, 109 (8), 2693–2727, 10.1257/aer.20171445.

Hernán, Miguel A. and James M. Robins (2016) “Using Big Data to Emulate a Target Trial When a Randomized Trial Is Not Available,” *American Journal of Epidemiology*, 183 (8), 758–764, 10.1093/aje/kwv254.

Hessel, Philipp, Mauricio Avendano, Carlos Rodríguez-Castelán, and Tobias Pfutze (2018) “Social Pension Income Associated With Small Improvements In Self-Reported Health Of Poor Older Men In Colombia,” *Health Affairs*, 37 (3), 456–463, 10.1377/hlthaff.2017.1284.

Hofer, Scott M. and Andrea M. Piccinin (2009) “Integrative Data Analysis Through Coordination of measurement and Analysis Protocol across Independent Longitudinal Studies.,” *Psychological Methods*, 14 (2), 150–164, 10.1037/a0015566.

Horn, Brady P., Johanna Catherine Maclean, and Michael R. Strain (2017) “Do minimum wage increases influence worker health?” *Economic Inquiry*, 55 (4), 1986–2007, 10.1111/ecin.12453.

Huang, Chen, Feng Liu, and Shijun You (2021) “The impact of minimum wage increases on cigarette smoking,” *Health Economics*, 30 (9), 2063–2091, 10.1002/hec.4362.

Hudomiet, Péter, Michael D. Hurd, and Susann Rohwedder (2022) "Trends in inequalities in the prevalence of dementia in the United States," *Proceedings of the National Academy of Sciences*, 119 (46), e2212205119, 10.1073/pnas.2212205119.

Hultsch, David F., Christopher Hertzog, Brent J. Small, and Roger A. Dixon (1999a) "Use it or lose it: Engaged lifestyle as a buffer of cognitive decline in aging?" *Psychology and Aging*, 14 (2), 245–263, 10.1037/0882-7974.14.2.245.

——— (1999b) "Use it or lose it: engaged lifestyle as a buffer of cognitive decline in aging?" *Psychology and Aging*, 14 (2), 245–263, 10.1037//0882-7974.14.2.245.

Hultsch, D.F., C. Hertzog, B.J. Small, and R.A. Dixon (1999) "Use it or lose it: Engaged lifestyle as a buffer of cognitive decline in aging?" *Psychology and Aging*, 14 (2), 245–263, 10.1037/0882-7974.14.2.245.

Hurd, Michael D., Paco Martorell, Adeline Delavande, Kathleen J. Mullen, and Kenneth M. Langa (2013) "Monetary Costs of Dementia in the United States," *New England Journal of Medicine*, 368 (14), 1326–1334, 10.1056/NEJMsa1204629, PMID: 23550670.

Hwang, Inuk and Tae-Jin Lee (2022) "Health improvements of older adults based on benefit duration: Lessons from Korean social pension policies," *Social Science & Medicine*, 315, 115514, 10.1016/j.socscimed.2022.115514.

Idler, Ellen L. and Yael Benyamini (1997) "Self-Rated Health and Mortality: A Review of Twenty-Seven Community Studies," *Journal of Health and Social Behavior*, 38 (1), 21–37.

Imai, Kosuke, In Song Kim, and Erik H. Wang (2023) "Matching Methods for Causal Inference with Time-Series Cross-Sectional Data," *American Journal of Political Science*, 67 (3), 587–605, 10.1111/ajps.12685.

Imai, Kosuke and Marc Ratkovic (2013) "Covariate Balancing Propensity Score," *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 76 (1), 243–263, 10.1111/rssb.12027.

——— (2014) "Covariate balancing propensity score," *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 76 (1), 243–263, 10.1111/rssb.12027.

International Labour Organization (2022) "International Standard Classification of Occupations (ISCO)," `https://ilostat.ilo.org/resources/concepts-and-definitions/classification-occupation/`, Accessed: 2022-04-01.

Janssens, A Cecile J W and Forike K Martens (2020) "Reflection on modern methods: Revisiting the area under the ROC Curve," *International Journal of Epidemiology*, 49 (4), 1397–1403, 10.1093/ije/dyz274.

Jardim, Ekaterina, Mark C. Long, Robert Plotnick, Emma van Inwegen, Jacob Vigdor, and Hilary Wething (2022) "Minimum-Wage Increases and Low-Wage Employment: Evidence from Seattle," *American Economic Journal: Economic Policy*, 14 (2), 263–314, 10.1257/pol.20180578.

Jorm, A. F. (1994) "Disability in dementia: assessment, prevention, and rehabilitation," *Disability and Rehabilitation*, 16 (3), 98–109, 10.3109/09638289409166286, PMID: 7919403.

Jorm, A. F. and P. A. Jacomb (1989) "The Informant Questionnaire on Cognitive Decline in the Elderly (IQCODE): socio-demographic correlates, reliability, validity and some norms," *Psychological Medicine*, 19 (4), 1015–1022, 10.1017/S0033291700005742.

Jung, Taimyun (2011) *The Minimum Wage System in Korea: An introductory guide*: Korea Labor Institute.

Kang, Yeon Wook, Duk L. Na, and Seung Hae Hahn (1997) "A validity study on the korean mini-mental state examination (K-MMSE) in dementia patients," *J Korean Neurol Assoc*, 15 (2), 300–308, `http://www.jkna.org/journal/view.php?number=4088`.

Kenkel, Donald S., Maximilian D. Schmeiser, and Carly Urban (2014) "Is Smoking Inferior? Evidence from Variation in the Earned Income Tax Credit," *The Journal of Human Resources*, 49 (4), 1094–1120.

Khang, Young-Ho, John W. Lynch, and George A Kaplan (2005) "Impact of economic crisis on cause-specific mortality in South Korea," *International Journal of Epidemiology*, 34 (6), 1291–1301, 10.1093/ije/dyi224.

Kim, Dae-il (2018) "최저임금의 경제효과 (The economic effects of minimum wages)," *경제논집*, 57 (1), 95–114, `http://scholar.kyobobook.co.kr/article/detail/4010026509658`, Publisher: Institute of Economic Research, Seoul National University.

Kim, In Song, Adam Rauh, Erik Wang, and Kosuke Imai (2018) *Matching Methods for Causal Inference with Time-Series Cross-Sectional Data*, `https://cran.r-project.org/web/packages/PanelMatch`, R package version 2.14.0.

Kim, Ji Hwan, Jungmin Lee, and Kyungho Lee (2023a) "Minimum wage, social insurance mandate, and working hours," *Journal of Public Economics*, 225, 104951, 10.1016/j.jpubeco.2023.104951.

Kim, Ji In, Mun Kyung Sunwoo, Young H. Sohn, Phil Hyu Lee, and Jin Y. Hong (2016) “The MMSE and MoCA for Screening Cognitive Impairment in Less Educated Patients with Parkinson’s Disease,” *Journal of Movement Disorders*, 9 (3), 152–159, 10.14802/jmd.16020.

Kim, Jung Hyun, Graciela Muniz-Terrera, and Anja K Leist (2023b) “Does (re-)entering the labour market at advanced ages protect against cognitive decline? A matching difference-in-differences approach,” *Journal of Epidemiology & Community Health*, 77 (10), 663–669, 10.1136/jech-2022-220197.

Kim, Jung Hyun, Marc Suhrcke, and Anja K. Leist (2025) “The unintended effects of a large minimum wage increase on health: Evidence from South Korea,” *Social Science & Medicine*, 365, 117626, https://doi.org/10.1016/j.socscimed.2024.117626.

Kivipelto, Miia, Francesca Mangialasche, and Tiia Ngandu (2018) “Lifestyle interventions to prevent cognitive impairment, dementia and Alzheimer disease,” *Nature Reviews Neurology*, 14 (11), 653–666, 10.1038/s41582-018-0070-3.

Kobayashi, Lindsay C (2024) “Adverse Childhood Experiences and Later-Life Cognitive Aging: Persistent Methodological Challenges Limit the Evidence Base,” *The Journals of Gerontology: Series A*, 79 (8), glae138, 10.1093/gerona/glae138.

Kobayashi, Lindsay C, Alden L Gross, Laura E Gibbons et al. (2021) “You Say Tomato, I Say Radish: Can Brief Cognitive Assessments in the U.S. Health Retirement Study Be Harmonized With Its International Partner Studies?” *The journals of gerontology. Series B, Psychological sciences and social sciences*, 76 (9), 1767–1776, 10.1093/geronb/gbaa205, Publisher: Oxford University Press.

Korea Minimum Wage Commission (2023) “2023 Wage Status and Analysis Report,” `https://www.minimumwage.go.kr/open/research/view.do?bultnId=4446&pageUnit=10&pageIndex=1&bultnCd=BB&searchCondition=&searchKeyword=`, Accessed: 2024-09-26.

Kronenberg, Christoph, Rowena Jacobs, and Eugenio Zucchelli (2017) “The impact of the UK National Minimum Wage on mental health,” *SSM - Population Health*, 3, 749–755, 10.1016/j.ssmph.2017.08.007.

Bureau of Labor Statistics, U.S. Department of Labor (2019) “Labor force participation rate for workers age 75 and older projected to be over 10 percent by 2026 : The Economics Daily: U.S. Bureau of Labor Statistics,” `https://www.bls.gov/opub/ted/2019`.

Langa, Kenneth M., Brenda L. Plassman, Robert B. Wallace et al. (2005) “The Aging, Demographics, and Memory Study: Study Design and Methods,” *Neuroepidemiology*, 25 (4), 181–191, 10.1159/000087448.

Langa, Kenneth M, Lindsay H. Ryan, Ryan McCammon et al. (2020) "The Health and Retirement Study Harmonized Cognitive Assessment Protocol (HCAP) Project: Study Design and Methods," *Neuroepidemiology*, 54 (1), 64–74, 10.1159/000503004.

Langa, K.M., L.H. Ryan, R.J. McCammon et al. (2020) "The Health and Retirement Study Harmonized Cognitive Assessment Protocol Project: Study Design and Methods," *Neuroepidemiology*, 54 (1), 64–74, 10.1159/000503004.

Lee, Jungmin and Geumbi Park (2023) "Minimum Wage, Employment, and Margins of Adjustment," *Journal of Human Resources*, 10.3368/jhr.0820-11082R3.

Lee, Sunmin, Ichiro Kawachi, Lisa F. Berkman, and Francine Grodstein (2003) "Education, Other Socioeconomic Indicators, and Cognitive Function," *American Journal of Epidemiology*, 157 (8), 712–720, 10.1093/aje/kwg042.

Lee, Yeonjin and Wei-Jun Jean Yeung (2020) "The Country That Never Retires: The Gendered Pathways to Retirement in South Korea," *The Journals of Gerontology: Series B*, 76 (3), 642–655, 10.1093/geronb/gbaa016.

Leigh, J., Wesley A. Leigh, and Juan Du (2019) "Minimum wages and public health: A literature review," *Preventive Medicine*, 118, 122–134, 10.1016/j.ypmed.2018.10.005.

Leigh, J. Paul (2021) "Treatment design, health outcomes, and demographic categories in the literature on minimum wages and health," *Economics & Human Biology*, 43, 101043, 10.1016/j.ehb.2021.101043.

Leist, Anja K, M Maria Glymour, Johan P Mackenbach, Frank J van Lenthe, and Mauricio Avendano (2013) "Time away from work predicts later cognitive function: differences by activity during leave," *Annals of epidemiology*, 23 (8), 455–462, 10.1016/j.annepidem.2013.05.014.

Leist, Anja K, Philipp Hessel, and Mauricio Avendano (2014) "Do economic recessions during early and mid-adulthood influence cognitive function in older age?" *Journal of Epidemiology & Community Health*, 68 (2), 151–158, 10.1136/jech-2013-202843.

Leist, Anja K., Matthias Klee, Jung Hyun Kim, David H. Rehkopf, Stéphane P. A. Bordas, Graciela Muniz-Terrera, and Sara Wade (2022) "Mapping of machine learning approaches for description, prediction, and causal inference in the social and health sciences," *Science Advances*, 8 (42), eabk1942, 10.1126/sciadv.abk1942.

Lenhart, Otto (2017) "Do Higher Minimum Wages Benefit Health? Evidence From the UK," *Journal of Policy Analysis and Management*, 36 (4), 828–852, 10.1002/pam.22006.

Lewis, Nathan A., Nicholas A. Turiano, Brennan R. Payne, and Patrick L. Hill (2016) "Purpose in life and cognitive functioning in adulthood," *Aging, Neuropsychology, and Cognition*, 24 (6), 662–671, 10.1080/13825585.2016.1251549.

Lin, Pei-Jung and Peter J. Neumann (2013) "The economics of mild cognitive impairment," *Alzheimer's & Dementia*, 9 (1), 58–62, 10.1016/j.jalz.2012.05.2117.

Livingston, Gill, Jonathan Huntley, Kathy Y Liu et al. (2024) "Dementia prevention, intervention, and care: 2024 report of the Lancet standing Commission," *The Lancet*, 404 (10452), 572–628, 10.1016/S0140-6736(24)01296-0, Publisher: Elsevier.

Lövdén, Martin, Laura Fratiglioni, M. Maria Glymour, Ulman Lindenberger, and Elliot M. Tucker-Drob (2020) "Education and Cognitive Functioning Across the Life Span," *Psychological Science in the Public Interest*, 21 (1), 6–41, 10.1177/1529100620920576.

Maestas, Nicole, Kathleen J. Mullen, David Powell, Till von Wachter, and Jeffrey B. Wenger (2023) "The Value of Working Conditions in the United States and the Implications for the Structure of Wages," *American Economic Review*, 113 (7), 2007–47, 10.1257/aer.20190846.

Manly, Jennifer J. (2005) "Advantages and disadvantages of separate norms for African Americans," *The Clinical Neuropsychologist*, 19 (2), 270–275, 10.1080/13854040590945346.

Manly, Jennifer J and Ruben J Echemendta (2007) "Race-specific norms: Using the model of hypertension to understand issues of race, culture, and education in Neuropsychology," *Archives of Clinical Neuropsychology*, 22 (3), 319–325, 10.1016/j.acn.2007.01.006.

Manly, Jennifer J., Richard N. Jones, Kenneth M. Langa, Lindsay H. Ryan, Deborah A. Levine, Ryan McCammon, Steven G. Heeringa, and David Weir (2022) "Estimating the Prevalence of Dementia and Mild Cognitive Impairment in the US: The 2016 Health and Retirement Study Harmonized Cognitive Assessment Protocol Project," *JAMA Neurology*, 79 (12), 1242–1249, 10.1001/jamaneurol.2022.3543.

Maxwell, Jacob, Robert Pryce, and Luke B. Wilson (2022) "The impact of increasing the United Kingdom national minimum wage on self-reported health," *Health Economics*, 31 (6), 1167–1183, 10.1002/hec.4490.

Mayeda, Elizabeth Rose, M.Maria Glymour, Charles P. Quesenberry, and Rachel A. Whitmer (2016) "Inequalities in dementia incidence between six racial and ethnic groups over 14 years," *Alzheimer's & Dementia*, 12 (3), 216–224, 10.1016/j.jalz.2015.12.007.

Mazzuco, STEFANO, SILVIA MEGGIOLARO, FAUSTA ONGARO, and VERONICA TOFFOLUTTI (2017) “Living arrangement and cognitive decline among older people in Europe,” *Ageing and Society*, 37 (6), 1111–1133, 10.1017/S0144686X16000374.

McArdle, John J, James P Smith, and Robert Willis (2009) “Cognition and Economic Outcomes in the Health and Retirement Survey,” Working Paper 15266, National Bureau of Economic Research, 10.3386/w15266.

Meiselbach, Mark K. and Jean M. Abraham (2023) “Do minimum wage laws affect employer-sponsored insurance provision?” *Journal of Health Economics*, 92, 102825, 10.1016/j.jhealeco.2023.102825.

Ministry of Employment and Labor (2023) “Minimum Wage Commission Republic of Korea,” `https://www.minimumwage.go.kr/minWage/policy/influenceMain.do?division=S`, Accessed on: ugust 22, 2023.

Mitchell, Meghan B., Cynthia R. Cimino, Andreana Benitez et al. (2012) “Cognitively Stimulating Activities: Effects on Cognition across Four Studies with up to 21 Years of Longitudinal Data,” *Journal of Aging Research*, 2012 (1), 461592, https://doi.org/10.1155/2012/461592.

Muniz-Terrera, Graciela, Fiona Matthews, Tom Dening, Felicia A. Huppert, Carol Brayne, and CC75C Group (2009) “Education and trajectories of cognitive decline over 9 years in very old people: methods and risk analysis,” *Age and Ageing*, 38 (3), 277–282, 10.1093/ageing/afp004.

Neumark, David (2024a) “Age Discrimination in Hiring,” *Journal of Human Resources*, 59 (1), 1–34, 10.3368/jhr.0420-10831R1, Publisher: University of Wisconsin Press _eprint: https://jhr.uwpress.org/content/59/1/1.full.pdf.

——— (2024b) “The effects of minimum wages on (almost) everything? A review of recent evidence on health and related behaviors,” *LABOUR*, 38 (1), 1–65, 10.1111/labr.12263.

——— (2024c) “The effects of minimum wages on (almost) everything? A review of recent evidence on health and related behaviors,” *Labour*, 38 (1), 1–65, 10.1111/labr.12263.

Neumark, David, Mark Schweitzer, and William Wascher (2004) “Minimum Wage Effects throughout the Wage Distribution,” *Journal of Human Resources*, XXXIX (2), 425–450, 10.3368/jhr.XXXIX.2.425.

Ngandu, Tiia, Jenni Lehtisalo, Alina Solomon et al. (2015) “A 2 year multidomain intervention of diet, exercise, cognitive training, and vascular risk monitoring versus control to prevent cognitive decline in at-risk elderly people (FINGER): a randomised controlled trial," *The Lancet*, 385 (9984), 2255–2263, https://doi.org/10.1016/S0140-6736(15)60461-5.

Nichols, Emma, Derek K Ng, Bryan D James, Jennifer A Deal, and Alden L Gross (2022a) "Measurement of Prevalent Versus Incident Dementia Cases in Epidemiologic Studies," *American Journal of Epidemiology*, 192 (4), 520–534, 10.1093/aje/kwac197.

Nichols, Emma, Jaimie D Steinmetz, Stein Emil Vollset et al. (2022b) "Estimation of the global prevalence of dementia in 2019 and forecasted prevalence in 2050: an analysis for the Global Burden of Disease Study 2019," *The Lancet Public Health*, 7 (2), e105–e125, 10.1016/S2468-2667(21)00249-8.

OECD (2018) *Working Better with Age: Korea*, 136, 10.1787/9789264208261-en.

——— (2021a) *Pensions at a Glance 2021*, 224, 10.1787/ca401ebd-en.

OECD (2021b) *Pensions at a Glance 2021*, 224, 10.1787/ca401ebd-en.

OECD (2023a) "OECD.Stat LFS - Real minimum wages," `https://stats.oecd.org/index.aspx?DataSetCode=RMW#`, Accessed: 2024-01-16.

OECD (2023b) "OECD.Stat LFS by sex and age - indicators," `https://stats.oecd.org/Index.aspx?DataSetCode=lfs_sexage_i_r`, Accessed: 2023-03-14.

OECD (2024) "OECD.Stat LFS by sex and age - indicators," `https://stats.oecd.org/Index.aspx?DataSetCode=lfs_sexage_i_r`, Accessed: 2024-09-02.

Okamoto, Shohei and Erika Kobayashi (2020) "Social Isolation and Cognitive Functioning: A Quasi-Experimental Approach," *The Journals of Gerontology: Series B*, 76 (7), 1441–1451, 10.1093/geronb/gbaa226.

Oshio, Takashi, Emiko Usui, and Satoshi Shimizutani (2020) *7. Labor Force Participation of the Elderly in Japan*, 163–178: University of Chicago Press, doi:10.7208/9780226619323-009.

Otsu, Taisuke and Yoshiyasu Rai (2017) "Bootstrap inference of matching estimators for average treatment effects," *Journal of the American Statistical Association*, 112 (520), 1720–1732, 10.1080/01621459.2016.1231613.

Ozenne, Brice, Fabien Subtil, and Delphine Maucort-Boulch (2015) "The precision–recall curve overcame the optimism of the receiver operating characteristic curve in rare diseases," *Journal of Clinical Epidemiology*, 68 (8), 855–859, 10.1016/j.jclinepi.2015.02.010.

Pan, Sinno Jialin and Qiang Yang (2010) "A Survey on Transfer Learning," *IEEE Transactions on Knowledge and Data Engineering*, 22 (10), 1345–1359, 10.1109/TKDE.2009.191.

Reeves, Aaron, Martin McKee, Johan Mackenbach, Margaret Whitehead, and David Stuckler (2017) "Introduction of a National Minimum Wage Reduced Depressive Symptoms in Low-Wage Workers: A Quasi-Natural Experiment in the UK," *Health Economics*, 26 (5), 639–655, 10.1002/hec.3336.

Regmi, Krishna (2020) "The effect of the minimum wage on children's cognitive achievement," *Labour Economics*, 65, 101844, 10.1016/j.labeco.2020.101844.

Rohwedder, Susann and Robert J. Willis (2010) "Mental Retirement," *Journal of Economic Perspectives*, 24 (1), 119–38, 10.1257/jep.24.1.119.

Rosenbaum, Paul R. and Donald B. Rubin (1983) "The central role of the propensity score in observational studies for causal effects," *Biometrika*, 70 (1), 41–55, 10.1093/biomet/70.1.41.

Rosenberg, Molly, Erika T. Beidelman, Xiwei Chen et al. (2024) "Effect of a cash transfer intervention on memory decline and dementia probability in older adults in rural South Africa," *Proceedings of the National Academy of Sciences*, 121 (40), e2321078121, 10.1073/pnas.2321078121.

Rossor, Martin and Martin Knapp (2015) "Can we model a cognitive footprint of interventions and policies to help to meet the global challenge of dementia?" *The Lancet*, 386 (9997), 1008–1010, 10.1016/S0140-6736(15)60248-3, Publisher: Elsevier.

Roth, Jonathan, Pedro H. C. Sant'Anna, Alyssa Bilinski, and John Poe (2023a) "What's trending in difference-in-differences? A synthesis of the recent econometrics literature," *Journal of Econometrics*, 235 (2), 2218–2244, 10.1016/j.jeconom.2023.03.008.

Roth, Jonathan, Pedro H.C. Sant'Anna, Alyssa Bilinski, and John Poe (2023b) "What's trending in difference-in-differences? A synthesis of the recent econometrics literature," *Journal of Econometrics*, 235 (2), 2218–2244, 10.1016/j.jeconom.2023.03.008.

Rubin, Donald B. (1980) "Randomization analysis of Experimental Data: The fisher randomization test comment," *Journal of the American Statistical Association*, 75 (371), 591, 10.2307/2287653.

Rufibach, Kaspar (2010) "Use of brier score to assess binary predictions," *Journal of Clinical Epidemiology*, 63 (8), 938–939, 10.1016/j.jclinepi.2009.11.009.

Salthouse, Timothy A. (2006) "Mental Exercise and Mental Aging: Evaluating the Validity of the "Use It or Lose It" Hypothesis," *Perspectives on Psychological Science*, 1 (1), 68–87, 10.1111/j.1745-6916.2006.00005.x, PMID: 26151186.

Saunders, Matthew, Ben Barr, Phil McHale, and Christoph Hamelmann (2017) *Key policies for addressing the social determinants of health and health inequities*, Health Evidence Network synthesis report;52: World Health Organization. Regional Office for Europe.

Schwingel, Andiara, Mathew M. Niti, Catherine Tang, and Tze Pin Ng (2009) "Continued work employment and volunteerism and mental well-being of older adults: Singapore longitudinal ageing studies," *Age and Ageing*, 38 (5), 531–537, 10.1093/ageing/afp089.

Scott, Andrew J (2021) "The longevity economy," *The Lancet Healthy Longevity*, 2 (12), e828–e835, 10.1016/S2666-7568(21)00250-6.

Seblova, Dominika, Martin Fischer, Stefan Fors et al. (2020) "Does Prolonged Education Causally Affect Dementia Risk When Adult Socioeconomic Status Is Not Altered? A Swedish Natural Experiment in 1.3 Million Individuals," *American Journal of Epidemiology*, 190 (5), 817–826, 10.1093/aje/kwaa255.

Segar, Matthew W., Byron C. Jaeger, Kershaw V. Patel et al. (2021) "Development and validation of machine learning–based race-specific models to predict 10-year risk of heart failure: A multicohort analysis," *Circulation*, 143 (24), 2370–2383, 10.1161/circulationaha.120.053134.

Seok, Byoung Hoon and Hye Mi You (2022) "Macroeconomic impacts of increasing the minimum wage: The case of Korea," *Economic Modelling*, 113, 105880, 10.1016/j.econmod.2022.105880.

Shanahan, Michael J. (2000) "Pathways to Adulthood in Changing Societies: Variability and Mechanisms in Life Course Perspective," *Annual Review of Sociology*, 26 (Volume 26, 2000), 667–692, 10.1146/annurev.soc.26.1.667.

Shiba, Koichiro, Naoki Kondo, Katsunori Kondo, and Ichiro Kawachi (2017) "Retirement and mental health: does social participation mitigate the association? A fixed-effects longitudinal analysis," *BMC Public Health*, 17 (1), 526, 10.1186/s12889-017-4427-0.

Sigaud, Liam, Angela Daley, Jonathan Rubin, and Caroline Noblet (2022) "The effects of recent minimum wage increases on self-reported health in the United States," *Social Science & Medicine*, 305, 115110, 10.1016/j.socscimed.2022.115110.

Sisco, Shannon, Alden L. Gross, Regina A. Shih et al. (2014) "The Role of Early-Life Educational Quality and Literacy in Explaining Racial Disparities in Cognition in Late Life," *The Journals of Gerontology: Series B*, 70 (4), 557–567, 10.1093/geronb/gbt133.

Smith, James P. (2021) "The HRS around the world surveys—A review," *The Journal of the Economics of Ageing*, 18, 100295, 10.1016/j.jeoa.2020.100295.

Sonnega, Amanda, Jessica D Faul, Mary Beth Ofstedal, Kenneth M Langa, John WR Phillips, and David R Weir (2014) "Cohort Profile: the Health and Retirement Study (HRS)," *International Journal of Epidemiology*, 43 (2), 576–585, 10.1093/ije/dyu067.

Steingrimsson, Jon A, Constantine Gatsonis, Bing Li, and Issa J Dahabreh (2022) "Transporting a Prediction Model for Use in a New Target Population," *American Journal of Epidemiology*, 192 (2), 296–304, 10.1093/aje/kwac128.

Stekhoven, Daniel J. and Peter Bühlmann (2011) "MissForest—non-parametric missing value imputation for mixed-type data," *Bioinformatics*, 28 (1), 112–118, 10.1093/bioinformatics/btr597.

Stern, Yaakov (2002) "What is cognitive reserve? Theory and research application of the reserve concept," *Journal of the International Neuropsychological Society*, 8 (3), 448–460, 10.1017/S1355617702813248.

Stevens, Richard J. and Katrina K. Poppe (2020) "Validation of clinical prediction models: what does the "calibration slope" really measure?" *Journal of Clinical Epidemiology*, 118, 93–99, 10.1016/j.jclinepi.2019.09.016.

Steyerberg, Ewout W. and Frank E. Harrell (2016) "Prediction models need appropriate internal, internal–external, and external validation," *Journal of Clinical Epidemiology*, 69, 245–247, 10.1016/j.jclinepi.2015.04.005.

Steyerberg, Ewout W. and Yvonne Vergouwe (2014) "Towards better clinical prediction models: seven steps for development and an ABCD for validation," *European Heart Journal*, 35 (29), 1925–1931, 10.1093/eurheartj/ehu207.

Steyerberg, Ewout W., Andrew J. Vickers, Nancy R. Cook, Thomas Gerds, Mithat Gonen, Nancy Obuchowski, Michael J. Pencina, and Michael W. Kattan (2010) "Assessing the Performance of Prediction Models: A Framework for Traditional and Novel Measures," *Epidemiology*, 21 (1), `https://journals.lww.com/epidem/Fulltext/2010/01000/Assessing_the_Performance_of_Prediction_Models__A.22.aspx`.

Stuart, Elizabeth A. (2010) "Matching methods for causal inference: A review and a look forward," *Statistical Science*, 25 (1), 10.1214/09-sts313.

Sun, Liyang and Sarah Abraham (2021) "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects," *Journal of Econometrics*, 225 (2), 175–199, 10.1016/j.jeconom.2020.09.006, Themed Issue: Treatment Effect 1.

Szinovacz, Maximiliane E. and Adam Davey (2005) "Predictors of Perceptions of Involuntary Retirement," *The Gerontologist*, 45 (1), 36–47, 10.1093/geront/45.1.36.

Taylor, Philip, Wendy Loretto, Victor Marshall, Catherine Earl, and Christopher Phillipson (2016) "The Older Worker: Identifying a Critical Research Agenda," *Social Policy and Society*, 15 (4), 675–689, 10.1017/S1474746416000221.

Tian, Ye and Yang Feng (2022a) *glmtrans: Transfer Learning under Regularized Generalized Linear Models*, 10.32614/CRAN.package.glmtrans, R package version 2.0.0.

——— (2022b) "Transfer learning under high-dimensional generalized linear models," *Journal of the American Statistical Association*, 1–30, 10.1080/01621459.2022.2071278.

Tibshirani, Robert (1996) "Regression Shrinkage and Selection via the Lasso," *Journal of the Royal Statistical Society. Series B (Methodological)*, 58 (1), 267–288, http://www.jstor.org/stable/2346178.

Torrey, Lisa and Jude Shavlik (2010) "Transfer Learning," in Olivas, Emilio Soria et al. eds. *Handbook of Research on Machine Learning Applications and Trends: Algorithms, Methods, and Techniques*, 242–264: IGI Global, 10.4018/978-1-60566-766-9.ch011.

Tymula, Agnieszka, Lior A. Rosenberg Belmaker, Lital Ruderman, Paul W. Glimcher, and Ifat Levy (2013) "Like cognitive function, decision making across the life span shows profound age-related changes," *Proceedings of the National Academy of Sciences*, 110 (42), 17143–17148, 10.1073/pnas.1309909110.

UKCPR (2023) "UKCPR National Welfare Data, 1980-2021," Lexington, KY, http://ukcpr.org/resources/national-welfare-data.

Vaghul, Kavya and Ben Zipperer (2022) "Historical State and Sub-state Minimum Wages," https://github.com/benzipperer/historicalminwage/releases/tag/v1.4.0.

Van Calster, Ben, David J. McLernon, Maarten van Smeden et al. (2019) "Calibration: the Achilles heel of predictive analytics," *BMC Medicine*, 17 (1), 230, 10.1186/s12916-019-1466-7.

Vergouwe, Yvonne, Karel G. M. Moons, and Ewout W. Steyerberg (2010) "External Validity of Risk Models: Use of Benchmark Values to Disentangle a Case-Mix Effect From Incorrect Coefficients," *American Journal of Epidemiology*, 172 (8), 971–980, 10.1093/aje/kwq223.

Virtanen, Marianna, Archana Singh-Manoux, Jane E. Ferrie et al. (2009) "Long Working Hours and Cognitive Function: The Whitehall II Study," *American Journal of Epidemiology*, 169 (5), 596–605, 10.1093/aje/kwn382.

Wickrama, Kandauda (K.A.S.), Catherine W. O'Neal, Kyung H. Kwag, and Tae K. Lee (2013) "Is Working Later in Life Good or Bad for Health? An Investigation of Multiple Health Outcomes," *The Journals of Gerontology: Series B*, 68 (5), 807–815, 10.1093/geronb/gbt069.

Wimo, Anders, Katrin Seeher, Rodrigo Cataldi et al. (2023) "The worldwide costs of dementia in 2019," *Alzheimer's & Dementia*, 19 (7), 2865–2873, 10.1002/alz.12901.

World Bank (2022a) "Inflation, consumer prices (annual %)," `https://data.worldbank.org/indicator/FP.CPI.TOTL.ZG?end=2016&start=2006&view=chart`, Accessed: 2022-04-01.

——— (2022b) "PPP conversion factor, GDP (LCU per international $) - Korea, Rep.," `https://data.worldbank.org/indicator/PA.NUS.PPP?end=2016&locations=KR&start=2006`, Accessed: 2022-04-01.

——— (2024) "Purchasing Power Parity for South Korea," `https://data.worldbank.org/indicator/PA.NUS.PPP?end=2023&locations=KR&skipRedirection=true&start=2016&view=chart`, Accessed: 2024-07-24.

World Health Organization (2022) "Optimizing Brain Health Across the Life Course: WHO Position Paper," Geneva: World Health Organization, `https://creativecommons.org/licenses/by-nc-sa/3.0/igo/`, Licence: CC BY-NC-SA 3.0 IGO.

Xue, Baowen, Dorina Cadar, Maria Fleischmann, Stephen Stansfeld, Ewan Carr, Mika Kivimäki, Anne McMunn, and Jenny Head (2018) "Effect of retirement on cognitive function: the Whitehall II cohort study," *European Journal of Epidemiology*, 33 (10), 989–1001, 10.1007/s10654-017-0347-7.

Yu, Zhixiu (2024) "Why are older men working more? The role of social security," *Journal of Public Economics*, 231, 105071, 10.1016/j.jpubeco.2024.105071.

Appendices

Table A1.1: Cognitive measurement

Data	KLoSA	HRS
Measurement (point)	K-MMSE (30)	HRS-TICS (27)
Immediate word recall (3/10)	✓(three words)	✓(ten words)
Delayed word recall (3/10)	✓(three words)	✓(ten words)
Serial 7s (5)	✓	✓
Backwards counting (2)		✓
Date (5—4)	✓	
Place (5)	✓	
Language (9)	✓	

Table A1.2: Descriptive statistics by labor force transition in KLoSA

	Entry case N_{obs}=260	Entry control N_{obs}=1904	Exit case N_{obs}=691	Exit control N_{obs}=2260	*P value*	N_{obs}
K-MMSE	24.8 (4.60)	24.6 (4.87)	25.0 (4.55)	25.8 (4.07)	<0.001	5115
Age	71.0 (4.65)	72.5 (5.33)	72.2 (5.38)	70.8 (4.57)	<0.001	5115
Birth Year<1945	176 (67.7%)	1450 (76.2%)	531 (76.8%)	1609 (71.2%)	<0.001	5115
Female	140 (53.8%)	930 (48.8%)	319 (46.2%)	886 (39.2%)	<0.001	5115
Education:					0.042	5115
Up to Primary	157 (60.4%)	1083 (56.9%)	428 (61.9%)	1328 (58.8%)		
Secondary	43 (16.5%)	288 (15.1%)	102 (14.8%)	371 (16.4%)		
High School	42 (16.2%)	380 (20.0%)	119 (17.2%)	436 (19.3%)		
Above High School	18 (6.92%)	153 (8.04%)	42 (6.08%)	125 (5.53%)		
Spouse/Partner	201 (77.3%)	1391 (73.1%)	516 (74.7%)	1914 (84.7%)	<0.001	5115
Household Asset:					0.001	5115
Low	98 (37.7%)	682 (35.8%)	262 (37.9%)	753 (33.3%)		
Middle	103 (39.6%)	600 (31.5%)	242 (35.0%)	783 (34.6%)		
High	59 (22.7%)	622 (32.7%)	187 (27.1%)	724 (32.0%)		
Household Income:					<0.001	5098
Low	108 (41.7%)	776 (40.9%)	211 (30.6%)	552 (24.5%)		
Middle	79 (30.5%)	589 (31.1%)	270 (39.1%)	902 (40.0%)		
High	72 (27.8%)	531 (28.0%)	209 (30.3%)	799 (35.5%)		
Occupation Level:					<0.001	4088
Elementary	60 (48.8%)	565 (40.5%)	243 (40.6%)	565 (28.7%)		
Service/Skilled-Manual	58 (47.2%)	730 (52.3%)	325 (54.3%)	1291 (65.5%)		
Managerial/Professional	5 (4.07%)	101 (7.23%)	31 (5.18%)	114 (5.79%)		

continued on next page

Table A1.2 – *continued from previous page*

	Entry case N_{obs}=260	Entry control N_{obs}=1904	Exit case N_{obs}=691	Exit control N_{obs}=2260	*P value*	N_{obs}
Self-Reported Health:					.	5115
Poor	66 (25.4%)	568 (29.8%)	161 (23.3%)	414 (18.3%)		
Fair	104 (40.0%)	778 (40.9%)	297 (43.0%)	959 (42.4%)		
Good	78 (30.0%)	500 (26.3%)	215 (31.1%)	782 (34.6%)		
Very good	10 (3.85%)	53 (2.78%)	15 (2.17%)	96 (4.25%)		
Excellent	2 (0.77%)	5 (0.26%)	3 (0.43%)	9 (0.40%)		

Notes: All covariates are measured at one wave prior to the transition. Listed values are mean (± standard deviation) or total number (%). Asset/income are inflation adjusted. Occupation level is calculated with last observation due to high missingness. *Source*: KLoSA 2006-2020, own calculations.

Table A1.3: Descriptive statistics by labor force transition in HRS

	Entry case N_{obs}=533	Entry control N_{obs}=4890	Exit case N_{obs}=1353	Exit control N_{obs}=3241	*P value*	N_{obs}
HRS-TICS	15.5 (3.93)	15.3 (3.99)	15.8 (3.96)	16.2 (3.90)	<0.001	10017
Age	71.4 (5.22)	72.6 (5.56)	71.7 (5.18)	71.2 (4.95)	<0.001	10017
Birth Year<1945	397 (74.5%)	3694 (75.5%)	1002 (74.1%)	2362 (72.9%)	0.061	10017
Female	264 (49.5%)	2815 (57.6%)	725 (53.6%)	1632 (50.4%)	<0.001	10017
Education:					<0.001	10003
up to 6 yrs	13 (2.44%)	163 (3.34%)	30 (2.22%)	77 (2.38%)		
7-9 yrs	28 (5.25%)	247 (5.06%)	82 (6.07%)	143 (4.42%)		
10-12 yrs	212 (39.8%)	2139 (43.8%)	543 (40.2%)	1108 (34.3%)		
> 12 yrs	280 (52.5%)	2337 (47.8%)	696 (51.5%)	1905 (58.9%)		
Spouse/Partner	348 (65.5%)	3071 (62.8%)	891 (65.9%)	2186 (67.5%)	<0.001	10010
Household Asset:					<0.001	10017
Low	197 (37.0%)	1707 (34.9%)	474 (35.0%)	995 (30.7%)		
Middle	166 (31.1%)	1727 (35.3%)	463 (34.2%)	1077 (33.2%)		
High	170 (31.9%)	1456 (29.8%)	416 (30.7%)	1169 (36.1%)		
Household Income:					<0.001	10017
Low	215 (40.3%)	2130 (43.6%)	388 (28.7%)	701 (21.6%)		
Middle	176 (33.0%)	1703 (34.8%)	486 (35.9%)	1115 (34.4%)		
High	142 (26.6%)	1057 (21.6%)	479 (35.4%)	1425 (44.0%)		
Occupation Level:					<0.001	8311
Elementary	57 (17.1%)	474 (12.0%)	134 (11.8%)	290 (9.98%)		
Service/Skilled-Manual	178 (53.3%)	2343 (59.5%)	645 (56.9%)	1689 (58.1%)		
Managerial/Professional	99 (29.6%)	1120 (28.4%)	354 (31.2%)	928 (31.9%)		

continued on next page

Table A1.3 – *continued from previous page*

	Entry case N_{obs}=533	Entry control N_{obs}=4890	Exit case N_{obs}=1353	Exit control N_{obs}=3241	*P value*	N_{obs}
Self-Reported Health:					<0.001	10010
Very Bad	10 (1.88%)	190 (3.89%)	24 (1.78%)	26 (0.80%)		
Bad	76 (14.3%)	882 (18.1%)	194 (14.3%)	356 (11.0%)		
Fair	193 (36.2%)	1830 (37.5%)	501 (37.1%)	1045 (32.3%)		
Good	191 (35.8%)	1613 (33.0%)	509 (37.6%)	1372 (42.4%)		
Very Good	63 (11.8%)	371 (7.59%)	124 (9.17%)	440 (13.6%)		
Race/Ethnicity:					0.020	10017
Non-Hispanic white	405 (76.0%)	3537 (72.3%)	1018 (75.2%)	2457 (75.8%)		
Non-Hispanic black	68 (12.8%)	792 (16.2%)	206 (15.2%)	455 (14.0%)		
Hispanic	49 (9.19%)	437 (8.94%)	101 (7.46%)	245 (7.56%)		
Non-Hispanic other	11 (2.06%)	124 (2.54%)	28 (2.07%)	84 (2.59%)		
Foreign birh:	47 (8.82%)	525 (10.7%)	133 (9.83%)	290 (8.95%)	0.050	10017

Notes: All covariates are measured at one wave prior to the transition. Listed values are mean (± standard deviation) or total number (%). Asset/income are inflation adjusted. Occupation level is calculated with last observation due to high missingness. *Source*: HRS 2006-2020, own calculations.

Table A1.4: Descriptive statistics by survey participation ≥ 5 in KLoSA at the entry of the study

	< 5 waves N=2161	≥ 5 waves N=1872	*P value*	N
K-MMSE	27.0 (3.58)	25.9 (4.01)	<0.001	4033
Age	63.0 (3.71)	64.9 (4.46)	<0.001	4033
Birth Year<1945:	444 (20.5%)	1151 (61.5%)	<0.001	4033
Female:	941 (43.5%)	816 (43.6%)	1.000	4033
Education:			<0.001	4033
Up to Primary	656 (30.4%)	1038 (55.4%)		
Secondary	431 (19.9%)	306 (16.3%)		
High School	800 (37.0%)	392 (20.9%)		
Above High School	274 (12.7%)	136 (7.26%)		
Spouse/Partner:	1863 (86.2%)	1578 (84.3%)	0.095	4033
Household Asset:			<0.001	2450
Low	448 (26.1%)	255 (34.8%)		
Middle	525 (30.6%)	248 (33.9%)		
High	745 (43.4%)	229 (31.3%)		
Household Income:			<0.001	3950
Low	373 (17.5%)	698 (38.5%)		
Middle	622 (29.1%)	573 (31.6%)		
High	1141 (53.4%)	543 (29.9%)		
Occupation Level:			0.001	2460
Elementary	431 (32.1%)	302 (27.1%)		
Service/Skilled-Manual	780 (58.0%)	731 (65.5%)		

continued on next page

Table A1.4 – *continued from previous page*

	< 5 waves N=2161	≥ 5 waves N=1872	*P value*	N
Managerial/Professional	133 (9.90%)	83 (7.44%)		
Self-Reported Health:			<0.001	4033
Poor	264 (12.2%)	386 (20.6%)		
Fair	746 (34.5%)	597 (31.9%)		
Good	966 (44.7%)	720 (38.5%)		
Very good	166 (7.68%)	140 (7.48%)		
Excellent	19 (0.88%)	29 (1.55%)		

Notes: All covariates are measured at the study entry regardless of waves. Listed values are mean (± standard deviation) or total number (%). Less than 5 waves is a group that participated survey less than five waves. Asset/income are inflation adjusted. Occupation level is calculated with last observation due to high missingness. *Sources*: KLoSA 2006-2020, own calculations.

Table A1.5: Descriptive statistics by survey participation ≥ 5 in HRS at the entry of the study

	< 5 waves N=6089	≥ 5 waves N=4070	*P value*	N
HRS-TICS	16.1 (4.23)	16.6 (3.87)	<0.001	10159
Age	63.3 (4.28)	65.5 (4.90)	<0.001	10159
Birth Year<1945:	1036 (17.0%)	2596 (63.8%)	0.000	10159
Female:	3150 (51.7%)	2194 (53.9%)	0.033	10159
Education:			<0.001	10103
up to 6 yrs	299 (4.95%)	122 (3.00%)		
7-9 yrs	254 (4.20%)	209 (5.15%)		
10-12 yrs	2066 (34.2%)	1565 (38.5%)		
$>$ 12 yrs	3424 (56.7%)	2164 (53.3%)		
Spouse/Partner:	3563 (69.0%)	2892 (71.1%)	0.032	9236
Household Asset:			<0.001	9238
Low	2029 (39.3%)	1182 (29.0%)		
Middle	1676 (32.4%)	1360 (33.4%)		
High	1463 (28.3%)	1528 (37.5%)		
Household Income:			<0.001	9238
Low	1573 (30.4%)	972 (23.9%)		
Middle	1555 (30.1%)	1415 (34.8%)		
High	2040 (39.5%)	1683 (41.4%)		
Occupation Level::			0.001	5282
Elementary	302 (12.8%)	328 (11.2%)		
Service/Skilled-Manual	1196 (50.7%)	1636 (56.0%)		

continued on next page

Table A1.5 – *continued from previous page*

	< 5 waves N=6089	≥ 5 waves N=4070	*P value*	N
Managerial/Professional	860 (36.5%)	960 (32.8%)		
Self-Reported Health::			<0.001	9232
Very Bad	196 (3.80%)	67 (1.65%)		
Bad	995 (19.3%)	537 (13.2%)		
Fair	1709 (33.1%)	1340 (32.9%)		
Good	1707 (33.1%)	1499 (36.8%)		
Very Good	557 (10.8%)	625 (15.4%)		
Race/Ethnicity:			<0.001	10159
Non-Hispanic white	3633 (59.7%)	2964 (72.8%)		
Non-Hispanic black	1261 (20.7%)	642 (15.8%)		
Hispanic	972 (16.0%)	362 (8.89%)		
Non-Hispanic other	223 (3.66%)	102 (2.51%)		
Foreign birh:	1003 (16.5%)	417 (10.2%)	<0.001	10159

Notes: All covariates are measured at the study entry regardless of waves. Listed values are mean (± standard deviation) or total number (%). Less than 5 waves is a group that participated survey less than five waves. Asset/income are inflation adjusted. Occupation level is calculated with last observation due to high missingness. *Sources*: HRS 2006-2020, own calculations.

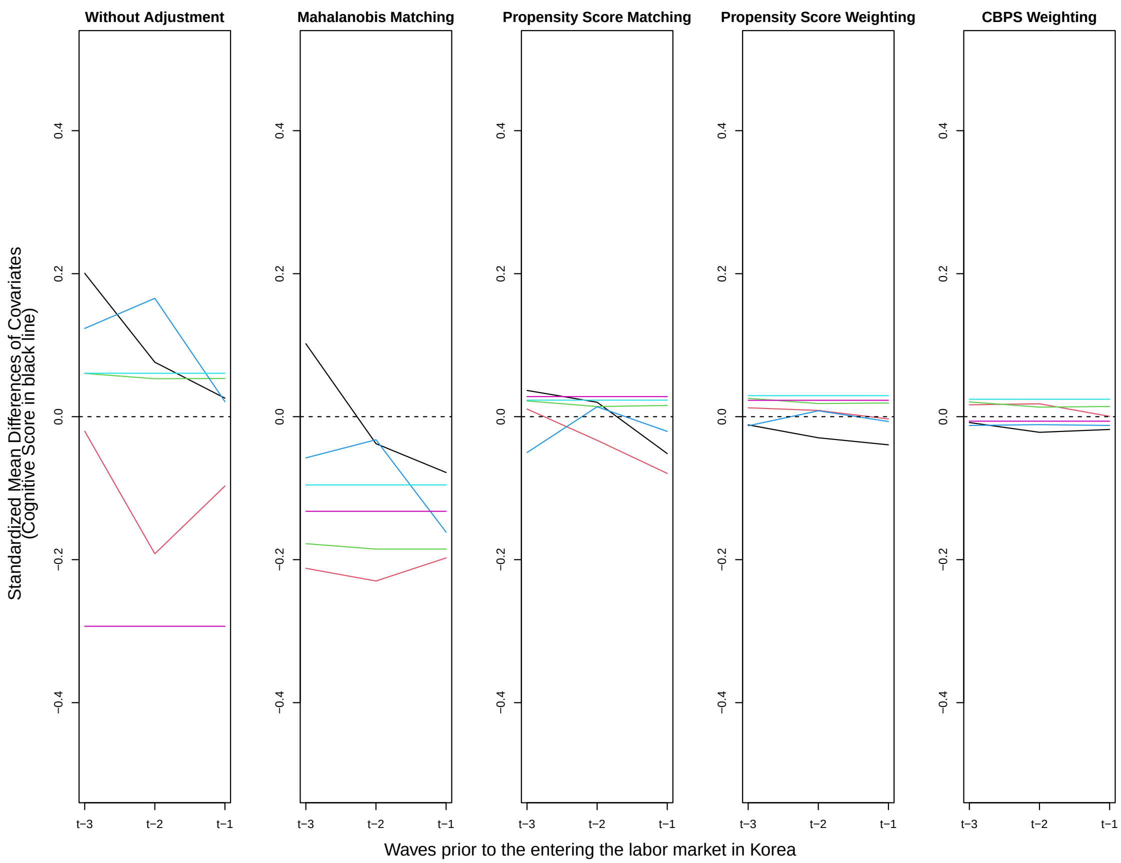


Figure A1.1: **Covariate balances comparisons in KLoSA of entering the labor market** Each plot presents the standardized mean difference of covariates over the pre-treatment time period with KLoSA data for the case of entering the labor market. The first column represents the unadjusted balance, and the next four columns compare the different balancing methods. The black line represents the balance of the lagged cognitive scores, whereas the colored lines represent highlighted covariates; age (purple), health (red), education (green), asset (blue), and female (light blue).

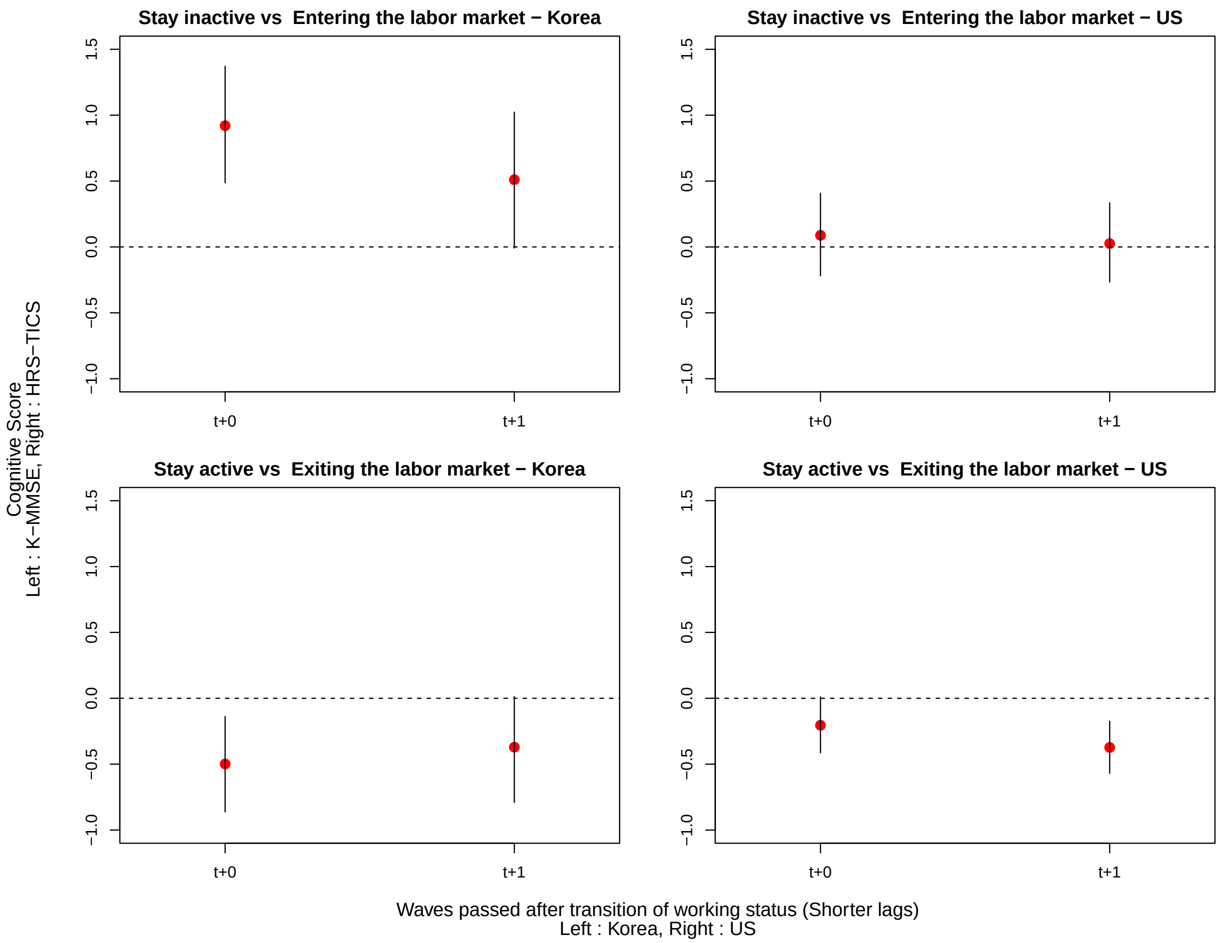


Figure A1.2: **Estimated effects of entry to and exit from the late-life labor market on cognitive function with shorter lags** The estimation results are obtained after matching according to treatment history and covariate balancing propensity score (CBPS) weighting with covariate histories during the two waves before the treatment. The left panel indicates the results from the Korean sample and the right panel from the US sample. The estimates for the average effects of entering the labor market (upper panel) and exiting (bottom panel) are shown for the period of immediate and one wave after the transition, with 95% asymptotic confidence intervals as vertical bars. CBPS weighting is chosen for its best performance in adjustment.

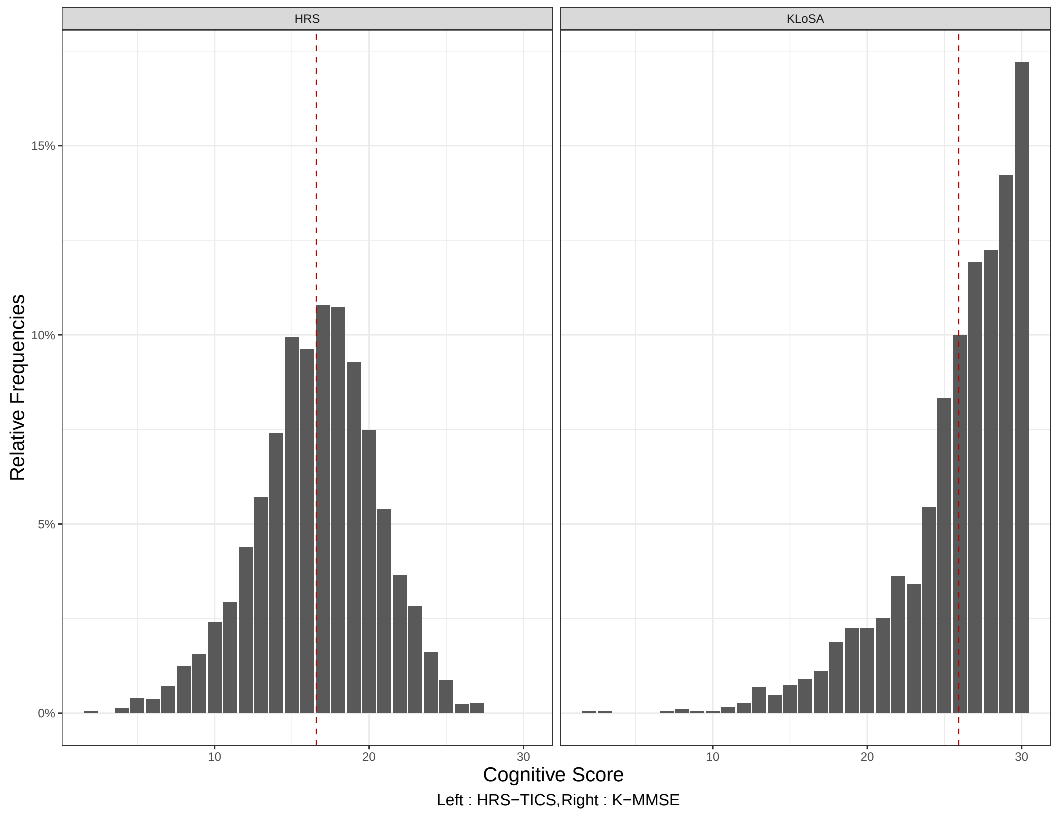


Figure A1.3: **Distribution of cognitive score** The bar graphs show the distribution of relative frequencies in each value of cognitive score within each data set. The left panel indicates the distribution of US data. Cognitive function is measured by HRS-TICS ranging from 0 to 27. The right panel displays the distribution of Korean data. Cognitive function is measured by K-MMSE, ranging from 0 to 30. For both measurements, higher values indicate better function. The red dotted line represents the average cognitive score.

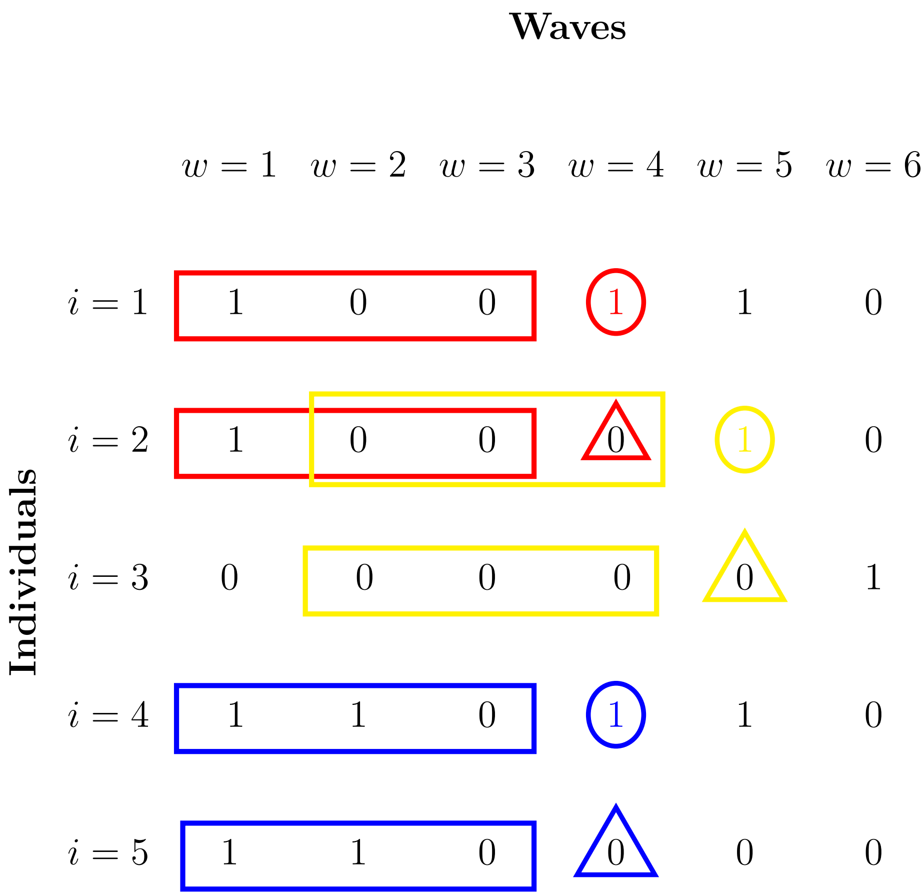


Figure A1.4: **An example of employment history matching for the case of entry to the labor market** This panel shows how matched sets are made when the number of lags is 3 with one wave lead. Waves are read from left to right. We present the case when the treatment is "entering the labor market", value 1 indicates working and 0 for not-working. Treatment observation (circles) and control observations (triangles) with the same color share the same employment history (rectangles). Likewise, we make separate matching sets for the treatment "exiting the labor market.
Source: Adapted from Imai et al. (2023), Figure 2.

Table A2.1 : Minimum wage and binary version of self-reported health.

	Self-reported health	
	Before weighting	After weighting
MW increase	0.025	-0.019
	(0.049)	(0.044)
Observations	924	924

Notes: This table presents an estimate of the impact of the 2016 to 2018 minimum wage increase on health outcomes. The intervention group comprised participants who reported hourly wages below the minimum wage. Participants reporting hourly wages equal to 100-150% of the minimum wage were selected as the control group. Self-reported health was re-coded into binary variable with fair/good cutoff. Column 1 report the unadjusted estimation results. Column 2 show propensity-weighted estimation results. All specifications used time-varying variables such as pension status, marital status and 5-year age categorisation. The standard errors are reported in parentheses. *p<0.05, **: p<0.01, ***: p<0.001.

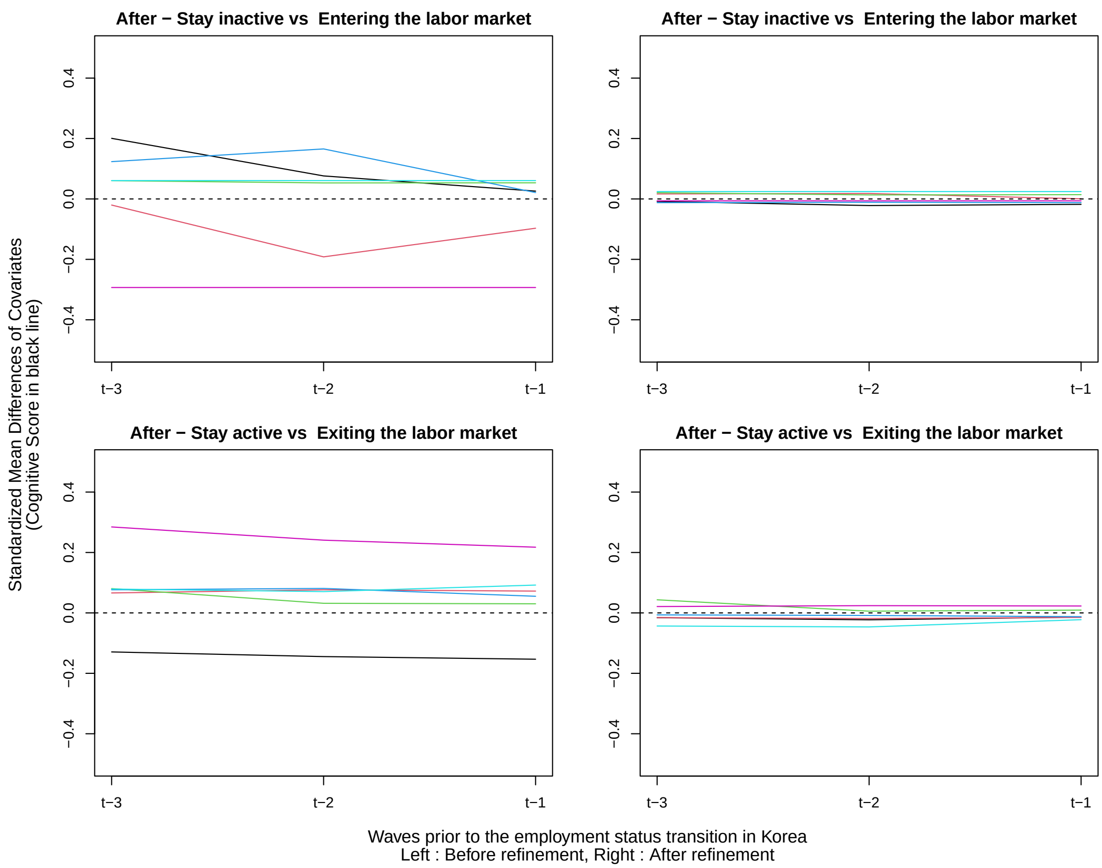


Figure A1.5: **Covariate balance in KLoSA** Each plot presents the standardized mean difference of covariates over the pre-treatment time period with Korean data. The upper panel represents the balance from entering the labor market and the bottom from the exit. The left column shows the balance before refinement. The right column displays covariate balance after CBPS weighting. The black line represents the balance of the lagged cognitive scores, whereas the colored lines represent highlighted covariates; age (purple), health (red), education (green), asset (blue), and female (light blue).

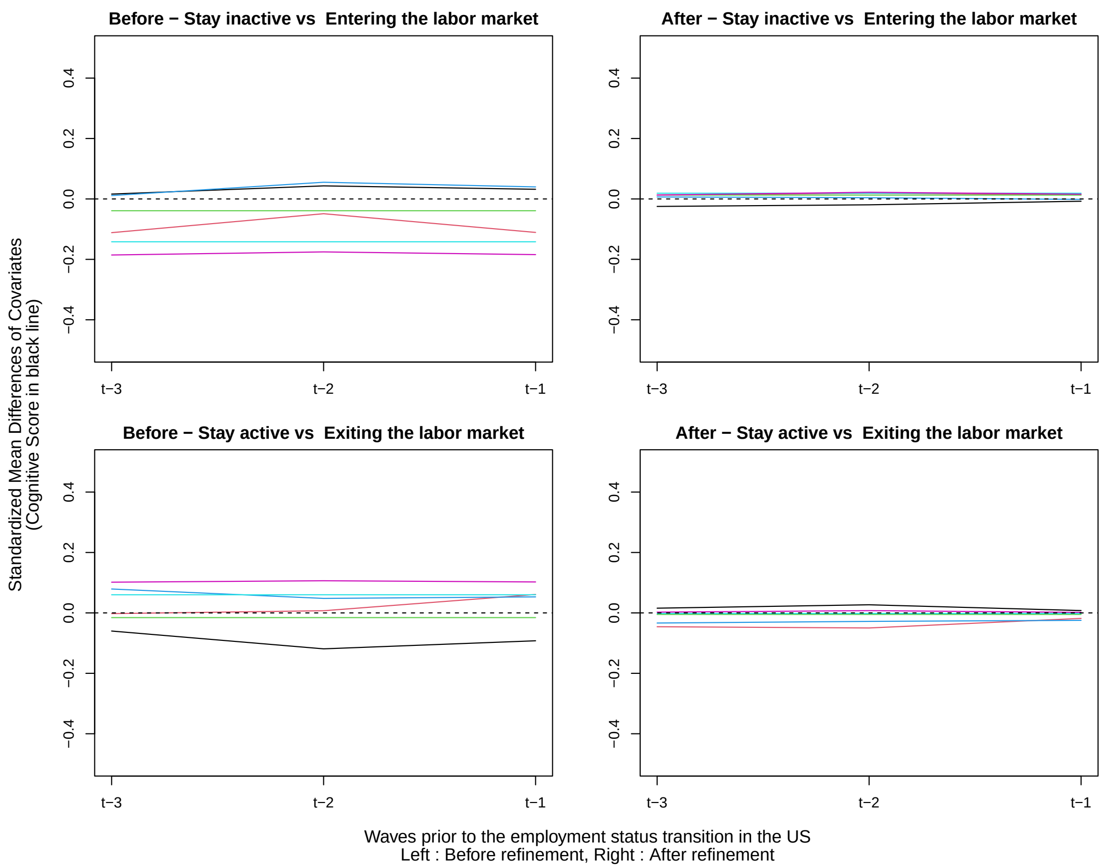


Figure A1.6: **Covariate balances in HRS** Each plot presents the standardized mean difference of covariates over the pre-treatment time period with US data. The upper panel represents the balance from entering the labor market and the bottom from the exit. The left column shows the balance before refinement. The right column displays covariate balance after CBPS weighting. The black line represents the balance of the lagged cognitive scores, whereas the colored lines represent highlighted covariates; age (purple), health (red), education (green), asset (blue), and female (light blue).

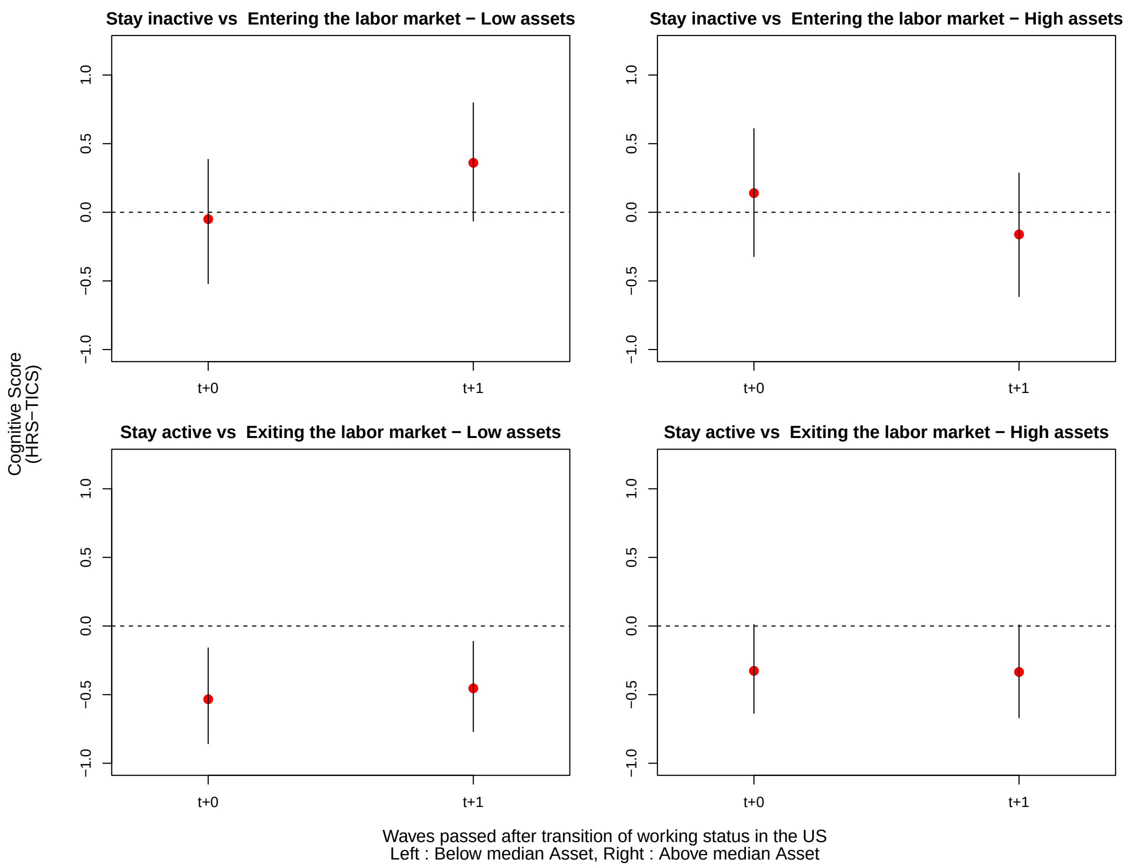


Figure A1.7: **Subgroup analyses by baseline median asset level with HRS sample.** The estimation results are obtained after matching according to treatment history and CBPS weighting with covariate histories during the three waves before the treatment. The left panel indicates the results from individuals with baseline asset levels below the median, and the right panel above the median. The estimates for the average effects of entering the labor market (upper panel) and exiting (bottom panel) are shown for the period of immediate and one wave after the transition, with 95% asymptotic confidence intervals as vertical bars. CBPS weighting is chosen for its best performance in adjustment.

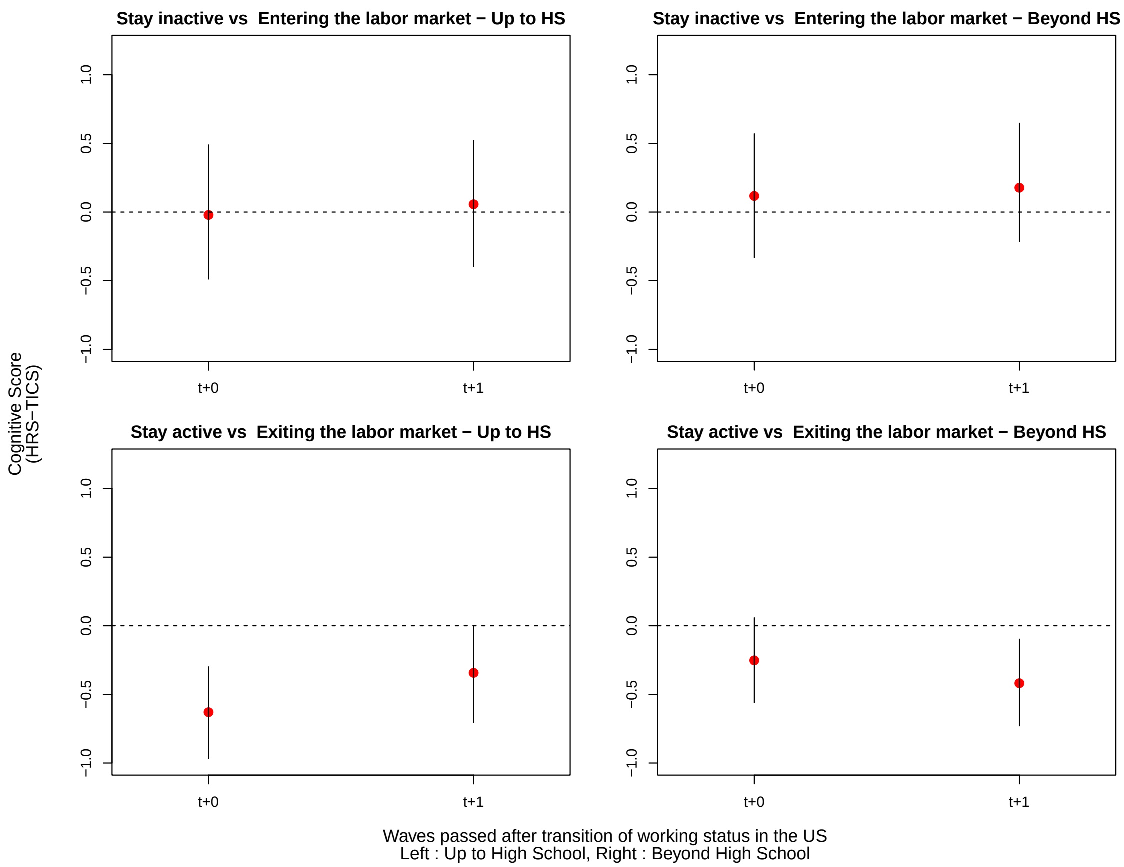


Figure A1.8: **Subgroup analyses by education level with HRS sample.** The estimation results are obtained after matching according to treatment history and CBPS weighting with covariate histories during the three waves before the treatment. The left panel indicates the results from individuals up to high school education, and the right panel for those beyond high school. The estimates for the average effects of entering the labor market (upper panel) and exiting (bottom panel) are shown for the period of immediate and one wave after the transition, with 95% asymptotic confidence intervals as vertical bars. CBPS weighting is chosen for its best performance in adjustment.

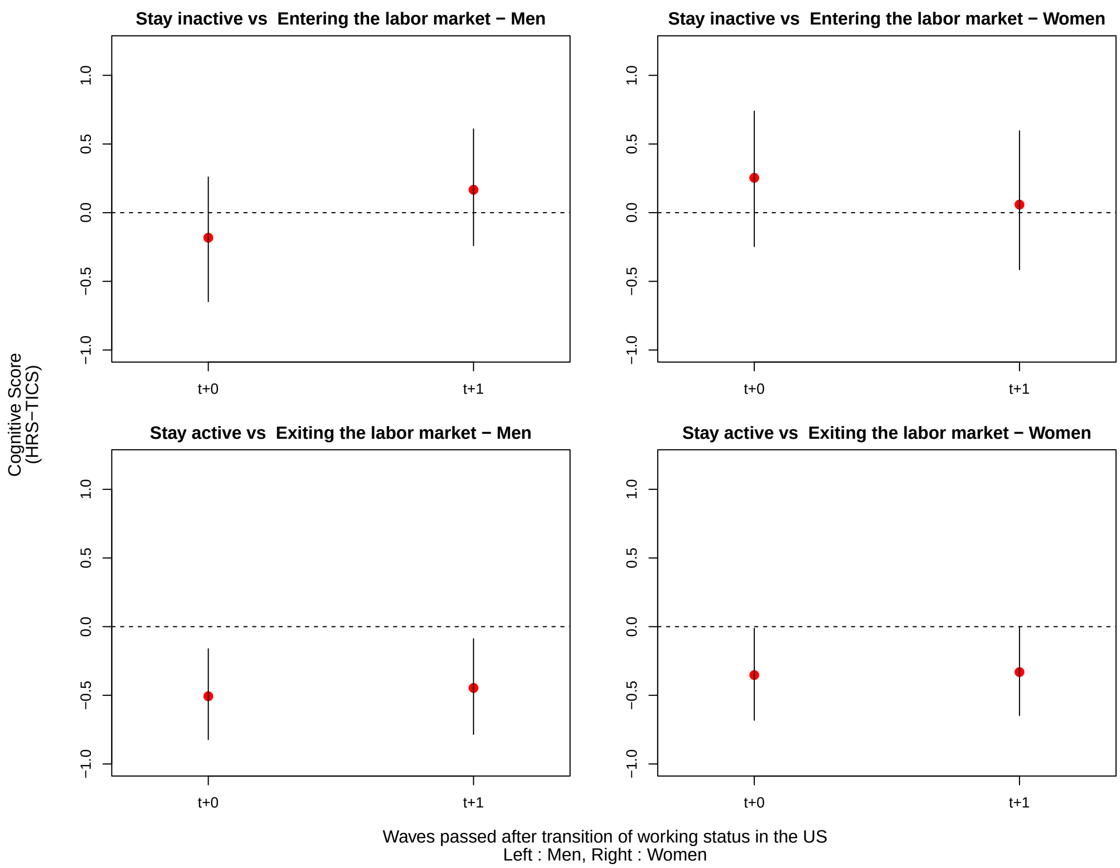


Figure A1.9: **Subgroup analyses by sex/gender level with HRS sample.** The estimation results are obtained after matching according to treatment history and CBPS weighting with covariate histories during the three waves before the treatment. The left panel indicates the results from the men's sample and and the right panel for the women. The estimates for the average effects of entering the labor market (upper panel) and exiting (bottom panel) are shown for the period of immediate and one wave after the transition, with 95% asymptotic confidence intervals as vertical bars. CBPS weighting is chosen for its best performance in adjustment.

Table A2.2 : Descriptive statistics of targeted individuals regardless of subsequent employment status

Variable	Out of labour market N=123	Remain in labour market N=313	p-value	N
	Mean (SD) for continuous variable otherwise %			
Cognitive function	26.09 (4.29)	27.59 (2.56)	0.001	436
Self-Reported Health:			0.040	436
Bad	16	7.9		
Normal	45	41		
Good	38	44		
Very Good	1.9	6.5		
Best	0	0.3		
Age	64.11 (6.18)	62.47 (5.90)	0.015	436
Female	68	52	0.007	436
Education:			0.005	436
$\leq$ Elementary school	49	29		
Middle school	19	28		
High school	31	36		
$\geq$ College/University	1.4	7.5		
Married:	75	84	0.066	436
Working hours (week)	42.01 (17.29)	46.86 (20.51)	0.055	436
Working days (week)	4.86 (1.28)	4.97 (1.05)	0.4	436
Monthly Income (10,000KRW)	92.32 (41.09)	107.92 (41.99)	0.002	436

Notes: This table describes the means of the observable characteristics comparing individuals with earnings below the minimum wage based on their subsequent employment status. Listed values are mean (standard deviation) for continuous variables and percentages otherwise. Survey sampling weights were used in the summary statistics. P-values indicate statistical differences between the two groups. All values were measured in 2016, prior to the minimum wage hike.

Table A2.3 : Potential mechanisms.

Dependent variable:	Working hours	Income	Job satisfaction	Job security	Drinking	Smoking
MW increase	-4.061^{***}	17.46^{***}	-0.021	0.103	-0.004	0.027
	(1.122)	(4.372)	(0.048)	(0.053)	0.004	0.015
Observations	924	924	922	924	924	924

Notes: This table presents an estimate of the impact of the 2016 to 2018 minimum wage increase on health outcomes. The intervention group comprised participants who reported hourly wages below the minimum wage. Participants reporting hourly wages equal to 100-150% of the minimum wage were selected as the control group. Working hours refer to the weekly working hours. Income is the current monthly salary. Job satisfaction and job security are re-coded into binary variables with 1 indicating positive experience. Drinking and smoking are binary variables representing the current status (Yes/No). All specifications used time-varying variables including pension status, marital status and 5-year age categorisation. The standard errors are reported in parentheses. *p<0.05, **: p<0.01, ***: p<0.001.

Table A2.4 : Descriptive statistics with stringent intervention group

Variable	Intervention group N=60	Control group N=149	p-value	N
	Mean (SD) for continuous variable otherwise %			
Cognitive function	28.00 (2.09)	27.82 (2.65)	0.6	209
Self-Reported Health:			0.13	209
Bad	12	2.4		
Normal	39	33		
Good	39	57		
Very Good	8.1	5.3		
Best	1.3	2.1		
Age	61.47 (5.57)	59.82 (4.31)	0.036	209
Female	57	44	0.14	209
Education:			0.008	209
$\leq$ Elementary school	31	16		
Middle school	16	16		
High School	49	52		
$\geq$ College/University	3.2	16		
Married:	82	84	0.8	209
Working hours (week)	44.81 (11.89)	41.85 (10.07)	0.076	209
Working days (week)	5.23 (0.93)	5.10 (0.88)	0.4	209
Monthly Income (10,000KRW)	116.14 (29.65)	164.07 (42.14)	<0.001	209

Notes: This table describes the means of the characteristics when comparing the intervention and control groups. The intervention group was defined as participants whose new hourly wage after the policy change was between 100-120% of the minimum wage and whose pre-intervention hourly wages were below the minimum wage. Participants reporting hourly wages equal to 100-150% of the minimum wage were selected as the control group. Listed values are mean (standard deviation) for continuous variables and percentages otherwise. Survey sampling weights were used. P-values indicate statistical differences between the two groups. All values were measured in 2016, prior to the intervention.

Table A2.5 : Minimum wage and health - stringent intervention group.

	Stringent sample		Placebo test	
Dependent variable:	Cognitive function	SR health	Cognitive function	SR health
MW increase	-1.02^{*}	0.072	0.340	0.268^{**}
	(0.400)	(0.105)	(0.256)	(0.083)
Observations	418	418	542	542

Notes: This table presents an estimate of the impact of a minimum wage increase on health outcomes. The intervention group was defined as participants whose new hourly wage after the policy change was between 100-120% of the minimum wage and whose pre-intervention hourly wages were below the minimum wage. Participants reporting hourly wages equal to 100-150% of the minimum wage were selected as the control group. Propensity score weights were then applied. Cognitive scores range from 0 to 30, and self-rated health from 1 to 5. Columns 2-3 report large minimum wage increase from 2016 to 2018. Columns 4-5 show the modest increase from 2014 to 2016, which served as the placebo test. All specifications used time-varying variables such as pension status, marital status and 5-year age categorisation. Standard errors are reported in parentheses. *p<0.05, **: p<0.01, ***: p<0.001.

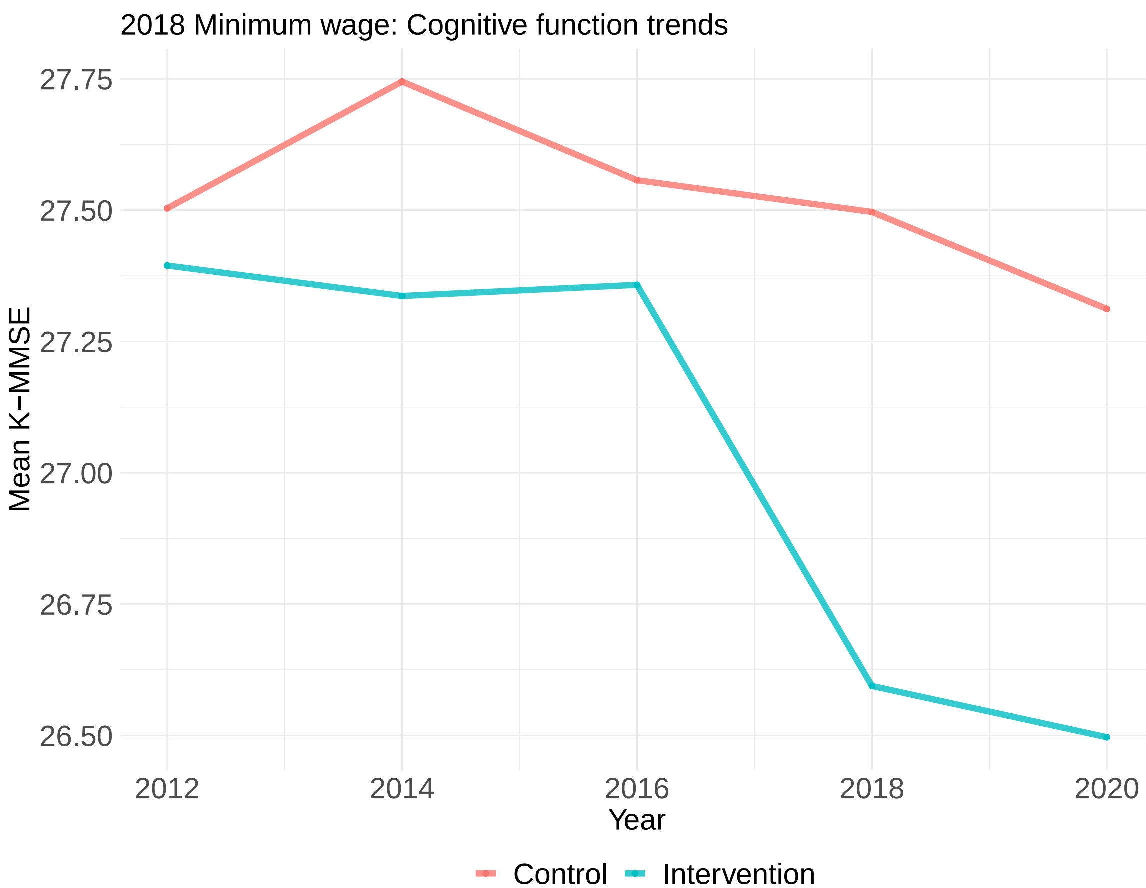


Figure A2.1 : **Trends in mean cognitive functioning** This figure presents the trends in mean cognitive functioning for intervention and control groups for the large minimum wage increase from 2016 to 2018. Cognitive function was measured by the Korean version of Mini-Mental State Examination (K-MMSE). K-MMSE ranges from 0 to 30. The intervention group comprised participants whose reported hourly wages in 2016 were below the new minimum wage. The control group included participants whose hourly wages in 2016 were between 100-150% of the new minimum wage.

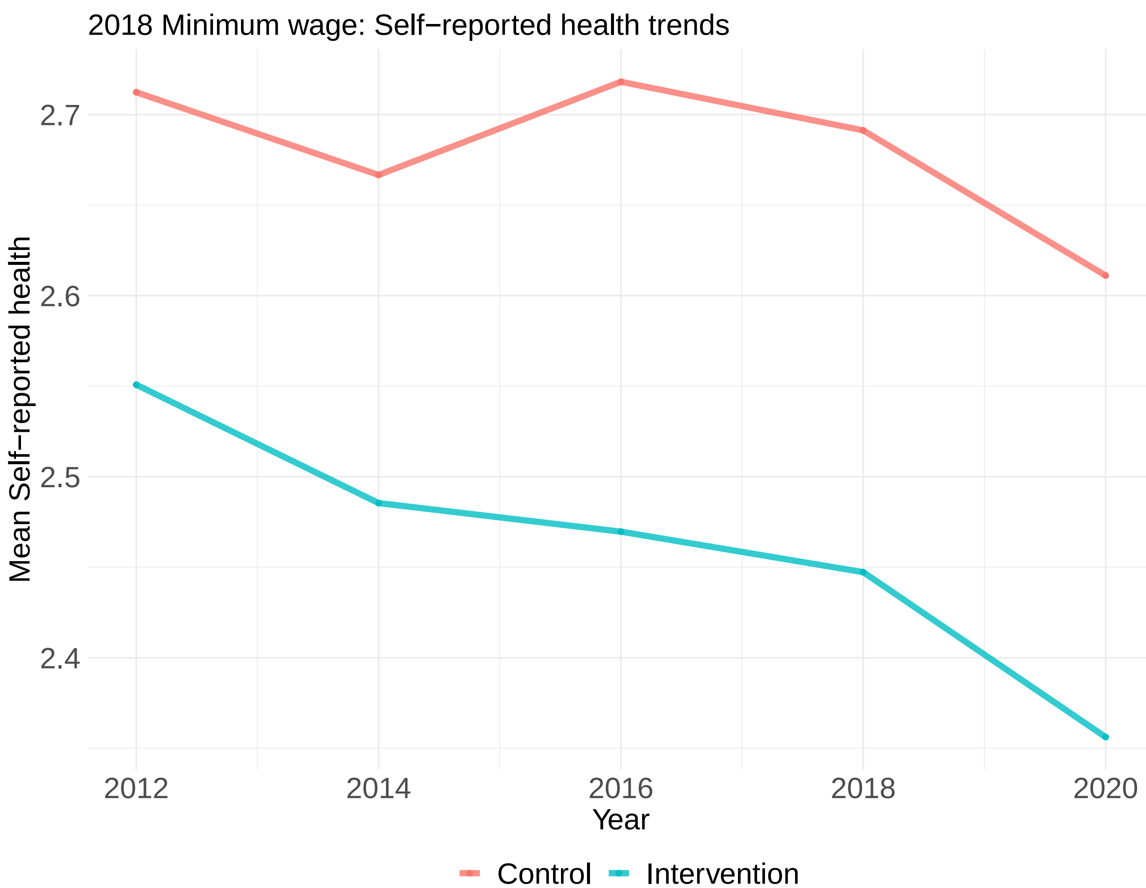


Figure A2.2 : **Trends in mean self-reported health** This figure presents the trends in mean self-reported health for intervention and control groups for the large minimum wage increase from 2016 to 2018. Self-reported health ranges from 0 to 5. The intervention group comprised participants whose reported hourly wages in 2016 were below the new minimum wage. The control group included participants whose hourly wages in 2016 were between 100-150% of the new minimum wage.

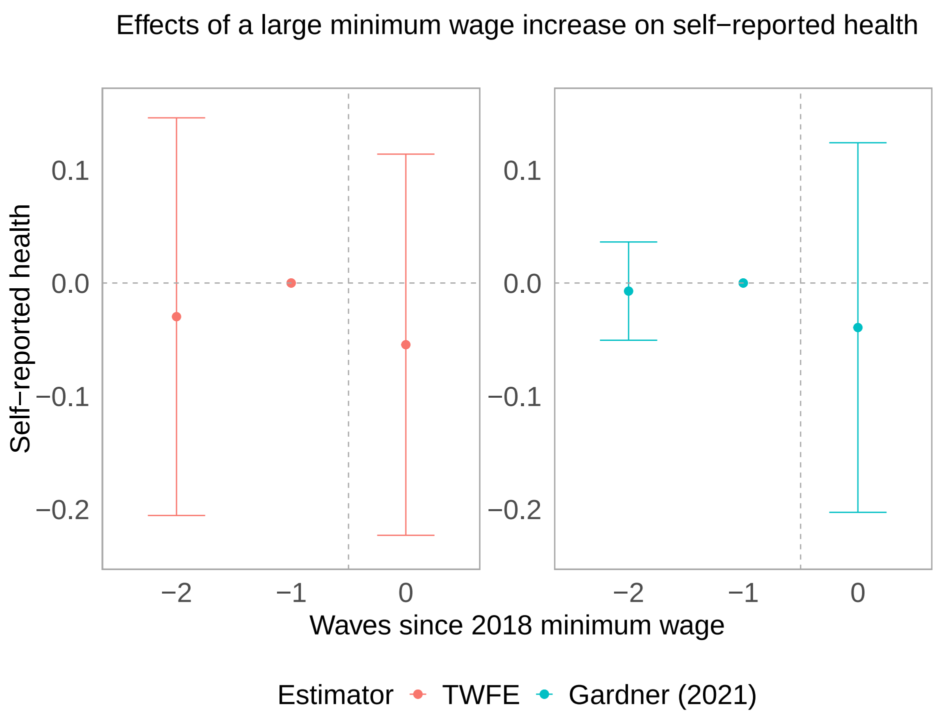


Figure A2.3 : **Event study results regarding self-reported health** These figures present the dynamic effects of the large minimum wage increase from 2016 to 2018 on cognitive functioning. The left panel shows the results from using a two-way fixed effects estimator, while the right panel displays the results from the two-stage difference-in-differences estimator. Self-reported health ranges from 0 to 5. The intervention group comprised participants whose reported hourly wages in 2016 were below the new minimum wage. The control group included participants whose hourly wages in 2016 were between 100-150% of the new minimum wage.

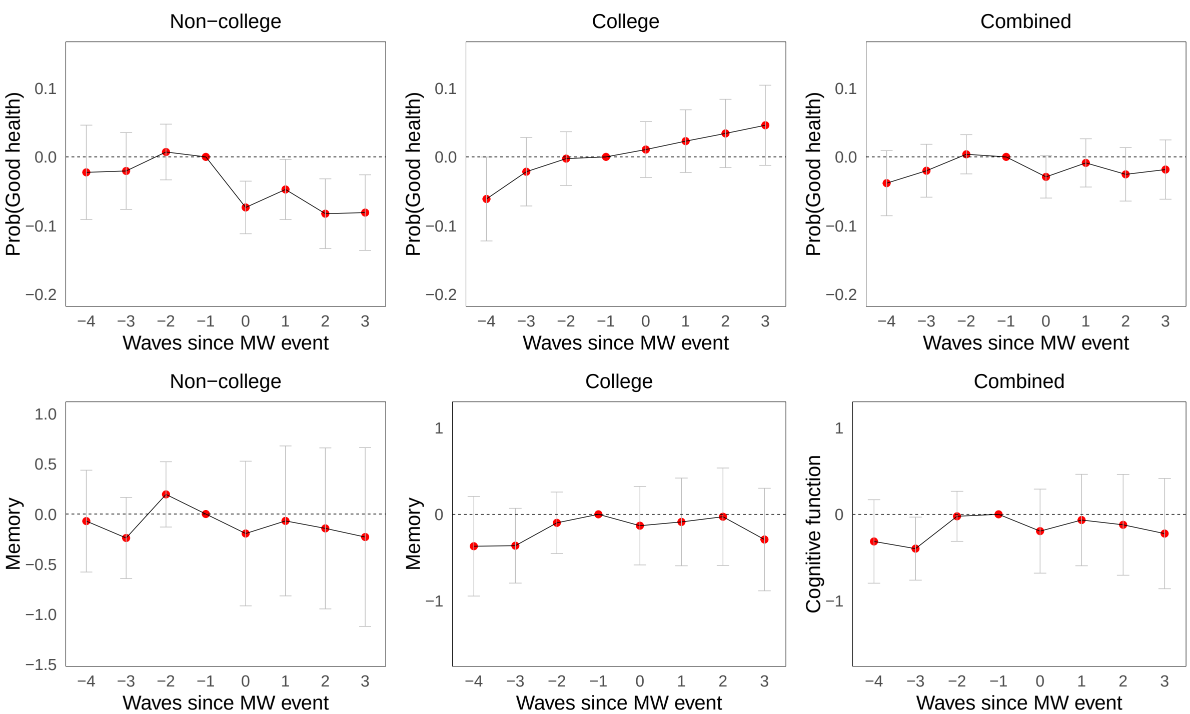


Figure A3.1 : **Minimum wage effects using alternative health outcomes.** The upper panels illustrate the minimum wage effects on the probability of reporting excellent or very good health and the bottom panels show the impacts on memory score measured by the immediate and delayed word recall. *Source:* Health and Retirement Study 1996-2016

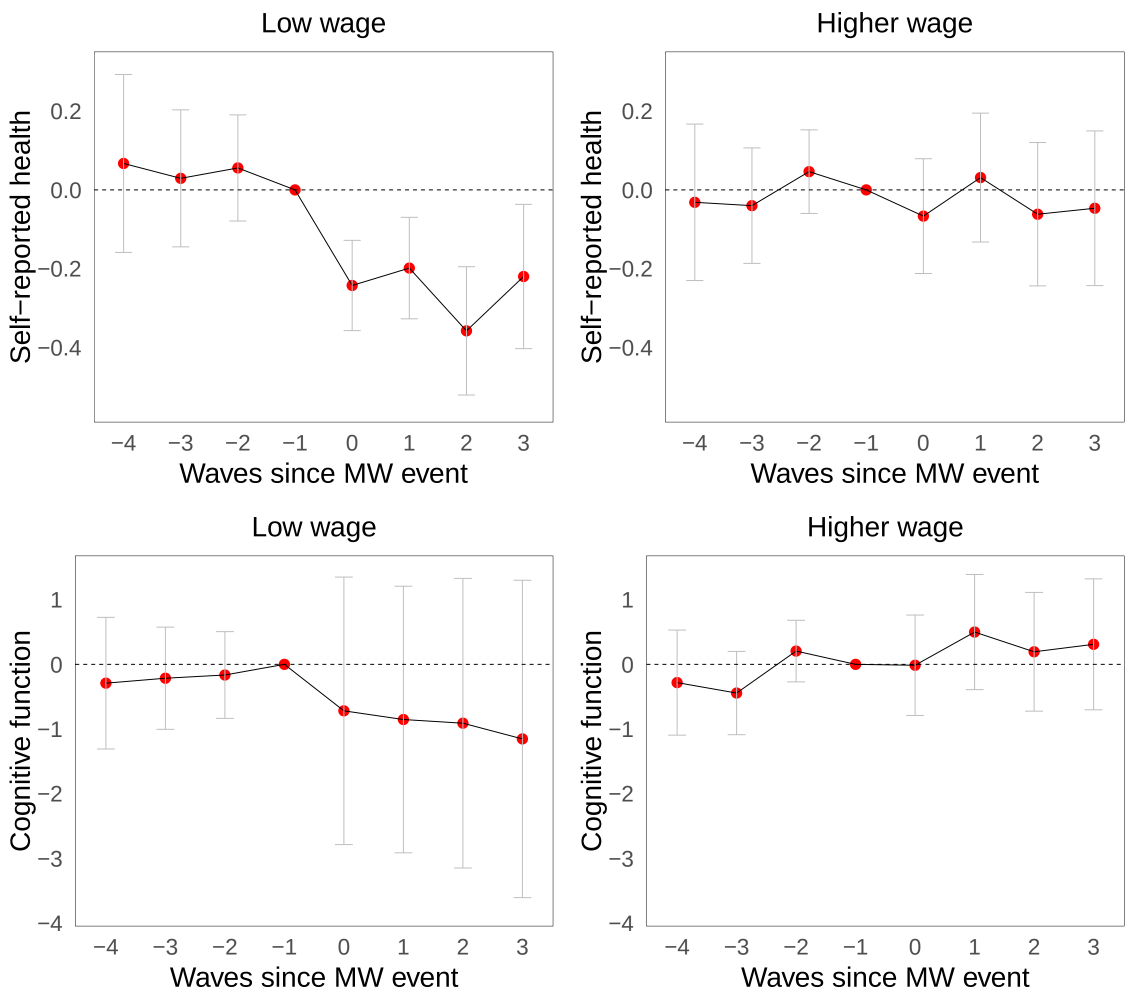


Figure A3.2 : **Minimum wage effects using alternative treatment design.** The upper panels illustrate the minimum wage effects on self-reported health by the wage levels regardless of the education level. The bottom panels show the impacts on cognitive function. Low-wage indicates the hourly wage below the prevailing minimum wage plus two dollars and higher wage is the hourly wage that falls between minimum wage plus two dollars and the double of the prevailing minimum wage. *Source:* Health and Retirement Study 1996-2016

Table A3.1 : State-level characteristics by gender and educational attainment

Gender	Women		Men	
Education	HS or less	BA or higher	HS or less	BA or higher
Minimum wage	7.7	7.9	7.7	7.8
	(0.8)	(0.9)	(0.8)	(0.9)
Observations	4945	3813	4369	3837
log GDP	12.8	13.0	12.8	13.0
	(0.9)	(1.0)	(1.0)	(0.9)
Observations	4945	3813	4369	3837
log Population	15.9	16.0	15.9	16.1
	(0.8)	(0.9)	(0.9)	(0.9)
Observations	4945	3813	4369	3837
log Share of SSI	12.1	12.2	12.1	12.3
	(1.0)	(1.1)	(1.1)	(1.1)
Observations	4945	3813	4369	3837

Notes: Table describes the state-level statistics of the sample of older workers aged 65 and above, covering years 1996-2016. Values in parentheses the standard deviations. Survey weights are applied.

Table A3.2 : Effects of minimum wage by wage group

	(1)	(2)	(3)	(4)	(5)	(6)
	Self-reported Health		Cognitive function		Income	Employment
Panel A: Low wage						
log MW	-0.605*	-0.559*	1.062	1.713	5846*	0.085
	(0.246)	(0.250)	(1.122)	(1.136)	(2859)	(0.130)
Observation	3180	3180	3036	3036	3180	3180
Panel B: Higher wage						
log MW	0.087	0.085	-0.122	-0.062	5670	0.075
	(0.183)	(0.065)	(0.818)	(0.828)	(3078)	(0.092)
Observation	5625	5625	5326	5326	5625	5625
Covariates	No	Yes	No	Yes	Yes	Yes

Notes: Self-reported health ranges from 0 to 5 and the cognitive function from 0 to 35, both with higher values indicating better health and cognitive function, respectively. Low-wage indicates the hourly wage below the prevailing minimum wage plus two dollars and higher wage is the hourly wage that falls between minimum wage plus two dollars and the double of the prevailing minimum wage. Income refers to annual earnings. Covariates include 5-year age categorization dummies, log state GDP, log social security income recipients, log population, and affordable care act expansion. All the models include individual and year fixed effects. Standard errors in parentheses clustered at the individual level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A3.3 : Effects of minimum wage increases on older adults with different age eligibility
(Age 65 for those born before 1943, 66 for those before 1960, 67 for those born in 1960 and later)

	(1)	(2)	(3)	(4)
	Self-reported Health		Cognitive function	
Panel A: High school or less				
log MW	-0.305*	-0.302*	-0.018	0.083
	(0.145)	(0.146)	(0.635)	(0.640)
Observation	8959	8959	8346	8346
Panel B: BA or higher				
log MW	-0.140	-0.127	-0.073	0.185
	(0.146)	(0.150)	(0.693)	(0.708)
Observation	7210	7210	6936	6936
Panel C: Combined				
log MW	-0.232*	-0.229*	-0.036	0.103
	(0.103)	(0.105)	(0.468)	(0.474)
Observation	16169	16169	15282	15282
Covariates	No	Yes	No	Yes

Notes: Self-reported health ranges from 0 to 5 and the cognitive function from 0 to 35, both with higher values indicating better health and cognitive function, respectively. Covariates include 5-year age categorization dummies, log state GDP, log social security income recipients, log population, and affordable care act expansion. All the models include individual and year fixed effects. Standard errors in parentheses clustered at the individual level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A3.4 : Effects of minimum wage increases on income and working hours

	(1) Annual income	(2) Weekly working hours
Panel A: High school or less		
Log Minimum Wage	8900**	3.95
	(3218)	(0.219)
Observations	9314	4526
Panel B: BA or higher		
Log Minimum Wage	1132	-0.16
	(6486)	(3.29)
Observations	7650	4378
Panel C: All older workers		
Log Minimum Wage	5236	1.96
	(3395)	(2.24)
Observations	16964	8904
Panel D: Women, HS or less		
Log Minimum Wage	4258	-1.90
	(3029)	(4.28)
Observations	4945	2356
Panel E: Men, HS or less		
Log Minimum Wage	13888*	10.61*
	(5908)	(4.27)
Observations	4369	2170
Covariates	Yes	Yes

Notes: Covariates include 5-year age categorization dummies, log state GDP, log social security income recipients, log population, and affordable care act expansion. All the models include individual and year fixed effects. Standard errors in parentheses clustered at the individual level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A3.5 : Effects of minimum wage increases on health by employment status

	(1)	(2)	(3)	(4)
	Self-reported health		Cognitive function	
Panel A: HS or less, become unemployed				
Log Minimum Wage	-0.077***	-0.083***	0.003	-0.038
	(0.011)	(0.012)	(0.031)	(0.051)
Observations	9314	9314	8678	8678
Panel B: HS or less, stay employed				
Log Minimum Wage	-0.162	-0.148	-0.763	-0.589
	(0.232)	(0.235)	(1.001)	(1.018)
Observations	4376	4376	4127	4127
Panel C: BA or more, become unemployed				
Log Minimum Wage	-0.032**	-0.036**	-0.001	-0.064
	(0.011)	(0.011)	(0.053)	(0.054)
Observations	7650	7650	7353	7353
Panel D: BA or more, stay employed				
Log Minimum Wage	-0.065	-0.070	-0.529	-0.601
	(0.205)	(0.207)	(0.983)	(0.992)
Observations	4190	4190	4048	4048
Covariates	No	Yes	No	Yes

Notes: Covariates include 5-year age categorization dummies, log state GDP, log social security income recipients, log population, and affordable care act expansion. All the models include individual and year fixed effects. Standard errors in parentheses clustered at the individual level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

A. Detailed explanation of cognitive test items.

The predictor list follows the original and the modified Hurd dementia estimation model Hurd et al. (2013); Gianattasio et al. (2020).

- *Date recall* is measured by whether the respondent correctly reported today's date (day, week, month, year), and has a score of 0 to 4.
- *Immediate recall* is measured by the number of correctly and immediately recalled nouns and it has score 0 to 10.
- *Delayed recall* is measured by the number of correctly recalled nouns after 5 minutes and has a score of 0 to 10.
- *Serial 7's* is measured by the number of the correct answers of subtracting 7 from 100 consecutively five times and has a score of 0 to 5.
- *Backward count* is measured by the number of correctly counting backward form 10 consecutive numbers from 20. If the respondent successfully performs the task, the score is 1, otherwise 0.
- *Name* is measured by whether the respondent correctly reported the names of the objects (scissors, cactus) and the current president and each has a score of 0 to 1.
- *Changes in cognitive item scores* measures the changes in the scores between the years 2014 and 2016.

Predictors for the proxy respondents included the 16-item *Informant Questionnaire on Cognitive Decline in the Elderly* (Jorm IQCODE). The questions include: 1) Remembering things about family and friends, such as occupations, birthdays, and addresses. 2) Remembering things that have happened recently 3) Recalling conversations a few days later 4) Remembering (her/your) address and telephone number 5) Remembering what day and month it is 6) Remembering where things are usually kept 7) Remembering where to find things which have been put in a different place than usual 8) Knowing how to work familiar machines around the house 9) Learning to use a new gadget or machine around the house 10) Learning new things in general 11) Following a story in a book or on TV 12) Making decisions on everyday matter 13) Handling money for shopping 14) Handling financial matters, that is, (her/your) pension or dealing with the bank 15) Handling other everyday arithmetic problems, such as knowing how much food to buy, knowing how long between visits from family or friends 16) Using (her/your) intelligence to understand what's going on and to reason things through.

If the proxy respondents reported much improvement we gave value 1, a bit improved value 2, same 3, a bit worse 4, much worse 5. We then averaged these responses over 16 items. The final IQCODE had a value between 0 to 5, 5 indicating worse cognitive health conditions. We operationalized the *change in cognitive status* by the response status. If the respondents' previous wave was answered by IQCODE, we calculated the change in IQCODE score between the two waves. If the respondents' previous wave was self-reported, we included the prior cognitive test score.

B. Performance metrics.

The Brier score measures the model's overall accuracy of the performance by the mean squared error between predictions and actual outcomes with values ranging from 0 to 1, the lower, the better overall accuracy. The calibration slope and intercept show how well the prediction is fitted to the actual observations, and it is obtained from the logistic regression of log odds ratios (In cases where the predicted probability equals zero or one, we replaced the zero to 1×10^{-15} and one to $1 - 1 \times 10^{-15}$.) of the predicted probabilities on observed outcomes with a slope close to 1 and intercept approaching 0 to be the better fit. The calibration intercept measures the systematic bias of the model, and the slope detects overfitting or underfitting Steyerberg et al. (2010). AUC is the aggregated area of a curve between sensitivity (true positives/actual positives) and specificity (true negatives/actual negatives) to quantify the discriminative power of the model in all thresholds. The value ranges from 0 to 1, with the higher value, the stronger the discriminative ability. AUPRC is the aggregated area of a curve between precision (true positives/predicted positives) and recall (equivalent to sensitivity, true positives/actual positives) at all thresholds, which is particularly useful when data is highly imbalanced, ranging from 0 to 1 with higher value meaning better discriminative ability Ozenne et al. (2015).

C. Race and ethnicity information in dementia status estimation.

There are three main approaches to treating the race and ethnicity variable in the dementia status estimation. First, we have the deconstruction of race and ethnicity Manly (2005); Brickman et al. (2006); Manly and Echemendta (2007); Cerdeña et al. (2020). This approach requires a comprehensive inclusion of predictors such as cultural, educational, linguistic background, literacy level Chin et al. (2011), early education quality Sisco et al. (2014), and socioeconomic status Glymour and Manly (2008). Thus, the racialized experience is fully decomposed. This is an ideal approach, as there is no solid evidence of biological differences in race/ethnic groups in dementia. However, it requires high-quality data with maximum inclusion of items that are related to experiences living as racial/ethnic minorities.

The second is to take a race-specific norms or cutoff approach Manly (2005); Manly and Echemendta (2007), which uses race as a proxy for racialized experiences, and it compares within demographically similar groups to build different cutoffs. However, potential differences in each predictor and why such bias arises remain to be investigated.

Third, the race-specific risk score approach Brickman et al. (2006); Segar et al. (2021). This approach builds a separate prediction model for each racial/ethnic group. It allows to capture race-specific associations of predictors and the outcome, enabling comparisons of predictors across racial/ethnic groups. However, the sample size of racial/ethnic minority groups is often limited for building meaningful separate prediction models.

Table A4.1 : Distributions of characteristics of analytical sample from HRS 2016 and HCAP.

Characteristic	**HCAP** N = 2388	**HRS** N = 6630
	Mean (SD) or %	
Age, years		
70-74	26%	26%
75-79	32%	32%
80-84	22%	23%
85-89	12%	12%
90-	7.2%	7.6%
Female, sex	59%	59%
Race and ethnicity		
Hispanic	8.8%	9.0%
Black, non-Hispanic	14%	14%
White, non-Hispanic	77%	77%
Schooling, years		
<6	3%	3.1%
6-8	6.3%	6.5%
9-11	12%	13%
12	35%	35%
>12	44%	43%
Difficulties in ADL	0.53 (1.18)	0.55 (1.20)
Difficulties in IADL	0.53 (1.19)	0.56 (1.23)

Abbreviation. ADL, activities of daily living; HCAP, Harmonized Cognitive Assessment Protocol; HRS, Health and Retirement Study; IADL, instrumental activities of daily living; SD, standard deviation.

Note. Difficulties in ADL/IADL (0-5, the higher the worse condition).

Table A4.2 : Distributions of characteristics by missing values in cognitive elements, HCAP.

Characteristic	**Complete** N = 2388	**Missing** N = 169
	Mean (SD) or %	
Age, years		
70-74	26%	17%
75-79	32%	27%
80-84	22%	28%
85-89	12%	20%
90-	7.2%	8.9%
Female, sex	59%	66%
Race and ethnicity		
Hispanic	8.8%	22%
Black, non-Hispanic	14%	13%
White, non-Hispanic	77%	64%
Schooling, years		
<6	3%	12%
6-8	6.3%	9.5%
9-11	12%	14%
12	35%	30%
>12	44%	34%
Difficulties in ADL	0.53 (1.18)	0.99 (1.48)
Difficulties in IADL	0.53 (1.19)	1.05 (1.54)

Abbreviation. HCAP, Harmonized Cognitive Assessment Protocol; ADL, activities of daily living; IADL, instrumental activities of daily living; SD, standard deviation. Difficulties in ADL/IADL (0-5, the higher the worse condition).

Table A4.3 : Distributions of characteristics by missing values in cognitive elements, HRS.

Characteristic	**Complete** N = 6630	**Missing** N = 557
	Mean (SD) or %	
Age, years		
70-74	26%	22%
75-79	32%	28%
80-84	23%	22%
85-89	12%	18%
90-	7.6%	9.3%
Female, sex	59%	65%
Race and ethnicity		
Hispanic	9.0%	19%
Black, non-Hispanic	14%	15%
White, non-Hispanic	77%	65%
Schooling, years		
<6	3.1%	13%
6-8	6.5%	9.4%
9-11	13%	13%
12	35%	30%
>12	43%	35%
Difficulties in ADL	0.55 (1.20)	1.04 (1.63)
Difficulties in IADL	0.56 (1.23)	1.02 (1.60)

Abbreviation. HRS, Health and Retirement Study; ADL, activities of daily living; IADL, instrumental activities of daily living; SD, standard deviation. Note. Difficulties in ADL/IADL (0-5, the higher the worse condition).