Does (Re-)Entering the Labor Market at Advanced Ages Protect Against Cognitive Decline? A Panel-Matching Difference-in-differences Approach *

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Abstract

While prolonged labor market participation becomes increasingly important in ageing societies, evidence of the impacts of entering or exiting work beyond age 65 on cognitive functioning is scarce. We estimate these effects using panel-matching difference-in-differences with population-representative panel datasets from South Korea and the United States. We compare countries and across socioeconomic characteristics. We find general positive effects of entering the labor market in South Korea, while only individuals with high assets in the US benefit from entering the labor market. Exiting the labor market does not result in changes in cognitive functioning in Korea but is followed by a cognitive decline in individuals with low assets in the US. Findings suggest that the benefits and disincentives from late-life labor status transitions on cognitive functioning vary between South Korea and the US and across socioeconomic groups.

Keywords— older-age labor market, cognitive function, difference-in-differences, South Korea
JEL Classification: I12, J1, J26

*The data used in this study are publicly available on the Health and Retirement Study website (http://hrsonline.isr.umich.edu/) and the Korean Longitudinal Study of Ageing website (http://survey.keis.or.kr). STATA code for reproducing our datasets and R code for analyzing the data is available by the time of publication on: [dataset] Kim, 2022.

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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). Advanced-age participation rates in the labor market will keep rising through 2030, according to the Organisation for Economic Co-operation and Development (hereafter OECD) (Geppert et al., 2019). We thus need to understand better the impacts of labor market participation at advanced ages on various health outcomes.

In this paper, we focus on the labor market "entry and exit" health effects at age 65+ and specifically investigate the outcome cognitive functioning. Cognitive functioning includes memory, spatial orientation, learning, executive functions, and language (Hendrie et al., 2006). Poor cognitive functioning is a growing public health concern for aging societies (Anderson and McConnell, 2007). A decline in cognitive functioning impacts older-aged individuals negatively, as even minimal declines in cognitive function at advanced ages are associated with poor decision-making and endangering individuals to fraud (Boyle et al., 2012).

Entering and exiting the labor force in later adulthood has received public health and economics attention due to its importance in increasing sustainability of public pensions systems to buffer the effects of population aging. Yet, very few studies have looked at late-life working beyond age of sixty-five, despite its growing importance (Taylor et al., 2016). Age of sixty-five has been the compulsory retirement age in many European countries and is the age at which cognitive impairment starts to increase in prevalence. Until now, an empirical investigation evidenced protective effects of entering the labor market at advanced ages (Schwingel et al., 2009, Wickrama et al., 2013). Further, there is a need to test labor market entry and exit effects across cultural contexts and with different methodologies to collect evidence on the robustness of these findings.

From a methodological perspective, in countries with compulsory retirement age or age-associated pension eligibility, these policies can be used for instrumental-variable designs, and there is consolidated evidence on the detrimental effects of withdrawal from the labor market on cognitive outcomes at early older ages. One study, using national policies on retirement as an instrument, showed negative causal effects of retirement on cognitive decline with data from the US, England, and European countries (Rohwedder and Willis, 2010). Related results are well documented in US, French, UK, and Australian samples (Bonsang et al., 2012, Dufouil et al., 2014, Xue et al., 2018, Atalay et al., 2019).

In our analysis, however, as we are interested in the association of employment status at very advanced ages, such age eligibility, cannot be proper instruments. In the meantime, a means-tested social security program may be taken up by population groups with systematically distinct levels of cognitive functioning compared to the general population. This will violate the exogeneity condition. To conclude, there are no sufficiently strong exogenous determinants of labor market participation or –exit at ages beyond 65 at the time of investigation, which is why an instrumental variable approach is not available.

To address the causality in the absence of the proper instruments, we use the panel-matching difference-in-differences method from the potential outcomes framework. Matching methods have gained popularity across disciplines to answer causal questions with observational and non-randomized data by balancing covariates between the treated and control groups (Stuart, 2010). Following the definition from the original paper (Stuart, 2010), we call all the methods that balances the covariates between the treated and control groups as “matching”. Matching methods have been applied to similar research questions over the last years. Several studies used propensity score methods to reduce selection bias associated with employment status of older adults (Behncke, 2012. Carr et al., 2020, Eyjólfsdóttir et al., 2019, Baumann et al., 2020). Furthermore, matching methods have been used in combination with the difference-in-differences estimator, which compares changes over time between groups that are exposed to interventions, treatments, or shocks and the groups without such transitions (Heckman et al., 1997, Stuart et al., 2014). A difference-in-differences combined with matching on pre-treatment characteristics can control unobserved time-invariant confounding (Blundell and Dias, 2009, O’Neill et al., 2016). A difference-in-differences method with propensity score matching was used to analyze the impact of employment transition on physical and psychological health for the working-age population in Germany (Gebel and Voßemer, 2014).

This paper uses population-based data from South Korea (hereafter Korea) and the United States, the first for the country’s exceptionally active labor participation in later life and accelerating transition into a super-aged society (K. W. Kim and Kim, 2020), and the latter for the United States’ notable decline in the share of middle-skill jobs in the advanced-age labor market participation (Tuzemen and Willis, 2013, Rutledge and Guan, 2015). We contrast the two countries on possibly different impacts of advanced-age labor market entry and exit on cognitive functioning while gaining insights on the generalizability of the observed patterns. The large US sample will further allow us to differentiate financial asset levels, which may be a more important indicator of socioeconomic status than income in relation to health at older ages (Pollack et al., 2007). We further run analyses stratified by sex/gender and education, and thus explore possible heterogeneity of the employment-cognition relationship.

Our contributions to the knowledge on employment status transitions and cognitive functioning are the following. First, we contribute to the vital research question of how labor market participation and withdrawal at age 65+ may impact the cognitive performance of older workers and retirees. Research on labor participation beyond age sixty-five has received less attention despite its increasing presence (Taylor et al., 2016). We investigate two countries where advanced-age labor market participation is already important and may even gain further importance over the coming years. This paper is, to our knowledge, the first to use South Korean and US population-representative aging survey data to study the impact of employment status transition at age 65+ on cognitive function in two different socioeconomic and cultural contexts. Secondly, we use the panel-matching difference-in-differences method (Imai et al., 2021), which takes advantage of available information from both treatment[1] and confounder trajectories prior to the treatment through matching. Past employment history is an important confounder affecting both future employment status (Dingemans and Möhring, 2019) and cognitive health (Leist et al., 2013) and may capture further to unobserved confounders such as work attitude, desire to work, or job insecurity related to treatment and outcome.

To elaborate further on the differences of the method (Imai et al., 2021) to other difference-in-differences approaches, many recent works on difference-in-differences methods (Callaway and Sant'Anna, 2021, Sun and Abraham, 2021, Athey and Imbens, 2021) have staggered adaptation designs where the treatment cannot be reversed. A panel-matching difference-in-differences, which matches according to the treatment history, is more suitable to our analysis as late-life labor market participation is often on-and-off patterned across countries (Cho et al., 2016). The method described above was implemented using an open-source statistical software package *PanelMatch* (I. S. Kim et al., 2018) in R version 4.1.2 (R Core Team, 2021). STATA version 17.0 was used for data preparation (StataCorp., 2021).

The outline of the paper is as follows. The section 2 presents the background, theory, and hypotheses. The section 3 is dedicated to data description. In section 4, we demonstrate the empirical strategy. In section 5, we present our results. We discuss the findings in section 6 and conclude in section 7.

2 Background and Hypotheses

2.1 Late-life financial conditions in the South Korea and US

According to the latest report (OECD, 2021), earnings from work as a source of income account for more than half of the total income of older adults aged 65+ in Korea. This is the second-largest share of work income contributing to total income among all OECD countries, exceeded only by Mexico. The share of public transfers[2] on total income at ages 65+ is only slightly above 25% in Korea, while public transfers contribute to 57% of advanced-age incomes in the average OECD countries. 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. Among OECD countries, Korea ranked highest in the share of older adults in relative income poverty, defined by having an income below half the national median equalized household disposable income (OECD, 2021). With few alternative income sources to compensate for insufficient public transfers, a large share[3] of 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, which is roughly 10% higher than the OECD average. More than 40% of the total income is covered by public transfers[4]. Retirees on average have around 94% of the average total income of the total population, which is higher than the OECD average. The labor force participation of older adults in the US aged 65+ was 19.4% in 2020, 4.1% higher than the average OECD countries (OECD, 2022). Overall, older adults in the US are better financially than the average older adults across OECD countries. However, an alarming amount of income inequality measured by the Gini coefficient implies that the favorable conditions of older adults are disproportionately shared (OECD, 2021).

[1] This paper defines treatment as entering or exiting the labor market at age 65+ respectively.

[2] In Korea, the pension age was 60 in 2007 and 62 in 2020 (OECD, 2007, OECD, 2021).

[3] Korea's labor force participation rate among those aged 65+ was 35.3% in 2020, the highest among OECD countries (OECD, 2022).

[4] In the US, the normal retirement age was between 65 and 66 in 2004. It is 66 years and eight months for workers aged 62 in 2020 (OECD, 2007, OECD, 2021).

2.2 Theory and Hypotheses

Drawing from theories of aging, continuity theory argues that individuals experience a discontinuity in personal constructs when there is a tough transition between the former and current environment (Atchley, 1989). It suggests that individuals adapt to changes through "continuity strategies" resulting from past experiences. In parallel, activity theory (Havighurst, 1963) argues that the typical reaction is to rebuild the previous equilibrium.

According to the "use it or lose it" theory (Hultsch et al., 1999), intellectually stimulating activities can protect against cognitive decline in later life. This is in line with the well-known cognitive reserve theory (Katzman, 1993, Stern, 2009, Stern, 2012), which suggests that lifelong experiences, not only educational and occupational attainment but also experiences in later life, can increase this reserve which acts as a buffer against cognitive decline in advanced age. Based on the previous theories, we firstly suggest the following hypotheses:

Hypothesis 1. Entering the labor market at age 65+ has positive effects on individuals' cognitive function.
Hypothesis 2. Exiting from the labor market at age 65+ has negative effects on individuals' cognitive function.

Harmonizing strategy of data analysis allows us to build a set of hypotheses assuming cross-national differences between the strength of the effects of entering and exiting the labor market in the two countries, Korea and the US.

Secondly, we want to test the hypothesis that Korean older adults experience salient positive effects from entering and adverse effects from withdrawing from the labor force compared to the US. A study argued that occupational identity is related to the sense of self (Rudman and Dennhardt, 2008). Traditionally strong collective identity in Korea compared to the US (Moon et al., 2018) might appreciate labor participation to contribute to the family, community, and society, resulting in a positive relationship between work and cognitive function even at very advanced ages.

Hypothesis 3. Korean older adults experience more salient positive effects from entering the labor market at 65+ than in the US.
Hypothesis 4. Korean older adults experience more salient negative effects from exiting the labor market at 65+ than in the US.

Thirdly, we would like to test the hypothesis that employment status transition effects differ according to household asset levels with US data, which we can test due to its large sample size. Asset level was chosen as a moderator to illustrate the differences in the motivations of labor participation at advanced ages. We contrast income from work as an indispensable element in older adults' economic resources versus high asset levels. Possessing sufficient financial capital gives individuals the choice to work or not, where income being a 'side effect' of work but not the main incentive. In the first case, individuals would be more likely to be involved in jobs with less favorable work environments, possibly involving cognitive and physical load. In the latter case, if older adults have enough assets to live comfortably without income from work-related earnings, they have a higher chance of choosing jobs on their terms, leading to higher job satisfaction and cognitive stimulation.

For the case of exit, if older adults with low asset levels exit the labor market, this may lead to increased stress level due to a lack of sufficiently high alternative sources of income. Increased levels of stress may lead to negative effects on cognitive performance. Loss of income with insufficient assets might also hinder older adults from gaining cognitively stimulating experiences. On the contrary, cognitively stimulating activities might still be available for individuals with high assets through leisure activities and social networks even after withdrawing from the labor market.

Hypothesis 5. Individuals with high assets experience more salient positive effects from entering the labor market at 65+ than those with low assets.
Hypothesis 6. Individuals with low assets experience more salient adverse effects from exiting the labor market at age 65+ than those with high assets.

3 Data

We use two population-representative longitudinal data: the Korean Longitudinal Study of Aging (KLoSA) from South Korea and the Health and Retirement Study (HRS) from the United States.

3.1 The Korean Longitudinal Study of Aging (KLoSA)

Korean Longitudinal Study of Aging (KLoSA) was first collected in 2006 and is designed to be nationally representative of Korean households. It is a biennial panel survey on approximately 10,000 individuals on demographics, family composition, health, health care utilization, employment, financial status, and subjective expectations and satisfaction 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).

In our analyses, data from 2006 to 2016 was used. We selected individuals aged 65 or older. We excluded individuals without sex/gender information (n = 13,529, 35.2%). We included individuals who have participated in the labor market at least once after age 65 (n = 8343, 33.53%). This is to investigate the effect of employment transition at post-retirement ages for individuals capable of and interested in being employed at an advanced age. Individuals without cognitive measurement were excluded (n = 310, 3.86%). A total number of 8033 person-period observations were included.

3.2 Health and Retirement Study (HRS)

For the analysis of the US case, we used the HRS, which is a nationally representative sample of private households with members aged 51 years and older in the United States starting in 1992. It is a biennial follow-up data on more than 43,000 individuals on demographics, family structure, self-reported health, health care utilization, and economic resources and behavior. Further information is available from the following paper ([dataset] Sonnega et al., 2014). Specifically, we used the RAND HRS Longitudinal File (HRS) from 2006 to 2016, which contains cleaned and harmonized information from the Core and Exit Interviews across waves of the HRS.

We selected individuals aged 65 or older. We excluded individuals without sex/gender and ethnicity/race information (n = 235, 0.15%). We included individuals who have participated in the labor market at least once after age 65 (n = 23,713, 15.36%). We excluded individuals with missing information on cognitive performance (n = 4886, 20.60%). A total number of 18827 person-period observations were included.

3.3 Measurement of cognitive functioning

In KLoSA, the Korean version of the Mini-Mental State Examination (K-MMSE, Kang et al., 1997) was used to measure global cognitive function. The MMSE (Folstein et al., 1975) is the most widely used quantitative assessment of global cognitive function. It takes integer values between 0 and 30, with higher values indicating better functioning. K-MMSE is a modified version of MMSE adjusted to the older Korean population.

In HRS, the Telephone Interview for Cognitive Status (TICS) was applied to measure global cognitive function (Langa et al., 2018). TICS is modeled after MMSE for large-scale population-based cognitive assessment via telephone or face-to-face administration. It takes integer values between 0 and 35, with higher values indicating better functioning. HRS provides imputation of missing values in cognitive function (MacCammon et al., 2019), yet proxy interviews are excluded from the imputation.

Comparison of the composition of these two measurements and the distributions of each measurement can be found separately in Table A3 and Figure A3 in the appendix. Two measures of cognitive functioning are not identical, however, several studies argued that TICS and MMSE scores correlates very highly (Brandt et al., 1988, Fong et al., 2009). We use raw numbers and apply $log(x+1)$-transformation of each score to account that a one-point decrease or increase has different significance across the range of possible values and is more severe at the lower level of cognitive functioning. The estimated effect cannot be compared by its magnitude, yet it is sufficient to present the direction of the effect.

3.4 Measuring employment status transitions

Using the terminology of the difference-in-differences method, the so-called treatment "exiting the labor market" identifies employment transitions from being employed at wave $t-1$ to non-employed at wave t. We 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. Likewise, the treatment "entering the labor market" captures employment transitions from being non-employed at wave $t-1$ to employed at wave t. We 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. In this study, we restrict the treatment years to 2012 or 2014, allowing for three lags to capture employment histories and two follow-ups to capture possibly longer-term effects of entry or exit from the labor market.

3.5 Description of matching variables for the analytical sample

We match[5] for age, age squared, sex/gender, education, household net income, household net asset, occupation level[6], a dummy variable for living with a spouse/partner, self-reported health, a birth year before 1940, and pre-treatment cognitive scores except for one period immediately before the treatment. For the US data, we additionally match for foreign birth and ethnicity/race for its availability in the data. Financial values[7] listed in Table 1 are in absolute terms to directly compare the financial situations of respondents between Korea and the US. In the analyses, we transformed asset and income values to tertiles as proxies for relative economic status.

Table 1 describes the distinct characteristics of the selected Korean and US samples. The values are measured at the study entry regardless of waves. HRS participants have higher asset and income levels compared to those in Korea. The share of education above the high school level is almost nine times higher in the US sample. These differences are also visible in the shares of occupational levels.

Table 1: Descriptive Statistics of HRS and KLoSA.

	HRS N=4845	KLoSA N=2043	P-value	N
Cognitive Function	23.7 (4.39)	25.6 (4.32)	<0.001	6888
Age	68.7 (4.47)	67.7 (3.72)	<0.001	6888
Age Category:			<0.001	6888
65-69	3445 (71.1%)	1612 (78.9%)		
70-74	847 (17.5%)	298 (14.6%)		
75-79	494 (10.2%)	124 (6.07%)		
85-	59 (1.22%)	9 (0.44%)		
Birth Year<=1940	0.49 (0.50)	0.44 (0.50)	<0.001	6888
Female	0.49 (0.50)	0.39 (0.49)	<0.001	6888
Education:			0.000	6873
Up to Primary	151 (3.13%)	1182 (57.9%)		

continued on next page

[5]Following the definition from the paper (Stuart, 2010), we call all the methods that balances the covariates between the treated and control groups as “matching”.

[6]We classified occupations based on the skill levels following the International Standard Classification of Occupations (International Labour Organization, 2022).

[7]Asset and income are harmonized into USD in thousands adjusted for purchasing power parity (hereafter PPP) ([dataset] World Bank, 2022b) and inflation ([dataset] World Bank, 2022a).

Table 1 – *continued from previous page*

	HRS N=4845	KLoSA N=2043	p.overall	N
Secondary	294 (6.09%)	325 (15.9%)		
High School	1828 (37.8%)	406 (19.9%)		
Above High School	2557 (52.9%)	130 (6.36%)		
Spouse/Partner	0.69 (0.46)	0.84 (0.37)	<0.001	6888
Household Asset	586.9 (1536.1)	150.8 (230.2)	<0.001	5867
Annual Income	82.5 (167.5)	12.6 (12.9)	<0.001	6840
Occupation Level:			<0.001	4675
Elementary	401 (12.3%)	447 (31.4%)		
Service/Skilled-Manual	1756 (54.0%)	889 (62.4%)		
Managerial/Professional	1094 (33.7%)	88 (6.18%)		
Self-Reported Health:			<0.001	6883
Very Bad	96 (1.98%)	88 (4.31%)		
Bad	655 (13.5%)	475 (23.3%)		
Fair	1614 (33.3%)	875 (42.8%)		
Good	1802 (37.2%)	581 (28.4%)		
Very Good	673 (13.9%)	24 (1.17%)		
Ethnicity/Race:			.	4845
Non-Hispanic White	3610 (74.5%)	. (.)		
Non-Hispanic Black	720 (14.9%)	. (.)		
Hispanic	401 (8.28%)	. (.)		
Non-Hispanic Others	114 (2.35%)	. (.)		
Foreign Birth	0.10 (0.30)	. (.)	.	4841

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.
Asset/income are harmonized into thousands USD with inflation and PPP adjustment.
Ethnicity/Race and Foreign Birth are not asked in the KLoSA survey.
Source: HRS 2006-2016, KLoSA 2006-2016 own calculations.

3.6 Comparisons by employment transitions

Table A1 and Table A2 in the appendix show the descriptive statistics by entry to or exit from the labor market for both datasets. The values are measured one wave before the transition, either in 2012 or 2014. Individuals are divided into four categories based on their working status change, with individuals entering the labor market (1), inactive individuals not participating in the labor market (2), individuals exiting the labor market (3), and individuals remaining active in the labor market (4).

In the Korean data, comparing the group entering the labor market, exiting the labor market, staying active, and staying inactive, individuals entering the labor market had the lowest average cognitive performance. Conversely, in the US, individuals entering the labor market had the second-highest average cognitive score.

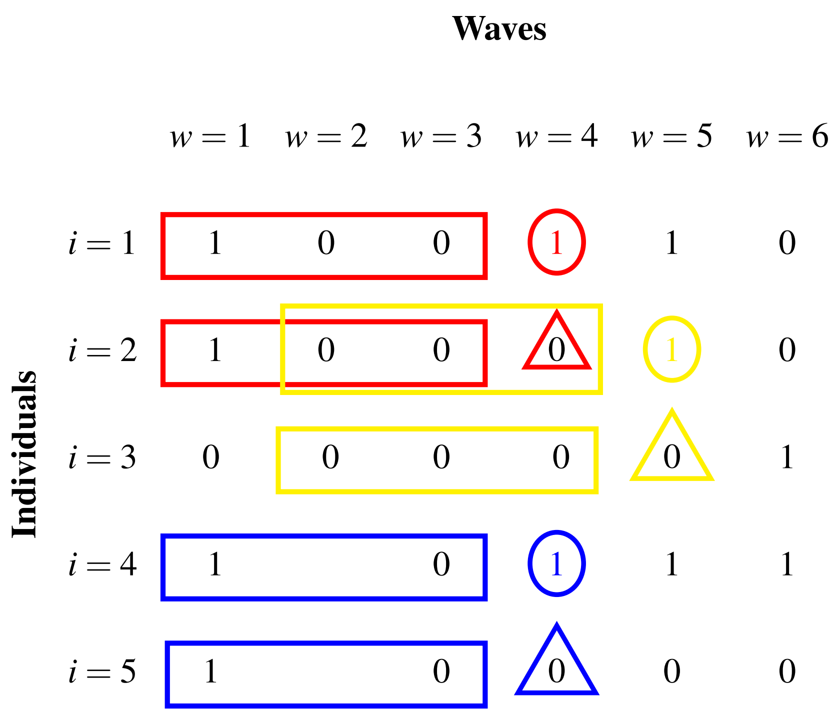

Figure 1: **An Example of Employment History Matching across Individuals and Waves** This panel shows how matched sets are made when the number of lags is 3. Waves are read from left to right. When the treatment is "entering the labor market", value 1 indicates working and 0 for not-working. Treatment observation (circles) and control observations (triangles) with the same color share the same employment history (rectangles). Cells without values represent missingness in the employment status. Adapted from Imai et al., 2021 Figure 2.

4 Empirical analysis

We apply the panel-matching difference-in-differences method (Imai et al., 2021). This method makes causal inference using longitudinal observational data situated in the potential outcomes framework. It first matches control observations with identical employment histories in the same period as the treatment group. Borrowing from Imai et al., 2021, we refer to the set of matched control observations as a *matched set*. Figure 1 explains an example of different matching across individuals and waves.

Then, it refines the matched sets via weighting by using pre-treatment covariate histories[8]. Finally, it computes the difference-in-differences estimators among refined matched sets.

[8] Age, age squared, sex/gender, education, household net income, household net asset, occupation level, a dummy variable for living with a spouse, self-reported health, a birth year before 1940, pre-treatment cognitive scores except for one period immediately before the treatment, and additional matching of foreign birth and ethnicity only for the US data

4.1 Causal quantity of interest

The causal quantity of interest is the following. F indicates lead, and L lags. i denotes individual, and t is time of assessment. The average effect of switching employment status of individuals who made the transition is described as follows:

$$\begin{aligned}ATT(F,L) = \mathbb{E}[&Y_{i,t+F}(X_{it}=1, X_{i,t-1}=0, \{X_{i,t-l}\}_{l=2}^{L}) - \\ &Y_{i,t+F}(X_{it}=0, X_{i,t-1}=0, \{X_{i,t-l}\}_{l=2}^{L}))|X_{it}=1, X_{i,t-1}=0] \end{aligned} \quad (1)$$

where $Y_{i,t+F}$ represents the cognitive score of an individual i at time $t+F$; X_{it} is a binary variable with value 1 if an individual i participates in labor force at time t, and 0 otherwise. $Y_{i,t+F}(X_{it}=1, X_{i,t-1}=0, \{X_{i,t-l}\}_{l=2}^{L})$ is the potential cognitive function score under the condition of an employment status change occurred between $t-1$ and t. $Y_{i,t+F}(X_{it}=0, X_{i,t-1}=0, \{X_{i,t-l}\}_{l=2}^{L})$ illustrates the counterfactual outcome without the employment status change in between $t-1$ and t. Both share the same employment history $\{X_{i,t-l}\}_{l=2}^{L}$ up to L lags.

In our analysis, we are interested in $ATT(3,0)$ and $ATT(3,1)$. These are the average causal effects of changes in employment status on cognitive functioning immediately and one period after the treatment. This causal quantity assumes that adjusting for employment history up to three waves back removes most of the possible confounding due to employment histories, while at the same time adjusting for non-employment histories related confounding. With more waves in the lags to adjust for employment histories, we would arrive at less biased but also, less efficient estimations. We chose the number of lags to be three to include more than one wave of past treatment history while balancing against the need to have enough individuals in the matched set. We set the number of leads to be one, again to have enough individuals in the matched set and to avoid effects from interference coming from the lead period. We present separate sensitivity analysis with two waves of past histories of treatment. Missingness in the treatment histories is treated as information by matching individuals with similar patterns of missingness.

4.2 Covariate balancing using pre-treatment covariate trajectories

We first match individuals by their employment histories and build a matched set, which is the total of matched control observations who experienced the same employment histories as treated individuals for the last three waves but did not experience the treatment in question, i.e., the entry or exit from the labor market in the current wave (Figure 1). Subsequently, we balance the covariates of the control group 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. 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. Propensity score weights are obtained from logistic regression, which calculates the conditional probability of belonging to the treatment group based on the pre-treatment covariates. Then covariate balances are calculated by the standardized mean differences between the treated and the refined control group. We tested several covariate balancing methods, such as Mahalanobis distance matching (Rubin, 1980), propensity score matching (Rosenbaum and Rubin, 1983), covariate balancing propensity score (hereafter CBPS, Imai and Ratkovic, 2014), and propensity score weighting method best adjusted the covariates. We provide the results of sensitivity analysis with a CBPS weighting.

4.3 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 to check the validity of this assumption (Figures A1 and A2) indicates that the parallel assumption might be valid, as the standardized mean difference on cognitive score of the pre-exposed period after balancing was close to zero or, in the case of transitioning to employment in Korea, reduced and remained constant compared to the pre-balancing values.

The second assumption is the absence of *spillover effects*, which means that one's employment status transition should not affect others' cognitive function. We cannot rule out the possibility of spillover effects as we do not have information on the connectedness of individuals through living in close geographical proximity or sharing the work environment etc. However, we 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, we must assume that the potential outcome is independent of the treatment history beyond the number of lags, three waves. We believe that employment histories of up to three waves (six years) are enough to capture unobserved confounders related to employment status.

4.4 Empirical estimation of causal quantity

We now present the empirical estimation of the causal quantity from the equation (1). M_{it} is the number of individuals in the matched set. $w_{it}^{i'}$ is the non-negative weight constructed from matched set constituting the control group. The weights are obtained through propensity score conditioning on covariates histories. D_{it} is an indicator function that has value 1 if the individual experiences an employment status transition and has any positive number of individuals from the matched set. N is the number of observations.

$$\widehat{ATT}(F,L) = \frac{1}{\sum_{i=1}^{N}\sum_{t=L+1}^{T-F} D_{it}} D_{it}\left[(Y_{i,t+F} - Y_{i,t-1}) - \sum_{i' \in M_{it}} w_{it}^{i'}(Y_{i',t+F} - Y_{i',t-1})\right] \tag{2}$$

where $Y_{i,t+F} - Y_{i,t-1}$ is the difference in cognitive score between time $t-1$ and $t+F$ for the group with transitions in employment status. Whereas $w_{it}^{i'}(Y_{i',t+F} - Y_{i',t-1})$ is the difference in cognitive scores between time $t-1$ and $t+F$ for the control group who stayed at the same employment status with identical past employment history and weighted by its similarity to the treated group. Depending on the number of matched set M_{it}, the level of refinement may vary. For example, the refinement will be rough if there is a rare treatment pathway with a small number of individuals in the matched set. In our study, even with the smallest number of treated cases, which is the individuals transitioning into employment in South Korea matched with three lags, most treated observations have more than ten control observations in the matched set, with the mean value of 34 observations.

Standard errors of the estimator from equation (2) are calculated with 1000 repetitions of the weighted block bootstrap procedures. The weighted bootstrap method is suited to matching estimators as it treats the number of times each individual partakes in the matched set as a characteristic (Otsu and Rai, 2017). By doing so, it provides an asymptotically valid inference for a matching estimator. Detailed explanations and calculations of the standard errors can be found in the Imai et al., 2021.

5 Results

5.1 Main estimation results

We demonstrate in Figure 2 the estimated effects of entering the labor market (upper panel) and exiting (bottom panel) on cognitive functioning for immediate and one wave after the transition. The left panel indicates the results from the Korean sample and the right panel for the US. Regarding entry to the labor market, the effects of entering the labor market were positive and statistically significant during the year of transition and one wave after in the Korean sample. We did not find statistically significant effects from entering the labor market in the US. For the exit from the labor market, we did not observe statistically significant effects on both data. Table 2 compares the

Table 2: Average treatment effect on treated (ATT).

	Cognitive Function							
	Unadjusted				Adjusted			
	ATT	S.E.	2.5%	97.5%	ATT	S.E.	2.5%	97.5%
Entering the labor market								
Korea at $t+0$	0.069*	0.021	0.032	0.113	0.060*	0.022	0.016	0.104
Korea at $t+1$	0.063*	0.030	0.008	0.126	0.060*	0.029	0.005	0.118
US at $t+0$	0.013	0.011	−0.008	0.033	0.011	0.011	−0.009	0.031
US at $t+1$	0.007	0.012	−0.017	0.029	−0.001	0.011	−0.022	0.021
Exiting the labor market								
Korea at $t+0$	−0.029*	0.014	−0.057	−0.002	−0.028	0.016	−0.059	0.001
Korea at $t+1$	−0.037	0.020	−0.078	0.003	−0.027	0.022	−0.071	0.015
US at $t+0$	−0.018*	0.008	−0.034	−0.003	−0.015	0.008	−0.032	0.001
US at $t+1$	−0.022*	0.011	−0.041	−0.001	−0.013	0.014	−0.037	0.018

Notes: ATT, average treatment effects on the treated
S.E., Weighted bootstrapped standard errors with 1000 repetitions.
2.5%, 97.5%., 95% asymptotic confidence intervals, $*p < 0.05$.
Source: KLoSA 2006-2016, HRS 2006-2016, own calculations.

unadjusted and adjusted estimation results. The magnitude of positive effects from entering the labor market in Korea was reduced but remained significant after the covariate balancing. Regarding exit from the labor market, we observed immediate adverse effects for Korea and negative effects unfolding over time in the US from exiting the labor market when we did not adjust for the covariate histories. However, negative effects disappeared in both datasets after adjusting the covariate histories.

5.2 Heterogeneous effects by socioeconomic status and sex/gender

We now show the estimated ATT based on subgroup analyses by median asset level, assuming that asset levels may moderate the positive effects of entering, and negative effects of exiting the labor market. Only HRS data allow subgroup analyses due to its relatively large sample size. Figure 3 shows the estimated effects of entering (upper panel) and exiting the labor market (bottom panel) on cognitive performance for immediate and one wave after the transition. The left panel indicates the effects in individuals with low asset levels, and the right panel in

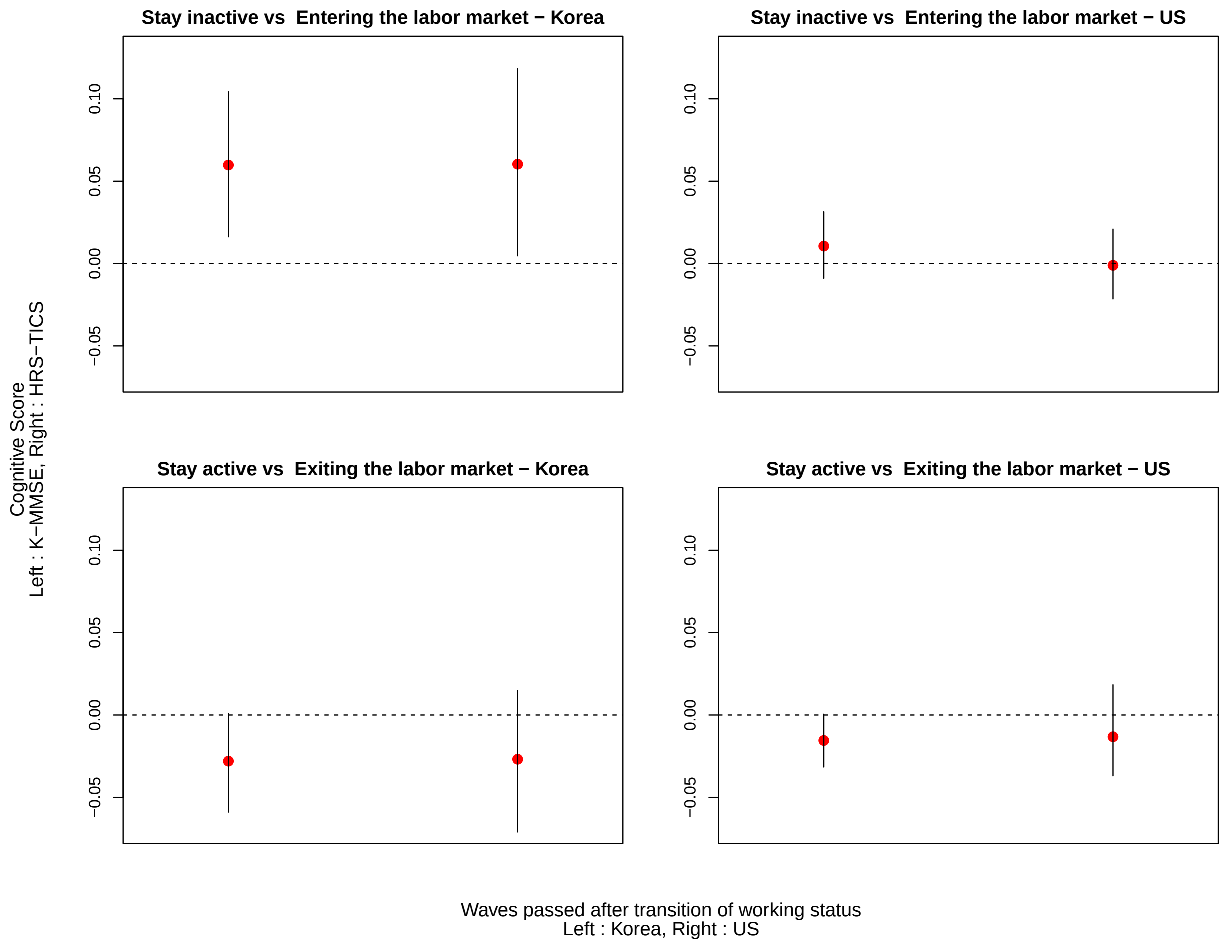

Figure 2: **Average Treatment Effects on the Treated (ATT) for Entry to and Exit from Labor Market in Korea and the US** The estimation results are obtained after matching according to treatment history and propensity score weighting with covariate histories during the three waves before the treatment. The left panel indicates the results from the Korean sample and the right panel 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. Propensity score weighting is chosen for its best performance in adjustment.

individuals with high asset levels.

For individuals with high asset levels, we find that the point estimates of entering the labor market are positive and statistically significant during the transition year. The estimated impact of exiting the labor market is null during the year of change and one wave after. For individuals with low asset levels, we find that the point estimates of entering the labor market were null during the year of transition and one wave after. However, in low asset level individuals, the estimated impact of exiting the labor market was negative and statistically significant during the transition period.

Similar results, although not statistically significant, were found for entering the labor market when stratified by educational level in Figure A4 in the appendix. We did not find statistically significant differences in the effects of entry to nor exit from the labor market in analyses stratified by sex/gender in Figure A5.

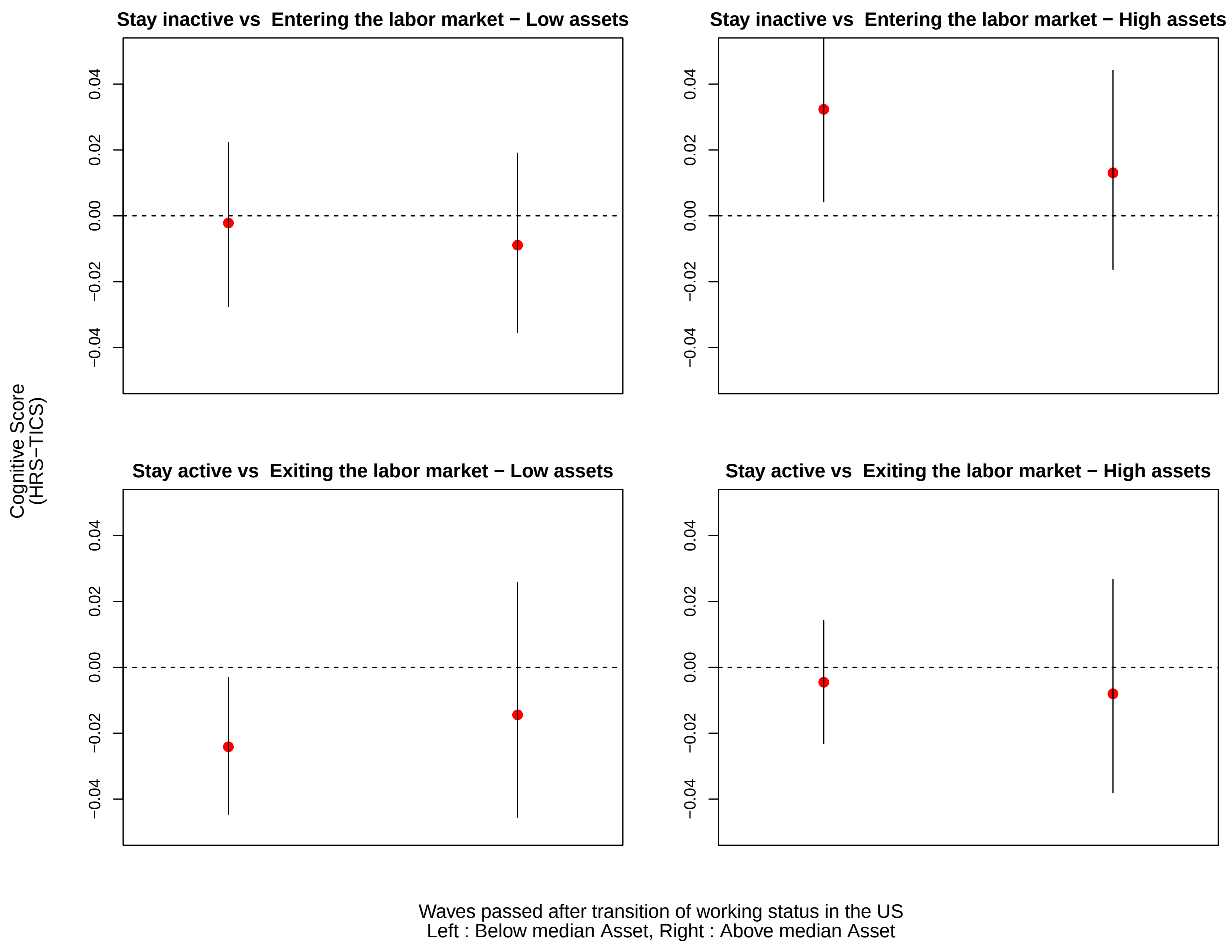

Figure 3: **Average Treatment Effects on the Treated (ATT) for Entry to and Exit from Labor Market in the US Moderated by Asset** The estimation results are obtained after matching according to treatment history and propensity score weighting with covariate histories during the three waves before the treatment. The left panel indicates the below-median asset level sample results, and the right panel for the above-median asset level. 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. Propensity score weighting is chosen for its best performance in adjustment.

5.3 Robustness checks

We show that our main results are robust to the alternative balancing method and to the matching with shorter lags.

Alternative balancing method. Firstly, we compared different balancing methods. Figure A6 compares the covariate balances of entering the labor market in Korea, which has the smallest sample size. Overall, propensity score weighting and CBPS weighting best adjusted the balance. Covariate balancing propensity score (Imai and Ratkovic, 2014) optimizes prediction assignment and covariate balances at the same time. This method is attractive in its robustness to misspecification of the propensity score model and possible biasing of the treatment effect. Therefore, we provide sensitivity analysis with CBPS weighting. Balances for overall covariates improved except for the lagged outcomes. We list the estimation results in Table 3. All results move in the same direction with the alternative weighting method. For the heterogeneous effects based on the asset level in the US, immediate positive effects from entering the labor market were observed during the transition period in above-median asset individuals, and we found immediate adverse effects from exiting the labor market in the low asset groups. Both are in the same direction as the main analysis.

Table 3: ATT comparison between CBPS Weighting and PS Weighting.

	Cognitive Function							
	CBPS Weighting				PS Weighting			
	ATT	S.E.	2.5%	97.5%	ATT	S.E.	2.5%	97.5%
Entering the labor market								
Korea at $t+0$	0.059*	0.022	0.017	0.104	0.060*	0.022	0.016	0.104
Korea at $t+1$	0.059*	0.027	0.008	0.115	0.060*	0.029	0.005	0.118
US at $t+0$	0.011	0.011	−0.011	0.033	0.011	0.011	−0.009	0.031
US at $t+1$	−0.001	0.011	−0.022	0.021	−0.001	0.011	−0.022	0.021
Exiting the labor market								
Korea at $t+0$	−0.025	0.016	−0.056	0.004	−0.028	0.016	−0.059	0.001
Korea at $t+1$	−0.024	0.022	−0.070	0.019	−0.027	0.022	−0.071	0.015
US at $t+0$	−0.016	0.008	−0.032	0.000	−0.015	0.008	−0.032	0.001
US at $t+1$	−0.013	0.015	−0.036	0.020	−0.013	0.014	−0.037	0.018

Notes: ATT, average treatment effects on the treated
CBPS Weighting, Covariate balancing propensity score weighting
PS Weighting, Propensity score weighting
S.E., Weighted bootstrapped standard errors with 1000 repetitions.
2.5%, 97.5%., 95% asymptotic confidence intervals, $*p < 0.05$.
Source: KLoSA 2006-2016, HRS 2006-2016, own calculations.

Shorter lags Secondly, a robustness check with a shorter length of employment and covariate history prior to the entry to or exit from the labor market is performed in Figure 4. Shorter employment and covariate history windows will allow more individuals to be included in the matched set, which leads to reduced variation in the estimation. Still, it cannot take into consideration the given rich covariate trajectories. For example, by considering two waves instead of three waves, we lose cognitive function change trajectories, which is a potential confounder affecting the current cognitive functioning and the employment status. Therefore, balancing with shorter waves leaves room for the potential confounders from the past periods. We redid the main analyses with two waves of pre-treatment histories as sensitivity analysis acknowledging this trade-off. The overall covariate adjustments improved with more matched sets. The estimated coefficients vary but move in the same direction once we match with shorter waves of lags. The positive effect of entering the labor market in Korea holds for the immediate time and the magnitude increased. The one-wave-after effects of entering the labor market in Korea are statistically marginally significant. We suppose this weak statistical significance comes from more individuals in the matched sets who switch their employment status from working to not-working during the post-treatment period. This is likely because we allowed more heterogeneous individuals in terms of employment and covariate trajectories to be matched with shorter lags. However, such interference effects in the post-treatment period are less common for the case of exiting the labor market as more individuals exit than entering. Instead, it contributed to reduced variance in the estimation for the case of exiting the labor market. We observe the adverse effects of exiting the labor market for both the immediate and one wave after in the US. We consider this finding attributable to the larger matched set and higher power. We observed cognitive benefits from entering the labor market during the transition period in above-median asset individuals in the US. Immediate adverse effects presented from quitting the paid job in the low asset groups in the US. Both are in the same direction as the main analysis.

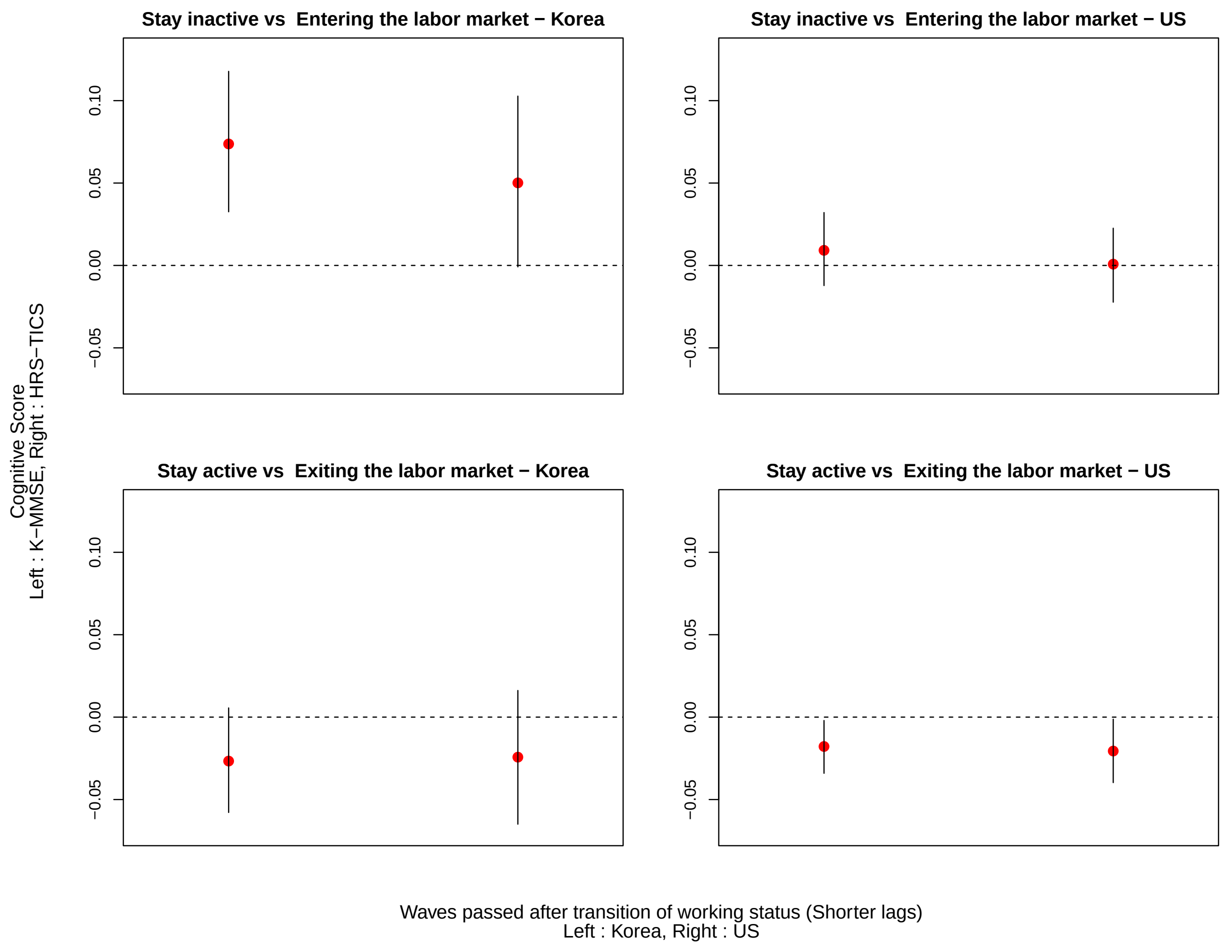

Figure 4: **ATT for Entry to and Exit from Labor Market in Korea and the US with Shorter Lags** The estimation results are obtained after matching according to treatment history and propensity score weighting with covariate histories during the two waves before the treatment. The left panel indicates 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. Propensity score weighting is chosen for its best performance in adjustment.

6 Discussion

In this study, we tested the hypotheses of cognitive benefits from entering the labor market and detrimental effects from exiting the labor market extending up to advanced older ages, specifically to ages 65+. We hypothesized that effects might differ between countries and by socioeconomic status measured by asset levels. We tested these hypotheses using data from two large population-representative samples from Korea and the US.

Using causal methods, we observed that entering the labor market at age 65+ showed favorable immediate and unfolding effects over time on cognitive functioning in Korea. In contrast, cognitive benefits from entering the labor market were observed only during the transition period in above-median asset individuals in the US. Negative effects from exiting the labor market at advanced ages disappeared after the covariate adjustment in both countries. However, we found immediate adverse effects from exiting the labor market in the low asset groups in the US.

Our findings confirm previous studies of the protective effects of labor market participation at advanced ages on cognitive functioning (Schwingel et al., 2009, Wickrama et al., 2013). However, our findings suggest that the general positive effects are country-specific and apply solely to individuals with high asset levels in the US. Concerning the well-established detrimental effects from labor market withdrawal (Bonsang et al., 2012, Dufouil et al., 2014, Xue et al., 2018, Atalay et al., 2019), our study questions that such adverse effects are not universal but more pronounced in groups with low socioeconomic status. We discuss the potential mechanisms of the heterogeneous effects between Korea and the US in A.1 and A.2 in the appendix.

There are limitations to this study. First, the treated group in our analysis comprises a small portion of individuals who transitioned into or out of work in Korea and the US. This limited obtaining an ideal covariate balance, particularly the estimation of the effect of entering the labor market in Korea. Although matching upon treatment histories and weighting based on pre-treatment covariates are conducted to minimize bias, a larger data set would be needed to acquire an ideal covariate balance. Concerning the possible reverse causality, we present Table A1, which measured cognitive function one wave before the transitions. We observe that in Korea, individuals who enter the labor force have the lowest cognitive functioning, which is contrary to the argument of reverse causality.

Second, as is the case in many longitudinal data, we observe attrition due to loss to follow-up and note differential missingness in baseline data (US: 20.60%; Korea: 3.86%). We report the descriptive statistics by attrition in HRS in Table A4. This non-random missingness might generate survival bias. Individuals who dropped out of surveys are higher in age, lower in the cognitive score, and have an inferior self-reported health condition at the baseline. Therefore, our findings of the US case are likely to be conservative in light of the selective attrition.

Third, with biennial data, a person might change their employment status multiple times within the period between the waves. This is likely, especially since jobs for the advanced age population are often flexible. Thus, the control group that does not transition to employment might include a portion of respondents who may actually have experienced transitions in employment status or other confounders between the waves.

Fourth, the two cognitive measurements in each data set are not identical. Although it shares common elements in the questionnaires, some parts differ. Compared to the US data, the distribution in Korean data is more skewed to the right. As we are not looking into the absolute numbers but the difference between pre-treatment and the post-treatment outcome, we believe that the difference in measurements will not be problematic in showing the direction of the effects.

Our contribution to the knowledge on employment status transitions at advanced ages and cognitive functioning is as follows: First, we use South Korean and US population aging survey data with a harmonized strategy of data analysis. These datasets have not been investigated to answer the impact of changes in employment status at very advanced ages on cognitive performance. Comparative analysis from different country datasets allows contrasting the effects in different socioeconomic and cultural contexts. Furthermore, 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).

Second, we use the novel panel-matching difference-in-differences method (Imai et al., 2021), which reduces various forms of bias to answer causal questions. Bias from unobserved confounders related to employment status is addressed through matching according to the employment histories, and selection bias is tackled by balancing the covariates through weighting with pre-treatment covariate histories.

An analysis incorporating future waves of the surveys would improve our knowledge by investigating how these transition effects unfold overtime beyond the designated treatment years. Our findings are restricted to work transitions occurring in 2012 and 2014 and may not be generalizable beyond these years. Therefore, further investigation with more extended periods of observation might hold the key to understanding the generalizability of our findings.

Future research should add by testing more potential pathways and confounders of effects of labor market entry and exit by assessing possible effects of heterogeneity in more fine-grained types of occupation and psychosocial work characteristics (job complexity and working hours), health conditions, and ethnic groups. Due to the limited sample size, we were not able to investigate possible heterogeneous effects. Further study with heterogeneous populations or methods to address such diversity will further our understanding of employment effects on cognition, and possibly other health outcomes relevant to healthy aging, beyond our selected sample.

7 Conclusion

Cognitive performance is crucial to work ability and performance for those entering the labor market at advanced ages. The importance of unimpaired cognitive performance also applies to those leaving the labor market for healthy aging post-retirement. An increase in advanced-age labor force participation, beyond age 65+, in aging countries calls for the need to understand better the impacts of labor market participation and withdrawal at very advanced ages on cognitive functioning.

Our findings suggest that employment transitions at age 65+ on cognitive function are specific to country contexts and socioeconomic groups. The estimated effects of entering the labor market were positive and lasted in South Korea. In the US, positive effects were shorter-lasting and found only in high-asset individuals. In both datasets, we did not find general effects from exiting the labor market. However, we observed adverse effects for individuals with low asset levels in the US.

Based on these results, we recommend removing age-related barriers and discrimination further to encourage the Korean population at advanced ages to gain financial and cognitive benefits from labor force participation. For the case in the US, the labor market environment and work characteristics for advanced-age individuals, particularly with low socioeconomic groups, need to be reexamined to bring cognitive gains for older workers.

CRediT authorship contribution statement

Jung Hyun Kim: Conceptualization, Methodology, Data curation, Formal analysis, Writing – original draft;
Graciela Muniz Terrera: Methodology, Writing - review & editing;
Anja K. Leist: Conceptualization, Supervision, Writing – original draft, Funding acquisition.

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Declaration of competing interest

The authors have nothing to disclose.

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Appendices

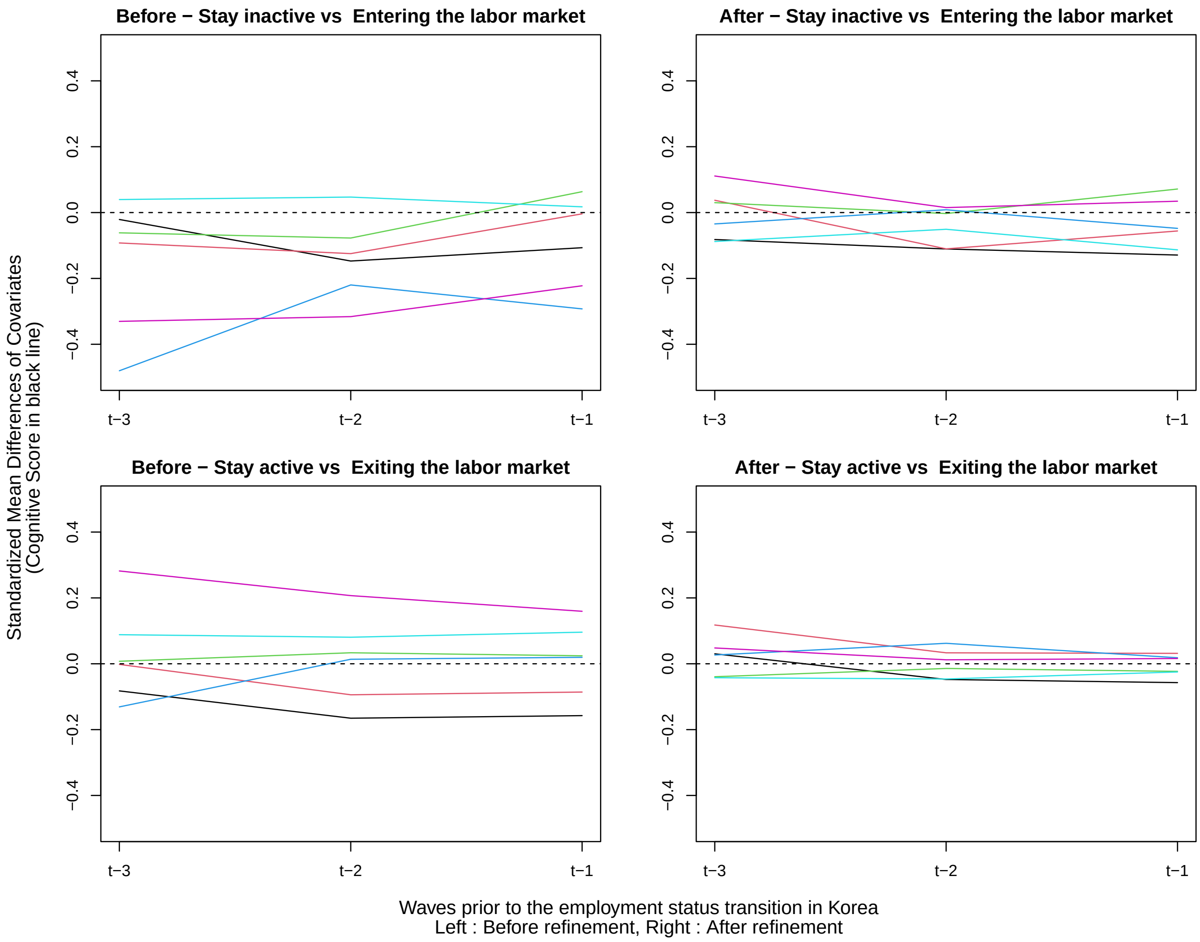

Figure A1: **Covariate Balance in KLoSA** Each plot presents the standardized mean difference of covariates over the pre-treatment time period with Korean data. The upper panel represents the balance from entering the labor market and the bottom from the exit. The left column shows the balance before refinement. The right column displays covariate balance after propensity score 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 gender (light blue). Adapted from Imai et al., 2021 Figure 5.

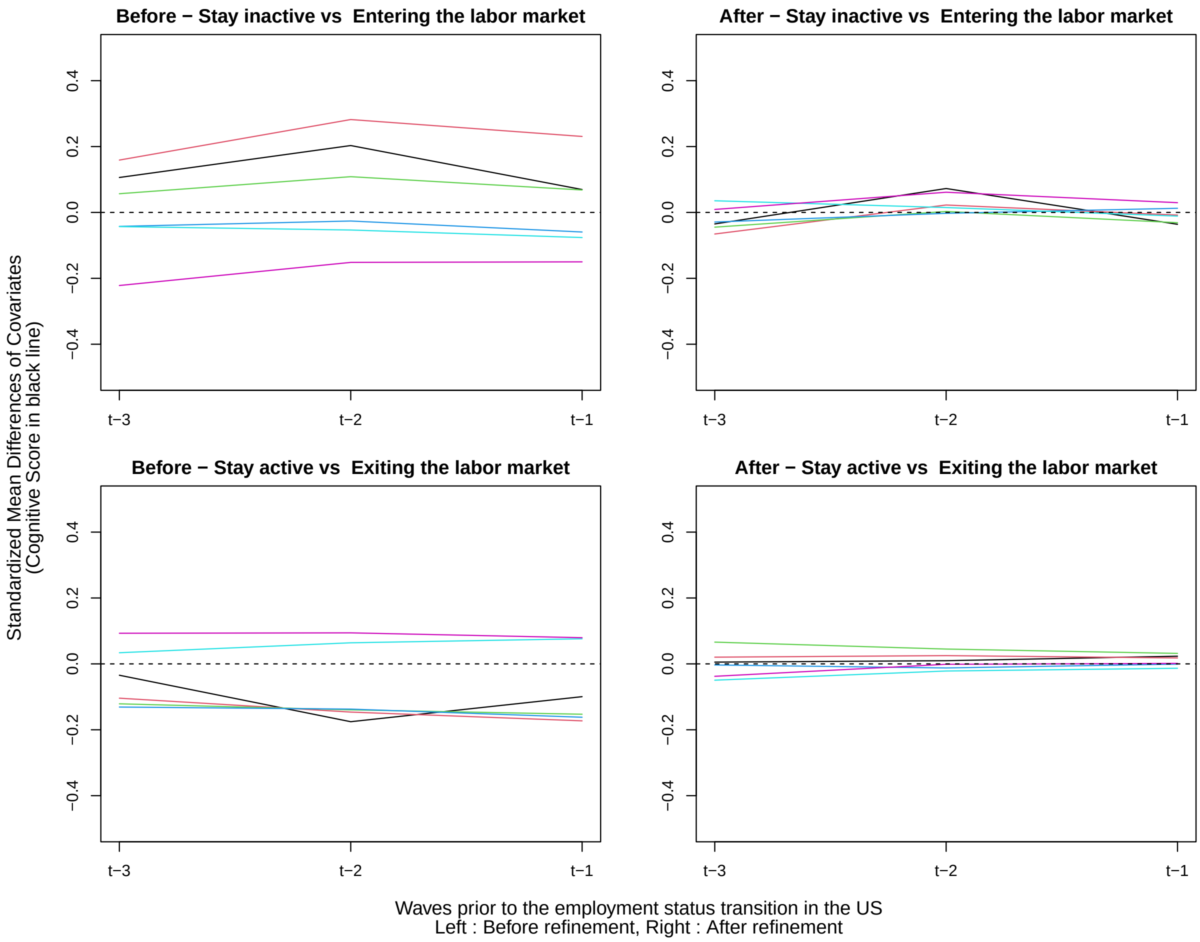

Figure A2: **Covariate Balances in HRS** Each plot presents the standardized mean difference of covariates over the pre-treatment time period with US data. The upper panel represents the balance from entering the labor market and the bottom from the exit. The left column shows the balance before refinement. The right column displays covariate balance after propensity score 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 gender (light blue). Adapted from Imai et al., 2021 Figure 5.

Table A1: Descriptive Statistics by Labor Force Transition in KLoSA

	Entry N=95	Inactive N=567	Exit N=341	Active N=1009	P-value	N
K-MMSE	24.1 (4.82)	24.6 (4.67)	24.5 (4.42)	25.2 (4.09)	0.003	2012
Age	69.9 (3.70)	71.8 (4.75)	71.5 (5.04)	70.2 (4.18)	<0.001	2012
Age Category:					.	2012
65-69	51 (53.7%)	201 (35.4%)	140 (41.1%)	514 (50.9%)		
70-74	32 (33.7%)	228 (40.2%)	118 (34.6%)	346 (34.3%)		
75-79	12 (12.6%)	126 (22.2%)	76 (22.3%)	144 (14.3%)		
85-	0 (0.00%)	12 (2.12%)	7 (2.05%)	5 (0.50%)		
Birth Year<=1940	0.57 (0.50)	0.72 (0.45)	0.68 (0.47)	0.59 (0.49)	<0.001	2012
Female	0.55 (0.50)	0.45 (0.50)	0.45 (0.50)	0.39 (0.49)	0.002	2012
Education:					.	2012
Up to Primary	70 (73.7%)	375 (66.1%)	232 (68.0%)	690 (68.4%)		
Secondary	10 (10.5%)	84 (14.8%)	42 (12.3%)	121 (12.0%)		
High School	11 (11.6%)	80 (14.1%)	47 (13.8%)	154 (15.3%)		
Above High School	4 (4.21%)	28 (4.94%)	20 (5.87%)	44 (4.36%)		
Spouse	0.75 (0.44)	0.75 (0.44)	0.74 (0.44)	0.83 (0.38)	<0.001	2012
Household Asset:					0.414	2012
Low	47 (49.5%)	235 (41.4%)	153 (44.9%)	399 (39.5%)		
Middle	28 (29.5%)	181 (31.9%)	101 (29.6%)	339 (33.6%)		
High	20 (21.1%)	151 (26.6%)	87 (25.5%)	271 (26.9%)		
Household Income					<0.001	1995
Low	44 (46.8%)	209 (37.1%)	117 (34.9%)	275 (27.4%)		
Middle	22 (23.4%)	192 (34.0%)	101 (30.1%)	386 (38.5%)		
High	28 (29.8%)	163 (28.9%)	117 (34.9%)	341 (34.0%)		
Occupation Level:					.	1293
Elementary	11 (40.7%)	101 (39.8%)	67 (30.3%)	200 (25.3%)		
Service/Skilled-Manual	16 (59.3%)	144 (56.7%)	141 (63.8%)	557 (70.4%)		
Managerial/Professional	0 (0.00%)	9 (3.54%)	13 (5.88%)	34 (4.30%)		
Self-Reported Health:					.	2012
Very Bad	6 (6.32%)	42 (7.41%)	14 (4.11%)	15 (1.49%)		
Bad	33 (34.7%)	177 (31.2%)	98 (28.7%)	260 (25.8%)		
Fair	32 (33.7%)	224 (39.5%)	160 (46.9%)	464 (46.0%)		
Good	23 (24.2%)	112 (19.8%)	66 (19.4%)	254 (25.2%)		
Very Good	1 (1.05%)	12 (2.12%)	3 (0.88%)	16 (1.59%)		

(1) Entry (2) Inactive (3) Exit (4) Active.
Notes: All covariates are measured at one wave prior to the transition.
Listed values are mean (± standard deviation) or total number (%).
Asset/income are harmonized into thousands USD with inflation and PPP adjustment.
Source: KLoSA 2006-2016, own calculations.

Table A2: Descriptive Statistics by Labor Force Transition in HRS

	Entry N=298	Inactive N=2057	Exit N=798	Active N=1844	P-value	N
HRS-TICS	23.3 (4.20)	22.8 (4.37)	22.9 (4.20)	24.0 (4.01)	<0.001	4997
Age	70.9 (4.87)	72.6 (5.03)	71.6 (4.96)	70.8 (4.48)	<0.001	4997
Age Category:					<0.001	4997
65-69	138 (46.3%)	666 (32.4%)	326 (40.9%)	850 (46.1%)		

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Table A2 – *continued from previous page*

	Entry N=298	Inactive N=2057	Exit N=798	Active N=1844	P-value	N
70-74	113 (37.9%)	770 (37.4%)	272 (34.1%)	651 (35.3%)		
75-79	39 (13.1%)	575 (28.0%)	186 (23.3%)	326 (17.7%)		
85-	8 (2.68%)	46 (2.24%)	14 (1.75%)	17 (0.92%)		
Birth Year<=1940	0.62 (0.49)	0.76 (0.42)	0.68 (0.47)	0.64 (0.48)	<0.001	4997
Female	0.50 (0.50)	0.53 (0.50)	0.50 (0.50)	0.47 (0.50)	0.004	4997
Education:					<0.001	4993
Up to Primary	7 (2.36%)	73 (3.55%)	23 (2.89%)	44 (2.39%)		
Secondary	17 (5.72%)	134 (6.51%)	62 (7.78%)	83 (4.51%)		
High School	126 (42.4%)	923 (44.9%)	331 (41.5%)	670 (36.4%)		
Above High School	147 (49.5%)	927 (45.1%)	381 (47.8%)	1045 (56.7%)		
Spouse/Partner	0.66 (0.48)	0.63 (0.48)	0.65 (0.48)	0.68 (0.47)	0.005	4995
Household Asset:					<0.001	4997
Low	100 (33.6%)	712 (34.6%)	255 (32.0%)	483 (26.2%)		
Middle	105 (35.2%)	703 (34.2%)	279 (35.0%)	623 (33.8%)		
High	93 (31.2%)	642 (31.2%)	264 (33.1%)	738 (40.0%)		
Household Income:					<0.001	4997
Low	104 (34.9%)	817 (39.7%)	241 (30.2%)	387 (21.0%)		
Middle	102 (34.2%)	723 (35.1%)	274 (34.3%)	628 (34.1%)		
High	92 (30.9%)	517 (25.1%)	283 (35.5%)	829 (45.0%)		
Occupation Level:					0.001	2989
Elementary	20 (17.1%)	116 (15.3%)	63 (11.5%)	157 (10.0%)		
Service/Skilled-Manual	59 (50.4%)	424 (55.9%)	305 (55.6%)	850 (54.3%)		
Managerial/Professional	38 (32.5%)	219 (28.9%)	181 (33.0%)	557 (35.6%)		
Self-Reported Health:					<0.001	4996
Very Bad	4 (1.34%)	80 (3.89%)	19 (2.38%)	18 (0.98%)		
Bad	31 (10.4%)	345 (16.8%)	106 (13.3%)	181 (9.82%)		
Fair	114 (38.3%)	752 (36.6%)	284 (35.6%)	579 (31.4%)		
Good	106 (35.6%)	697 (33.9%)	294 (36.9%)	784 (42.5%)		
Very Good	43 (14.4%)	183 (8.90%)	94 (11.8%)	282 (15.3%)		
Ethnicity/Race:					0.146	4997
Non-Hispanic White	232 (77.9%)	1571 (76.4%)	625 (78.3%)	1458 (79.1%)		
Non-Hispanic Black	41 (13.8%)	296 (14.4%)	111 (13.9%)	249 (13.5%)		
Hispanic	18 (6.04%)	153 (7.44%)	45 (5.64%)	92 (4.99%)		
Non-Hispanic Others	7 (2.35%)	37 (1.80%)	17 (2.13%)	45 (2.44%)		
Foreign Birth	0.08 (0.27)	0.10 (0.30)	0.09 (0.29)	0.07 (0.26)	0.061	4991

(1) Entry (2) Inactive (3) Exit (4) Active.

Notes: All covariates are measured at one wave prior to the transition.
Listed values are mean (± standard deviation) or total number (%).
Asset/income are harmonized into thousands USD with inflation and PPP adjustment.

Source: HRS 2006-2016, own calculations.

Table A3: Cognitive Measurement

Cognitive measurement comparison		
Data	KLoSA	HRS
Variable (point)	K-MMSE (30)	HRS-TICS (35)
Immediate word recall (3|10)	O (three words)	O (ten words)
Delayed word recall (3|10)	O (three words)	O (ten words)
Serial 7s (5)	O	O
Backwards counting (2)	X	O
Date (5|4)	O	O
Place (5)	O	X
Object naming (2)	X	O
President naming (2)	X	O
Language (9)	O	X

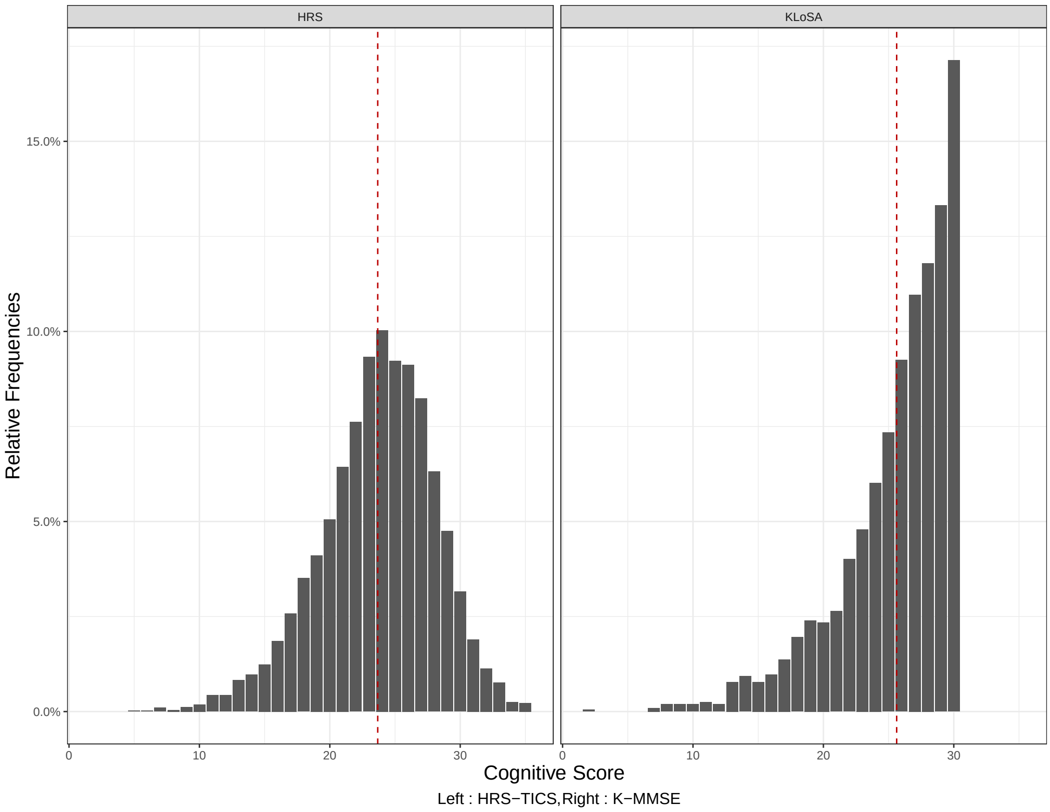

Figure A3: **Distribution of Cognitive Score** The bar graphs show the distribution of relative frequencies in each value of cognitive score within each data set. The left panel indicates the distribution of US data. Cognitive function is measured by HRS-TICS ranging from 0 to 35. The right panel displays 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.

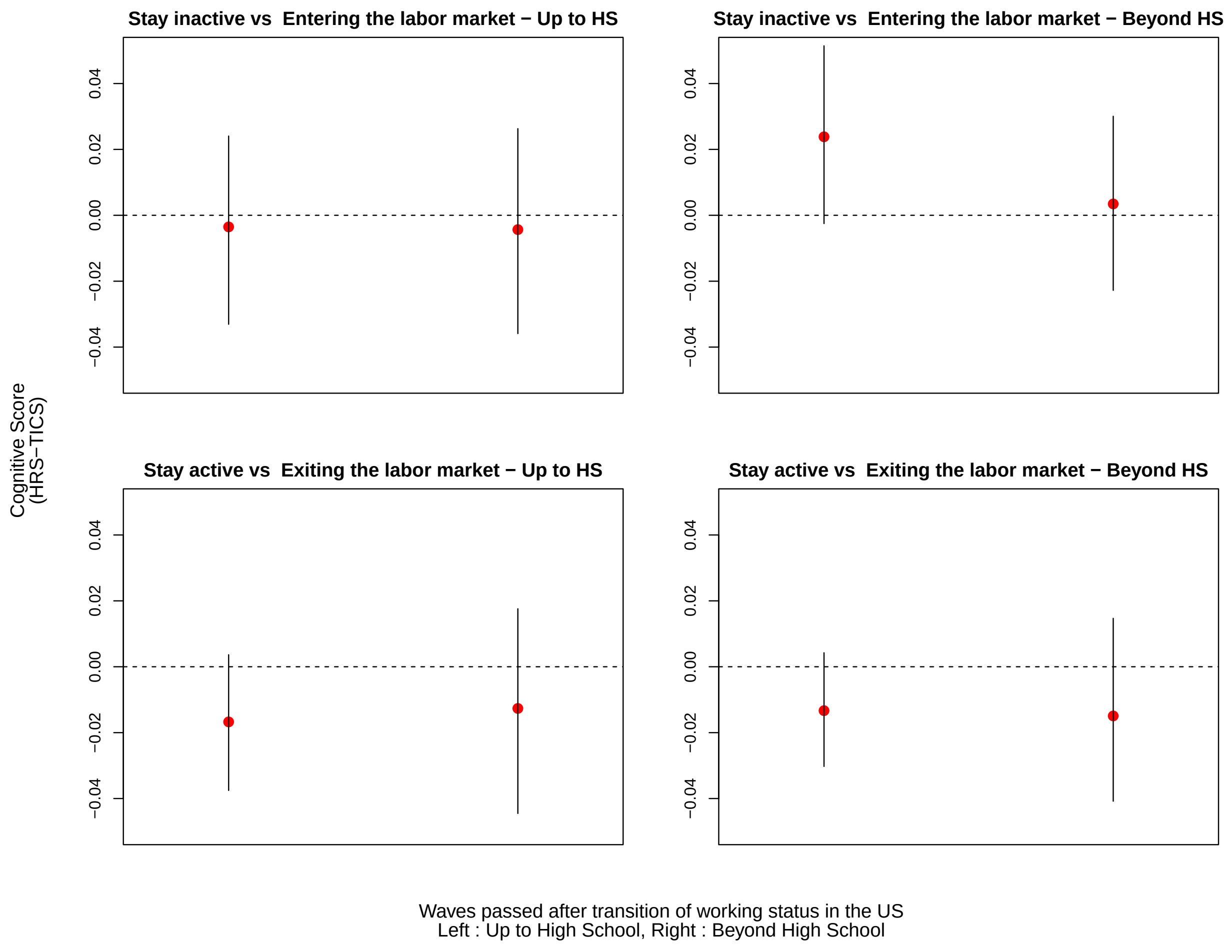

Figure A4: **Average Treatment Effects on the Treated (ATT) for Entry to and Exit from Labor Market in the US Moderated by Education** The estimation results are obtained after matching according to treatment history and propensity score weighting with covariate histories during the three waves before 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. Propensity score weighting is chosen for its best performance in adjustment.

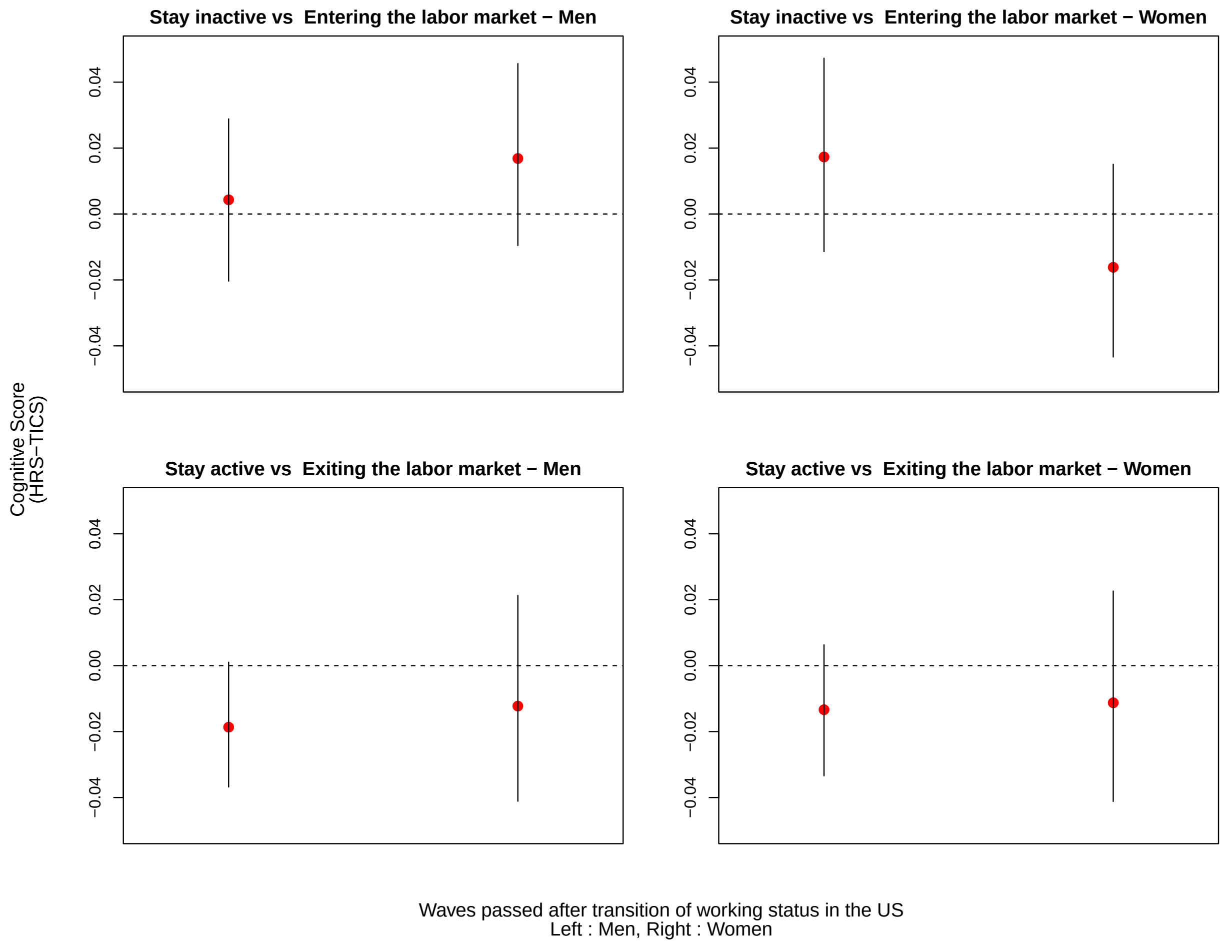

Figure A5: **Average Treatment Effects on the Treated (ATT) for Entry to and Exit from Labor Market in the US Moderated by Sex/Gender** The estimation results are obtained after matching according to treatment history and propensity score weighting with covariate histories during the three waves before 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. Propensity score weighting is chosen for its best performance in adjustment.

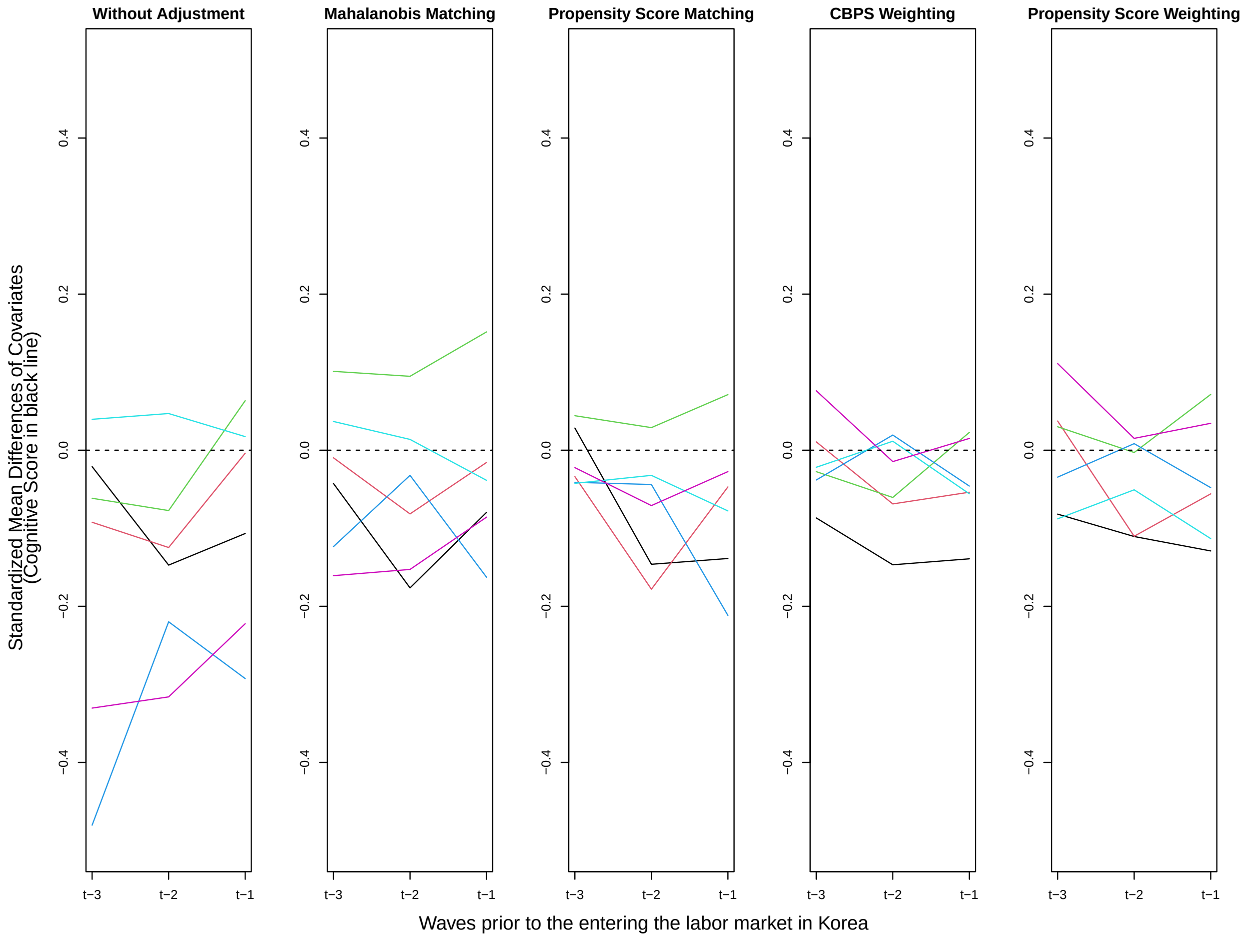

Figure A6: **Covariate Balances Comparisons in KLoSA of Entering the Labor Market** Each plot presents the standardized mean difference of covariates over the pre-treatment time period with KLoSA data for the case of entering the labor market. The first column represents the unadjusted balance, and the 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 gender (light blue). Adapted from Imai et al., 2021 Figure 5.

Table A4: Descriptive Statistics by Attrition in HRS at entry of the study

	Non-Dropout N=3623	Missing N=404	Dropout N=1037	P-value	N
HRS-TICS	24.2 (4.17)	. (.)	22.8 (4.53)	<0.001	3977
Age	67.5 (3.52)	67.1 (3.73)	71.2 (6.03)	<0.001	5064
Age Category:				.	5064
65-69	2877 (79.4%)	340 (84.2%)	525 (50.6%)		
70-74	519 (14.3%)	36 (8.91%)	244 (23.5%)		
75-79	220 (6.07%)	27 (6.68%)	226 (21.8%)		
85-	7 (0.19%)	1 (0.25%)	42 (4.05%)		
Birth Year<=1940	0.42 (0.49)	0.36 (0.43)	0.76 (0.43)	<0.001	5064
Female	0.52 (0.50)	0.34 (0.47)	0.43 (0.49)	<0.001	5064
Education:				<0.001	5047
Up to Primary	106 (2.94%)	16 (3.98%)	40 (3.86%)		
Secondary	187 (5.18%)	33 (8.21%)	88 (8.49%)		
High School	1316 (36.5%)	166 (41.3%)	437 (42.1%)		
Above High School	1999 (55.4%)	187 (46.5%)	472 (45.5%)		
Spouse/Partner	0.70 (0.46)	0.82 (0.39)	0.67 (0.47)	<0.001	4821
Household Asset:				0.631	4821
Low	1087 (31.4%)	90 (28.3%)	313 (30.2%)		
Middle	1137 (32.8%)	116 (36.5%)	354 (34.1%)		
High	1242 (35.8%)	112 (35.2%)	370 (35.7%)		
Household Income:				<0.001	4821
Low	820 (23.7%)	47 (14.8%)	290 (28.0%)		
Middle	1141 (32.9%)	115 (36.2%)	372 (35.9%)		
High	1505 (43.4%)	156 (49.1%)	375 (36.2%)		
Occupation Level:				0.012	3393
Elementary	274 (11.6%)	44 (18.5%)	102 (12.8%)		
Service/Skilled-Manual	1268 (53.7%)	107 (45.0%)	432 (54.4%)		
Managerial/Professional	819 (34.7%)	87 (36.6%)	260 (32.7%)		
Self-Reported Health:				<0.001	4817
Very Bad	40 (1.15%)	11 (3.46%)	41 (3.97%)		
Bad	409 (11.8%)	53 (16.7%)	174 (16.8%)		
Fair	1140 (32.9%)	118 (37.1%)	344 (33.3%)		
Good	1353 (39.0%)	99 (31.1%)	355 (34.3%)		
Very Good	523 (15.1%)	37 (11.6%)	120 (11.6%)		
Ethnicity/Race:				<0.001	5064
Non-Hispanic White	2637 (72.8%)	283 (70.0%)	841 (81.2%)		
Non-Hispanic Black	570 (15.7%)	68 (16.8%)	116 (11.2%)		
Hispanic	322 (8.89%)	42 (10.4%)	63 (6.08%)		
Non-Hispanic Others	94 (2.59%)	11 (2.72%)	16 (1.54%)		
Foreign Birth	0.11 (0.31)	0.12 (0.33)	0.08 (0.28)	0.045	5058

Notes: All covariates are measured at the study entry regardless of waves.
Listed values are mean (± standard deviation) or total number (%).
Missing is a group without cognitive function observations throughout the survey.
Asset/income are in thousands USD with inflation and PPP adjustment.
Sources: HRS 2006-2016, own calculations.

A Potential mechanisms

A.1 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 (Fasbender et al., 2016) 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. 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 (Szinovacz and Davey, 2005) might have caused the exit from the labor market. These external push factors plus the reduced earnings may lead to more stressful challenges during exiting work, which will result in a decline in cognitive functioning.

A.2 Financial conditions and work attachment in South Korea

In the Korean sample, we 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 culturally strongly tied to work might explain the roots of the benefit beyond monetary ones.