Long-term Distributional Prediction of Cognitive Function

Young-Joo Kim

This study examines the long-term effects of diverse risk factors on the distribution of cognitive function measures, paying special attention to potential heterogeneities across different levels of cognitive function scores. It employs quantile regression techniques on a 10-year panel dataset from the Korean Longitudinal Study of Aging to assess the predictability of risk factors on cognitive decline. Findings indicate that factors such as age, education level, social interactions with close friends, and health status have more pronounced effects on cognitive function at lower quantiles of the Mini-Mental State Examination (MMSE) scores than at higher quantiles. This study also reveals that social interactions with parents, spouses, or close friends significantly predict cognitive function beyond age and education level, which are established nonmodifiable risk factors. It also identifies gender-specific predictors of cognitive function, namely, parental living status, marital status, and satisfaction with health and life for men and income and handgrip strength for women. The differential impact of these risk factors on MMSE score distribution suggests that interventions tailored according to the assessed cognitive function levels could be effective in identifying the cognitive decline risk group and implementing preventive measures.

Keywords: Cognitive function, Cognitive decline, Quantile regression, Prediction, Risk Factors
JEL Classification: I12, C55

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I. Introduction

As global demographics shift toward an increasingly aged population, the economic implications of aging, particularly in the context of cognitive decline, have become a pressing concern. Cognitive decline affects individual quality of life and imposes significant economic burdens on families, healthcare systems, and societies. Economists have highlighted that the costs associated with cognitive impairment not only include direct medical expenses but also long-term care needs, lost productivity, and the emotional and financial strain on caregivers (Angrisani and Lee 2019; Cantarero-Prieto *et al.* 2020). In Korea, where the proportion of older adults is rapidly increasing, the number of people who have dementia is estimated to be 0.8 million, with a prevalence rate of 7.21% in 2019 (National Institute of Dementia 2021), and is projected to increase to 1.9 million in 2050 (Nichols *et al.* 2022). Accordingly, the economic costs individuals and society have to bear for the care and treatment of people afflicted with cognitive decline and dementia are expected to proliferate. Therefore, identifying and mitigating risk factors associated with cognitive decline becomes paramount for the aged society.

The recent literature in economics emphasizes the important role of prediction analysis, diverting from causal inference, in designing effective health policies and social welfare programs. Kleinberg *et al.* (2015) demonstrate that prediction is a critical issue for an optimal allocation of resources for Medicare treatment in older adults before implementing healthcare services. Evaluating the effects of risk factors with the aid of prediction analysis can aid in understanding the necessary preparations for an aging population.

This study investigates the intricate relationship between various risk factors and cognitive function measures, focusing on the heterogeneity in the effects of risk factors across different levels of cognitive function and between genders. By utilizing data from the Korean Longitudinal Survey of Aging (KLoSA), which provides an extensive decade-long dataset for middle-aged and older adults in Korea, this study employs quantile regression analyses to evaluate the long-term influences of identified risk factors derived from a machine learning approach on the distribution of cognitive function. The significance of this research lies in its comprehensive approach to understanding the long-term distributional prediction of cognitive function from the new and established risk factors. These factors encompass demographic variables such as age; education level; health-related measures, including chronic disease prevalence and physical health indicators; and socioeconomic and lifestyle factors, such as income, life satisfaction, and social interactions.

Previous literature on cognitive function provides insights into health and lifestyle risk factors other than age and genetic factors that are nonmodifiable by individual behavior (Baumgart *et al.* 2015). For example, obesity, chronic diseases, social engagement, healthy diet, and physical activities have been studied to support the association between these modifiable risk factors and a risk for cognitive decline (Dong *et al.* 2016; Kivipelto *et al.* 2018; Lehtisalo *et al.* 2016; Ma *et al.* 2020; Singh-Manoux *et al.* 2018). However, little is known about how the effects of risk factors on cognitive function vary depending on whether individuals fall within the cognitive function distribution, given that most studies have examined the effects on the mean level of cognitive function or the incidence of cognitive decline.

This study aims to provide a detailed and comprehensive understanding of the long-term distributional prediction of cognitive function, measured by the Mini-Mental State Examination (MMSE) scores, based on diverse risk factors. By identifying potential heterogeneous effects of risk factors across different segments of the population depending on their cognitive function scores, this study offers valuable insights into what factors are likely to be effective in delaying or preventing cognitive impairment at different stages of cognitive function.

This study further aims to examine the gender-specific differences in the predictability of cognitive decline. By comparing the influences of risk factors on cognitive function separately for men and women, this study attempts to shed light on gender-specific pathways for the development of tailored preventative strategies aimed at combating cognitive decline, thereby contributing significantly to public health strategies and geriatric care policies.

II. Methods

A. Data

We used a longitudinal cohort study derived from the KLoSA. The main objective of the KLoSA was to establish a comprehensive database to examine the factors influencing the life and health of middle-aged and older adults in Korea. The participants of the KLoSA were adults randomly recruited across the regions except those residing at institutions and in Jeju Island, all aged 45 years and older in the first survey year of 2006–2007 (N=10,254). Data were collected by field investigators through computer-assisted personal interviews, adhering to specified guidelines. The investigation covered sociodemographic characteristics, health status, lifestyle, economic activities, and environmental factors. The KLoSA data are publicly available through public repositories (https://survey.keis.or.kr/eng/klosa/klosa01.jsp). This study used data from the 2nd (2008) and 7th (2018) surveys, spanning ten years. Given that some information, including monthly income for personal needs and other economic status measures, was collected from the 2nd survey, we used these data as our baseline reference.

B. Measures

The primary outcome of interest for this study is cognitive function, measured by the Korean version of the MMSE. The MMSE is a widely used battery of tests to assess cognitive function for orientation, memory, attention, language, and visual–spatial skills (Kang *et al.* 1997). The MMSE scores range from 0 to 30, with higher scores indicating better cognitive function (Lee *et al.* 2009). The MMSE scores are used to screen for three stages of cognitive function: normal cognitive function(MMSE scores≥24), mild cognitive impairment(MMSE scores<24), and dementia(MMSE scores<18). In KLoSA, the MMSE was administered for cognitive function assessment until the 7th survey. Thus, we relied on data up to the 7th survey, rather than the most recent one from the 8th survey.

From the 5,238 individuals tracked from the 2nd to the 7th surveys, we excluded 375 without MMSE scores, 751 individuals classified as cognitively impaired or at risk of dementia at the baseline, and 103 with mental health disorders, and 248 without key predictors reported. Thus, we followed up on individuals who were healthy in terms of cognitive function and mental health as of the baseline year. The final analytical sample comprised 3,761 individuals.

C. Statistical Methods

Our primary interest is evaluating the long-term predictability of risk factors for cognitive decline in various quantiles. As an initial screening of potential risk factors, we defined cognitive decline as MMSE scores below 24 and applied logistic least absolute shrinkage and selection operator (LASSO) regression. The LASSO regression analysis method is a useful approach for screening potential predictors out of an extensive set of information, as in our study, where we observe individual characteristics that describe sociodemographic factors, health status, and behavioral factors that are likely associated with cognitive function. As a machine learning method, the LASSO has gained recognition in recent research for its ability to select relevant variables, thereby improving the prediction of diseases, such as cardiovascular disease (CVD) and cognitive decline (Kim 2023; Lu *et al.* 2020; Murdaca *et al.* 2022; Qian *et al.* 2022).

We examined the predictability of cognitive function observed 10 years later based on the selected risk factors from the baseline year. By having a 10-year gap between the predictors and predicted values, we aim to evaluate the long-term predictability of potential risk factors, thereby eliminating the possibility of reverse causality. The conventional least squares method can be useful for examining how potential risk factors predict cognitive function scores. However, risk factors can have different effects in predicting the MMSE score distribution, and predicting the change in the risk group is practically more relevant. Furthermore, even if the mean of the MMSE score distribution has not changed, different effects may exist across the MMSE score distribution associated with a change in risk factors. For example, the thresholds for the risk of cognitive impairment and dementia are 18 and 24, respectively. Around these threshold points, different effects may be observed from a change in risk factors, although the mean of the distribution remains the same. In such cases, the least squares method is limited in delivering information on how risk factors are differently associated with the predicted cognitive function scores. As we focus on the group of individuals who are at risk of having lower MMSE scores toward cognitive impairment or dementia, we must implement a method that provides a comprehensive overview of the score distribution.

To account for potential heterogeneity in the long-term predictability of the selected risk factors, we used quantile regression methods developed by Koenker and Bassett (1978) and Koenker (2005) and estimated the effects of risk factors on the MMSE score distribution. We focused on the 25th, 50th, and 75th percentiles of the distribution and estimated the quantile regressions simultaneously. We also use Ordinary Least Squares (OLS) regression to contrast the OLS regression results with those from quantile regressions at the 25th, 50th, and 75th percentiles. This comparison allows for examining how risk factors differentially impact cognitive function across the MMSE score distribution.

III. Results

A. Descriptive Statistics

For potential risk factors, we examined an extensive list of individual characteristics and behavioral and environmental factors. The full list of variables that are included in the variable selection procedure can be found in Kim (2023). In Table 1, we provide key factors of individual characteristics observed in the baseline year.

About 47 percent of the sample is men (men=1,755; women=2,008), and the average age in the baseline year is 59, ranging from 47 to 85. The average of the initial MMSE scores from the baseline is 27.9, ranging between 24 and 30. The average MMSE score from the 7th survey is 26.4, with an increased standard deviation from 1.884 in the baseline to 4.292 in the 7th survey. The 25th, 50th, and 75th percentiles of the MMSE scores from the 7th survey are 25, 28, and 30, respectively. Figure 1 shows a detailed illustration of the MMSE score distribution. About 30% of the sample are clustered at the top score of 30; and 20% are located below 24, which is the cutoff point for the mild cognitive impairment risk group.

The education level is categorized into four groups, where elementary education (32%) is the lowest, and college education (12%) is the highest. Most survey participants (88%) are married and living with a spouse. About 26% of the sample reported having a mother alive, whereas 62% reported that both their parents had passed away. Social activities and interactions were measured by how often the participants meet close friends, and variation exists across frequencies. Approximately 2% of the sample met friends once or twice a year, 16% met friends once a year, and 31% met friends four times or more weekly. Labor market activity was measured by employment experience in the past and current periods. About 21% had no employment experience in the past, and 56% reported having worked in the current period. Satisfaction scores on health or overall life were measured and they range from 0 to 100, with higher scores for better satisfaction levels.

Health measures include having a chronic disease of CVD, which includes hypertension, diabetes, heart disease, and cerebrovascular disease. About 33% of the sample had CVD in the baseline year. Handgrip strength was included for measuring muscle mass, and its average is 26.5, ranging from 5 to 55.8. Smoking experience was considered, and most of the participants were never smokers or past smokers, with 20% being current smokers.

B. Estimation Results with the Full Sample

Out of an extensive set of individual characteristics likely associated with cognitive decline, the logistic Lasso regression selected 11 risk factors to predict cognitive function, which comprised sociodemographic factors, health measures, economic status, and subjective life scores. The sociodemographic factors include age, elementary education level; an indicator of living parents; and indicators of meeting close friends almost every day, once a month, or once a year. The selected health-related measures were CVD, handgrip strength, satisfaction scores on perceived health status, and satisfaction scores on overall life. The economic component of the selected factors was the monthly income for personal needs.

We also selected separate sets of predictors for men and women from the Lasso. For men, we included an indicator of having a mother alive, employment experience in the past or the current period, and marital status. For women, we included high school education level and past smoking experience.

Subsequently, we estimated how the risk factors observed in the baseline year are associated with the cognitive function measured in 10 years using the 11 risk factors of cognitive decline selected from the full sample and a male indicator. Table 2 shows a comparison of the OLS regression results with quantile regression results at different percentiles. This result reveals how the influence of each predictor changes across the cognitive function distribution.

Column 1 of Table 2 shows the estimation results from the OLS. It indicates that, except for gender and handgrip strength, all risk factors are significant predictors of cognitive function. When the magnitudes of the estimated coefficients are compared, the indicators of meeting close friends are the most significant predictors next to education level. Older age, having a lower education level, meeting close friends daily or rarely, having no parents alive, and having a chronic disease of CVD are all predicted to reduce MMSE scores. By contrast, higher satisfaction scores on health and life and a higher monthly income are predicted to increase MMSE scores.

Next, we examined how these risk factors predict cognitive function differently across the MMSE score distribution. In Columns 2-4 of Table 2, we present the estimation results from quantile regressions. Significant predictors included age, education level, presence of living parents, frequency of social interactions, chronic disease status, and income. The coefficients indicated the direction and magnitude of these effects, with quantile regressions highlighting how the effects of risk factors vary at different points in the cognitive function distribution.

First, among the risk factors, age was examined. The effect of age on cognitive function varies across the quantiles. At lower quantiles, representing lower cognitive function, the negative influence of age is more pronounced, suggesting that older individuals with already lower cognitive function are more susceptible to further decline. Second, the elementary education level is significantly and negatively associated with MMSE scores. This finding may indicate the benefit of higher education on cognitive function. However, given that we focus on prediction, not causality, we do not exclude the possibility that a low education level may indicate a deprived educational environment for older cohorts whose compulsory education level is low.

Third, the role of social interactions with close friends exhibits variability across quantiles. Frequent or rare interactions are associated with lower cognitive function in later years, whereas interactions once a month are associated with higher scores and a greater effect at lower quantiles. The magnitude of the interaction effect is more than two to ten times the age effect across the MMSE score distribution. These findings highlight the importance of social engagement for individuals at greater risk of cognitive impairment.

Fourth, having chronic diseases, such as CVD, is predictive of lower cognitive function, but greater life and health satisfaction demonstrate protective effects on cognitive function with greater effects at lower quantiles. The results suggest that physical health and self-evaluated overall well-being are crucial for those at risk of cognitive impairment.

Lastly, regarding socioeconomic status measures, monthly income has a contrasting effect compared to other risk factors. Having a higher income has a greater effect on the cognitive function at the median or upper quantile than at the lower quantile.

In summary, most of the risk factors associated with cognitive decline are estimated to have a greater effect on MMSE scores at the lower quantile than at the upper quantile. Given that the 25th percentile of MMSE scores is 25, which is right above the threshold of mild cognitive impairment, the larger effects of risk factors at the lower quantile than at the upper quantile implies a higher risk of cognitive decline associated with these risk factors for the group of individuals who already reached lower cognitive function scores.

C. Estimation Results by Gender

To explore heterogeneity between men and women, we examined the predictability of risk factors for cognitive function by gender. We use the same set of risk factors from Table 2 to analyze the subsamples of men and women. Tables 3 and 4 present the results for men and women, respectively.

Table 3 shows that most of the risk factors considered have greater impacts at the lower quantiles than at the upper quantiles, which is consistent with the prior results in Table 2. The other key aspect is that the effects of parental living status and satisfaction with their health are greater for men than the general population described in Table 2. The results in Table 4 for women present different aspects of gender-specific findings. It shows that social interactions with close friends significantly affect the lower and upper quantiles of cognitive function, although some variation exists in the strength of the association between social interactions and cognitive function. Other risk factors, such as handgrip strength and monthly income, are estimated to have significant effects but with a greater impact at the lower quantiles, as in the full sample.

Next, we use different sets of risk factors for men and women separately derived for the prediction of cognitive decline. First, Table 5 shows the results for men. Among the risk factors examined, age, education level, having a mother alive, marital status, life satisfaction scores, and no employment experience are all estimated to be significant predictors of cognitive function when evaluated at the mean of MMSE scores with OLS. Given that we considered the differential marginal effects of risk factors for men across quantiles, the heterogeneity of the marginal effects on cognitive function is observed as in the prior results from the full sample. Age, education level, marital status, and life satisfaction have greater impacts at lower quantiles, whereas no employment experience significantly affects only the median and mean. Specifically, the impact of age is more pronounced at lower quantiles in Table 5 compared with Table 2, indicating that older men with already lower cognitive scores are at a heightened risk of further decline. Life satisfaction scores positively affect cognitive function with a greater influence at lower quantiles, indicating a protective factor against cognitive decline for those with lower cognition.

Table 6 presents the results for women. The significant predictors among the risk factors we selected for women are age, education level, handgrip strength, and monthly income. Similar to the prior results from the full and male samples, most risk factors have greater effects at lower quantiles than upper quantiles. The protective effects of handgrip strength and monthly income suggest that certain factors uniquely influence women's cognitive health with greater effects.

For additional robustness checks, we divided the sample into two age groups and examined the effects of risk factors on the MMSE score distribution across the groups. We split the sample based on 65 as it is the conventional cutoff age for the classification of older adults. The OLS and quantile regression results are presented in Table 7 for those 65 and younger, and Table 8 for those older than 65. The aging process of cognitive function and the effects of risk factors on this aging process may vary at different stages of life. However, the results in Tables 7 and 8 show that the critical risk factors of cognitive decline and their overall effects are similar across relatively younger and older adults.

IV. Discussion

The current study examines the long-term distributional prediction of cognitive function with various risk factors that describe an individual's health, socioeconomic and environmental characteristics. Age; education level; social interactions with parents, spouses, or close friends; health status measured by CVD; handgrip strength; and satisfaction with health and life are all estimated to be significant predictors of cognitive function for middle-aged and older adults in the long run. Furthermore, we show that most of the risk factors have greater effects at the lower quantiles than at the upper quantiles, suggesting that those who already reached lower cognitive function face higher risk of further decline in cognitive function. The finding that age, education level, and social interactions are significantly associated with cognitive function in late life confirms previous findings (Brown *et al.* 2012; Crooks *et al.* 2008; Jefferson *et al.* 2011; Meng and D'Arch 2012; Seeman *et al.* 2011). In addition, this study presents new evidence on the different effects of risk factors across the distribution of cognitive function.

By looking into how the effects of long-term risk factors on cognitive function vary depending on where individuals fall within the cognitive function distribution, we provide critical insights into what factors should be monitored at an early stage of life to identify the at-risk group before the development of cognitive impairment or dementia.

This study also provides empirical evidence on how risk factors affect cognitive function differently in men and women. For men, parental living status, marital status, social interactions, and satisfaction with health or overall life, among other risk factors, are estimated to have greater effects at the lower quantiles than at the upper quantiles. For women, handgrip strength and monthly income have greater effects at the lower quantiles on cognitive function, with variability that social interactions have similar effects across the distribution of cognitive function.

However, this study has some limitations. Given that we use longitudinal data that have been followed up over 10 years, we focus on individuals who have survived and could be traced over the survey years. In case individuals who dropped out of the sample due to death or other reasons are systematically different from those who remained in the sample, our findings will be limited to applications for the general population of older adults. At the same time, this limitation reflects the other side of the longitudinal data, which allows us to examine long-term relationships. In this light, the empirical findings of this study provide insights into how risk factors differentially affect cognitive function in men and women across different quantiles in the long run and how these effects compare to the general population trends. This long-term comparative analysis is vital for understanding gender-specific pathways in cognitive health and developing targeted strategies at an early stage to mitigate cognitive decline in older adults. The findings of detrimental and protective factors across the distribution of cognitive function can be utilized to develop strategies more effectively tailored to those most in need, potentially leading to more successful outcomes in preventing or slowing cognitive decline.

V. Conclusion

Recent research in economics has explored the impact of aging on work, income distribution, and, consumer spending, particularly as they relate to health and longevity, retirement income, and social engagement (Angrisani and Lee 2019). Economic analysis has also focused on the timing of retirement, which is influenced by health, resources available for retirement, and cultural norms (Ataly *et al.* 2019; Bonsang *et al.* 2012). Studies have shown that bridge employment (Beehr and Bennett 2015; Bennett *et al.* 2016), which includes part-time or temporary jobs taken after retirement, can offer health benefits in addition to income, suggesting a positive influence on cognitive health. Moreover, previous research has underscored the influence of income inequality on the well-being of older people (Deaton and Paxson 1998), highlighting how lifetime shocks and socioeconomic status affect health outcomes and engagement in civic life. The findings of our study that emphasize the role of social interactions, satisfaction on health and life, and economic status and activities support this notion.

The economic perspectives of aged society underline the importance of considering the economic consequences of cognitive decline, not only in terms of direct healthcare costs but also concerning broader socioeconomic implications, such as workforce participation, retirement planning, and income distribution. By understanding risk factors that are predicted to lead to cognitive decline, we can contribute to policy discussions aimed at designing effective health intervention policies and programs that address these challenges in aging populations.

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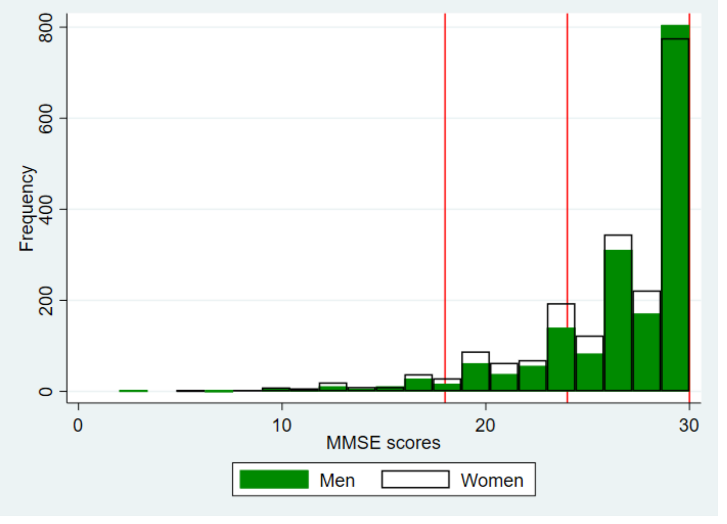
TABLE 1
SUMMARY STATISTICS

	All		Men		Women	
	N=3,761		N=1,753		N=2,008	
VARIABLES	Mean	S.D.	Mean	S.D.	Mean	S.D.
Male	0.466	0.499				
Age	58.86	8.228	59.69	8.264	58.14	8.131
MMSE scores at 7th survey	26.42	4.179	26.72	4.027	26.16	4.292
MMSE scores at 2nd survey	27.92	1.850	28.07	1.799	27.79	1.884
Education level						
- Primary education	0.321	0.467	0.225	0.418	0.406	0.491
- Middle school education	0.198	0.399	0.176	0.381	0.217	0.412
- High school education	0.358	0.480	0.406	0.491	0.317	0.465
- College+ education	0.122	0.327	0.193	0.395	0.0603	0.238
Married	0.883	0.321	0.945	0.228	0.829	0.377
Mother alive	0.263	0.440	0.262	0.440	0.264	0.441
No parents alive	0.620	0.486	0.621	0.485	0.619	0.486
No work experience	0.218	0.413	0.0405	0.197	0.374	0.484
Currently work	0.556	0.497	0.726	0.446	0.407	0.491
Meet friends 4+ a week	0.313	0.464	0.288	0.453	0.336	0.473
Meet friends 1 a month	0.158	0.365	0.185	0.388	0.135	0.342
Meet friends 1 a year	0.0202	0.141	0.0245	0.155	0.0164	0.127
CVD	0.330	0.470	0.339	0.474	0.322	0.467
- Hypertension	0.259	0.438	0.260	0.439	0.258	0.438
- Diabetes	0.101	0.302	0.114	0.318	0.0901	0.286
- Heart disease	0.0420	0.201	0.0434	0.204	0.0408	0.198
- Cerebrovascular disease	0.0154	0.123	0.0165	0.128	0.0144	0.119
No-smoke	0.809	0.393	0.613	0.487	0.981	0.136
Handgrip strength	26.54	7.855	32.99	5.849	20.91	4.207
Satisfaction scores on health	62.41	18.23	64.90	17.34	60.24	18.71
Satisfaction scores on life	64.90	16.54	65.64	16.45	64.26	16.59
Monthly income	18.21	17.47	24.12	20.98	13.05	11.42
Private insurance	0.466	0.499	0.447	0.497	0.483	0.500

Notes: N for sample size, S.D. for standard deviation. Monthly income in 10,000 won.



Notes: MMSE scores from the 7th survey, which is the primary outcome of this study. The red lines at 18 and 24 are the cutoff points for mild cognitive impairment and dementia risk groups, respectively. The red line at 30 is the top achievable score.

Figure 1
Histogram of MMSE Scores for Men and Women

Table 2
OLS and Quantile Regressions of Cognitive Function on Risk Predictors

	(1)	(2)	(3)	(4)
	OLS	Quantile Regression		
Predictors		0.25 Quantile	0.50 Quantile	0.75 Quantile
Male	0.215	0.387	0.183	-0.0481
	(0.210)	(0.314)	(0.231)	(0.0718)
Age	-0.138***	-0.197***	-0.122***	-0.0386***
	(0.00971)	(0.0160)	(0.0136)	(0.0119)
Primary education	-1.202***	-1.972***	-1.520***	-0.880***
	(0.151)	(0.230)	(0.255)	(0.226)
No parents alive	-0.262*	-0.421*	-0.198	0.0203
	(0.144)	(0.218)	(0.143)	(0.0428)
Meet friends 4+ a week	-0.834***	-0.592**	-0.827***	-0.283*
	(0.140)	(0.239)	(0.174)	(0.146)
Meet friends 1 a month	0.347**	0.632***	0.292**	0.0243
	(0.177)	(0.243)	(0.135)	(0.0371)
Meet friends 1 a year	-1.558***	-2.171***	-2.188***	-1.138*
	(0.440)	(0.754)	(0.574)	(0.616)
CVD	-0.263*	-0.325	-0.272	0.0281
	(0.136)	(0.207)	(0.178)	(0.0487)
Handgrip strength	0.00990	0.0203	0.00974	0.00655
	(0.0132)	(0.0185)	(0.0133)	(0.00458)
Satisfaction with health	0.0120***	0.0142**	0.00735*	0.00269*
	(0.00393)	(0.00597)	(0.00431)	(0.00157)
Satisfaction with life	0.0134***	0.0177**	0.00241	0.00185
	(0.00430)	(0.00718)	(0.00552)	(0.00154)
Monthly income	0.00996**	0.00801	0.00997***	0.00193*
	(0.00395)	(0.00597)	(0.00358)	(0.00113)
Observations	3,761	3,761	3,761	3,761
R-squared	0.193			

Notes: Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 3
OLS and Quantile Regressions of Cognitive Function with Full Sample Predictors for Men

	(1)	(2)	(3)	(4)
	OLS	Quantile Regressions		
Predictors		0.25 Quantile	0.50 Quantile	0.75 Quantile
Age	-0.114***	-0.182***	-0.109***	0.000
	(0.0139)	(0.0228)	(0.0144)	(0.0183)
Primary education	-1.243***	-2.151***	-1.351***	-1.000***
	(0.229)	(0.434)	(0.342)	(0.267)
No parents alive	-0.477**	-0.543*	-0.407**	-0.000
	(0.208)	(0.307)	(0.184)	(0.0418)
Meet friends 4+ a week	-0.911***	-0.742*	-0.886***	-1.000**
	(0.208)	(0.405)	(0.222)	(0.392)
Meet friends 1 a month	0.348	0.598*	0.140	-0.000
	(0.241)	(0.326)	(0.149)	(0.0489)
Meet friends 1 a year	-1.431**	-1.517*	-2.171***	-1.000
	(0.577)	(0.824)	(0.718)	(0.612)
CVD	-0.169	-0.250	-0.254	0.000
	(0.193)	(0.317)	(0.198)	(0.0582)
Handgrip strength	-0.0211	-0.0153	-0.0291**	0.000
	(0.0170)	(0.0316)	(0.0146)	(0.00406)
Satisfaction with health	0.0229***	0.0268***	0.0123**	-0.000
	(0.00588)	(0.0103)	(0.00556)	(0.00237)
Satisfaction with life	0.0114*	0.0188*	-0.00299	0.000
	(0.00619)	(0.00994)	(0.00601)	(0.00162)
Monthly income	0.00929**	0.00471	0.00668	-0.000
	(0.00450)	(0.00747)	(0.00441)	(0.00136)
Observations	1,753	1,753	1,753	1,753
R-squared	0.166			

Notes: Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 4
OLS AND QUANTILE REGRESSIONS OF COGNITIVE FUNCTION WITH FULL SAMPLE PREDICTORS FOR WOMEN

	(1)	(2)	(3)	(4)
	OLS	Quantile Regression		
Predictors		0.25 Quantile	0.50 Quantile	0.75 Quantile
Age	-0.163***	-0.227***	-0.128***	-0.0525***
	(0.0136)	(0.0248)	(0.0214)	(0.0119)
Primary education	-1.063***	-1.571***	-1.565***	-0.891***
	(0.206)	(0.328)	(0.299)	(0.232)
No parents alive	-0.0779	-0.234	-0.0136	0.0517
	(0.198)	(0.338)	(0.189)	(0.0757)
Meet friends 4+ a week	-0.770***	-0.481	-0.706***	-0.309**
	(0.190)	(0.327)	(0.234)	(0.124)
Meet friends 1 a month	0.255	0.563	0.342	-0.0536
	(0.260)	(0.408)	(0.223)	(0.0992)
Meet friends 1 a year	-1.590**	-2.281**	-2.105**	-1.887**
	(0.674)	(1.117)	(0.973)	(0.859)
CVD	-0.284	-0.404	-0.271	0.118
	(0.192)	(0.337)	(0.286)	(0.0931)
Handgrip strength	0.0684***	0.0601**	0.0902***	0.0249**
	(0.0215)	(0.0286)	(0.0267)	(0.0102)
Satisfaction with health	0.00370	0.00791	0.00536	0.00331*
	(0.00527)	(0.00851)	(0.00577)	(0.00196)
Satisfaction with life	0.0138**	0.0125	0.00373	0.00277
	(0.00598)	(0.0113)	(0.00636)	(0.00256)
Monthly income	0.0139*	0.0214*	0.0207***	0.00209
	(0.00810)	(0.0120)	(0.00674)	(0.00234)
Observations	2,008	2,008	2,008	2,008
R -squared	0.220			

Notes: Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5

OLS and Quantile Regressions of Cognitive Function with Unique Predictors for Men

	(1)	(2)	(3)	(4)
	OLS	Quantile Regressions		
Predictors		0.25 Quantile	0.50 Quantile	0.75 Quantile
Age	-0.110***	-0.170***	-0.113***	0.000
	(0.0140)	(0.0209)	(0.0161)	(0.0172)
Primary education	-1.417***	-2.234***	-1.358***	-1.000***
	(0.230)	(0.427)	(0.370)	(0.220)
Mother alive	0.437**	0.426	0.222	0.000
	(0.212)	(0.323)	(0.155)	(0.0267)
Married	0.672*	1.489*	0.778	0.000
	(0.405)	(0.793)	(0.662)	(0.123)
Satisfaction with life	0.0182***	0.0191**	0.00991*	-0.000
	(0.00570)	(0.00905)	(0.00585)	(0.0009)
No work experience	-0.855*	-1.021	-1.165*	-1.000
	(0.481)	(0.768)	(0.633)	(0.835)
Currently work	0.256	0.362	-0.0425	0.000
	(0.242)	(0.452)	(0.261)	(0.469)
Private insurance	0.299	0.319	0.297	-0.000
	(0.196)	(0.316)	(0.227)	(0.0411)
Observations	1,755	1,755	1,755	1,755
R-squared	0.145			

Notes: Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6
OLS and Quantile Regressions of Cognitive Function with Unique Predictors for Women

	(1)	(2)	(3)	(4)
	OLS	Quantile Regressions		
Predictors		0.25 Quantile	0.50 Quantile	0.75 Quantile
Age	-0.162***	-0.229***	-0.130***	-0.0475***
	(0.0128)	(0.0205)	(0.0206)	(0.0156)
Primary education	-1.063***	-1.434***	-1.673***	-1.036***
	(0.231)	(0.376)	(0.322)	(0.320)
High school education	0.305	0.350	0.177	-0.00566
	(0.224)	(0.304)	(0.225)	(0.0443)
CVD	-0.327*	-0.474	-0.279	0.113
	(0.192)	(0.308)	(0.274)	(0.0885)
Handgrip strength	0.0789***	0.0792**	0.0982***	0.0191**
	(0.0215)	(0.0343)	(0.0295)	(0.00883)
No-smoke	-0.148	-0.502	-0.557	-0.0910
	(0.629)	(0.760)	(0.759)	(0.366)
Monthly income	0.0174**	0.0231**	0.0196***	0.00229
	(0.00793)	(0.0102)	(0.00550)	(0.00164)
Observations	2,008	2,008	2,008	2,008
R-squared	0.208			

Notes: Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 7
OLS AND QUANTILE REGRESSIONS OF COGNITIVE FUNCTION FOR INDIVIDUALS AGED 65 AND YOUNGER

	(1)	(2)	(3)	(4)
	OLS	Quantile Regression		
Predictors		0.25 Quantile	0.50 Quantile	0.75 Quantile
Male	0.222	0.436	0.264	0.000**
	(0.219)	(0.414)	(0.217)	(0.000)
Age	-0.0899***	-0.147***	-0.0896***	-0.000***
	(0.0133)	(0.0241)	(0.0142)	(0.000)
Primary education	-1.082***	-1.927***	-1.499***	-1.000***
	(0.158)	(0.286)	(0.232)	(0.0834)
No parents alive	-0.269**	-0.374*	-0.188	-0.000
	(0.133)	(0.217)	(0.140)	(0.000)
Meet friends 4+ a week	-0.836***	-0.578**	-0.834***	-0.000
	(0.142)	(0.277)	(0.186)	(0.0547)
Meet friends 1 a month	0.365**	0.526*	0.260*	-0.000
	(0.175)	(0.288)	(0.139)	(0.000)
Meet friends 1 a year	-0.991**	-1.845**	-1.322**	-1.000
	(0.446)	(0.823)	(0.544)	(0.655)
CVD	-0.224	-0.129	-0.196	-0.000***
	(0.141)	(0.246)	(0.174)	(0.000)
Handgrip strength	-0.00343	0.00899	0.00620	-0.000***
	(0.0135)	(0.0239)	(0.0138)	(0.000)
Satisfaction with health	0.00954**	0.0159**	0.00631	0.000
	(0.00396)	(0.00772)	(0.00436)	(0.000)
Satisfaction with life	0.00833*	0.00847	0.000334	-0.000*
	(0.00433)	(0.00868)	(0.00490)	(0.000)
Monthly income	0.0105***	0.00744	0.00856**	-0.000
	(0.00373)	(0.00688)	(0.00390)	(0.000)
Observations	2,878	2,878	2,878	2,878
R-squared	0.102			

Notes: Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

TABLE 8
OLS AND QUANTILE REGRESSIONS OF COGNITIVE FUNCTION FOR INDIVIDUALS OLDER THAN 65

	(1)	(2)	(3)	(4)
	OLS	Quantile Regression		
Predictors		0.25 Quantile	0.50 Quantile	0.75 Quantile
Male	0.118	0.350	0.697	0.123
	(0.509)	(0.930)	(0.797)	(0.351)
Age	-0.261***	-0.372***	-0.331***	-0.108***
	(0.0438)	(0.0944)	(0.0826)	(0.0352)
Primary education	-1.544***	-2.326***	-1.942***	-1.144***
	(0.376)	(0.653)	(0.644)	(0.282)
No parents alive	-1.428**	-1.689*	-1.126*	-0.599*
	(0.642)	(0.901)	(0.668)	(0.338)
Meet friends 4+ a week	-0.730**	-0.0690	-0.927	-1.011***
	(0.369)	(0.597)	(0.597)	(0.301)
Meet friends 1 a month	0.308	0.623	-0.152	-0.228
	(0.507)	(0.682)	(0.778)	(0.345)
Meet friends 1 a year	-3.389***	-3.177	-4.127***	-2.588*
	(1.151)	(2.139)	(1.513)	(1.392)
CVD	-0.464	-1.040*	-0.923	0.246
	(0.338)	(0.534)	(0.565)	(0.288)
Handgrip strength	0.0526	0.0433	0.0167	0.0355
	(0.0352)	(0.0599)	(0.0510)	(0.0268)
Satisfaction with health	0.0204*	0.0299*	-0.00383	0.0129
	(0.0104)	(0.0171)	(0.0158)	(0.0103)
Satisfaction with life	0.0237**	0.0116	0.0264	0.0166**
	(0.0115)	(0.0172)	(0.0202)	(0.00822)
Monthly income	0.0135	0.0182	-0.00806	-0.0162
	(0.0145)	(0.0189)	(0.0163)	(0.0110)
Observations	883	883	883	883
R-squared	0.150			

Notes: Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

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