Examining Socioeconomic Variation in the Co-Evolution of Cognitive Decline and Functional Limitations among the Oldest Old

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Abstract

This research examines how socioeconomic status (SES) developed across the lifecourse influences the co-evolution of cognitive and functional trajectories among the oldest Americans. Parallel-process latent growth models with controls for mortality selection were used to examine the inter-relation of cognitive health, as measured by immediate and delayed word-recall scores, and functional health, as measured by an index of mobility functional limitation. Observations were drawn from the Assets and Health Dynamics among the Oldest Old Study (AHEAD; 1998-2008). Findings suggest initial word-recall scores are a consistent predictors of later functional limitations, but baseline functional limitations did not consistently predict later word-recall scores. Gender and household income moderated this relationship, and indicators of lifecourse SES were better equipped to predict variation in initial cognitive and functional status than change over time in these measures. These results suggest that socioeconomic disparities in cognitive and functional trajectories are largely crystallized prior to the latest years of adulthood.

For developed countries, the squaring age distribution reflects an increasing number of adults living to the furthest bounds of human longevity. The population health costs of morbidities common to late old age will inevitably place a growing burden on healthcare and social support systems that provide care for the aging. Two of the most costly health problems associated with aging are cognitive decline and increasing functional limitations, and these morbidities are often dealt in pairs. A substantial amount of research has shown declines in cognitive abilities increase the risk of functional limitations (McGuire, Ford, and Ajani 2005; Moody-Ayers et al 2005; Stuck et al 1999), and both in turn increase the risk of disability and mortality (Gallacher et al. 2009; Scott et al. 1997). Evidence suggests that functional limitations and disability influence cognitive outcomes, with both cognitive and functional health mutually influencing the development of one another (Atkinson et al. 2005; Black and Rush 2002). Studies of socioeconomic variation in trajectories of mind/body health among the aged are present, but work that focuses on the socioeconomic context where cognitive and functional health co-evolve are less apparent. Another issue hampering examinations of the dynamics of co-morbidity development is mortality selection, creating potentially biased estimates in studies that do not adjust for presence of non-random missing data. Understanding the inter-relation between cognitive and functional health outcomes is essential for those responsible with the planning of health policy that will serve to protect from the manifold costs of an aging population.

To identify the complex relationship between cognitive decline, functional limitations, and socioeconomic resources, this project utilizes parallel process latent growth modeling with adjustment for mortality selection to model the co-evolution of cognitive abilities (as measured by immediate and delayed word-recall scores) and functional limitations over a ten-year period. Observations are drawn from the Assets and Health Dynamics among the Oldest Old Study

(AHEAD; 1998-2008). After determining the measurement model that best captures the inter-relation between development of cognitive and functional limitations, measurements of socioeconomic status (SES) will be introduced to understand how differential access to health-enabling resources contributes to variation in the relationship between trajectories of cognitive and functional health among America's oldest old. The measures of SES included account for access to socioeconomic resources across the lifecourse, including indicators of educational and monetary resources at time of interview, occupational position across working life, and finally, retrospective indicators of childhood socioeconomic circumstances. Estimates produced from traditional approaches to latent growth modeling in the presence of missing data will be compared to estimates taken from Diggle-Kenward selection models and pattern-mixture models, designed to control for the presence of non-random missing data on both growth trajectories being analyzed. By focusing on the inter-related development of cognitive and functional limitations controlling for a robust set of indicators of SES across the lifecourse, and by using innovative methods to account for the presence of mortality selection, this work provides a unique contribution to the study of health inequalities amongst aging Americans.

Cognitive and Physical Health in Socioeconomic Context

The disablement process provides a useful framework from which to understand the inter-relation of cognitive and functional health trajectories. Conceptually, the disablement process describes the pathway between disease pathology and disablement, where pathologies create impairments in specific body systems that produce restrictions is basic abilities and actions (functional limitations), in turn restricting one's abilities to carry out activities essential to survival and social functioning (disability; Verbrugge 1994). Demographic, social, and behavioral risk factors contribute to the development of disability, and represent potential points of intervention aimed at reducing disability. Health problems develop along this main pathway directly, can be enforced through feedback effects on the given outcome, and finally can initiate and enforce the development and progression of other ailments. Concerning measures of cognitive and functional health being analyzed here, both cognition and functional limitations are considered antecedents of disability that restricts one's ability to effectively carry out activities and essentially one's ability to survive (Verbrugge 1994). This work is specifically interested in the potential for a given health problem to influence the development of another health problem, and how social risk factors contribute to this relationship.

Cognitive functioning and physical limitations both work to produce disability in the lives of aging adults, and the inter-relation between these health conditions has been the focus of a good deal of research. Cognitive functioning is generally believed to be composed of both fluid abilities, related to complex problem solving, and crystallized abilities, referring to abilities developed by experience and culturally defined tasks (Alwin and Hofer 2008). This work utilizes a sum of immediate-and-delayed word recall tasks, providing a measure sensitive to cognitive change closer in line with fluid abilities (Small, Stern, Tang and Mayeux 1999). As a measure of functional limitations, this work utilizes limitations in functional mobility (Nagi 1969; Rosow and Breslau 1966) indicating whether the respondent has difficulties in performing tasks such as walking several blocks or sitting in a chair conformably for two hours. This measure of functional health, an indicator of general physical ability, is preferable to other popular measures of functional health such as activities of daily living (ADLs) and instrumental activities of daily living (IADLs), as mobility tasks minimize the influence of the built environment or adaptive technologies, both of which are influenced by SES. Using these measures of cognitive and functional health aims to provide a portrait of associated cognitive and physical functional limitations that are precursors to the development of more serious disabilities.

Disentangling the relationship between cognitive and functional health can provide guidance towards interventions that reduce the disability imposed by both cognitive and functional limitations. Review of work that has examined the relationship between cognitive health and functional limitations, either as a uni-directional relationship, or as inter-related processes, will provide direction towards clear hypotheses concerning the casual relationship between these outcomes. The co-development of cognitive and functional health must be understood within the socioeconomic context where health and health disparities arise, and this will be guided by socioeconomic perspectives focused on the individual's access to health-enabling resources across the life-course.

Associations between cognitive and physical health.

Both cognitive and functional health in the aging population receives a tremendous amount of attention by health researchers, and rightfully so: estimates predict that in 2050, the percentage of U.S. citizens age 65 and over will increase from around 13% in 2010 to nearly 21% of the entire population, with the percentage of adults age 85 or older jumping from 2% to 5% by 2050 (Alwin, McCammon, Wray, and Rodgers 2008). By 2050, the percentage of adults age 85 or older with low cognitive functioning will more than double from current estimates (Alwin, McCammon, Wray, and Rodgers 2008), and the number of adults age 65 and over experiencing physical limitations is also projected to double (Waidmann and Liu 2000). While the prevalence of cognitive and functional limitations has been decreasing (Freedman, Martin, and Schoeni 2002), the population health burden will continue to increase with a shifting population age-structure.

The relationship between cognitive and functional health has long been a focus in studies of health and aging, though these works tend not to examine the mutual influence that may occur in this relationship. The largest body of research supports the conclusion that cognitive functioning is associated with, and influences the development of, functional limitations and activity of daily living (ADL) limitations (McGuire, Ford, and Ajani 2005; Moritz, Kasl, and Berkman 1994; Moody-Ayers et al 2005; Speirs et al 2005; Stuck et al 1999; Wang, van Belle, Kukull, and Larson 2002). The bulk of work in this area has focused on cross-sectional associations between cognition and functional limitations, though the longitudinal analyses support that cognition influences the development of functional limitations over time (Moritz, Kasl, and Berkman 1994; Moody-Ayers et al 2005; Wang, van Belle, Kukull, and Larson 2002; Speirs et al 2005; Gill, Williams, Richardson, and Tinetti 1996).

Much less work has investigated the concomitant development of cognitive and functional health, but existing research suggests that cognitive and functional health influence the development of one another over time. Atkinson et al. (2005) examined predictors of combined cognitive and physical decline in a female-only sample, finding that impairments in either cognition or instrumental activities of daily living (IADLs) predicted future decline in both processes. Similarly, Black and Rush (2002) found that when controlling for socio-demographics and chronic health conditions, baseline disability and cognitive performance predicted concomitant decline in both dimensions of health. Both of these studies used logistic regression models to predict the appearance of combined cognitive and functional decline, and neither of the studies accounted for the potential multicollinearity between cognitive and functional health that could potentially bias the coefficient estimates of cognitive and functional health being used as independent variables. Regardless, the few studies that examine the co-development of cognitive and functional decline provide support for further elaborations in this line of research.

The studies discussed provide compelling evidence of an association between cognitive and functional health, but to varying degrees, they overlook the role of SES in the association between these health processes. A number of the studies mentioned include controls for SES, but these are usually rudimentary measures that capture only a few dimensions of the socioeconomic context. Furthermore, no studies found explicitly examined the potential for SES to moderate the relationship between cognitive and functional health. For example, socioeconomic resources may protect an individual experiencing cognitive decline from increasing functional limitations in the future. Assistance from personnel or equipment designed to support an individual experiencing cognitive decline may reduce the risk of developing functional limitations. Likewise, those with limited access to socioeconomic resources across the lifecourse may be at greater risk of experiencing cognitive decline due to un-attended functional limitations than those with unrestricted access to these health-enabling resources. Study of the reciprocal relationship between cognitive and functional health necessitates an explicit focus on the socioeconomic context of aging, and can be loosely centered on a fundamental cause perspective.

Socioeconomic determinants of cognitive and physical aging.

It is commonly accepted that those with lower levels of socioeconomic resources have worse health outcomes than those with higher levels (Lynch and Kaplan 2000; Robert and House 2000). Differential access to health-enabling resources is considered a fundamental cause of disparities in health outcomes (Link & Phelan 1995, 2000, 2005), and the resources Link and Phelan refer to are various forms of economic, social, and cultural capital that embed individual health within a larger socio-cultural context. Socioeconomic status refers to a varied set of social and economic indicators that represents one's access to resources, which varies and accumulates across the lifecourse. Lynch and Kaplan (2000) weigh the relative contributions of traditional indicators of SES including education, occupation, and income in relation to health, suggesting the inclusion of a wider variety of resources. Socioeconomic status unfolds dynamically across the lifecourse and social chains of risk extend from childhood to late old age (Kuh, Power, Blane and Bartley 1997). Those who enjoyed high SES in childhood are more likely to have favorable SES in adulthood (Johnson and Reed 1996) as well as experience better health in adulthood (Haas 2007; Rahkonen, Lahelma, and Huuhka 1997). This research integrates measures of SES captured in late adulthood with retrospective measures of childhood socioeconomic circumstances, attempting to measure one's ability to access health enabling resources across the lifecourse.

SES and cognitive decline. Substantial evidence links SES to cognitive health among the aging. Previous studies of the relationship between SES and cognitive decline have tended to focus on education as the key indicator of SES. Education has been consistently related to cognitive health outcomes among the elderly (Alley, Suthers and Crimmins 2007; Cagney and Lauderdale 2002; Lee, Kawachi, Berkman and Grodstein 2003). The relationship between education and cognitive aging is complex as education can be an indicator of both SES as well as a marker of years spent developing and exercising cognitive abilities (Cagney and Lauderdale 2002). In studies with robust controls for SES including lifetime wealth and current income, the impact of education on cognitive function remains strong (Cagney and Lauderdale 2002; Lee, Kawachi, Berkman and Grodstein 2003).

Studies exploring the impact of SES on cognitive aging have also tested indicators of SES including lifetime wealth, current income, and occupation, in addition to indicators of childhood SES. Cagney and Lauderdale (2002) found lower cognitive function among whites with low income and assets, but these relationships did not hold for blacks or Hispanics. Lee and colleagues (2003) reported increased odds of cognitive decline among women whose fathers were farmers compared to white-collar workers, but household income was non-significant. Exploring the relationship between childhood SES and cognitive decline, Faul (2008) found that having comfortable childhood circumstances including high paternal education and occupational prestige was protective against cognitive decline among aging adults. Those with higher SES across the lifecourse consistently have better cognitive outcomes than those with low SES.

SES and functional limitations.

Functional limitations have been shown to be associated a number of socioeconomic indicators. Both education and income have been positively associated with physical functioning (Berkman et al. 1993; Guralink et al. 1993; Kaplan et al. 1993; Seeman et al. 1994), and disparities in disabilities based on education and income increased between 1982-2002 (Schoeni, Martin, Andreski, and Freedman 2005). Focusing on lifecourse SES, Haas (2008) found that in light of significant negative associations between functional limitations and adult SES, parents' education and childhood housing stability were both negatively associated with the development of functional limitations over time. Recent meta-analyses of studies examining functional health and childhood SES have substantiated these findings (Birnie et al. 2011).

Research Aims

In summary, a great deal of research has shown that there is a consistent relationship between cognitive and functional health, and evidence suggests that these health processes exert mutual influence upon one another across time. The bulk of existing studies on the inter-relation of cognitive and functional health utilize cross-sectional samples or create categorical thresholds of cognitive and functional health that are used to identify change in these measures over time, reducing the ability to estimate the amount of change in each dimension of health. Without accounting for the unobserved prior causes that influence baseline levels of cognition and functional health in tandem, assessments of how baseline cognition influences change in functional limitations across time, and vice-versa, may be biased by the omission of the initial relationship between these variables. Similarly, socioeconomic variation in baseline cognitive and functional measures may be quite different from socioeconomic variation in change in these processes over time. Accounting for socioeconomic variation in baseline measures of cognition and physical function will allow a more accurate estimation of how initial levels of these measures influences change in these outcomes over time. Also, including socioeconomic adjustments to the initial levels of each health process, as well as their trajectories of development, will provide insight into socioeconomic disparities in initial measures of cognitive and functional health, as well as provide guidance towards possible points of intervention that can help reduce the severity of change in these measures across time.

Once a structural model of the relation between cognitive and functional trajectories is developed, socioeconomic variation in the relationship between cognitive and functional health will be examined. Change in functional limitations over time will be regressed on interactions between the adjusted measures of baseline cognition and indicators of lifecourse SES, and this task will also be undertaken for the path between baseline functional health and change in cognition. This process will shed light on how lifecourse SES may moderate the relationship between cognitive and functional health, and provide evidence of socioeconomic disparities in aging produced through the interlocking nature of cognitive and functional health outcomes in aging adults.

Method

Created as a national panel survey employing biennial assessment of America's aging population, the Health and Retirement Study (HRS) began as a representative sample of the U.S population between ages 51-61 in 1992 (including spouses regardless of age; Hauser and Weir 2010). To supplement the HRS, the study of the Asset and Health Dynamics among the Oldest Old (AHEAD) began in 1993 as a spinoff of the HRS that focuses on Americans considered to be the oldest-old; birth cohorts born in 1923 or earlier, or who were 70 years of age or older in 1993 (Juster and Suzman 1995). This research utilizes the AHEAD survey from 1998 to 2008. Measurements of cognitive performance and functional limitations used in this analysis were taken over a decade ranging from 1998 to 2008, with all predictor variables being measured in 1998. Individual level weights were utilized, making the sample nearly representative of community-dwelling older adults in the United States in 1998. Restricting the analytic sample to individuals who had non-missing word-recall scores and function limitation counts in 1998, were age 65 or over at baseline measurement, and excluding individuals who were of a race/ethnicity other than white, black, or Hispanic resulted in a final sample size of n = 4,653.

Measures

Word-recall and functional limitations. The outcome variable analyzed was a composite score of two word-recall tasks given to AHEAD respondents. The immediate word-recall task asked respondents to recall a list of 10 common nouns immediately after hearing them and delayed word-recall was measured after five minutes of test administration had passed. Factor analysis on the HRS cognitive tests has shown that immediate and delayed word-recall load on a single factor with an Eigenvalue greater than one (Ofstedal et al. 2005).

The key indicator of functional limitations in this study is a summation of 11 indicators of limitation in functional mobility. Respondents were asked if they had difficulty in each of the following activities: stooping or crouching, climbing one flight of stairs without resting, climbing several flight of stairs without resting, moving large objects, sitting in a chair for two hours, getting up from a chair after sitting for long periods, lifting weights over 10 pounds, raising arms above shoulder level, walking one block, walking several blocks, and picking up a dime from a table (1 = yes; 0 = no). Respondents with 7 or more missing values on these 11 items were coded as missing. This summary has been found to have good reliability (Cronbach's alpha = .85; Fonda and Herzog 2004).

Socioeconomic position and race. Numerous variables were employed to capture the amount and variety of socioeconomic resources available to respondents across the lifecourse. The amount of education reported by the respondent was measured as a set of three dummy codes representing less than high school (0-11 years), high school graduates (reference group), and those with more than 12 years of education. Occupation was measured as the job with longest reported tenure. Individuals who reported their longest employment tenure as professional/ technical workers, managers, officials or proprietors, clerical and kindred workers, and those in sales were defined as white-collar workers. Individuals reporting longest employment tenure as craftsmen, foremen, operators, laborers, service workers or farmers were labeled as blue-collar workers. A dummy variable was included to capture the work experience of females who reported fewer than 4 years of lifetime work experience and who self-identified as a homemaker. A final category was created for individuals whose work experience did not fall within the previously defined categories. In all analyses, white-collar workers were used as the occupational reference group. Household income and household assets were summary measures of numerous sources of income and asset holdings included in the RAND HRS data (version J; St. Clair et al. 2010). Both household income and household assets were transformed on a log scale to reduce the right skew in these variables.

Parental education and father's occupation were included as indicators of childhood SES. Mother's and father's education were measured separately using a dummy indicator representing whether each parent had attained 8 or more years of education (1 = yes, 0 = no). Respondents were asked what their father's occupation was when the respondent was age 16. Father's occupation was coded as white-collar or other occupational status (1 = white-collar, 0 = other occupation).

Control variables. Controls were included to provide a more accurate assessment of the relation between SES, cognitive performance, and functional limitations. Analyses controlled for gender and the respondent's age at initial interview. Respondents who were white, black, and Hispanic were included in analysis, with white individuals serving as the reference group. Marital status at time of initial interview was included to control for possible associations between health and marital status, with those reporting being married, married with spouse absent, or partnered being defined as married, and those reporting being separated, divorced, widowed, or never married defined as un-married (1 = married, 0 = un-married).

Statistical analysis

Mplus version 6.1 (Muthén and Muthén 2010) was used to create and analyze multiple imputation data and estimate parallel process latent growth models. Latent growth modeling (LGM) is considered an extension of structural equation modeling (SEM) where the individual parameters that create trajectories are treated as latent variables (Bollen and Curran 2006). Parallel process latent growth modeling is an extension of LGM where an intercept and slope are estimated for two or more concurrent outcome variables of interest (Muthén and Curran 1997). To take advantage of the temporal ordering of the latent intercept and slope for each process, the structural paths investigated in this project extended from the intercept of one construct to the latent slope of the other construct. This specification assured that both latent and observed predictor variables preceded the specific outcomes of interest, namely change in cognition and functional limitations over time. An un-specified model that allowed all latent variables to correlate (excluding correlations between the latent intercept and slope across processes) was used as a baseline model, which served as a point of comparison for models that imposed theoretically relevant structural paths on the model. The four structural models examined are displayed in Figure 1. Importantly, the latent intercept for cognitive and functional trajectories were allowed to correlate in all models, assuring that the variation in intercepts used to predict change in the slope of the alternate process had been adjusted for the correlation between cognitive and functional health at baseline. To examine the possible moderating effects of lifecourse SES in the relation between baseline cognitive and functional health and change in the alternate process, change in each process was regressed on interactions specified between each indicator of SES and the latent intercept of the alternate process.

Conceptualization of the modeling process requires initial definition of the latent growth model. First, the unconditional growth model predicts y_{it}, or the value of the trajectory variable y for the ith case at time t, where α_i is the random intercept for case i, λ_t represents the time-trend variable, β_i is the random slope for case i, and ε_{it} is the error term for each individual i and each time t (Bollen and Curran 2006):

$$y_{it} = \alpha_i + \lambda_t \beta_i + \varepsilon_{it}$$

The intercept equation for the model represents the individual intercept α_i as a function of the mean intercepts for all cases μ_y and an error disturbance term $\zeta_{\alpha i}$. The slope equation represents the individual slope β_i as a function of the average slope for all cases μ_β and an error disturbance term $\zeta_{\beta i}$ (Bollen and Curran 2006):

$$\alpha_i = \mu_\alpha + \zeta_{\alpha i}$$

$$\beta_i = \mu_\beta + \zeta_{\beta i}$$

The previous equations are brought together to form the combined model, or the reduced-form equation of the trajectory model (Bollen and Curran 2006):

$$y_{it} = (\mu_\alpha + \lambda_t \mu_\beta) + (\zeta_{\alpha i} + \lambda_t \zeta_{\beta i} + \varepsilon_{it})$$

To create a model conditional on the effects of covariates, the intercept and slope equations are modified to incorporate the effects of covariates x_i , where α_i and β_i now represent the mean intercept and slope when x_i equals 0 (Bollen and Curran 2006):

$$\alpha_i = \mu_\alpha + \gamma_{\alpha i} x_{1i} + \zeta_{\alpha i}$$

$$\beta_i = \mu_\beta + \gamma_{\beta i} x_{1i} + \zeta_{\beta i}$$

This modification is represented in the reduced-form model as follows:

$$y_{it} = (\mu_\alpha + \lambda_t \mu_\beta) + (\gamma_\alpha + \lambda_t \gamma_{\beta 1}) x_{1i} + (\zeta_{\alpha i} + \lambda_t \zeta_{\beta i} + \varepsilon_{it})$$

In the parallel-processing framework, two conditional growth processes are modeled simultaneously, with the value of each trajectory being conditioned both on covariates and the latent intercept from the parallel, or opposite process (the opposite latent slope can also be utilized, but is not used here due to the nature of causality being examined). The latent intercept and slope can also be conditioned on the covariance between the latent constructs (allowing constructs to be correlated rather than imposing causal paths between the latent factors). The equations for these models become complex, and for purposes of simplicity, are not represented here. The causal diagrams presented in Figure 4 represent the hypothesized nature of association between the two growth processes being analyzed.

Missing Data

Mplus provides a useful suite of tools to account for multiple forms of missing data. Multiple imputation was used to account for missing data in predictor variables (20 datasets were imputed and analyzed, two variables had greater than 10% missing data; father's education > = 8 years = 10.12% missing; father white-collar occupation = 13.54%). All descriptive statistics reflect averages across the 20 imputed datasets.

To protect against potential biases introduced by mortality selection in longitudinal studies of aging, results from parallel-process models developed using the traditional assumption of data missing at random (MAR) were compared to estimates from parallel process growth models adjusted for the presence of non-random missing data (NMAR) on the outcomes of interest. Maximum-likelihood estimation is the default estimator used by Mplus when estimating outcome trajectories, and this estimation assumes that missingness is not related to the underlying values of the outcome variables. In longitudinal studies where the outcome of interest is associated with the propensity for missing data, a MNAR mechanism is at work and may produce biased parameter estimates (Enders 2011). As cognitive and physical functioning have both been associated with increased risk of mortality (Lavery, Dodge, Snitz, and Ganguli 2009; Scott, Macera, Cornman, and Sharpe 1997; van Gelder et al. 2007), adjustment for mortality selection helps provide more accurate estimates of the underlying form of trajectories and the influence of covariates on these trajectories.

Under assumptions of NMAR, the data (Y, observed or unobserved) and probability of missingness (R represents if Y is observed or not) are jointly distributed (Enders 2010): $p\ (Yi,\ Ri\ |$

θ, ϕ). Here p represents the probability distribution, Yi is the outcome for case i, Ri is the missing data indicator for case i, θ are the growth model parameters that describe how Y is distributed, and ϕ includes parameters that describe the likelihood of missing data on Y. This differs from a MAR mechanism where the parameters used to indicate missingness (θ) is not estimated. The NMAR models used here, a Diggle-Kenward selection model and a pattern-mixture model, adjust Y for the outcome of missingness in different ways, but both essentially condition the estimation of the latent growth process on the propensity for missing data in that process.

Selection modeling produces the joint distribution of observed and missing data with a two-part model: $p\ (Yi, Ri \mid \theta, \phi) = p\ (Yi \mid \theta)\ p\ (Ri \mid Yi, \phi)$. Here, $p\ (Yi \mid \theta)$ represents the marginal distribution of the growth model and $p\ (Ri \mid Yi, \phi)$ represents a conditional distribution produced by a regression model that uses Y to predict the probability of missing data (Enders 2010). For the Diggle-Kenward selection models, logistic regression estimates represent the hazard probability of dropout, where 0 represents periods before dropout occurs, 1 represents the period where dropout occurs, and missing for times after dropout has occurred (Muthén and Masyn 2005; Muthén, Asparouhov, Hunter, and Leuchter 2010). The first measurement y_{i1} is observed for all individuals included in analysis and incomplete measurements thereafter are assumed to be caused by drop-out only. Logistic regression estimates are produced for each observation of data at each wave of measurement t by regressing the indicator of drop-out on the observed values of the outcome variables at both t and t - 1. The logistic regression coefficient for dropout in study on current word recall score at the given wave (β_t) and the coefficient for dropout on word recall score at t - 1 ($\beta_{\mathrm{t-1}}$) are estimated separately for each measurement of dropout. β_{t} and $\beta_{\mathrm{t-1}}$ are averaged across models to create global estimates for the coefficients β_1 and β_2. For ease of interpretation, the coefficients for β_1 and β_2 are re-parameterized to represent dependence on level and increment in the response variable ($\theta_1 = (\beta_1 + \beta_2)/2$ and $\theta_2 = (\beta_1 - \beta_2)/2$) (Diggle and Kenward 1994; Muthén, Asparouhov, Hunter, and Leuchter 2010).

In contrast, pattern-mixture modeling switches the role Y and R where the conditional distribution of Y represents the growth model parameters for only those cases that share the same missing data pattern and R accounts for the number of missing data patterns ($p(Yi, Ri \mid \theta, \phi) = p(Yi \mid Ri, \theta)\, p(Ri \mid \phi)$). The pattern-mixture model decomposes the average latent trajectory for each pattern of missing data and produces a weighted average trajectory based on the number of waves each individual was observed (the slope for the pattern-mixture models was constrained to be equal for the 2nd and 3rd observations due to convergence issues). For example, the average intercept $\hat{\bar{\beta}}_0$ is determined by the number of missing data patterns (numeric superscript), the proportion of cases in missing data pattern p ($\hat{\pi}^{(p)}$), and the pattern-specific intercept estimate ($\hat{\beta}_0^{(p)}$), leading to the following equation representing three missing data patterns for simplicity:

$$\hat{\bar{\beta}}_0 = \hat{\pi}^{(1)}\hat{\beta}_0^{(1)} + \hat{\pi}^{(2)}\hat{\beta}_0^{(2)} + \hat{\pi}^{(3)}\hat{\beta}_0^{(3)}.$$

These NMAR models can be used to adjust both trajectories of the parallel-process model, meaning trajectories of word-recall and functional limitations were used to create dropout indictors subsequently used to adjust the trajectory of the given health outcome. These differing approaches to controlling for non-random data incorporate un-testable assumptions, requiring a sensitivity analysis to observe variation in estimates across models. To facilitate this process, Tables 3, 4, and 5 compare results from each of the NMAR models described to estimates taken from a traditional latent growth model. Table 2 presents the logistic regression estimates produced by the Diggle-Kenward selection model, as well as the regression estimates of the latent intercept and slope on dropout at each wave provided by the pattern-mixture model.

Results

Table 1 provides descriptive statistics for measures of word-recall, functional limitations, and sociodemographics, as well as percentages of observed dropout for both word-recall and functional limitations. The average number of words recalled at baseline on the immediate and delayed word-recall score tasks was 8.5, and this declined over the decade of observation to 5.7 words, or a 32.19% decrease. The average participant had around 3 functional limitations at baseline, which increased to about 6 functional limitations by 2008, or about an 89% increase. Dropout trends are reported for word-recall and functional limitations separately as dropout patterns were different across processes. For word-recall, around 67% of all participants had dropped out of the sample by the final observation, where about 63% of those reporting functional limitations had dropped out of the sample by 2008.

For observed predictor variables, the mean age at baseline was 79 years old, the racial/ethnic composition of the initial sample was 90% white, 6% black, and 4% Hispanic, 66% of the initial sample was female, and about 50% were married. For measures of adult SES, around 42% of respondents reported longest occupational tenure in white-collar positions, 30% in blue-collar occupations, 9% as home-makers, and 19% in other employment settings/situations, and about equal proportions reported attaining less than, equal to, or greater than a high school degree. The average household income was around $31,000 and the average household assets were worth $280,000. For measures of childhood SES, 59% reported that their mothers had attained 8 or more years of education, 55% reported their father had 8 or more years of education, and about 24% reported that their father worked in a white-collar occupation.

Parallel-Process Structural Model

Table 2 presents the model fit statistics for the four structural models pictured in Figure 4. Model fit statistics are provided separately for the latent growth model with assumptions of data MAR, the Diggle-Kenward selection model, and the pattern-mixture model. Model 1 represents the parallel-process model with no causal structure, Model 2 adds to Model 1 a regression path from initial word-recall score to the slope of functional limitations, Model 3 adds to Model 1 a regression path from initial functional limitations to the slope of word-recall score, and Model 4 adds to Model 1 both paths represented in Model 2 and Model 3. Traditional chi-square goodness of fit tests are not possible with the current model specifications, thus requiring an informal comparison of available fit statistics to determine the most appropriate structural model. For all fit statistics including the log-likelihood, Akaike information criteria (AIC), Bayseian information criteria (BIC), and sample-adjusted BIC, Model 4 seems to fit the data better than less restricted models, and this is consistent for both MAR and Diggle-Kenward selection models. The pattern-mixture model provides some conflicting evidence about the best fitting model, with the log-likelihood and AIC suggesting Model 4 provides the best fit to the data, with both version of the BIC suggesting Model 3 provides the best model fit. With the majority of evidence suggesting that model 4 provides the best model fit of all hypothesized structural models, Model 4 was used in the subsequent analyses.

Estimates from Non-Random Missing Data Models

Table 3 presents the estimates from the Diggle-Kenward selection model and the pattern-mixture model adjustments to the final structural model. The estimates provided in Table 2 were taken from the final structural model conditioned on all covariates. Both the Diggle-Kenward selection model and pattern-mixture model suggest that dropout was non-random in both trajectories of interest. Focusing on the re-parameterized estimates from the Diggle-Kenward selection model, both the initial level of word-recall and the increment between word-recall scores from $t - 1$ and t were negatively associated with the hazard of dropout. Conversely, initial functional limitations and change in functional limitations from $t - 1$ to t were positively associated with the hazard of dropout. Put simply, those with low initial word recall scores and who displayed rapid decline across time in word-recall scores were more likely to dropout, and those with greater initial functional limitation and greater increases were more likely to dropout.

Findings from the pattern-mixture model also support the necessity of controlling for data NMAR in this study. For word-recall, those who dropped out in the earliest phases of the study had lower initial word-recall scores than those dropping out in the later phases of the study, to the point that dropout in 2008 was not significantly associated with initial word-recall score. For change in word-recall, the effects of dropout for observations at 2000 and 2002 were constrained to be equal due to convergence issues, but those who dropped out of the study between 2004 and 2008 had significantly more rapid cognitive decline than those who did not drop out. The pattern-mixture model estimates of functional limitations show that those with greater initial functional limitations were more likely to drop out early in the study, and the strength of association between initial functional limitations and dropout decreased over time. Those who dropped out in 2004 experienced significantly greater increases in slope over time than those who had not dropped out, but this association weakened for following observations.
Estimates from both the Diggle-Kenward model and the pattern-mixture model suggest that those who were initially healthier and who experienced less rapid change towards poor health had a greater likelihood of being observed throughout the study, thus introducing potential biases into estimates that did not control for these dynamics.

Main Effects of Covariates on Trajectories of Word-recall and Functional Limitations

Tables 4, 5, and 6 present the estimates of latent and observed predictor variables on trajectories of word-recall and functional limitations for parallel-process models with MAR assumptions, the Diggle-Kenward selection model, and pattern-mixture model, respectively. To aid interpretation of these estimates across models with differing assumptions, discussion of the latent trajectories and relationships between these variables will be discussed first, followed by comparison of estimates for covariates that displayed similarities and differences across models.

Beginning with the estimates of the latent intercept and slope for trajectories of word-recall and functional limitations, there was substantial variation in the estimated latent intercept and slope across models. In the parallel-process model assuming MAR data, the estimated word-recall intercept was 8.13 with an estimated slope of -2.93, where functional limitations had an estimated intercept of 2.41and an estimated slope of 3.70. The Diggle-Kenward model produced estimated intercepts for both word-recall and functional limitations similar to those produced by the MAR model, but produced estimated slopes indicating more dramatic change towards poor health in both processes. In contrast, the pattern-mixture model produced estimates of the latent intercept that were more advantageous than the MAR model (higher initial word-recall scores and lower initial functional limitations), but produced estimates of the latent slope that were similar to those produced by the MAR parallel-process model. The varying estimated values for the trajectories of word-recall and functional limitations signify the differential adjustments to the outcome trajectories provided by the Diggle-Kenward and pattern-mixture models.

Examining the estimates of the latent predictor variables on the slope of word-recall and functional limitations reveals consistent effects of initial word-recall on change in functional limitations across models with different missing data assumptions, but this was not true for the effect of initial number of functional limitations on word-recall. Specifically, initial word-recall scores were consistently negatively associated with change in functional limitations, with the MAR model providing the smallest effect ($b = -.08$, $p < .05$), followed by the pattern-mixture model ($b = -.13$, $p < .001$), and finally, the Diggle-Kenward model ($b = -.22$, $p < .001$). For the effect of initial functional limitations on change in word-recall scores, the model with MAR assumption displayed a significant positive effect of initial functional limitations on word-recall trajectory ($b = .09$, $p < .05$), which is in contrast to the significant association between these variables found in the Diggle-Kenward model ($b = -.18$, $p < .001$). This estimate was not significant in the pattern-mixture model, and may explain the better-model fit of Model 3 according to the pattern-mixture fit statistics displayed in Table 2.

Turning to the estimates of observed predictor variables on the latent trajectories of word-recall and functional limitations, the majority of estimates that were significant predictors of the latent intercept for both word-recall and functional limitations were significant and in the same direction across models. For baseline word-recall, older individuals had lower scores than younger individuals, blacks and Hispanics had lower scores than whites, females had higher scores than males, and those who were married had lower scores than those who were un-married. Compared to those reporting longest occupational tenure in white-collar positions, those reporting blue-collar occupational tenure or longest occupational tenure as a homemaker had lower initial word-recall scores. Education was positively associated with baseline word-recall, as were household income and assets. Finally, those reporting that their mother had 8 or more years of education had higher initial word-recall scores than those whose mothers had less than 8 years of education, and those who reported that their father had a white-collar occupation had better initial word-recall than those whose fathers were employed in non-white-collar settings.

Fewer predictor variables were significantly associated with baseline functional limitation. Being older and being female were associated with more initial functional limitations, and Hispanics had significantly fewer initial functional limitations than whites. Those reporting occupational tenure in positions other than white-collar, blue-collar, or homemaker had more initial functional limitations than those with white-collar occupational tenure, and those with less than a high school degree had more initial functional limitations than those with a high school degree. Both household assets and household income were protective against initial functional limitations, though the effect of household income was not significant across models with differing assumptions about missing data on the trajectory of functional limnitations.

Concerning the estimated slopes of word-recall, far fewer predictor variables were significantly associated with change over time than initial status, and there were more inconsistencies across MAR and NMAR models. For slope of word-recall, those reporting occupational tenure in blue-collar positions had significantly less rapid cognitive decline than those in white-collar positions, which may be a result of their initially lower starting values. Age was inconsistently associated with word-recall trajectory, being significantly associated with more rapid cognitive decline only in the Diggle-Kenward selection model. According to the MAR and pattern-mixture models, females had significantly more rapid decline in word-recall than males, but this was not confirmed in the Diggle-Kenward model.

For slope of functional limitations, age was the only significant predictor across models, displaying a positive association with increase in functional limitations. Both Hispanics and females had less rapid increase in functional limitations than their reference categories, but these effects were only significant in the Diggle-Kenward model. There was some evidence that those who were married had less rapid increase in functional limitations, but this was only confirmed in the MAR and pattern-mixture model. Finally, household assets were positively associated with increasing functional limitations in the MAR and pattern-mixture model, but this association was non-significant in the Diggle-Kenward model.

Interactive Effects between Latent and Observed Variables.

Table 7 presents the significant interaction effects found between latent intercepts, lifecourse SES, and trajectories of cognitive and functional health for the MAR parallel-process model. Figure 5 presents the fully conditional model diagram including main effects and interactive effects. Interactions were explored separately for MAR and NMAR assumptions, and only interactive effects that were significant in all models were probed further. Furthermore, parallel-process model specifications restricted the types of probing that could be conducted, allowing only for post-hoc tests of differences between groups in the point estimate of interest. Two significant interactions were found between latent intercepts and indicators of SES; functional limitations slope on the interaction between initial word-recall and female, and word-recall slope on the interaction between initial functional limitations and household income.

Estimating the influence of initial word-recall on change in functional limitations separately for men and women, controlling only for age , revealed evidence that initial word-recall had a statistically significant relationship with change in functional limitations in men, but this relationship was not significant for women (male $b = -.14$, $SE = .06$, $p < .05$; female $b = -.03$, $SE = .04$, $p = .45$). Greater values in initial word-recall may protect men from increase in functional limitations more than women, however, this difference cannot be considered statistically significant as the 95% confidence intervals for the point estimate had considerable overlap (shown in Figure 5).

To probe the interaction between household income and initial functional limitations, the effect of initial functional limitations on word-recall slope was assessed separately for participants one standard deviation above the mean of household income and one standard deviation below the mean of household income, including controls for age (shown in Figure 6). For the group with household income 1 standard deviation above the mean, initial functional limitations did not significantly predict change in word-recall (b = -.16, SE = .12, p = .17). For participants one standard deviation below the mean of household income, initial functional limitations were positively associated with the slope of word recall, where a one unit increase in initial functional limitations predicted a .29 unit increase in the slope of word-recall (b = .29, SE = .09, p < .01). Furthermore, since the 95% confidence intervals do not overlap between these comparison groups, evidence suggests that there was a significant difference in the effect of initial functional limitations on word-recall score for those with different amounts of household income (> = 1 SD HH Inc. 95% CI = -.39 to .07, < = - 1 SD HH Inc. 95% CI = .10 to .482).

Discussion

This research examined the co-evolution of cognitive and functional health in the context of lifecourse SES, using methods able to address the potential biases introduced into longitudinal studies of aging through mortality selection. Greater initial memory scores were consistently associated with less rapid increase in functional limitations, with conflicting evidence regarding the direction and amount of variation in cognitive trajectories that could be attributed to initial functional limitations. Variation in the influence of initial cognitive and functional health on change in the opposite process was found for gender and household income, indicating the importance of sociodemographic mechanisms in the co-evolution of mind/body health. Multiple indicators of lifecourse SES were found to predict variation in initial memory scores and functional limitations, but fewer measures of lifecourse SES were associated with change in these outcomes over time. After discussing the structural relationship between cognitive and functional health trajectories, and the role of lifecourse SES in their co-development, a brief discussion of the contributions and limitations of the modeling strategy employed is provided.

Through modeling the development of cognitive and functional health as contingent processes, findings support the conclusion that initial word-recall is a consistent and significant predictor of change in functional limitations. Across all treatments of missing data, those with better working memory had less rapid increase in functional limitations, and this was accounting for initial functional limitations, the association between change in cognitive and functional health across time, and socioeconomic variation in both trajectories. Initial functional limitations displayed an inconsistent relationship with change in word-recall, with estimates from the traditional MAR model showing protective effects, and estimates from the pattern-mixture model displaying significant influence towards more rapidly declining cognitive function. As initial word-recall was shown to consistently protect individuals from increasing functional limitations, this work supports others finding that cognitive function is a predecessor to functional decline, and can be targeted by professional as an early warning sign of potential functional health problems in the future. The casual mechanism driving this association is somewhat unclear, with initial memory influencing the manifestation of functional limitations over time, possibly through the individual's perceived decrease in cognitive function driving reduced physical activity and self-care that could lead to increased functional limitations, or possibly reduced memory being perceived by the individual's social support system who in turn actively constrains the opportunities for physical functioning and conditioning. Controlling for the relation between cognitive and physical change over time reduces the likelihood that senescence in both processes was driving these results, and provides further support for the conclusion that current memory can be associated with future functional limitations for older adults.

In the final model examining interactive effects between observed and latent predictor variables, there was some evidence that initial word-recall was especially protective of future functional limitations for men. While significant differences were not found in this effect when comparing the point estimates of men and women, men did seem to experience greater benefit from higher initial memory scores than women. All estimates were controlled for age, decreasing the likelihood that gender differences in longevity were contributing to the observed estimates, but it is also likely that men who had survived to the relatively late age of the participants included in analyses may be select in terms of being in good health. Men included in the sample may have had higher initial word-recall scores, and were also predisposed to have more favorable functional trajectories, meaning the observed finding may be an artifact of mortality selection occurring prior to observation. Alternatively, men's functional health may be more sensitive to change in other dimensions of health as compared to women since at comparable ages, men's overall health may be more fragile than the health of comparable women.

Across all missing data treatments, the interaction between initial functional limitations and household income exhibited a significant relationship with change in word-recall over time. For participants one standard deviation below the mean of household income, initial functional limitations were positively associated with the slope of word-recall, meaning for those with lower income, higher initial functional limitations reduced the rapidity at which word-recall scores declined across the observation period. Household income was positively associated with initial word-recall in all models, and negatively associated with initial number of functional limitations in two out of three models, indicating that those with lower household income may have experienced less dramatic cognitive decline due to the initial association between functional limitations and word-recall scores. Rather than indicating the significance of household income on the relationship between functional limitations and fluid memory, this finding highlights how lower income may influence the co-development of cognitive and functional health before the late adulthood, but with repercussions that unfold during the latest years of life.

As indicated by the relationship between cognitive health, functional limitations, and household income, the set of socioeconomic covariates tested here predicted a greater range of variation in the initial status of memory and physical function than change in either of these health measures. For example, those with less than a high school degree had significantly worse cognitive and functional health at baseline than their counterparts with a high school degree, but education was not significantly associated with change in these outcomes over time. For word-recall, only longest occupational tenure was significantly associated with change in word-recall, and this effect again reflected the lower initial word-recall of those with blue-collar occupation tenure as compared to white-collar occupation tenure. There were no measures of lifecourse SES consistently associated with change in functional limitations over time. These results indicate that disparities in cognitive and functional limitations are crystallized prior to the latest years of life and do not offer potential points of intervention to benefit the health of older adults. Indicators of lifecourse SES are by definition developed across the lifespan, and the constantly evolving construct of SES influences the development of cognitive and functional health across the lifecourse as well. The fact that disparities in these health outcomes are cemented before the latest years of life indicates that interventions to reduce socioeconomic disparities in cognitive and physical function among the elderly must focus on earlier points in life.

The findings of this study are strengthened by accounting for the potential biases introduced by mortality selection in longitudinal studies of aging. By comparing variation in estimates across traditional growth models and those with controls for NMAR data, effects that remain consistent across models can be taken as more trustworthy estimates, and the estiatmes produced here provide a strong reference point when examining other investigations of cognitive and functional trajectories that have not accounted for NMAR data. The variation in estimates across models is itself an interesting finding, indicating how each model attempts to control for observations NMAR. The Diggle-Kenward model provided greater adjustments to the trajectories of the outcomes when compared to the traditional MAR model, and this likely results from the fact that the Diggle-Kenward employs dropout indicators that are endogenous to the growth process, in comparison to the pattern-mixture model that employs dropout indicators exogenous to the growth process. The pattern-mixture model produced baseline estimates of word-recall and functional limitations that were more advantageous than either the MAR or Diggle-Kenward model, and likely indicates that those who were observed for greater amounts of time were given greater weight in the model, making the initial estimates of word-recall and functional limitations favor those who were initially healthier. These models incorporate a number of un-testable assumptions, and are certainly not a panacea for NMAR data, but provide a useful point of comparison for traditional growth models that do not account for the potential biases produced by mortality selection.

Limitations and Future Directions

While this research provides a number of insights into the contingent nature of cognitive and functional health in the socioeconomic context of aging, the modeling strategy employed restricted the potential questions that could be addressed. Greater examination of interactive effects between observed variables is warranted, especially between race/ethnicity and lifecourse SES, as research suggests that SES can mean substantially different things for those of different racial/ethnic backgrounds (Adler and Rehkopf 2008). Also, further decomposing the floor effects observed through careful examination of quadratic effects in the outcome trajectories could provide further insight into how trajectories of cognitive and functional health evolve, and what predictors influence change in these outcomes in the presence of controlling for non-linearity. Finally, further exploration of the interactions found between the latent and observed variables will provide more evidence of how SES can moderate the relationship between cognitive and functional health. This work provides a strong starting point from which a number of further investigations can be launched.

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Table 1: Descriptive Statistics

		Mean	%	SD	% Present	% Dropout
Word-recall and Functional Limitations						
Total word-recall 1998		8.45		3.72	100	
Total word-recall 2000		7.79		3.61	80.96	19.04
Total word-recall 2002		7.28		3.57	66.47	33.53
Total word-recall 2004		6.70		3.44	53.64	46.36
Total word-recall 2006		6.10		3.45	42.55	57.45
Total word-recall 2008		5.73		3.61	32.67	67.33
Functional limitations 1998		3.02		2.91	100	
Functional limitations 2000		3.44		3.05	85.92	14.08
Functional limitations 2002		4.14		3.15	72.51	27.49
Functional limitations 2004		4.54		3.27	60.11	39.89
Functional limitations 2006		5.38		3.43	48.31	51.69
Functional limitations 2008		5.71		3.47	36.54	63.46
Independent Variables						
Age		79.13		5.31		
White			89.90	0.37		
Black			6.40	0.24		
Hispanic			3.70	0.19		
Female			65.60	0.48		
Married			49.30	0.50		
White-collar occupation tenure			41.70	0.37		
Blue-collar occupation tenure			29.80	0.46		
Homemaker job tenure			9.10	0.29		
Other job tenure			19.40	0.40		
Less than H.S. degree			33.10	0.47		
H.S. degree			35.10	0.47		
Greater than H.S. degree			31.80	0.47		
Household income	($)	31,144.68		39,663.97		
Household assets	($)	280,441.80		75,7295.40		
Mother > = 8 yrs. Education			59.40	0.49		
Father > = 8 yrs. Education			54.80	0.50		
Father White Collar			23.90	0.43		

Note: N = 4,653; all estimates averaged over 20 imputed data sets.

Table 2: Model Fit Statistics

	Model 1			Model 2		
	M.A.R.	D.K.	P.M.M.	M.A.R.	D.K.	P.M.M.
Free parameters	24	38	51	25	39	52
Log-Likelihood	-86407.05	-100828.31	-103245.32	-86398.18	-100824.37	-103241.65
Akaike information criteria (AIC)	172862.10	201732.62	206592.63	172846.35	201726.74	206587.301
Bayesian information criteria (BIC)	173016.79	201977.54	206921.34	173007.48	201978.11	206922.46
Sample-adjusted BIC	172940.53	201856.79	206759.28	172928.04	201854.18	206757.22
	Model 3			Model 4		
	M.A.R.	D.K.	P.M.M.	M.A.R.	D.K.	P.M.M.
Free parameters	25	39	52	26	40	53
Log-Likelihood	-86390.34	-100762.89	-103222.89	**-86385.08**	**-100744.58**	**-103221.78**
Akaike information criteria (AIC)	172830.69	201603.77	206549.77	**172822.16**	**201569.15**	**206549.57**
Bayesian information criteria (BIC)	172991.82	201855.14	**206884.92**	**172989.73**	**201826.96**	206891.17
Sample-adjusted BIC	172912.38	201731.21	**206719.69**	**172907.11**	**201699.86**	206722.75

Note: N = 4,653; M.A.R. = missing at random, D.K. = Diggle-Kenward selection model, P.M.M. = pattern-mixture model; bold numbers indicate best model fit

Table 3: Estimates from NMAR model parameters

	b	SE
Diggle-Kenward Selection Model		
Word-recall		
	b	*SE*
Word-recall *t* - 1	0.16***	0.02
Word-recall *t*	-0.76***	0.05
Level word-recall	-0.30***	0.02
Increment word-recall	-0.46***	0.04
Functional Limitations		
Functional limitation *t* - 1	-0.15***	0.02
Functional limitation *t*	0.46***	0.03
Level functional limitation	0.16***	0.01
Level increment functional limitations	0.30***	0.03
Pattern-Mixture Model		
Word-recall		
Intercept	*b*	*SE*
Dropout 2000	-2.18***	0.16
Dropout 2002	-1.72***	0.15
Dropout 2004	-1.06***	0.16
Dropout 2006	-0.77***	0.17
Dropout 2008	-0.15	0.18
Slope		
Dropout 2000 - 2002	-0.25	0.48
Dropout 2004	-2.32***	0.39
Dropout 2006	-1.77***	0.31
Dropout 2008	-1.66***	0.25
Functional limitations		
Intercept	*b*	*SE*
Dropout 2000	1.99***	0.15
Dropout 2002	1.59***	0.15
Dropout 2004	1.01***	0.15
Dropout 2006	0.87***	0.14
Dropout 2008	0.34*	0.15
Slope		
Dropout 2000 - 2002	-0.25	0.48
Dropout 2004	2.37***	0.36
Dropout 2006	0.97***	0.27
Dropout 2008	0.82***	0.20

Note: N = 4,653; * $p < .05$, ** $p < .01$, *** $p < .001$.

Table 4: Data Missing at Random

	Word-recall				Functional Limitations			
	Intercept		Slope		Intercept		Slope	
	b	*SE*	*b*	*SE*	*b*	*SE*	*b*	*SE*
Intercepts	8.13	0.17	-2.93	0.28	2.41	0.15	3.70	0.40
Latent Predictor Variables								
Intercept word-recall							-0.08*	0.04
Intercept functional limitations			0.09*	0.04				
Observed Predictor Variables								
Age	-0.22***	0.01	-0.03	0.02	0.08***	0.01	0.10***	0.02
Black	-0.82***	0.16	0.00	0.27	-0.15	0.16	0.06	0.24
Hispanic	-0.93***	0.23	0.50	0.37	-0.66***	0.22	0.19	0.36
Female	1.12***	0.12	-0.72***	0.20	0.75***	0.10	-0.10	0.16
Married	-0.44***	0.12	0.22	0.19	0.14	0.10	-0.35**	0.15
Blue-collar occ. tenure	-0.64***	0.14	0.52**	0.22	0.04	0.12	0.21	0.18
Home-maker occ. tenure	-0.63***	0.18	0.11	0.29	0.25	0.16	0.30	0.23
Other occ. tenure	-0.20	0.15	0.10	0.24	0.53***	0.14	0.13	0.19
< H.S. degree	-0.68***	0.13	-0.03	0.22	0.35***	0.12	-0.27	0.18
> H.S. degree	0.41***	0.13	0.11	0.21	-0.03	0.11	0.08	0.16
H.H. income (log)	0.21***	0.08	-0.08	0.10	-0.14*	0.07	-0.08	0.09
H.H. assets (log)	0.10***	0.02	-0.04	0.03	-0.12***	0.02	0.07**	0.03
Mother >= 8 yrs. education	0.33**	0.13	-0.08	0.21	-0.15	0.12	0.13	0.18
Father > = 8 yrs. education	-0.04	0.13	-0.04	0.21	-0.21†	0.12	-0.17	0.17
Father white-collar occ. tenure	0.27*	0.13	0.06	0.21	-0.08	0.12	0.02	0.17
R-Squared	0.37		0.05		0.13		0.09	

Note: N = 4,653; † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$.

Table 5: Diggle-Kenward Selection Model

	Word-recall				Functional Limitations			
	Intercept		Slope		Intercept		Slope	
	b	*SE*	*b*	*SE*	*b*	*SE*	*b*	*SE*
Intercepts	8.21***	0.18	-6.21***	0.41	2.33***	0.15	7.07***	0.56
Latent Predictor Variables								
Intercept word-recall							-0.22***	0.05
Intercept functional limitations			-0.18***	0.06				
Observed Predictor Variables								
Age	-0.23***	0.01	-0.22***	0.02	0.08***	0.01	0.19***	0.02
Black	-0.94***	0.16	0.45	0.34	-0.12	0.16	-0.17	0.27
Hispanic	-0.91***	0.24	0.82†	0.48	-0.68***	0.22	-0.52***	0.20
Female	1.15***	0.12	0.25	0.27	0.74***	0.11	-0.44**	0.17
Married	-0.52***	0.12	0.34	0.24	0.17	0.11	0.11	0.21
Blue-collar occ. tenure	-0.63***	0.14	0.54*	0.28	0.02	0.12	0.10	0.27
Home-maker occ. tenure	-0.65***	0.19	0.13	0.38	0.26	0.17	0.12	0.22
Other occ. tenure	-0.21	0.15	0.09	0.31	0.52***	0.14	-0.10	0.40
< H.S. degree	-0.74***	0.14	-0.09	0.27	0.36***	0.12	-0.29	0.21
> H.S. degree	0.39***	0.13	-0.05	0.26	-0.01	0.11	0.15	0.19
H.H. income (log)	0.23***	0.08	0.09	0.13	-0.14*	0.07	-0.16	0.11
H.H. assets (log)	0.10***	0.02	0.00	0.04	-0.12***	0.02	0.05	0.03
Mother >= 8 yrs. education	0.34**	0.14	-0.17	0.27	-0.14	0.12	0.29	0.21
Father > = 8 yrs. education	-0.03	0.13	0.00	0.27	-0.21†	0.12	-0.20	0.21
Father white-collar occ. tenure	0.29*	0.13	0.00	0.27	-0.09	0.12	0.08	0.19
R-Squared	0.37		0.13		0.13		0.21	

Note: N = 4,653; † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$.

Table 6: Pattern-Mixture Model

	Word-recall				Functional Limitations			
	Intercept		Slope		Intercept		Slope	
	b	*SE*	*b*	*SE*	*b*	*SE*	*b*	*SE*
Intercepts	9.10***	0.19	-2.65***	0.29	1.56***	0.16	3.88***	0.43
Latent Predictor Variables								
Intercept word-recall							-0.13***	0.04
Intercept functional limitations			0.07	0.04				
Observed Predictor Variables								
Age	-0.17***	0.01	-0.01	0.02	0.03***	0.01	0.07***	0.02
Black	-0.80***	0.15	-0.19	0.26	-0.15	0.16	0.10	0.24
Hispanic	-1.03***	0.23	0.43	0.36	-0.57***	0.21	0.14	0.35
Female	0.92***	0.11	-0.66***	0.20	0.95***	0.10	-0.04	0.16
Married	-0.41***	0.12	0.16	0.18	0.14	0.10	-0.32*	0.14
Blue-collar occ. tenure	-0.63***	0.13	0.53**	0.21	0.05	0.12	0.16	0.18
Home-maker occ. tenure	-0.57***	0.18	0.10	0.29	0.26	0.16	0.30	0.23
Other occ. tenure	-0.18	0.14	0.14	0.23	0.52***	0.13	0.10	0.19
< H.S. degree	-0.58***	0.13	-0.08	0.21	0.29**	0.12	-0.29	0.18
> H.S. degree	0.41***	0.13	0.07	0.20	-0.02	0.11	0.13	0.16
H.H. income (log)	0.16*	0.07	-0.07	0.10	-0.09	0.06	-0.08	0.09
H.H. assets (log)	0.07***	0.02	-0.04	0.03	-0.10***	0.02	0.07***	0.03
Mother >= 8 yrs. education	0.32**	0.13	-0.07	0.21	-0.18	0.12	0.15	0.18
Father > = 8 yrs. education	-0.05	0.13	-0.06	0.20	-0.19†	0.11	-0.16	0.17
Father white-collar occ. tenure	0.26*	0.13	0.05	0.20	-0.08	0.11	0.03	0.17
R-Squared	-[a]		-[a]		-[a]		-[a]	

Note: N = 4,653; † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$.; [a] standardized estimates necessary for calculation of R-square unavailable with categorical predictor variables unavailable.

Table 7: Data Missing at Random

	Word-recall				Functional Limitations			
	Intercept		Slope		Intercept		Slope	
	b	*SE*	*b*	*SE*	*b*	*SE*	*b*	*SE*
Intercepts	8.12***	0.17	-2.94***	0.28	2.41***	0.15	4.69***	0.54
Latent Predictor Variables								
Intercept word-recall							-0.20***	0.06
Intercept functional limitations			0.09*	0.04				
Observed Predictor Variables								
Age	-0.22***	0.01	-0.03	0.02	0.08***	0.01	0.10***	0.02
Black	-0.82***	0.16	0.00	0.27	-0.15	0.16	0.05	0.24
Hispanic	-0.94***	0.23	0.54	0.37	-0.66***	0.22	0.19	0.35
Female	1.12***	0.12	-0.70***	0.20	0.76***	0.11	-1.50***	0.56
Married	-0.44***	0.12	0.23	0.19	0.14	0.10	-0.36**	0.15
Blue-collar occ. tenure	-0.64***	0.14	0.53**	0.22	0.04	0.12	0.18	0.18
Home-maker occ. tenure	-0.63***	0.18	0.10	0.29	0.25	0.16	0.34	0.23
Other occ. tenure	-0.20	0.15	0.09	0.24	0.53***	0.14	0.13	0.19
< H.S. degree	-0.67***	0.13	-0.05	0.22	0.35***	0.12	-0.28	0.18
> H.S. degree	0.41***	0.13	0.09	0.21	-0.03	0.11	0.10	0.16
H.H. income (log)	0.22***	0.08	0.06	0.12	-0.13*	0.07	-0.08	0.09
H.H. assets (log)	0.10***	0.02	-0.03	0.03	-0.12***	0.02	0.07**	0.03
Mother >= 8 yrs. education	0.33**	0.13	-0.09	0.21	-0.15	0.12	0.14	0.18
Father > = 8 yrs. education	-0.04	0.13	-0.04	0.21	-0.21#	0.12	-0.19	0.17
Father white-collar occ. tenure	0.27*	0.13	0.06	0.21	-0.08	0.12	0.01	0.17
*Latent * Observed Interactions*								
Intercept word-recall * Female							0.16***	0.06
Intercept functional Limitations * HH income			-0.07**	0.03				

Note: N = 4,653; † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$.

Figure 1. Parallel process growth curve measurement model. y0 – y4: cognitive outcome variable; z0 – z4: functional limitations variable; i_y, s_y: random intercept and slope word-recall; i_z, s_z: random intercept and slope functional limitations; d0-d4: dropout indicators. Note: Unit factor loadings (latent variable loadings) and random error terms are omitted to reduce clutter.

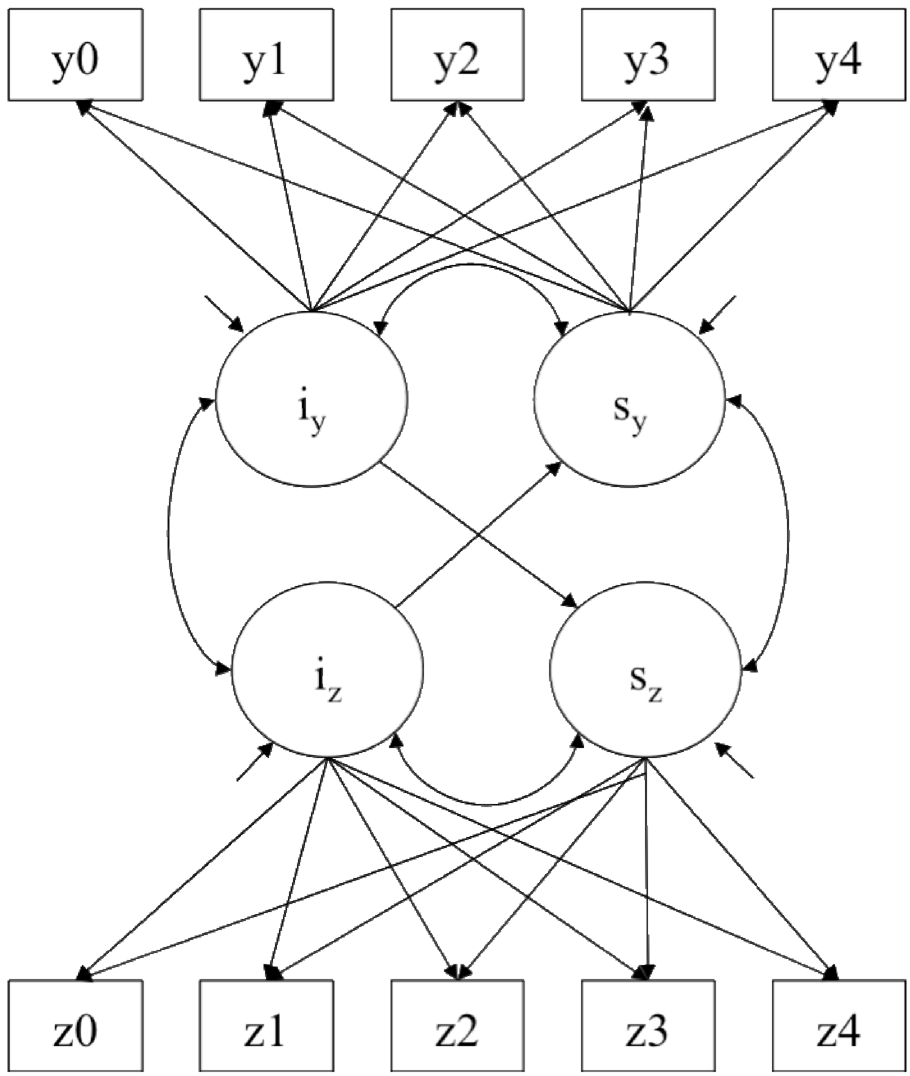


Figure 2. Parallel process growth curve measurement model with Diggle-Kenward selection model. Observed functional limitations represented by z0 – z4. Random intercept and slope word-recall represented by i_y, s_y. Random intercept and slope functional limitations represented by i_z, s_z. Discrete-time dropout indicators for each process represented by d_y1 - d_y4 and d_z1 - d_z4. Note: Dashed paths indicate logistic regression; unit factor loadings (latent variable loadings) and random error terms are omitted to reduce clutter.

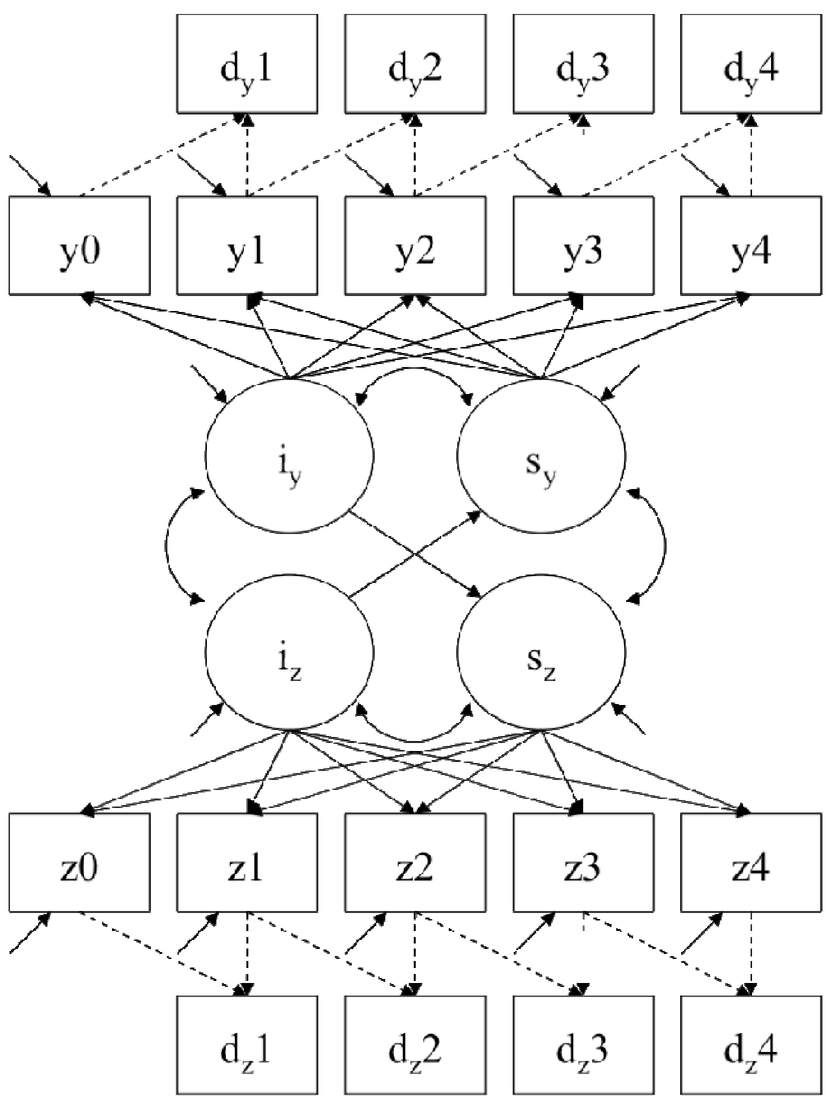


Figure 3. Parallel process growth curve measurement model with pattern-mixture model. Observed cognitive outcome variable represented by y0 – y4. Observed functional limitations represented by z0 – z4. Random intercept and slope word-recall represented by i_y, s_y. Random intercept and slope functional limitations represented by i_z, s_z. Dropout dummy indicators for each process represented by d_y1 - d_y4 and d_z1 - d_z4. Note: Unit factor loadings (latent variable loadings) and random error terms are omitted to reduce clutter.

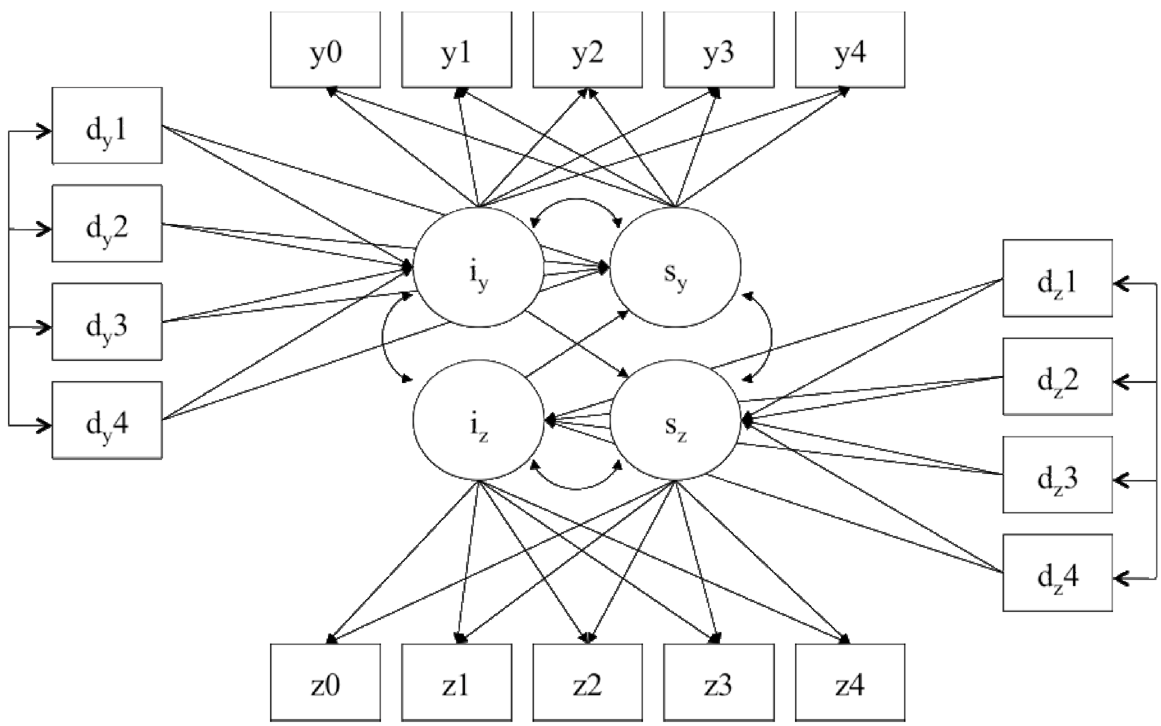
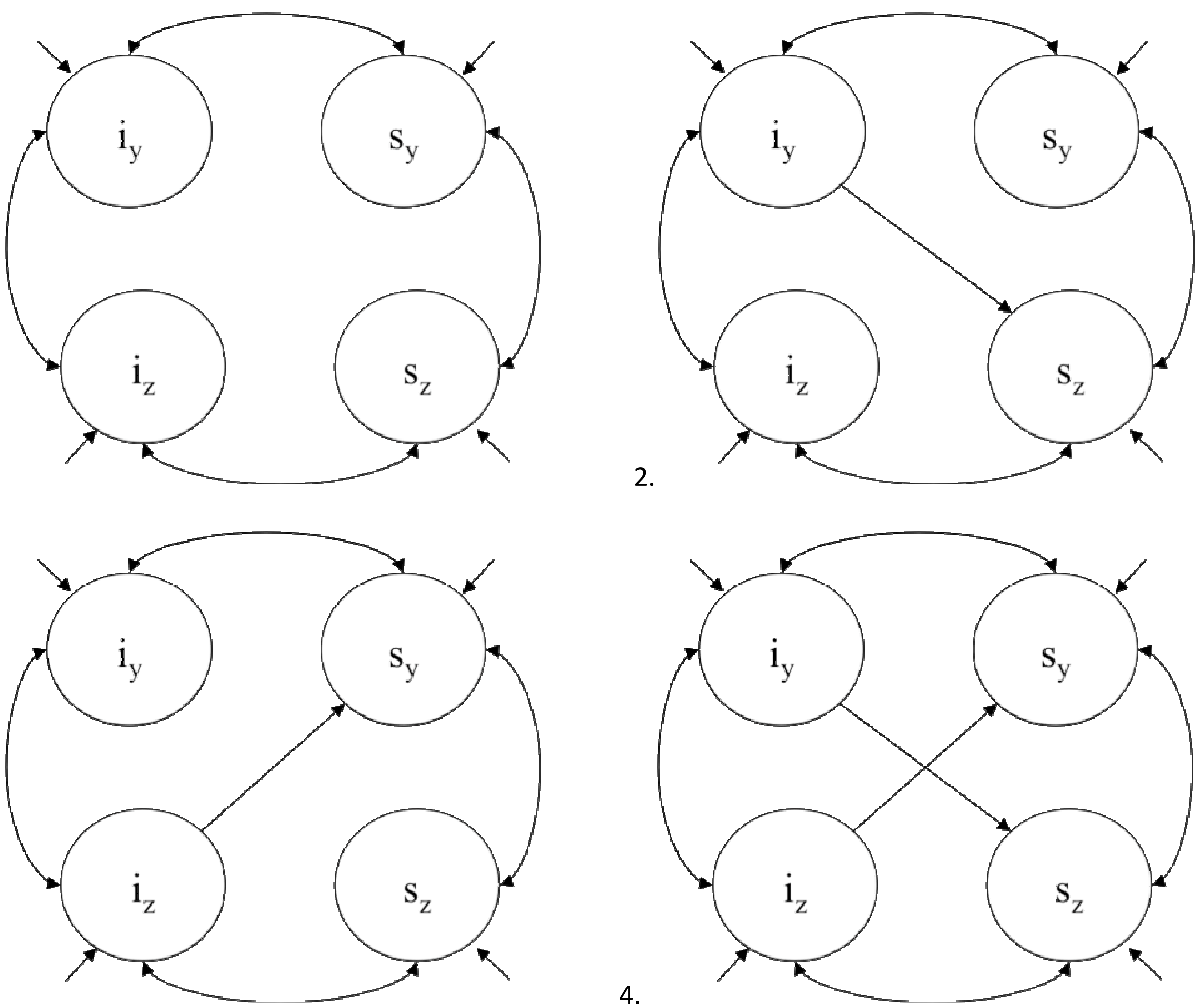


Figure 4. Parallel process structural model development. Model 1 represents structural model with no causal structure including correlations within process, between intercepts for each process, and between slopes for each process. Model 2 adds a casual path from word-recall intercept to functional limitation slope to Model 1. Model 3 adds a causal path from functional limitation intercept to word-recall slope to Model 1. Model 4 represents the final structural model that includes causal paths from the intercept of each process to the slope of the alternate process.



1. 2. 3. 4.

Figure 5. Conditional parallel-process strucutral model with interactions between latent and observed variables. Random intercept and slope word-recall represented by i_y, s_y. Random intercept and slope functional limitations represented by i_z, s_z. Observed predictor variables are represented by x_i.

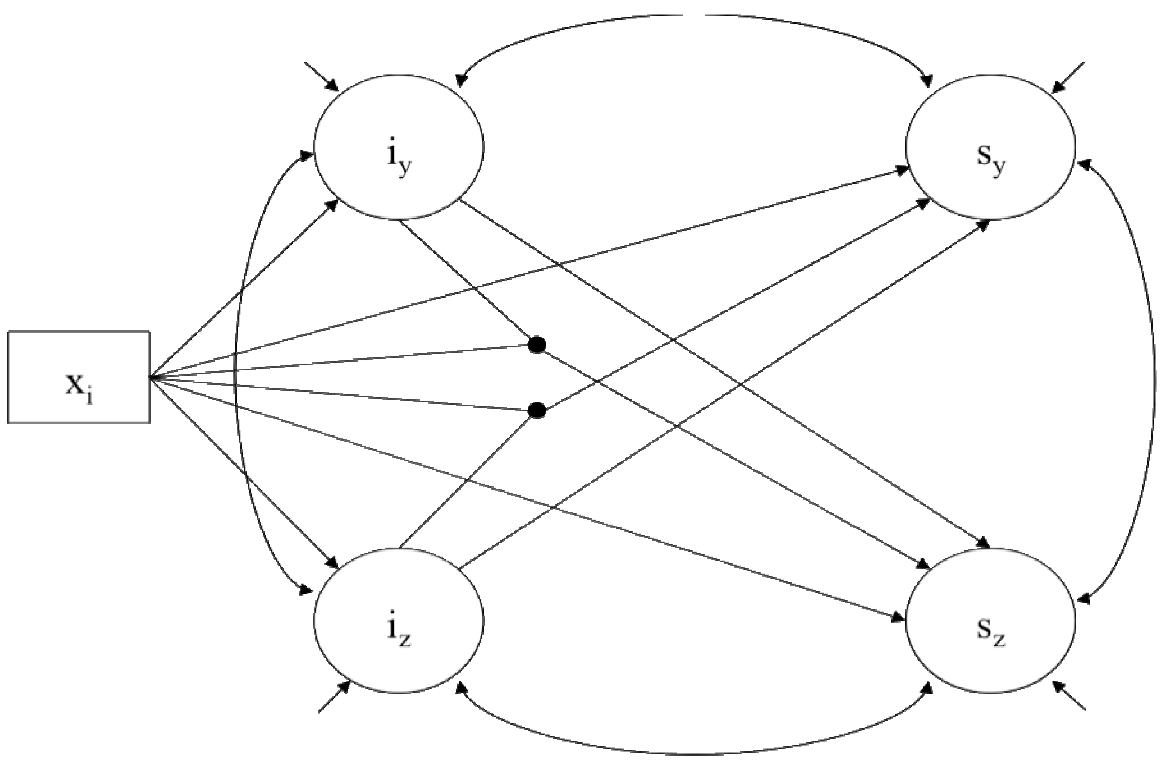


Figure 6. Regression point estimates and 95% confidence intervals for functional limitations slope on initial word-recall for men and women.

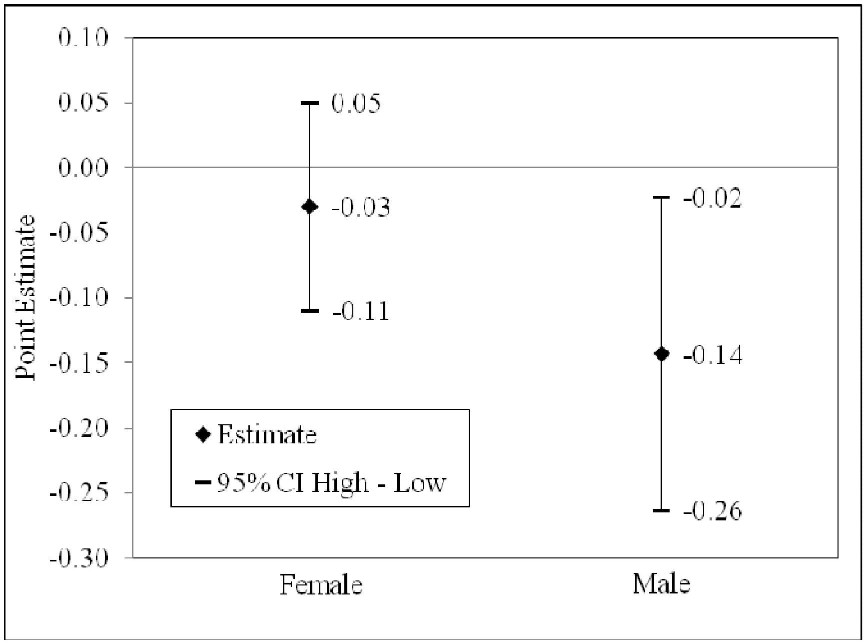


Figure 7. Regression point estimates and 95% confidence intervals for word-recall slope on initial functional limitations for one standard deviation above and one standard deviation below mean of household income.