Health and Functional Limitations Predict Depression Scores in the Health and Retirement Study: Results Straight from MARS

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Abstract

Objective: To examine the effects of chronic health conditions and functional status limitations on depression scores in a large representative sample of Americans. **Method:** The data included 27,461 respondents ages 50 to 90 who completed up to eight test occasions from the Health and Retirement Study. Multivariate adaptive regression splines (MARS) modeling was applied. Possible covariates of depression included arthritis, lung disease, back pain, diabetes, heart disease, high blood pressure, cancer, 28 pairwise combinations of the aforementioned conditions, ADL functional limitations, age, education and being female, being white, and being Hispanic. **Results:** The best fitting model had a GRSq of 0.18 (comparable to R^2) and included 12 of 42 covariates. Depression score was predicted by: 1) ADL limitations, 2) education, 3) back pain, 4) lung disease, 5) being female, 6) being Hispanic, 7) heart disease, 8) being white, 9) high blood pressure plus stroke, 10) age, 11) back pain plus arthritis, and 12) back pain plus diabetes. **Conclusions:** Functional limitations was the strongest predictor of depression; reporting one limitation increased depression scores by nearly double the increase associated with two or more limitations. Back pain and lung disease were the strongest chronic disease predictors of depression; both are associated with considerable discomfort.

Keywords: aging, depression, mood, chronic disease, health

Introduction

The interaction between depression and chronic disease is an important predictor of health outcomes. Studies have shown that the onset of various chronic diseases correlate with future depression (Dubovsky et al., 2005; Roberts, Kaplan, Shema, & Strawbrige, 1997). Alternatively, studies have shown that depression can negatively affect treatment outcomes for treatment of chronic diseases (see for example Wulsin et al., 2005). Thus, the cause and effect relationship between depression and disease appears to be complex and often bi-directional (for a comprehensive review see, Freedland & Carney, 2005). The identification of directionality between disease and depression can be a tricky issue involving several factors including temporal ordering and proximity. While many studies have been reported on these issues, few studies have examined such relationships with large population-based (representative) samples.

Thus, the purpose of this study is to examine the relationship between health status (chronic disease and functional limitations) and depression in the Health and Retirement Study's (HRS) panel data. A major advantage to studying depression in the HRS is that it includes a large, representative sample of middle aged and older adult Americans tested longitudinally. The HRS also includes a rich database of health related measures including participant-reported information of chronic diseases and daily functioning. In the current study, the health related covariates of depression included arthritis, lung disease, back pain, diabetes, heart disease, high blood pressure, cancer, all possible pairwise

combinations of the chronic conditions, and ADL (activities of daily living) functional limitations. In this study, self-reported diagnosis of disease temporally preceded (in most cases) the administration of the depression scale but the duration between the two was not considered. The analysis was conducted with a unique analytical approach known as MARS (multivariate adaptive regression splines), which identifies multivariate trends in the dependent measures of depression. The MARS approach and its advantages to traditional regression analysis are described in detail in the method section.

A variety of diseases have been associated with elevated depression levels (Freedland & Carney, 2005). One study in particular is worth reviewing because it involves the HRS data set and uses similar covariates. Polsky and colleagues (Polsky et al., 2005) examined the relationship between depression and various medical conditions with Cox proportional hazard models in five waves of the HRS. Depression was assessed with the CES-D-8 depression scale, whereby scores of five or greater were identified as being depressed. Cancer was associated with the highest hazard ratio, but that risk decreased over time and was no longer significant after 2 years. Lung disease exhibited a similar pattern of results. Heart disease presented a significant risk for depression over the entire eight-year period. Arthritis was associated with increased risk for depression two to four years after diagnosis. High Blood pressure, diabetes, and stroke did not present a significant risk for depression. In other models reported by the authors that included a variety of demographic covariates and functional limitations, only heart disease and lung disease remained significant covariates of depression. These results suggest that different chronic conditions have varying effects on risk of depression and that additional measures such as a person's functional status may play an important role in whether depression develops.

Health conditions that cause pain or discomfort may be among the most frequently reported and strongest covariates of depression (Currie & Wang, 2003; Patten, 2001). Among the diseases included in this study back pain, arthritis, lung disease, and cancer are most strongly associated with pain or discomfort. All of these may be significant covariates of depression score.

Various functional limitations have been linked to depression in adults (Cole & Denukuri, 2003; Gatz & Zarit, 1999). Among the array of possible limitations are ADLs, which includes difficulties associated with toileting, bathing, feeding, dressing, and walking. Highlighting the importance of functional limitations, a meta-analysis of 20 studies on the predictors of depression found that functional limitations was the most important covariate of depression (Cole & Denukuri, 2003). Lesser covariates included poor health status and new medical illness.

Age has been linked to depression. Generally, older age has been associated with lower depression scores than either middle age or young adulthood (Gatz & Zarit, 1999; Blazer & Hybels, 2009). However, the trend for depression within the range of older ages is less well understood. First-time diagnoses of depression in older adults is rather uncommon (Roberts et al., 1997) and may involve dementia or mild cognitive impairment (see Zelinski & Kennison, 2004). Depression scores appear to rise somewhat with age but this trend has often been linked to increased levels of disease and functional limitations (Gatz & Zarit, 1999) and dementia (see Zelinski & Kennison, 2004). Thus, older age itself may not be directly linked to higher depression scores.

While multiple hypotheses are possible, we highlight only some of the more important ones here. First, the presence of various chronic diseases is likely to be associated with higher depression scores. Second, conditions that are associated with considerable chronic pain or discomfort will be among the strongest covariates of depression. Third, the presence of functional limitations will be associated with greater depression. Fourth, functional limitations may be a more important covariate of depression

than any single chronic condition or pairwise combination of conditions.

Method

Sample

The sample was from the RAND HRS data file (RAND, 2008) and included 27,461 respondent's data collected on as many as eight test occasions completed in 1993-1994, 1995-1996, 1998, 2000, 2002, 2004, 2006, and 2008. The 1993-1994 and 1995-1996 testing occasions represent the combined data for the Asset and Health Dynamics in the Oldest-Old (AHEAD; Soldo, Hurd, Rodgers, & Wallace, 1997) and HRS studies, which were integrated under the HRS in 1996. The baseline data of HRS collected in 1992 was omitted from the analysis because the CES-D was administered in a different format, which cannot be combined with the other waves to form a valid longitudinal measure (Steffick et al., 2000). New participants were added at various test occasions to replace dropouts and to add additional birth cohorts.

Demographic information for the sample appears in Table 1. The upper and middle panels of the table display the baseline means (upper panel) and standard deviations (middle panel) for age, education, CES-D-8 depression score, and the number of ADL limitations. The lower panel displays percentages of females and the number of subjects at each test occasion. It should be noted that the apparent trends in age education and other measures, whereby the sample appears to be getting younger and more educated with each passing wave of testing, cannot be attributed solely to attrition bias because the HRS introduced new younger participants on several test occasions. Thus, attrition bias, if it exists, is likely confounded with the inclusion of younger, better performing participants.

For the disease indicators: 55.6% (n = 15,256) of the sample reported having had back pain; 13.6% (n = 3721) of the sample reported lung disease; 62.6% (n = 17,204) of the sample reported having arthritis; 60.9% (n = 16,724) of the sample reported having high blood pressure; 32.5% (n = 8913) of the sample reported having heart disease; 22.7% (n = 6234) of the sample reported having diabetes; 18.1% (n = 4959) of the sample reported having had cancer; and 13.1% (n = 3610) of the sample reported having had a stroke.

Materials and Procedure

Depression Scale. The eight-item version of the Center for Epidemiological Studies Depression Scale (CES-D-8; Radloff, 1977) was used to measure the frequency of adult depressive symptoms at each of the eight waves of HRS data. Longitudinal sequences, however, were not nested within subjects but were instead treated as independent cases. The HRS changed the CES-D-8 from a rating scale format to a two-alternative yes/no format during the 1993/1994 data collection (Steffick et al., 2000). This invalidated the baseline measure collected in 1992. Although neither the CES-D nor the CES-D-8 were intended to be used as a clinical diagnostic tool, higher scores have been associated with depressive disorders such as major depression (Pandya, Metz & Patten, 2005; Radloff, 1977). The CES-D-8 two alternative version has reasonable reliability; coefficient range from Cronbach's $\alpha = 0.83$ to 0.72 (Choi & Bohman, 2007; Fliege, Becker, Walter, Bjorner, & Klapp, 2005). Respondent's scores were the sum of responses to each of the eight questions. Two questions were reverse scored to yield a consistent indicator whereby higher scores indicated more depressive symptoms.

Disease Indicators. Lifetime incidence of arthritis, lung disease, back pain, diabetes, heart disease, high blood pressure, cancer, and stroke were assessed from self-reported health questions asked at each wave of testing. Coding was 1 for presence of a condition and 0 for its absence. Co-morbidity of any two diseases was assessed by creating all possible pairwise interaction terms resulting in 28 new variables. This allowed us to assess whether, for example, having diabetes and high blood pressure is associated with higher depression scores.

Demographic Measures. *Age* was calibrated to represent a respondent's age in 1993. *Education* was the reported number of years of formal

education beginning with first grade. The range of education was 0 to 17. *Gender* was referenced to females (coded as 1). Functional limitations in activities of daily living (*ADLs*) were assessed with the ADL summary measure formulated by Wallace (Wallace & Herzog, 1995) with a range of 0 to 3. Functional limitations were measured at each wave of testing; longitudinal cases were not tested within subjects.

Table 1

Participant Characteristics Presented as a Function of Test Occasion

Measure	1993-94	1995-96	1998	2000	2002	2004	2006	2008
				Mean				
Age	64.58	63.62	61.28	60.58	59.73	56.63	56.11	55.42
Education	11.68	11.83	12.09	12.20	12.31	12.46	12.48	12.54
Depression	1.46	1.36	1.62	1.58	1.54	1.50	1.54	1.45
ADLs	0.09	0.19	0.21	0.22	0.22	0.21	0.23	0.24
				Standard Deviation				
Age	11.25	10.81	10.50	10.11	9.70	10.47	10.04	9.64
Education	3.43	3.35	3.27	3.24	3.18	3.18	3.18	3.17
Depression	2.00	1.90	1.95	1.93	1.98	1.99	2.01	1.98
ADLs	0.37	0.57	0.60	0.61	0.63	0.61	0.64	0.64
				Frequencies				
% female	59.80	60.00	59.78	60.43	60.82	59.11	58.87	58.80
N	17,955	16,230	19,083	17,244	15,833	17,385	16,316	15,174

Note. Depression = CES-D-8 depression score; ADLs = the number of ADL limitations reported.

Data File. A stacked data file was created from the RAND HRS data file in order to perform the MARS analyses. The file consisted of 126,521 cases. Respondent's longitudinal data were not nested within subjects, but rather were treated as independent cases. Cases with missing data on any of the measures included in the analysis were removed resulting in a 6.02% reduction in data from the original n of 134,629.

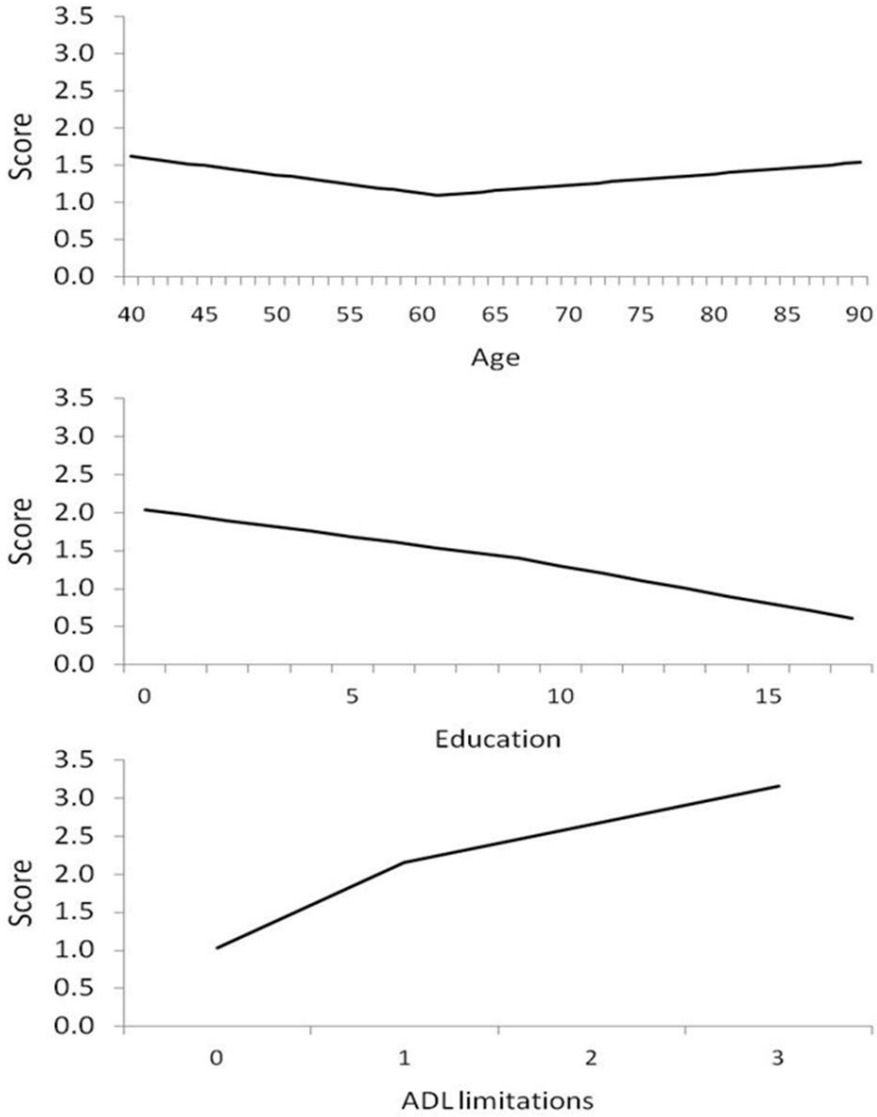
Analytical Approach

In this study we employed a unique analytical approach known as MARS (multivariate adaptive regression splines) to identify various trends in the prediction of depression. MARS is a semi-exploratory data analysis that is able to determine multiple linear splines and knot points (where a knot point is the intersection between two splines). An illustrative example can be seen in the top panel of Figure 1, which shows the effects of age on depression. Two splines and one knot point were selected by the MARS

analysis. The first spline shows that depression scores decreased from Ages 40 to 61 in a linear fashion. The knot point is at age 61 and connects the two splines. The second spline indicates a linear increase in depression scores from ages 61 to 90.

Figure 1

Depression Score Shown as a Function of Age (Top Panel), Education (Middle Panel), and ADL Limitations (Bottom Panel)



MARS has advantages over traditional regression-based analyses. In regression, the effects of semi-continuous measures such as age are typically understood as strictly linear (or curvilinear) functions. Yet, this forced linearity may not accurately characterize the relationship between the covariate and the outcome measure. In actuality the magnitude of the effect of a variable on the outcome (e.g., depression) may be different at different points along the scale. With the MARS approach, multiple splines and knot points may be identified within a continuous measure yielding a more fine grained

result and better characterizing the relationship between the two measures.

Another advantage of MARS is that it picks only the most important covariates from a user specified array of possible covariates. That is, the user may chose to include multiple covariates at the beginning of the analysis and MARS will select out only the most important ones to include in the final result. This pruning process eliminates covariates that have limited efficacy in the prediction of the outcome measure.

The MARS analysis is conducted in two steps. The first step involves identifying all possible spline and knot functions with a forward pass that repeatedly and recursively adds the functions that give maximum reduction in root mean square error (RMSE). This process results in the assumed maximum model. It may not include all of the variables that were initially introduced. The second step involves pruning the model in a backwards pass. That is, each term is successively removed, creating model subsets. These subsets are compared using the generalized cross validation (GCV) index, which makes adjustments to goodness-of-fit based on model complexity. The index penalizes for the addition of splines and knots thus preserving parsimony. The resulting final model is the one with the smallest GCV estimate.

Models are expressed in the form:

$$Y_n = \Sigma [\alpha_i (\beta_i \{ X_n \})] + e_n$$

where Y_n is a weighted sum of basis functions ($\beta_i \{ X_n \}$). Each α_i is a constant coefficient. Each basis function is: (a) a constant 1, (b) a hinge function (MAX{a,b}, or (c) a product of two or more hinge functions.

The MARS analyses were conducted in R version 2.13.1 (R Project, 2011) with the Earth data package (version 3.2-1) for MARS modeling (Milborrow, 2011). Standard errors, which are not reported by the Earth package were calculated by replicating the analysis in R using syntax provided in the Earth users guide (Milborrow, 2011).

Results

Model Building

Three models were fit and evaluated to determine whether, compared to a baseline model (Model 1), the addition of ADL limitations (Model 2) and disease indicators (Model 3) resulted in successively better fitting models. Model 1 included the covariates of age, gender, being white, being Hispanic, and education. Model 2 included the covariates of Model 1 plus ADL limitations. Model 3 included the forgoing covariates plus the all of the disease indicators (including the pairwise combinations of diseases). Model fit was indexed by the magnitude of the generalized cross validation (GCV) index, where smaller GCVs indicate better model fits (Milborrow, 2011). Another important summary statistic is GRSq, which is an estimate of the predictive power of the model. It is calculated as $(1\text{-gcv})/gcv_{null}$, where gcv_{null} is the GCV for the null model. In most cases GRSq is close to the estimated R^2 value.

Model 1 produced a GCV of 3.56 and GRSq of 0.07; Model 2 had a GCV of 3.30 and GRSq of 0.14; and Model 3 had a GCV of 3.16 and GRSq of 0.18. An ANOVA comparing the GCVs for Models 1 and 2 indicated a significantly smaller GCV for Model 2 indicating a better fit for that model, $F_{(126511, 1)} = 9903.20$, $p < .0001$. A second ANOVA comparing the GCVs for Models 2 and 3 resulted in a significantly smaller GCV for Model 3, $F_{(126505, 6)} = 939.00$, $p < .0001$. Thus, Model 3 produced the best fit of the three models and accounted for approximately 18% of the variance in depression score. Model three will be discussed in more detail below.

Model Estimates

Model 3 retained 12 of the 42 possible covariates and 16 of 17 terms identified in step 1 of the analysis. The predictors were: 1) age, 2) education, 3) being female, 4) being white, 5) being Hispanic, 6) ADL limitations, 7) back pain, 8) lung disease, 9) heart disease, 10) back pain and arthritis, 11) back pain and diabetes, and 12) high blood pressure and stroke. Chronic conditions rejected by the model were: 1)

arthritis, 2) high blood pressure, 3) cancer, 4) diabetes, 5) stroke, and 6) 25 of the 28 disease pairings.

The parameter estimates and knot points for the terms of Model 3 appear in Table 2. Two splines were identified for each of the continuous.

Table 2

Parameter Estimates and Knot Points for Selected Terms Included in MARS Model 3

Predictor	Estimate	Standard error	Importance
Intercept	2.102***	0.027	
Age spline 1			10
Knot	61 – age	--	
Slope	0.025***	0.002	
Age spline 2			10
Knot	age – 61	--	
Slope	0.015***	0.001	
Education spline 1			2
Knot	9 – ed	--	
Slope	0.071***	0.005	
Education spline 2			2
Knot	ed – 9	--	
Slope	-0.098***	0.002	
ADL limitations spline 1			1
Knot	1 – ADL	--	
Slope	-1.121***	0.019	
ADL limitations spline 2			1
Knot	ADL – 1	--	
Slope	0.507***	0.027	
Female	0.320***	0.010	5
White	-.252***	0.014	8
Hispanic	0.416***	0.021	6
Back pain	0.283***	0.016	3
Lung disease	0.466***	0.015	4
Heart disease	0.263***	0.011	7
Back pain & arthritis	0.234***	0.016	11
Back pain & diabetes	0.194***	0.015	12
High blood pressure & stroke	0.259***	0.018	9

Note. Importance was assessed by relative reduction in GCV; *Ed* = education; *ADL* = activities in daily living limitations.
***p < .0001;

measures: age, education and ADL limitations. Age was associated with a single knot at age 61 and two splines emanating upward from that point. As can be seen in the top panel of Figure 1, the spline from ages 40 to 61 (61 – age) decreases over age, where depression scores are lowest at age 61. The second age spline increases from age 61 to age 90. The middle panel of Figure 1 shows that depression scores decreased as a function of education. The knot at 9 years of education indicates that depression scores had a less steep slope for first spline than

for the second spline. The reduction in depression score is greatest from 9 to 17 years of education, but having more education consistently resulted in lower depression scores. The bottom panel of Figure 1 shows that depression scores increase as a function of ADL limitations. The greatest increase in depression score occurs from a score of 0 to 1 functional limitations. The addition of further ADL limitations increases depression scores, but not as steeply.

The associated increases in depression score for the dichotomous indicators appear in Table 2. Being female, non-white, and Hispanic were each associated with higher depression scores compared to being male, white, and not Hispanic, respectively.

Reporting lifetime incidence of lung disease, back pain, and heart disease were each associated with increases in depression score. The largest increase was for lung disease, which was associated with nearly a ½ item increase in depression score. Back pain and heart disease were associated with roughly ¼ items increases in depression score. Three of the 28 possible pairwise disease combinations were included in the model. Lifetime incidence of high blood pressure and stroke, back pain and arthritis, and back pain and diabetes were each associated with ¼ to 1/5 item increases in depression score.

The largest effects in terms of the magnitude of the regression coefficients were associated with functional limitations was the single most important predictor of depression in terms of its reduction to GCV. Below we discuss the results in somewhat greater detail.

Back pain had both unique and interactive effects on depression. As a single predictor, it was the most important health measure in terms of reduction to GCV. Back pain when combined with arthritis or combined with diabetes was also associated with higher depression scores. It is a condition that is associated with chronic pain, loss of mobility, and functional limitations (Elliott, Renier, & Palcher, 2003). This finding further supports the notion that pain is closely ADL limitations and education. For the dichotomous measures larger effects were associated with lung disease, being Hispanic and being female. Another way to evaluate the relative importance of the covariates, however, is reduction to GCV. As shown in the rightmost column of Table 2, the relative importance of the covariates was: 1) ADL limitations, 2) education, 3) back pain, 4) lung disease, 5) being female, 6) being Hispanic, 7) heart disease, 8) being white, 9) high blood pressure and stroke, 10) age, 11) back pain and arthritis, and 12) back pain and diabetes.

Discussion

Each of the formalized hypotheses received support. First, it was found that seven of the eight chronic conditions (back pain, lung disease, heart disease, high blood pressure, stroke and arthritis) played some role in depression. Back pain, lung disease and heart disease had unique effects on depression. Stroke, high blood pressure, arthritis, and diabetes were co-morbid with other diseases in their prediction of depression. Second, the chronic conditions that were most strongly associated depression tended to be the ones that were associated with the greatest pain or discomfort (e.g., back pain, lung disease, and arthritis). Third, functional limitations were associated with higher depression scores. The addition of functional limitations in MARS Model 3 increased the variance accounted for and reduced the role of various other chronic conditions. Fourth, linked with mood and depression (Currie & Wang, 2003).

Lung disease was associated with higher depression scores. It has been associated with considerable discomfort, decreased activity, decreased mobility, and depression (van Manen et al., 2002). Lung disease in later life is most strongly associated with COPD and a history of smoking.

Arthritis was found to increase depression only when it was reported in combination with back pain. However, in other models, which did not include functional limitations, it was a

significant covariate of depression, suggesting that functional limitations is an intervening variable between arthritis and depression (Dunlap et al., 2004).

Heart disease had a longitudinal association with depression scores. While it is a condition that has not often been linked to chronic pain or discomfort, it has been associated with a myriad of other conditions including mild cognitive decline and Alzheimer's disease (see Zelinski and Kennison, 2004). Depression has been viewed as a complicating factor in the treatment of heart disease and their co-morbidity is associated with functional limitations and mortality (Nicholson, Kuper, & Hemingway, 2006; Dunlop, Lyons, Manheim, Song, & Chang, 2004)

The co-morbidity of high blood pressure and stroke was associated with higher depression scores, while neither condition was associated with depression alone. This is perhaps not surprising because the two conditions have a high rate of co-occurrence, whereby strokes are strongly associated with having high blood pressure. Stroke has been linked to depression in several studies (see Freedland & Carney, 2005) and recent evidence suggests that strokes that occur regionally near to the left frontal pole may be associated with greater depression (Narushima, Kosier, & Robinson, 2002).

With the exception of heart disease, high blood pressure and diabetes, the chronic conditions identified as affecting depression scores have all been associated with considerable pain or discomfort. In addition to depression, living with chronic pain or discomfort has been associated with lowered life satisfaction and a sense of hopelessness for the future (Patten, 2001). It is likely, that a person's level of discomfort would be an independent covariate of depression if it were available in the HRS data.

Cancer was not selected as a covariate of depression score in any of the models considered and in other models of depression conducted by our research group. For example, Cox (2010) found no effect of cancer on depression in a series of growth curve models fit to the RAND HRS data set. In the larger literature, the link between cancer and depression is controversial and the focus of the literature has been on whether depression is associated with shorter survival times (Cole & Denukuri, 2003). Depression has been linked to specific forms of cancer (see Freedland & Carney, 2005) but in this study we did not consider type or severity of cancer. We posit therefore three possible explanations for these null effects. First, cancer, while often categorized a "chronic condition" is not always chronic in the sense that cancer can be cured or held in check with treatment. Thus, it is likely that some portion of the sample who reported having cancer was effectively treated. Second, cancer, when it is untreatable, is likely to lead to death within a fairly short period of time from diagnosis leading to sample attrition and loss of information. Third, because the link between cancer treatment and a patient's attitude has been emphasized in treatment regimens, potential depression associated with cancer may be mitigated by therapeutic interventions. While these are interesting possibilities, the results of this study do not help delineate between them.

Depression levels measured across the lifespan have been shown to peak in middle age with somewhat lower depression rates in older age and young adulthood (Gatz & Zarit, 1999; Blazer & Hybels, 2009). While the present findings are agnostic on the issue of depression in young adulthood, they generally support the notion that depression scores drop from middle age into young-old age. The lowest depression scores occurred in the late fifties and early sixties. However, as people transitioned from young-old age to old-old age, depression scores again began to rise in a linear fashion. These effects were maintained across the three models examined here suggesting that the addition of functional limitations and chronic disease did not mitigate or alter the age effect. These results suggest that depression levels rise in old age and that this rise cannot be fully attributed to health or functional status.

The importance of education as a predictor of depression score has once again been demonstrated (see Miech & Shanahan, 2000). Depression scores were reduced with each

additional year of education. The effect of education increased when it continued into high school and college (the education 9 to 17 year spline) suggesting that completion of high school and college are protective against depression.

Being non-white and being Hispanic were each associated with higher depression scores compared being white, and being not Hispanic, respectively. While these findings should not be trivialized, this study was not intended to examine such effects. The findings associated with race and ethnicity would probably be better understood in the context of other measures such as income and SES (Miech & Shanahan, 2000).

As with any correlational study there are some important limitations that should be considered. In population studies like this one, depression scales like the CES-D-8 are known to be positively skewed such that the mean tends to be very low (in this range of 1.5 out of a possible 8 for this study) because the typical respondent is not depressed. Highly skewed distributions are likely to affect the results of inferential statistics. We did not do anything to reduce this effect because many of the possible remedies have been, themselves, associated with a myriad of problems (Tabachnick & Fidell, 2013). Another limitation has to do with the choice of covariates. The HRS data set has extensive measures and many of them are likely to be associated with depression. The covariates used in this study were chosen because they were theoretically important to understanding depression in the context of health and functioning. The decision to report MARS analyses as opposed to traditional regression modeling or growth curve modeling presents limitations as well. The MARS approach is semi-exploratory in nature resulting in models that are not entirely theory driven. That is, MARS selects which measures are to be included in the final model. It also automatically fits the splines and knot points. However, there are also theoretically driven elements to the analysis. Variables are selected by the analyst and their inclusion should fit within a theoretical framework. Also, model comparisons can be made between different MARS models computed for the same outcome measure. Another criticism of MARS is that it does not provide for nesting of longitudinal cases within subjects, resulting in additional variability that would normally be accounted for. Finally missing data were removed before performing the MARS analysis introducing potential sources of attrition bias.

In summary, a unique analytical approach know as MARS was used to model linear splines among various health and functioning covariates of CES-D-8 depression scores. Diseases associated with pain and discomfort (e.g., back pain, lung disease) tended to be most strongly associated with elevated depression scores. Yet, the single most important covariate of depression score was ADL functional limitations. Reporting one of more functional limitations was associated with substantial increases in depression scores. Functional status along with the presence of painful conditions increases the likelihood of depression.

Acknowledgments

The Health and Retirement Study (HRS) is supported by the National Institute on Aging (NIA U01AG009740). We are grateful for guidance from Kevin Petway on MARS analyses

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