Using Hierarchical Linear Modeling to Simultaneously Model Mental Health Across Individual and Family-Level Characteristics

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Abstract

Prior studies have linked socioeconomic indicators to individual mental health and have suggested that income and mental wellbeing are correlated up to a point. However, less is known about the impact of family-level socioeconomic related factors on individual mental health. Surveying a public use NHIS national survey, representing the non-institutionalized American populace in the year of 2016, we applied a hierarchical linear modeling approach in order to assess the effects of socioeconomic family indicators, as well as race, on individual mental wellbeing. By sytematically applying a "step-up" model building procedure, we answered questions pertaining to the impact of related person-level characteristics on individual mental health, including the testing for a compositional effect of income. A finalized intercept and slopes-as-outcomes model, with non-randomly varying slopes, was settled upon; consequently, the 6 main research questions that motivated this research were addressed in light of this model-building process.

Using Hierarchical Linear Modeling to Simultaneously Model Mental Health Across Individual and Family-Level Characteristics

Introduction

Mental illnesses are common in the United States; from Any Mental Illness (AMI) to Serious Mental Illness, nearly one in five U.S. adults live with a mental illness, and the prevalency of mental illness has been suggested to be increasing (NSDUH, 2018). Coming to better model mental wellbeing is therefore of increasing importance. It is well-documented that poverty-related factors such as low-income and government aid increase stress and, by extension, may have negative effects on individual mental health (Vijaya & Femi, 2004). Furthermore, studies have shown that children of depressed mothers have impaired cognitive, behavioral and health outcomes, suggesting a potential family based correlate in mental health status (Turney, 2012). We think it important, then, to consider potential family-level characteristics that may influence individual mental health. Though myriad markers for mental health exist, the present analysis will rely on a composite score from a self-reported scale; all subsequent references to mental health or mental wellbeing assume values along this scale.

Family Effects

Regardless of personal characteristics such as career or living arrangement- with or without family members, family-related factors, both during child-rearing and into adulthood, may impact many aspects of an individual's social identity and perception of relationships; which may, in turn, impact individual mental health. A central issue concerns whether or not families, *as blood-related groups of two or more individuals*, have measurable effects on mental health outcomes, especially individual mental wellbeing.

Research Questions

We are motivated to determine if family-level effects on individual mental health exist. To even attempt to model such effects we must first have evidence suggesting that families vary in some measure of mental health. Correlations of mental-health measures within families would provide evidence for such a family-level "nesting effect". This, in turn, would necessitate the presence of between-family variance on the outcome of mental health, which could then be modeled.

Studies have suggested a negative relationship between individual income and stress, which itself can negatively impact both physical and mental health, and, along with linking income to stress, minority status has long been theorized and suggested to play a role in individual mental health. In a study examining the extent to which racial differences in socio-economic status (SES), social class, and indicators of perceived discrimination, as well as stress can account for racial differences in self-reported measures of mental health, Williams, Yu, and Anderson (1997) found that observed racial differences in health were markedly reduced when adjusted for income; they argued, however, that perceived discrimination and stress play a role in accounting for differences between races in mental health status. We'd like to corroborate such findings to better inform the complex relations between socio-economic position and race. Guided by prior research, we focus on the use of socioeconomic indicators as predictors for individual mental health; namely, income and race.

Person charateristics aside, we theorize that family characteristics can also explain some of the variance in mental wellbeing. We hypothesize that family-level variables related to income and poverty, such as family (mean) income and family use of food stamps, can predict mean family mental health and, by extension, individual mental health. We further care to determine if any family-level variables may explain between-person variance in mental health after having accounted for their associated person-level variables. This second point speaks to the existence of a contextual effect, otherwise known as a compositional effect, which provides clear evidence of a higher-level impact on an individual outcome. This is because the group variable is an aggregate of the person variable, and the effect of the person variable is succesfully removed from the compositional effect estimate. In contrast, ordinary least squares (OLS) regression estimates for a contextual effect are unable to remove the within-group component, making the testing for contextual effects of particular importance in multilevel model applications (Raudenbush & Bryk, 2012, chap. 5). We care to know if mean family income predicts changes in individual mental health after conditioning on individual income.

It may be the case that family-level factors can also explain possible reasons for variability in income and race differences between families. To the end of better understanding income and race differences in mental health, we investigate how these differences may vary between families that, themselves, vary in their aggregated income and their necessity for food stamps. Perhaps a family that necessitates the use of food stamps carries a significant association to a decreased strength in the relationship between individual family members and mental wellbeing.

The following list states our research questions for the family effects we are most interested in testing for, as well as the individual effects previously mentioned:

1. Can an individual's income and race predict their mental health as measured by a composite scale score?

2. Do we have evidence to suggest that mean values of mental health for families vary significantly about the overall mean mental health value?

3. Given 1) and 2), can the family social status indicators of family (mean) income and family use of food stamps predict a family's mean mental health status and, by extension, an individual family member's mental health status ?

4. Does family mean income affect the mental health of an individual independent of that person's income?

5. Does the relationship between individual income and individual mental health vary by family income? Similary, does the relationship between individual income and individual mental health vary as a function of whether or not a family purchases food stamps?

6. Does the relationship between necessity for food stamps and individual mental

health, or the relationship between family income and individual mental health, vary by race?

We provide the aforementioned research questions as Table 1 of the Appendix. Given our set of research objectives we opted for the use of Multilevel Modeling to best address our research questions. All Hierarchical Models reported in the present analysis were generated via the HLM software.

Method

Dataset

In order to both understand what factors relate to mental wellbeing as well as predict personal mental wellbeing, in a manner that is relatable and applicable to the American civilian populace, we have consulted the Medical Expenditure Panel Survey's Household Component 2016 Full Year Data File (MEPS HC-192); a public use file providing varied information collected on a nationally representative sample of the civilian noninstitutionalized population of the United States for the 2016 calendar year. This dataset provides information on health care use, expenditures, sources of payment, and health insurance coverage; constituting a whopping 1941 variables for an n = 34,655 sample. The 2016 MEPS dataset was released in August 2018 and it consolidates all of the final person level variables, as well as a few family level variables, onto one file.The set of households selected for the MEPS HC is a subsample of households participating in the previous year's National Health Interview Survey (NHIS) conducted by the *National Center for Health Statistics*. Moreover, most variables of the MEPS dataset stem from *previously established scales*. For these reasons, we believe the MEPS data to be valid and to permit for model estimates that are representative of the American populace.

Using computer assisted personal interviewing (CAPI) technology, information about each household member is collected, and the survey builds on this information from interview to interview. Though the NHIS sampling frame provides a nationally representative sample of the U.S. civilian noninstitutionalized population, it reflects an oversampling of Blacks, Hispanics, and Asians. Increased sample sizes for minority subpopulations allows for improved precision in estimation therein though, naturally, appropriate weights (provided by the original MEPS dataset) have to be applied to each subpopulation estimate in order to obtain national population estimates that are not distorted by a disproportionate contribution from oversampled (or undersampled) subgroups.

Most measures of the MEPS dataset stem from previously established scales and are therefore ordinal in nature; however, a few variables are computed as the sum of responses across numerous scale items and can arguably be treated as continuous or quasi-continuous. Though a few variables such as income and family income are continuous by nature. Individual level demographic variables are also included and tend to be nominal by nature. Bearing this in mind, we sought to work either with continuous variables or composite-score variables that more closely resembled quasi-continuity, using nominal variables only as covariates when our substantive research objectives deemed it necessary.

Data Cleaning

Prior to any exploratory analysis or hierarchical model building, we had to first consider weighting, our definition of family- and its manifestation in the dataset, variable distributions for our variables of interest as well as the interpretability of their response categories for our objectives, and the dummy-coding of a race variable that would capture the four groups represented.

This public use dataset contains variables and frequency distributions associated with 34,655 persons who participated in the MEPS Household Component of the Medical Expenditure Panel Survey in 2016. These persons received either a positive person-level weight, a family-level weight, or both (some participating persons belonged to families characterized as family-level nonrespondents while some members of participating families were not eligible for a person-level weight). We subsetted the original MEPS dataset to reflect only these individuals and families that carried non-zero sample weights, leaving 29,532 persons and 9,480 families. The person-level weight variable, PERWT16F, and the family-level weight variable, FAMWT16C, were specified under the weighting option of HLM. Consequently, our data for these persons and families could be used to make estimates for the civilian noninstitutionalized U.S. population for 2016.

Following weight subsetting, we considered how we wanted to define a family. The MEPS provides two definitions of a family, MEPS families and CPS families. Under both definitions, family generally consists of two or more persons living together in the same household who are related by blood, marriage, or adoption; however, foster children were included under the MEPS definition. So too, did MEPS include in the definition of a family unmarried persons living together who state they are a family, whereas CPS does not. We decided to abide by the CPS definition of family given our interest in contextual factors that may arise from blood-relation, albeit measured indirectly by means of a family identifier variable where an individual living alone still obtained their own family identifier variable. Given our interest in blood-related nesting factors we eliminated all cases from the MEPS 2016 dataset that carried a unique family identifier variable. We reduced our sample to be 28,266 cases nested in 8,901 families.

We enacted another round of subsetting after this following inspection of response rates for our few predictors and our outcome variable. The outcome measure, Mental Component Summary (MCS-12), was a composite score of unequal weighting across 12 questions that reflected individual mental wellbeing. Composite values ranged from 5.57 to 76.52. The measure, however, allowed for values of -9 (Not Ascertained) and -1 (Inapplicable). Figure 2 of the Appendix illlustrates the distribution of this variable, with a frequency of over 10,000 for the response category of -1. We eliminated responses of -9 and -1 in order to eliminate bi-modality and approximate normality as closely as possible. The variable was renamed MentalHealthInd and Figure 3 of the Appendix illustrates this transformed distribution. Suffice it to say, sample size was curtailed as a result of this, with person-level cases totaling 15,338 on this variable. For a similar reason, individual income exhibited an overwhelmingly positively skewed distribution.

Figures 4 and 5 of the Appendix depict the change in the distributiom of income that resulted from removal of the extraneous response category values.

Finally, we transformed a provided race variable into three dichotomous dummy variables, signaling the inclusion of four categories; White constituted the reference group (score of zero across the three variables), Hispanic constituted values of 1 under the Dummy1 variable, and Black as well as Asian were similarly denoted under Dummy2 and Dummy3, respectively.

Centering

Our choices for centering extended across three principles: interpretability of the intercept and slopes (given that they become outcome variables at level-2), consideration of how the choice of location for a metric,X_{ij}, may influence the estimation of level-2 variance components, τ, as well as the random level-1 coefficients (random slopes), β_{qj}, and consideration of our research interest in group effects and contextual effects.

Level-1 misspecification leads to biased level-2 estimates for the intercept if the specified level-1 predictor has a significant interaction with any level-2 predictor. To correct for this, we can group mean center the level-1 variable while adding its aggregated mean as a level-2 variable of the intercept-as-outcome model.

Both grand-mean and group-mean centering ultimately provide the same information regarding between group effects and contextual effects, provided that both cases include the person-level Xij in the level-1 model and its aggregate, Xbar.j, in the level-2 model for the intercept. It is simply a matter of what each approach expresses directly and indirectly. Under group-mean centering the relationship between X_{ij} and Y_{ij} is directly broken down into its within-group and between-group components. That is to say, $\gamma_{01} = \beta_b$ and $\gamma_{10} = \beta_w$. A non-zero value after subtracting these two would suggest a compositional effect is present. Group-mean-centered models are preferred when seeking to detect a compositional effect (see Raudenbush & Bryk, 2012, pg. 139). For these reasons we intend to group mean center person income at level-1 while including its aggregate, mean (family) income as a grand-mean centered level-2 predictor for the intercept-as-outcome model.

Because under group mean centering the effect of Wj is not adjusted for X in the analysis, Boj (representing the group mean of the outcome (unadjusted)) will be the same value for cross-family individuals who lie at their respective family means for X (conditional on all other predictors inputted, of course). Though this would inform us that such individuals have the same relative position with respect to their family income distributions, *we would be unable to discern their absolute location across all family incomes.* For this reason, we further justify the inclusion of a grand-mean centered $\bar{X}$ into the equation for β_{oj}.

All dummy-coded variables were specified as uncentered to simplify their interpretability. Discussing an unadjusted mean for a hispanic respondent when the proportion of hispanics and non-hispanics is equal in their family, or discussing a mean adjusted for differences in family deviation about the grand-mean proportion of a race category to its non-category in a manner that only applies to a member of that race, is cumbersome, confusing, and unnecessary.

Finally, we grand-mean centered the non-dichotomous level-2 predictors as interpreting a value of zero on their metric was non-sensical. Centering is generally preferred in multilevel modeling, but centering at level-2 is not as critical as for level-1 predictors, because problems of numerical instability are less likely, except when cross-product terms are introduced at level 2 (e.g. $W_{1j}W_{2j}$)(see Raudenbush & Bryk, 2012, pg. 35).

Model-Building

Before specifying hierarchical models, with our guiding theory in mind, we first ran an OLS regression for our reduced set of level-one predictors and, similarly, ran an OLS regression for our reduced set of level-2 predictors.

We opted for a “step-up” strategy in building our level-1 and, subsequently, our level-2 model. Though it is possible to begin by “over-saturating” a model by specifying many random level1 coefficients and then scaling back, an overfit model that specifies too many random level-1 coefficients will partition variance across many little pieces – none of which is of much significance. Such a large array of nonsignificant findings gives the researcher little direction as to next steps. We favor the "step-up" strategy which involves building up models based on promising sub-models. We fit the level-one model with a set of predictors selected for by drawing from external theoretical guidance. This can- in part- be informed by an ordinary least squares (OLS) multiple regression that provides evidence that the level-one predictors are related to the outcome.

We fit the model for the level-1 intercept first before proceeding to fit the models of any level-1 slopes. It is advised that whenever hierarchical models involve both random intercepts and random or nonrandomly varying slopes, that developing a tentative model for the intercept, β_{oj}, be done before proceeding to fit models for the random slopes (see Raudenbush & Bryk, 2012, pg. 267). Just like a general linear model seeks to fit the main effects first before considering interaction effects, so too does a hierarchical analysis hold off on cross-level interactions until the main effects are modeled by the inclusion of the level-2 predictors into the level-1 intercept equation, and this of course should be specified only after the relevant level-1 predictors are found to have a significant effect on the outcome or are found to have significant variability about their "average" relationship with the outcome. Finally, a level-1 predictor found to have a significant effect on the outcome, but whose random component lacked significance, benefited from a Chi-square test of the difference in their Deviance statistics.

Results

Individual-Level Measure

A short form 12 question survey was administered to respondents as part of the MEPS survey, and its analysis was broken across two summary scores: a Physical Component Summary (PCS) and a Mental Component Summary (MCS) that incorporated information from all 12 questions. As previously mentioned, we have selected the composite MCS score as our outcome variable, have curtailed its response distribution, and have labeled it MentalHealthInd. Our individual-level predictor candidates were Income, DummyRace (Hisp), Dummy2 (Black), Dummy3 (Asian), and MorJob- a dichotomized variable indicating if an individual has more than one job. Our outcome measure was treated as a continuous variable for analytic purposes, whereas income was our only truly continuous variable. The remaining four potential predictors were dichotomous. We note that MorJob has a substantially lower sample size than the other variables, a direct resulted from our dichotomizing of this variable. Descriptives for the outcome as well as the potential level-1 predictors are provided under Table 2 of the Appendix. We did not include MorJob into our model buliding process because of the extent to which it reduced an already-greatly-reduced dataset, given its lowest response number of all potential variables.

Though we recognize that our outcome reports a second-lowest sample size of 15,338 cases, our final analytic sample size was reported to have at most 24,590 cases, according to the HLM software-generated MDM file; suggesting the use of imputation methods durng estimation.

Family-Level Measure

With regards to family-level measures, our previous theorization led us to focus on family (mean) income and family necessity for food stamps as our level-2 predictors. We calculated Mean_Income as the average income per family in order to obtain an aggregate variable for income that allows for both the estimation of a contextual effect as well as the correction for potential level-1 mis-specification. We also included family size as a potential level-2 predictor. Table 3 of the Appendix depicts a number of descriptive statistics for these three potential predictors.

Of the 8,122 families that reported a family size, we found that the average family size was 3.18. Though Mean_Income demonstrated the lowest sample size of 7,906, our final HLM MDM file reported a maximum number of 7,813 level-2 units, suggesting the use of imputation. A lower number of mean group size with a higher number of groups results in a maximized effective sample size. Without directly calculating the effective sample size, given a final analytic family-level sample size of 7,813, and with a mean group size of 3.18, we proceed with hierarchical linear modeling understanding that our sample size will not bias or limit estimation.

The Unconditional Model

Before attempting to model group-level variation it is crucial to first provide evidence of the existence of such variation on the outcome. The existence of between-group variation on an outcome measure, or congruently, the existence of within-group correlations on measures of the outcome, signify the presence of nesting of observations within groups.

We ran an unconditional model to determine what percent of the variability in mental health exists between individuals and what percent exists between families. We calculate the unconditional Intraclass Correlation Coefficient (ICC) to determine if nesting is present in our sample:

$$ICC = \frac{\hat{\tau_{00}}}{\hat{\tau_{00}} + \hat{\sigma^2}} = \frac{28.40136}{28.40136+55.44303} = \frac{28.40136}{83.84439} = .3387389 \approx 33.87\%$$

With approximately 33.87 % of the variance in mental health being explained by between family differences; concurrent with a significant chi-square statistic testing this nesting ($p < .0005$); we argue for the justifiability behind multilevel models in modeling mental health. Naturally, the family-level variables that are in the model will attempt to explain the 33.87 % between-family variance and the individual-level variables will attempt to explain the 66.13% variance that exists between individuals.

Specifying the Level-1 Model

We first sought to specify the level-1 model, prior to specifying the intercept or slopes equations, by including Income, DummyRace, Dummy2, and Dummy3 as predictors. Because Income was group-mean centered, we concurrently specified the aggregate Mean_Income into the intercept equation. Without the inclusion of the aggregated term, model estimation would fail to converge. Our final level-1 model was first tested as an OLS multiple regression that yielded a significant F-test statistic ($F = 67.632$, $p < .001$) with an R square value of .025, suggesting that 2.5 % of the total variance in mental health is explained by the four predictors. We generated a scatterplot of MentalHealth and Income to inspect for linearity (Figure 6). The data swarm was not the ideal ellipsis in shape as it exhibited some amount of heterogeneity of variance. In terms of standardized residual analysis, skewness and kurtosis values of less than one standard error of MentalHealth suggested that these values were not significantly different from the expected values of zero for a normal distribution. A normal Q-Q Plot, however, showed minor deviations from the expected trend. It may be the case that our continuous predictor and our error terms may present some violation of their related assumptions.

Our specified level-1 model was ran without allowing the slopes to vary. The results of this model indicated that Income ($\gamma = .00002, SE < .00001, p < .001$), and Dummy2 ($\gamma = 1.22357, SE = 279017, p < .001$) significantly predicted MentalHealth:

$$\boldsymbol{Level - 1}$$

$$MENTALHEALTH_{ij} = \beta_{0j} + \beta_{1j} * (INCOME_{ij} - \overline{INCOME_{.j}}) + \beta_{2j} * (DUMMYRACE_{ij}) + \beta_{3j}$$

$$+ \beta_{4j} * (DUMMY3_{ij}) + r_{ij}$$

$$\boldsymbol{Level - 2}$$

$$\beta_{0j} = \gamma_{00} + \gamma_{03}(MEAN\_INC_j) + \mu_{0j}$$

$$\beta_{1j} = \gamma_{10}$$

$$\beta_{2j} = \gamma_{20}$$

$$\beta_{3j} = \gamma_{20}$$

$$\beta_{4j} = \gamma_{20}$$

$$\boldsymbol{MixedModel}$$

$$MENTALHEALTH_{ij} = \gamma_{00} + \gamma_{01}(MEAN\_INC_j) + \gamma_{10}(INCOME_{ij}) +$$

$$\gamma_{20}(DUMMYRAC_{ij}) + \gamma_{30}(DUMMY2_{ij}) + \gamma_{40}(DUMMY3_{ij}) + \mu_{0j} + r_{ij}$$

Having been made suspect for removal, models that independently allowed the slopes for DummyRace (hispanic indicator) and Dummy3 (asian indicator) to vary randomly were ran. Estimation for such models was not achieved, and these two predictors were subsequently eliminated from the modeling progression.

Specifying the Level-2 Models

Initially, an OLS regression, analogous to a level-2 single level multilevel equation, regressing the mental health outcome on the level-2 predictors, was ran and yielded a significant F-test statistic (F = 74.080, p < .001) with an R square value of .198. Its R square value of .198 suggests that 19.8 % of the variance of MentalHealth is explained by the level-2 predictors. A scatterplot of the outcome and Mean_Income (Figure 9) conveyed the same story as with the OLS regression for the level-1 predictors, given that this aggregated predictor was a monotonic transformation of its level-1 progenitor variable. A scatterplot of the outcome and FamSize was difficult to interpret given that responses to FamSize varied by discrete units from 2 to 12. Normality of residuals was tested with an exploratory analysis and a Normal Q-Q plot. For the residual analysis, values of skewness and kurtosis (.029, .057) of less than one standard error of MentalHealth suggested that these values were not significantly different from the expected values of zero for a normal distribution. However, the Normal Q-Q plot (Figure 11) demonstrated moderate deviation from the expected trendline, suggesting error distribution departure from normality. It may be the case that our continuous predictor and our error terms may present some violation of their related assumptions.

After settling on the level-1 model, the intercept model was fully specified with FamSize grand-mean centered. The intercept-as-outcome model suggested that the three inputted predictors of FamSize ($\gamma = .195504, SE < .08401, p = .02$), FamFoods($\gamma = -5.13254, SE = .52535, p < .001$), and MeanIncome($\gamma = .00002, SE < .00000, p < .001$) were significant predictors of individual mental health:

$$\boldsymbol{Level-1}$$

$$MENTALHEALTH_{ij} = \beta_{0j} \; + \beta_{1j} * (INCOME_{ij} - \overline{INCOME_{.j}}) + \beta_{2j} * (DUMMY2_{ij}) + \; r_{ij}$$

$$\boldsymbol{Level-2}$$

$$\beta_{0j} = \gamma_{00} + \gamma_{01}(FAMSZE_j - \overline{FAMSZE_{..}}) + \gamma_{02}(FAMFOODS_j) +$$

$$\gamma_{03}(MEAN\_INC_j) + \mu_{0j}$$

$$\beta_{1j} = \gamma_{10}$$

$$\beta_{2j} = \gamma_{20}$$

$$\boldsymbol{MixedModel}$$

$$MENTALHEALTH_{ij} = \gamma_{00} + \gamma_{01}(FAMSZE_j - \overline{FAMSZE_{..}}) + \gamma_{02}(FAMFOODS_j) +$$

$$\gamma_{03}(MEAN\_INC_j) + +\gamma_{10}(INCOME_{ij}) + \gamma_{20}(DUMMY2_{ij}) + \mu_{0j} + \; r_{ij}$$

The next logical step was to begin modeling the relationships between level-1 predictors and the outcome. Level-1 slopes were independently allowed to vary randomly as a first step in modeling the relationships between level-1 predictors and the outcome. A non-significant p-value was found for the Chi-square test of the random component of the Income slope ($\chi^2 = 228.008, p = .469$) whereas the attempt to specify a randomly-varying Dummy2 slope resulted in model non-convergence.

Subsequently, the level-1 slopes were treated as non-randomly varying by modeling their outcome equations with the incorporation FamSize, FamFoods, and MeanIncome. MeanIncome had to be removed as the estimation algorithm was unable to continue, with HLM stating an invertible matrix Vtheta1 as the reason. The process was repeated without MeanIncome specified for the slope models. It was at this juncture that FamSize was no longer indicated as being a significant predictor of individual mental health across all level-2 equations ($\gamma_{01}; p = .082, \gamma_{11}; p = .256, \gamma_{21}; p = .200$):

$$\boldsymbol{Level-1}$$

$$MENTALHEALTH_{ij} = \beta_{0j} \; + \beta_{1j} * (INCOME_{ij} - \overline{INCOME_{.j}}) + \beta_{2j} * (DUMMY2_{ij}) + \; r_{ij}$$

$$\boldsymbol{Level-2}$$

$$\beta_{0j} = \gamma_{00} + \gamma_{01}(FAMSZE_j - \overline{FAMSZE_{..}}) + \gamma_{02}(FAMFOODS_j) + \gamma_{03}(MEAN\_INC_j) + \mu_{0j}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11}(FAMSZE_j - \overline{FAMSZE_{..}}) + \gamma_{12}(FAMFOODS_j)$$

$$\beta_{2j} = \gamma_{20} + \gamma_{21}(FAMSZE_j - \overline{FAMSZE_{..}}) + \gamma_{22}(FAMFOODS_j)$$

$$\boldsymbol{MixedModel}$$

$$MENTALHEALTH_{ij} = \gamma_{00} + \gamma_{01}((FAMSZE_j - \overline{FAMSZE_{..}}) + \gamma_{02}(FAMFOODS_j) + \gamma_{03}(MEAN\_INC_j) + +\gamma_{10}(INCOME_{ij}) + \gamma_{11}(FAMSZE_j * INCOME_(ij)) + \gamma_{12}(FAMFOODS_j * INCOME_{ij}) + \gamma_{20}(DUMMY2_{ij}) + \gamma_{21}(FAMSZE_j * DUMMY2_{ij}) + \gamma_{22}(FAMFOODS_j * DUMMY2_{ij}) + \mu_{0j} + \; r_{ij}$$

Upon removal of the FamSize predictor, the final decision to make involved the consideration of the random component of the Income slope. Maintaing a randomly varying slope equation without evidence for variation about that predictor's mean slope, will not bias estimation, and will simply be considered over-specification. The hypothesis test using the Deviance Statistics comparing two (nested) models that differ only in the random effect for a slope helps us determine whether or not the reduction in deviance (invariably ocurring with additional parameters) is significant. Of which, a large p-value would be suggestive that the model fit is not improved by the addtional parameters (retaining the null that the coefficients of the additional predictors are 0). Following an insignificant deviance difference Chi-square statistic ($\chi^2 < .00001, p > .500$), the final intercept and slopes-as-outcomes model, with non-randomly varying slopes, was decided upon:

$$\boldsymbol{Level-1}$$

$$MENTALHEALTH_{ij} = \beta_{0j} + \beta_{1j} * (INCOME_{ij} - \overline{INCOME_{.j}}) + \beta_{2j} * (DUMMY2_{ij}) + r_{ij}$$

$$\boldsymbol{Level-2}$$

$$\beta_{0j} = \gamma_{00} + \gamma_{01}(FAMFOODS_j) + \gamma_{02}(MEAN\_INC_j) + \mu_{0j}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11}(FAMFOODS_j)$$

$$\beta_{2j} = \gamma_{20} + \gamma_{21}(FAMFOODS_j)$$

$$\boldsymbol{MixedModel}$$

$$MENTALHEALTH_{ij} = \gamma_{00} + \gamma_{01}(FAMFOODS_j) +$$

$$\gamma_{02}(MEAN\_INC_j) + \gamma_{10}(INCOME_{ij})$$

$$+ \gamma_{11}(FAMFOODS_j * INCOME_{ij}) + \gamma_{20}(DUMMY2_{ij})$$

$$+ \gamma_{21}(FAMFOODS_j * DUMMY2_{ij})$$

$$+ \mu_{0j} + r_{ij}$$

All resulting fixed and random components of the aforementioned final model are provided in the Appendix (Table 4 and Table 5).

Discussion

Upon finding evidence for a nesting structure of persons within families when partitioning individual mental health variance, we enacted a well-documented step-up hierarchical model building process; we sought to model variance along both individual and family levels. Our substantive theory and background research lead us to settle upon 4 potential level-1 predictors and 3 potential level-2 predictors that represented the terms used throughout constructed models; the parameters of which were either fixed components representing mean outcomes or strengths of relationships between terms and the outcome, as well as random components existing as variances and convariances of the lower-level constants (intercepts and slopes). We settled on a means and slopes-as-outcomes model wherein slopes varied non-randomly. The model was found to have an intercept reliability estimate of .431; a value considered to be low, suggesting a low ratio of the true population parameter, β_0, to the true population parameter β_0 plus error. This represents a large amount of noise in our measurement of this value, implying that estimates for β_0 across samples will vary greatly. Having ran our analysis from a large sample dataset generated by the NIH, we cannot theorize as to why our reliability is so low.

We established a null condition wherein 33.87% of mental health variance existed between families, and could therefore be modeled across level-2 predictors, leaving 66.13% of the variance to be modeled across individuals but within groups. Our Final Model explained approximately 11.22 % variance between families:

$\frac{28.40136-25.21477}{28.40136} = ..1122 \longrightarrow 11.22$ percent of variance between groups explained.

As well as approximately 4.59 % within group variance:

$\frac{55.44303-52.89866}{55.44303} = .04589 \longrightarrow 4.59$ percent of variance within groups explained.

This ultimated as approximately 6.84 % of the total variance in mental health being explained by the Final Model ($.3387 * 11.22 + .6613 * 4.59 = .068355$). Our prior OLS estimates had suggested 2.5 % of the total variance was explained as a level-1 only model and 19.8 % of the total variance was explained as a level-2 only model; it is clear that a multilevel modeling approach, then, would explain more between than within group variance upon use of the same predictors. Recall that two of our dichotomized race variables dropped out, suggesting that they acted as proxy variables that masked the effect of level-2 predictors in the absence of level-2 modeling.

We note that all fixed effect estimates were significant at the $\alpha = .001$ level with the exception of the coefficient of the interaction term between Income and FamFoods which, nevertheless, was found to be significant ($p = .018$). We believe that, although we've explained a substantial amount of the between-family variance in mental health, significant variation in mental health between families, after controlling for family use of food stamps and family (mean) income still exists, the further modeling of mean family mental health may be warranted; depending on the future analyst's research questions, of course. For this reason, and considering that an arbitrarily low percent (6.84) of total variance was explained, we believe that further level-1 and level-2 modeling of this dataset would prove prudent for future research.

Our research objectives were framed in terms of 6 questions that motivated our analysis; we present them here, once more, and address them in light of the Final Model estimates reported on Table 4 and Table 5.

1. Can an individual's income and race predict their mental health as measured by a composite scale score?

2. Do we have evidence to suggest that mean values of mental health for families vary significantly about the overall mean mental health value?

3. Given 1) and 2), can the family social status indicators of family (mean) income and family use of food stamps predict a family's mean mental health status and, by extension, an individual family member's mental health status ?

4. Does family mean income affect the mental health of an individual independent of that person's income?

5. Does the relationship between individual income and individual mental health vary by family income? Similary, does the relationship between individual income and individual mental health vary as a function of whether or not a family purchases food stamps?

6. Does the relationship between necessity for food stamps and individual mental health, or the relationship between family income and individual mental health, vary by race?

An OLS estimated multiple regression incorporating income and dichotomized race yielded a significant F-test statistic, suggesting that the model explained significant variation of mental health (as measured by a composite score). All predictors were significant at the $\alpha = .001$ level save for the asian-indicator dummy variable, which was found to be significant at the $\alpha = .05$ level (p = .032). A one unit increase in income was predicted to increase mental health by .00003 units below the mean mental health value; to put this into perspective, a 10,000 unit decrease in income (losing 10,000 dollars) is predicted to decrease mental health rating by .3 points (about $\frac{1}{30}$th of a standard deviation of the mental health score). A White individual, the reference category, is predicted to have a mental health rating of 50.607 A Hispanic individual is predicted to gain a 1.182 bump on mental health rating above the mean of 50.607. A Black individual is predicted to gain a 1.428 bump on mental health rating above the mean of 50.607. A Hispanic individual is predicted to gain a .656 bump on mental health rating above the mean of 50.607. This was surprising as we theorized that minoritized groups would experience lower ratings of mental health.

By analyzing the HLM output for the null model, the hypothesis that the between group variability equals zero was rejected($\hat{\tau_{00}} = 28.40136, p < .001$). The significance variation of this Wald Z test suggests that the variation in mental health ratings between families does not equal zero, thereby suggesting that families vary in their mean mental health rating about an overall mean.

Surveying the estimates for our final multilevel model (Table 4), family (mean) income was found to significantly predict mean family mental health rating and, by extension, person mental health rating ($t = 4.751, p < .001$). In terms of individual mental health, for a non black individual with an income equal to the mean income of their family and whose family does not purchase food stamps, a one unit increase in his/her family's income above the grand mean is predicted to increase his/her mental health rating by .000018. Similarly, family purchasing of food stamps was found to significantly predict mean family mental health rating and individual mental health rating ($t = -12.274, p < .001$); a non-black individual with an income equal to the mean income of their family (which happens to be at the grand mean of all personal income), transitioning to having at least one family member purchase food stamps, is predicted to decrease his/her mental health rating by -4.991432. This is a notable effect of family-access to food stamps on an individual's health, even when their family, on average, is doing as financially well as the mean in income across the U.S.

One of our research questions asks about the presence of a compositional effect. The compositional effect is the extent to which the magnitude of the family-level relationship, Mean Income, differs from the person-level effect, Individual Income: $\beta_c = \beta_b - \beta_w$. Consequently, our estimated compositional effect with respect to income is: $\gamma_{01}\breve{}\gamma_{10} = .000018 - .000014 = .000004$. With such a small value for a compositional effect, we interpret this to mean that, conditioning on group-mean centered individual income (for two individuals at their respective family mean incomes), two non-black individuals that differ by one unit in their family (mean) income, about the grand mean of income, are not predicted to carry a difference in predicted mental health. We cannot argue for the importance of a family-level effect of income (having aggregated individual-level income) in predicting individual mental health outcomes after having accounted for the relationship between individual-level income and mental health.

Our Final Model was unable to specify a cross-level interaction between family income and individual income. Our model did however specify an interaction between family purchase of food stamps and individual income. We found that the coefficient for this interaction equals .000071 (γ_{11}, p = .011). The interaction between FamFoods and Income tells us that slopes for individual income are different across the levels of FamFoods; more specifically, for an individual transitioning to a family that purchases food stamps, there is a significant (at an $\alpha = .05$ level) increase of .000071 in the relationship between their income and mental health rating; the bump in this relationship is arguably small, however. Every dollar increase above the mean of their family (mean) income, is associated with a .000071 predicted increase in their mental health. We caution the use of this statistical finding in informing policy changes; as this significant effect, of such low magnitude, may have resulted from an unusually large effective sample size and, consequently, power. That transitioning as a family to purchasing food stamps would have a positive effect on the relationship between individual income and mental health (at least as a statistical effect) can be interpretable in a substantive manner. It may be the case that, given the recognition that one's family purchases food stamps, an individual, who makes as much income as the average income in their family, perceives a greater satisfaction for every extra dollar earned than an individual whose family does not have to rely on wellfare.

Our Final Model was unable to generate estimates for any family income related interactions. However, HLM reports an interaction coefficient of 2.6237 between race and family purchase of food stamps ($p < .001$). This provides evidence that the relationship between race and mental health rating varies depending on whether or not a family purchases food stamps. A family that transitions to purchasing food stamps will have a positive effect on the relationship between race and mental health. For families that purchase food stamps, a black individual (whose income is at the mean for their family income) is predicted to experience a 2.624 (taking the non-black relationship to be effectively zero) bump over their non-black counterparts, who are at their respective means for family income, in in his/her slope between race and mental health; there is also an additional 1.081 increase in their predicted mental health rating as a contribution from the dichotomized race variable ($\gamma_{20}, p < .001$); for a total increase of *3.705 points on their expected mental health rating*; that is a rather large bump given an outcome standard deviation of 9.55!

We had included family size as a predictor because, analogously, school size and company size are often times cited in multilevel analysis research. Many policymakers and administrators, for example, believe "bigger is better", and consequently, school consolidation had proceeded apace (Lyons, 1999). However, Bickel, Smith, and Eagle (2002) argue that small schools maintain a sense of neighborhood and belonging, which in turn bolster early achievement. Still, it is not a surprise, in truth, that family size dropped out as a term from our Final Model; after all, our background research and guiding theory made no hypothesis as to family size predicting mental health.

The present analysis found evidence for the nesting of individuals within families on a mental health status outcome, and ultimately yielded significant person and family-level SES-related predictors of mental health that substantiated previous research, alongside a couple of notable interaction effects; for example, being a black individual whose family purchases food stamps confers a net 3.075 point increase in predicted mental health status. It is clear that race and socioeconomic indicators play a role in mental health, and further understanding the complexities between such relationships is warranted. Furthermore, family use of food stamps was found to have a large and significant main and interactive effect(s) on individual mental health.

We advocate for the further modeling of our settled upon final model, citing overall low-valued estimates and percentages of variances explained within and between groups. As previously mentioned, fixed effects associated with slopes were found to be near-zero in magnitude. Though these estimates are statistically significant, we find it hard to ascribe them practical value, as they denote such an arbitrarily small-valued relationship. Given such a large effective sample size, we recognize the heightened power and detection of significance behind our models, but we recognize the limitation in applying such small-valued coefficients to policy changes. Considering this in a positive light, perhaps we can say with great certainty, though, that the lack of significant variation about the average slope for our level-1 predictors is strong evidence for the lack of variability in these relationships at the population level.

References

Bickel, R., Smith, C., & Eagle, T. (2002, May). Poor, rural neighborhoods and early school achievement. *Journal of Poverty*, *6*(3), 89-107.

Lyons, J. (1999). K-12 construction facts. *The Association of Higher Education Facilities Officers*.

NSDUH. (2018, September). Results from the 2017 national survey on drug use and health. *samhsa.gov*, *3*(1), 59.

Raudenbush, S., & Bryk, A. (2012). *Hierarchical linear models: Applications and data analysis methods* (Vol. 10) (No. 4).

Turney, K. (2012). Prevalence and correlates of stability and change in maternal depression: Evidence from the fragile families and child wellbeing study. *Plos One*, *10*(4).

Vijaya, M., & Femi, O. (2004, May). Poverty, social inequity, and mental health. *Advances in Psychiatric Treatment*, *10*(3), 216-224.

Williams, D. R., Yu, Y. J., & Anderson, B. N. (1997, July). Racial differences in physical and mental health: Socio-economic status, stress and discrimination. *Journal of Health Psychology*, *2*(3), 335-351.

Appendix

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Item
1) Can an individual's income and race predict their mental health as measured by a composite scale score?
2) Do we have evidence to suggest that mean values of mental health for families vary significantly about the overall mean mental health value?
3) Does family mean income affect the mental health of an individual independent of that person's income?
4) Does the relationship between individual income and individual mental health vary by family income? Similary, does the relationship between individual income and individual mental health vary as a function of whether or not a family purchases food stamps?
5) Does the relationship between necessity for food stamps and individual mental health, or the relationship between family income and individual mental health, vary by race?

Table 1

Table of Research Questions.

Table 2

Descriptive Statistics for Potential Level-1 Predictors

Statistic	N	Mean	St. Dev.	Min	Max
MENTALHEALTH	15338	52.2531	9.55	25.57	76.52
INCOME	15747	37284.56	38184.809	-46761	272703
MORJOB	10811	.0710	.257	0	1
HISP	25156	.18	.384	0	1
BLACK	25156	.18	.384	0	1
ASIAN	25156	.18	.384	0	1

Table 3

Descriptive Statistics for Potential Level-2 Predictors

Statistic	N	Mean	St. Dev.	Min	Max
FAMSZE	8122	3.31	1.364	2	11
MEAN_INCOME	7906	37431.03	31468.2051	-24024.00	269424.00
FAMFOODS	8024	.18	.384	0	1

Table 4

Estimated Fixed Effects for Final Model

Fixed Effect	Coefficient	Standard Error	t-ratio.	p-value
For β_0				
γ_{00}	52.188101	0.216686	240.847	< 0.001
γ_{01}	-4.991432	0.406673	-12.274	< 0.001
γ_{02}	.000018	0.000004	4.751	< 0.001
For β_1				
γ_{10}	0.000014	0.000004	3.935	< 0.001
γ_{11}	0.000071	0.000030	2.377	0.018
For β_2				
γ_{20}	1.081683	0.312321	3.463	< 0.001
γ_{21}	2.623682	0.675953	3.881	< 0.001

Table 5

Estimated Variance Components for Final Model

Random Effect	Standard Deviation	Variance Component	χ^2	p-value
INTERCEPT, μ_0	5.02143	25.21477	12852.23957	< 0.001
level-1, r	7.27315	52.89866		

ADGENH42 –	General health today
ADDAYA42 –	During a typical day, limitations in moderate activities
ADCLIM42 –	During a typical day, limitations in climbing several flights of stairs
ADPALS42 –	During past 4 weeks, as result of physical health, accomplished less than would like
ADPWLM42 –	During past 4 weeks, as result of physical health, limited in kind of work or other activities
ADMALS42 –	During past 4 weeks, as result of mental problems, accomplished less than you would like
ADMWLM42 –	During past 4 weeks, as result of mental problems, did work or other activities less carefully than usual
ADPAIN42 –	During past 4 weeks, pain interfered with normal work outside the home and housework
ADCAPE42 –	During the past 4 weeks, felt calm and peaceful
ADNRGY42 –	During the past 4 weeks, had a lot of energy
ADDOWN42 –	During the past 4 weeks, felt downhearted and depressed
ADSOCA42 –	During the past 4 weeks, physical health or emotional problems interfered with social activities

Figure 1. Mental Health Component (MCS-12) Scale Items.

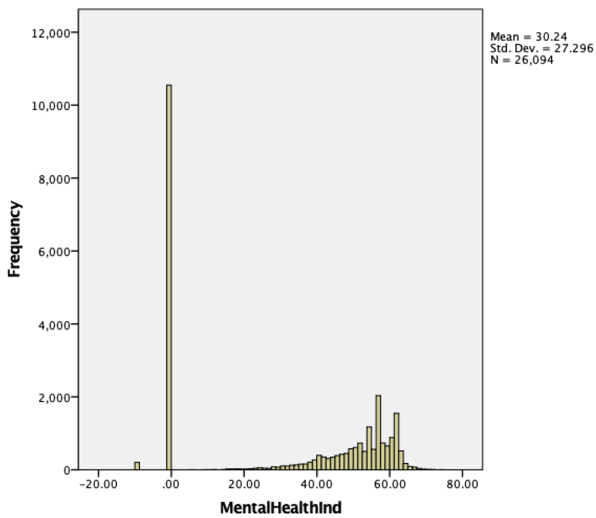

Figure 2. Histogram of MCS-12 Responses.

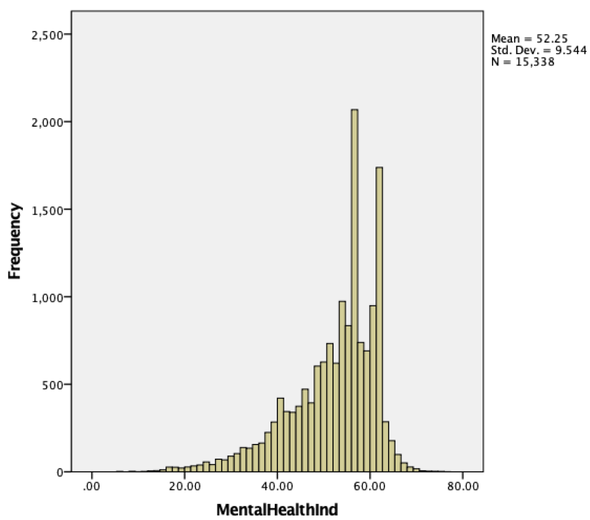

Figure 3. Histogram of MCS-12 Responses Following Sub-Setting.

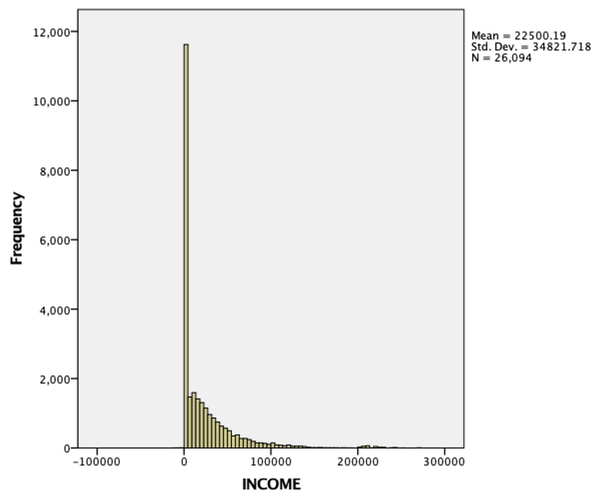

Figure 4. Histogram of Income Responses Prior to Sub-Setting.

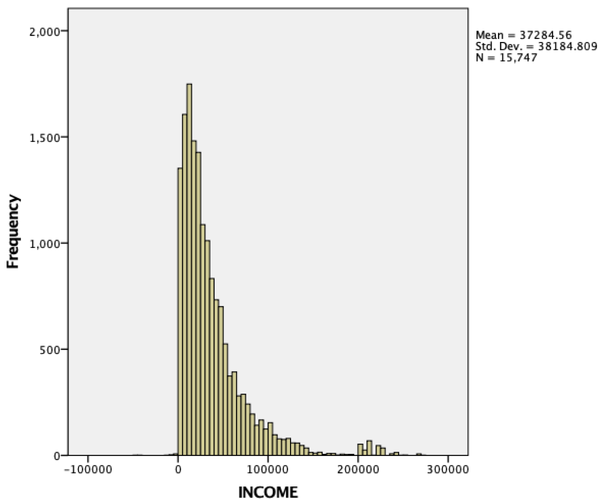

Figure 5. Histogram of Income Responses Following Sub-Setting.

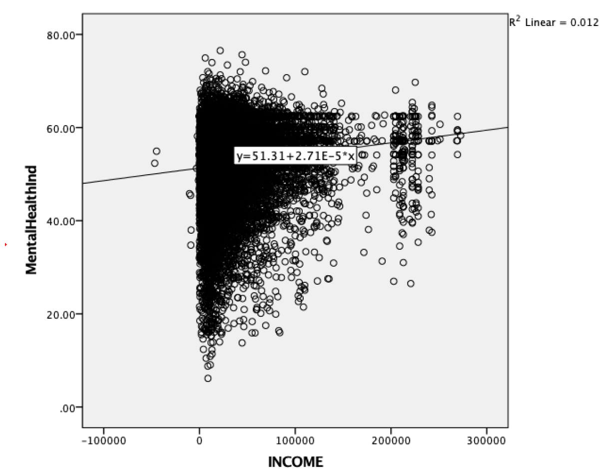

Figure 6. Scatterplot of Mental Health Indicator and Income.

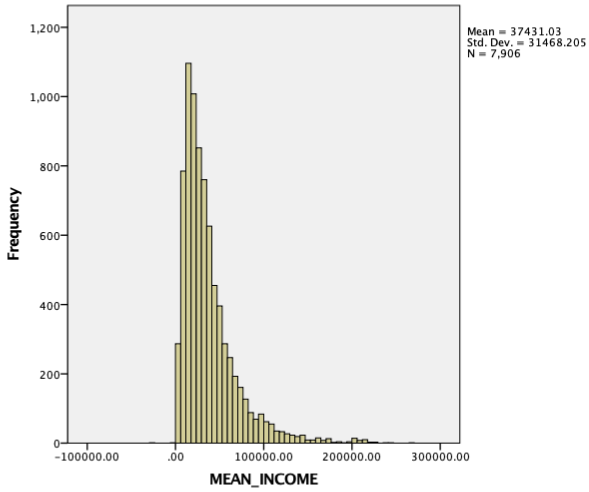

Figure 7. Histogram of Family (Mean) Income.

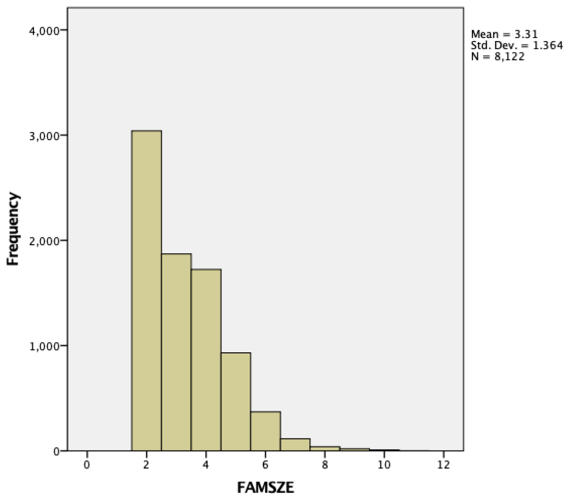

Figure 8. Histogram of Family Size.

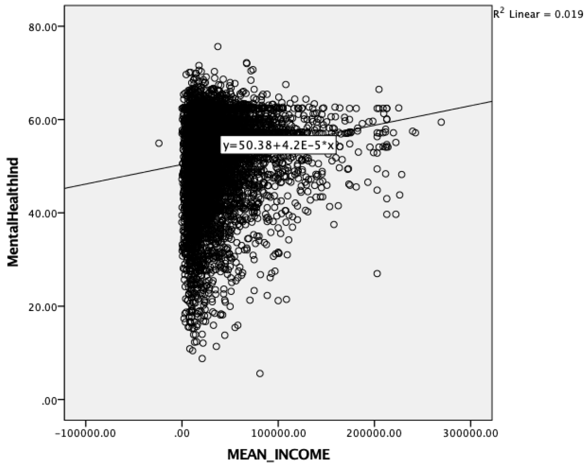

Figure 9. Scatterplot of Mental Health Indicator and Family (Mean) Income.

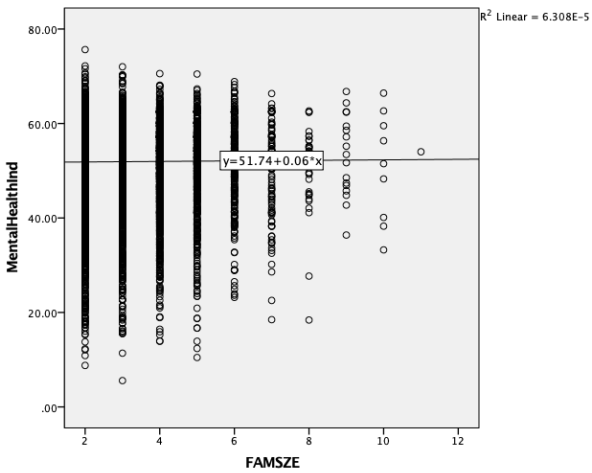

Figure 10. Scatterplot of Mental Health Indicator and Family Size .

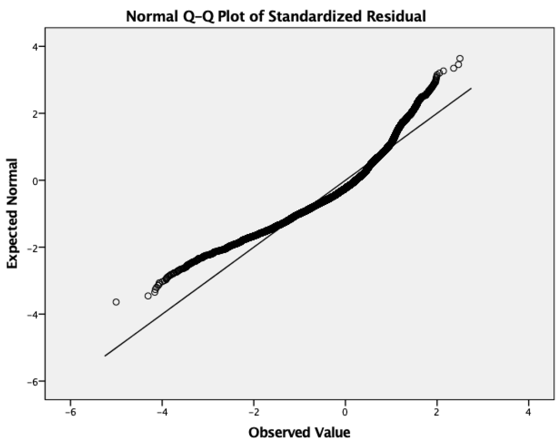

Figure 11. Normal Q-Q Plot of Standardized Residuals Following Analogous Level-2 OLS Regression.