Early Neighborhood Conditions and Trajectories of Depressive Symptoms across Adolescence and into Adulthood

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Abstract

Early life conditions, including childhood socioeconomic status (SES) or exposure to adverse conditions, can have long-term consequences on mental health. However, relatively little has examined the long-term influence of exposure to adverse neighborhood conditions in early life. Both neighborhood disadvantage and neighborhood disorder have been consistently linked to mental health outcomes, especially depression. The current analysis uses data from all waves of the National Study of Adolescent to Adult Health (Add Health) to determine the influence of neighborhood context on trajectories of depressive symptoms from adolescence into adulthood. We find that neighborhood disadvantage has no influence on initial levels or change over time in depressive symptoms after adjusting for individual level covariates. However, neighborhood disorder is associated with greater initial levels of depressive symptoms during adolescence and this difference persists throughout the early life course. Additionally, while female respondents had greater levels of depressive symptoms across time, the effect of neighborhood conditions did not vary by sex. Our results demonstrate that early neighborhood conditions are an important risk factor for long-term patterns of depressive symptoms, above and beyond important proximal factors such as family SES, family composition, and race-ethnicity.

Keywords: Neighborhoods; Longitudinal analysis; Depression; Adolescence; Young Adulthood

Mental health varies dynamically across the life course, conditional on factors such as social location, developmental stage, pyschosocial resources, and genetic liability. Early life experiences can be of particular importance, as these experiences have the potential to shape mental health for years to come. Researchers have examined numerous early life exposures, especially those related to childhood socioeconomic status (SES) and other adverse experiences (Gilman et al. 2002, Poulton et al. 2002). However, relatively few studies have examined the long-term influence of early neighborhood conditions. Neighborhoods are extremely important during childhood and early adolescence, representing one of the primary social contexts youth will occupy along with school and family.

Early life experiences can have a lasting influence on depression throughout the life course. Childhood disadvantage has been consistently linked to later life depression (Gilman et al. 2002, Goosby 2013, Poulton et al. 2002). Childhood disadvantage is associated with increased risk of major depression during early adulthood, even after accounting for adult SES and maternal depression, providing further evidence of long-term consequences of early childhood exposure (Goosby 2013). Adverse experiences such as family disruption (Gilman et al. 2003) and abuse (Danese et al. 2009) also have long-term influences on depression.

Along with increasing the overall risk of depression, these conditions are also related to changes in depression over time. Occupying lower status positions, such as lower status by SES, race, or sex, is associated with greater levels of depressive symptoms during adolescence as well is significantly greater increases over time. However, regardless of status, all groups follow a similar pattern where levels of depression peak during adolescence and decline as individuals entered young adulthood (Adkins et al. 2009). Part of this relationship between occupying lower status positions and increased levels of depressive symptoms is explained by greater exposure to stress over time (Adkins et al. 2009).

Beyond individual level factors, research drawing heavily from the intersection of the stress process (Pearlin et al. 1981) and social disorganization theory (Sampson and Groves 1989) has demonstrated that neighborhood conditions are also related to mental health mental health. Neighborhood characteristics related to mental health fall broadly into three categories: neighborhood structure, neighborhood social organization, and neighborhood disorder (Hill and Maimon 2013). Neighborhood structure focuses on aspects of neighborhood related to neighborhood advantage/disadvantage and racial segregation. Neighborhood social organization focuses on the social cohesion and social environment of a neighborhood. Finally, neighborhood disorder focuses on the breakdown in the physical and social order of a neighborhood. Indicators such as increased crime, dilapidated buildings, and open drug use characterize neighborhood disorder. These aspects of neighborhood context though distinct, are all highly related, as structural disadvantage is thought to lead to the breakdown in local institutions, such as the family and schools, leading to greater levels of disorder and crime (Sampson, Raudenbush and Earls 1997, Wilson 2012), resulting in noxious social conditions that endangers the mental health of residents.

Neighborhood disadvantage, above and beyond individual disadvantage, has been consistently associated with depression (Aneshensel and Sucoff 1996, Gary-Webb et al. 2011, Haines, Beggs and Hurlbert 2011, Ross 2000, Silver, Mulvey and Swanson 2002, Stockdale et al. 2007, Wight, Ko and Aneshensel 2011). There is also evidence that neighborhood disadvantage alters the effect of individual disadvantage (Wheaton and Clarke 2003, Wight et al. 2011) leading to a process of compound disadvantage in which those who are individually disadvantaged and living in disadvantaged neighborhoods are the most vulnerable. For example, the effects of individual wealth on depression varied as a function of neighborhood disadvantage (Wight et al. 2011). For those in highly disadvantaged neighborhoods, those with low wealth were at greater risk of depression. However the effect of individual wealth did not emerge in neighborhoods with low disadvantage.

Neighborhood social organization and neighborhood disorder, both highly interrelated, have been consistently linked to depression. Neighborhoods with more problems (e.g. poor physical conditions, fear of crime) are associated with an increased risk of depressive symptoms, though neighborhood social cohesion has produced mixed results (Echeverria et al. 2008). Both objective measures of neighborhood crime and perceptions of safety have direct effects on depressive symptoms in older adults (Mair, Diez Roux and Morenoff 2010a, Wilson-Genderson and Pruchno 2013). Neighborhoods perceived as being safe and free of physical disorder are associated with lower levels of psychological distress (Hill, Burdette and Hale 2009) and depression (Hale et al. 2013). These social aspects of neighborhood context may have differential impacts across sex. For girls, greater neighborhood collective efficacy – the mutual trust among neighborhood residents that allows them to maintain informal social control (Sampson et al. 1997) – reduces the impact of neighborhood disorder on internalizing symptoms (Browning et al. 2013). Collective efficacy also buffers the impact of exposure to violence on both internalizing and externalizing symptoms, though this was again only for girls (Browning et al. 2014).

The mechanisms through which neighborhoods influence mental health are often related to stress exposure. Ambient hazards, such as fear of victimization, are greater in disadvantaged neighborhoods and are linked to greater levels of both anxiety and depression (Aneshensel and Sucoff 1996). Perceived neighborhood disorder mediates the relationship between neighborhood disadvantage and depression (Ross 2000). This perceived disorder is further mediated by experiences with violence, both directly and through the witnessing of violence (Turner et al. 2013). Neighborhood violence also moderates the effect individual victimization on depression, such that the influence of individual victimization is reduced in neighborhoods with lower levels of violence (Stockdale et al. 2007).

While prior research on neighborhood effects has improved knowledge of important neighborhood characteristics and intervening mechanisms related to mental health, only a limited amount of research has examined the long-term impact of neighborhood conditions. Exposure to neighborhood disadvantage in early childhood has effects on externalizing behaviors into early adulthood, beyond the effect of current neighborhood context (Wheaton and Clarke 2003), similar to other findings comparing the impact of childhood and current SES. Additionally, the relationships between neighborhoods on mental health may be explained, in part, by the impact neighborhoods have on role transitions, such as employment and marriage (Clarke and Wheaton 2005), reducing the financial and psychosocial resources available later in life.

The current analysis builds on previous work by exploring the role of neighborhoods in changes in depressive symptoms across the early life course. While childhood SES is an important predictor of depression across adolescence and into adulthood (Adkins et al. 2009, Goosby 2013), contextual factors correlated with SES may also influence long-term patterns. In order to understand any influence of neighborhood conditions, we address the following questions. 1) Is neighborhood disadvantage during early adolescence associated with greater levels of depressive symptoms across the early life course and into young adulthood (both in initial levels and in change over time), independent of individual covariates? 2) Is the relationship between neighborhood disadvantage reduced after adjusting for neighborhood disorder and neighborhood organization? 3) Are the influences of neighborhood conditions equal across males and females? We use data from a nationally representative sample covering a period of roughly twenty years in the early life course.

Methods

Data

The data come from the National Longitudinal Study of Adolescent to Adult Health (Add Health). Add Health participants were selected from a stratified sample of 132 schools in the United States resulting in an initial, nationally representative sample of 90,118 students in grades 7-12. Of the original sample, 20,745 were selected for additional in-home interviews. Of those who completed the first in-home interview (1994-1995), 14,738 (71%) completed the second interview in 1996, 15,197 (73%) completed the third interview in 2001-2002, and 15,701 (75%) completed the fourth interview in 2007-2008 (Harris 2009). Most respondents completed the majority of the waves, with 16,278 (78%) completing three or more waves.

The study period covered roughly 14 years between Waves I and IV, from adolescence (11-18 years old) into adulthood (24-34 years old). Because we structured the data on age rather than the wave of data collection, the analyses cover a twenty-year period of the early life course. Due to the lower cell counts of those below the age of 12 and above the age of 32, these categories were collapsed to reflect age 12 and younger, and age 32 and above. Add health participants were matched to the corresponding census tracts to their home of record during Wave I, and these tracts were used to define participant's neighborhood. Neighborhood level data comes from the 1990 census and other existing sources. Analyses were limited to all individuals with appropriate longitudinal survey weights and a valid neighborhood-grouping indicator (n = 18,740). These individuals were spread across 2,344 neighborhoods, with a mean of 7.99 individuals per neighborhood (SD = 20.20, Range = 1 – 275).

Subsequent analyses revealed that results did not change when we constrained the analytic sample to neighborhoods with more than one respondent or removed neighborhoods with an extremely large number of respondents (> 200). Overall, respondents in the analytical sample provided an average of 3.3 observations out of a possible 4.

Neighborhood-level Measures

Neighborhood Disadvantage/Advantage. We included separate scales for both neighborhood disadvantage and neighborhood advantage in the analyses, in order to establish if the presence of disadvantage and/or the absence of advantage had distinct influences. Exploratory factor analysis of these items indicated two distinct factors rather than a single measure, with items for each loading on the appropriate factor. The scales for neighborhood advantage and disadvantage were constructed using items taken from the 1990 census from addresses linked to respondents' home addresses at Wave I, similar to items used in previous research (Harding 2009). Items for neighborhood disadvantage included: (1) percentage of families below the poverty line, (2) percentage of single-female headed households, (3) male unemployment rate, and (4) percent Black. Items related to neighborhood advantage included: (1) percent earning over $75,000 per year, (2) percent in managerial/professional occupations, and (3) percent over 25 with college degrees. The scale for both neighborhood disadvantage (alpha = .88) and the scale for neighborhood advantage (alpha = .93) demonstrated high reliability. Each item was standardized (Z-score) in order to allow direct comparison.

Neighborhood Disorder. Neighborhood disorder consisted of items measured at Wave I aggregated at the neighborhood level using the ecometrics approach (Mujahid et al. 2007, Raudenbush and Sampson 1999). Items came from both the parent and child surveys in Wave I of Add Health and include ratings from the child, parents, and field interviewer. The 6 items used in this scale include those related to neighborhood safety: "Child: Do you usually feel safe in your neighborhood," "Interviewer: When you went to the respondent's home, did you feel concerned for your safety," drug use/sales: "Parent: In this neighborhood, how big a problem are drug dealers and drug users," and physical conditions: "Interviewer: How well kept are most of the buildings on the street," "Interviewer: How well kept is the building in which the respondent lives", "Parent: In this neighborhood, how big a problem is litter or trash on the streets and sidewalks?” These items reflect perceptions of neighborhood safety and physical neglect, which are components of neighborhood disorder (Sampson et al. 1997). A full description of the items and creation of the scale can be found in Appendix A. In order to further ensure that individual psychopathology was not influencing perceptions of neighborhood disorder, we reran all analyses with a neighborhood disorder scale made up solely of parent and interviewer observations. These results were almost identical to the original models and we therefore included the full six items.

In order to aggregate these items, we fit a multilevel logistic regression, with items nested within individuals, nested within neighborhoods. This allowed respondents to contribute data regardless of whether they had complete or partially missing data. Overall, the items demonstrated moderate clustering at the neighborhood level (intraclass correlation = .22). Neighborhood disorder scores were calculated from the estimates of posterior means (also referred to as Empirical Bayes or BLUP scores) of the random effects at the neighborhood level. These scores represent each neighborhoods deviation from the grand mean of the overall estimated disorder across all neighborhoods included in the sample. This approach has been used in previous research on neighborhoods and health (Christine et al. 2015, Mair et al. 2009, Powell-Wiley et al. 2017). Items were then standardized and coded so that greater scores indicated greater levels of disorder. The scale demonstrated relatively high reliability (mean = .67, SD = .22) based on comparison of between neighborhood and within neighborhood variation, weighted by number of respondents per cluster and proportion of items endorsed (Harding 2009, Raudenbush and Sampson 1999). Disorder was moderately correlated with both neighborhood disadvantage (r = .66) and neighborhood advantage (r = -.56) in expected directions, adding to the validity of the measure.

Individual-level measures

Family Socioeconomic Status. Family SES was measured using the scale developed by Bearman and Moody (2004) specifically for the Add Health Data, combining mother or father's education (1=less than high school, 2=high school degree, 3=some college, 4=college degree, 5=graduate/professional degree) and occupational category (0=not in the labor force, 1=unskilled laborer, 2=skilled laborer, 3=white collar lower-level, 4=white collar upper-level, and 5=professional) to yield a score for each parent from 1 to 10. The final score was determined by whose score (of the mother and father in the case of both parents being present) was higher. *Race-ethnicity* was composed of five categories so that African-Americans, Asian/Pacific Islanders, Hispanics, and all other race-ethnicities were compared to non-Hispanic whites. Those who identified as being multi-racial were categorized under the racial-ethnic identity with which they most strongly identified. *Sex* was a binary variable (0 = male, 1 = female) measured at Wave I. *Self-esteem* was included using a short-item version of the Rosenberg Self-Esteem scale (Rosenberg 1965) to account in part, for important psychosocial resources related to mental health (alpha =.84). Finally, *family composition* categorized whether or not a respondent lived with both, one, or neither of their biological parents. Those who lived with both parents were coded as the reference category.

Additional Covariates

We included other covariates to account for possible confounding. At the neighborhood level, we included measure of neighborhood social cohesion and stability consisting of both objective census data (proportion of residents who own their home and the proportion of occupied housing units moved into 1985-1990) and the ecometrics approach (in-home survey questions that asked the respondent how close they felt to and how frequently they interacted with neighborhood residents). Measures of stability and social cohesion were standardized and combined into a single scale (alpha = .66). At the individual level, we included an indicator for foreign-born status, self-rated health (an ordinal measure asking respondents to assess their general health), and a dichotomous measure for whether or not the respondent was a low weight birth (< 5.5lbs), as this is associated with later depression (Gale and Martyn 2003). Finally, we included measures for urbanicity and the number of years the respondent had lived at their current address. All covariates were measured at Wave I. We only included the effect these covariates had on initial levels of depressive symptoms.

Outcome

Depressive Symptoms. Add Health includes measures of depressive symptoms across all four waves using an abbreviated version (9 item) of the Center for Epidemiological Studies-Depression Scale (CES-D) (Radloff

1977). Reliability for the scales remains relatively high across each wave (Wave I alpha =.79; Wave II alpha =.80; Wave III alpha =.80; Wave IV alpha =.81). Respondents were asked a range of questions dealing with the frequency of feelings that have occurred over the previous two weeks. Each item ranges from 1 (never) to 4 (always/everyday). Rather than using a composite score, we used the posterior means from item response models at each wave. We fit a series of item response models for depressive symptoms at each wave using the graded-response option of the *irt* function in Stata 14. The benefit of item response modeling is that it allows items to be differentially weighted by severity, taking into account the patterns of responses, and it includes information from those who have not responded to each item in a scale. Simulations have demonstrated item response modeling is better at producing unbiased estimates relative to sum scores in longitudinal analyses (Gorter, Fox and Twisk 2015). The item response derived CES-D scores were highly correlated with the sum scores at each wave (r = .94 - .95), though their distribution was much less skewed. Models using either score yielded near identical results, though the item response based scores achieved model convergence faster. A full description of results from the item response models can be found in Appendix A.

Analytic Strategy

In order to answer our research questions, we fit a series of multilevel growth models, which are well suited to handle longitudinal data that is unbalanced, as when individuals do not have the same number of assessments, and/or has unique response schedule, as when individuals answer at different time points (Fitzmaurice, Laird and Ware 2012, Singer and Willett 2003). For the current analysis, we fit two-level models with observations nested within individuals over time using the *mixed* command combined with the *cluster* option in Stata 14. The use of a two-level model with robust standard errors, rather than a three-level model with observations nested within individuals who were nested within neighborhood, allowed us to incorporate the Add Health longitudinal sampling weights. In addition, a three-level model would likely need to be cross-classified to adjust for any simultaneous clustering at the school level. We were therefore able to account for any clustering at the neighborhood level while also adjusting for the complex sampling design and the unequal probability of selection into the Add Health study. This adjustment is important if we hoped to retrieve unbiased estimates and correct standard errors (Chen and Chantala 2014).

The model fitting process went as follows: 1) determine the functional form that the depressive symptoms follows over the course of time, through both visual inspection of the data and fitting linear and polynomial models (quadratic and cubic) to compare the goodness of fit, 2) determine the appropriate structure of the random effects components of the model, 3) move on to the main research questions with which this paper is concerned. We included Add Health longitudinal survey weights to account for sample attrition and used multiple imputation (MI) to account for item non-response in explanatory variables, after examining patterns of missingness to ensure the assumptions of missing-at-random (MAR) were tenable. We followed the guidelines of missing imputation, then deletion (MID) in which all variables from the analysis, including the outcomes, are used in the imputation models and previously missing cases on the outcome variables were reset to missing before analysis (von Hippel 2007). All analyses were completed using Stata 14. Figures were constructed using *ggplot2* (Wickham 2009) in R 3.3.2 (R Core Development Team 2017).

Table 1: Survey-Weighted Descriptive Statistics for Continuous Variables in the Add Health Sample

	Females			**Males**		
	Mean/N	SE/%	Range	Mean/N	SE/%	Range
CESD - Wave I	0.10	0.02	-1.53 - 3.65	-0.19	0.02	-1.53 - 3.65
CESD - Wave II	0.12	0.02	-1.59 - 3.26	-0.20	0.02	-1.59 - 3.64
CESD - Wave III	0.08	0.02	-1.29 - 3.41	-0.11	0.02	-1.29 - 3.56
CESD - Wave IV	0.07	0.02	-1.48 - 3.74	-0.09	0.02	-1.48 - 3.74
Neighborhood Disadvantage	-0.05	0.06	-1.17 - 6.76	-0.08	0.06	-1.12 - 4.44
Neighborhood Advantage	0.03	0.09	-1.50 - 5.17	0.05	0.09	-1.61 - 4.68
Neighborhood Disorder	-0.06	0.07	-2.86 - 3.66	-0.06	0.06	-2.87 - 3.66
Neighborhood Social Cohesion	0.08	0.05	-2.86 - 1.64	0.06	0.06	-2.86 - 1.64
Age - Wave I	14.96	0.12	11.00 - 21.00	15.08	0.12	11.00 - 21.00
Age - Wave II	16.38	0.12	13.00 - 22.00	16.50	0.12	13.00 - 22.00
Age - Wave III	21.31	0.12	18.00 - 28.00	21.46	0.12	17.00 - 27.00
Age - Wave IV	27.79	0.12	24.00 - 34.00	27.95	0.12	24.00 - 34.00
Family SES	5.89	0.13	1.00 - 10.00	6.04	0.13	1.00 - 10.00
Self-esteem	4.02	0.02	1.00 - 5.00	4.24	0.02	1.00 - 5.00
Self-rated health	3.81	0.03	1.00 - 5.00	3.98	0.03	1.00 - 5.00
Years at current residence	7.25	0.16	0.00 - 21.00	7.20	0.18	0.00 - 21.00
Non-Hispanic White	5,014	65.83%	-	4,834	65.07%	-

African-American	2,113	16.53%	-	1,871	16.45%	-
Hispanic	1,615	12.67%	-	1,598	12.73%	-
Asian/Pacific Islander	619	3.47%	-	700	3.80%	-
Other Race-ethnicity	169	1.51%	-	171	1.95%	-
Lives w/ both biological parents	4,185	54.66%	-	4,166	55.08%	-
Lives w/ one biological parent	3,332	40.77%	-	3,100	40.30%	-
Lives w/ neither biological parents	525	4.57%	-	520	4.62%	-
Born in US	8,678	93.51%	-	8,325	94.15%	-
Immigrated younger than 5	300	2.46%	-	302	2.10%	-
Immigrated from 5 to 12 years old	318	2.62%	-	326	2.51%	-
Immigrated age 12 and older	218	1.41%	-	201	1.24%	-
Low Birth Weight	816	8.57%	-	672	7.27%	-
Lives in Urban Area	5,415	53.10%	-	5,190	53.86%	-
N		9550			9190	

All descriptive statistics adjusted for Add Health's complex sampling design. Percentages represent valid percentages.

Results

Table 1 presents descriptive statistics for the Add Health respondents included in the current analyses. All statistics are weighted to adjust for Add Health's complex sampling design. Overall we see that male and female respondents are comparable in overall sample size, as well as in age, race, family composition, and family SES. Additionally, males and females do not differ on the neighborhood measures. However, male and female respondents did differ on mean levels of depressive symptoms, which is both expected and in line with previous research.

Figure 1 displays the average scores of depressive symptoms from ages 12 to 32 for both males and females. Starting from the left, each plot had a linear function, quadratic function, and cubic function fit to the observations. The cubic form appeared to fit the data better than either the linear or quadratic options. Additional inspection of individual growth plots (not pictured) displayed curvilinear growth patterns, suggesting that either a quadratic or cubic function may be appropriate.

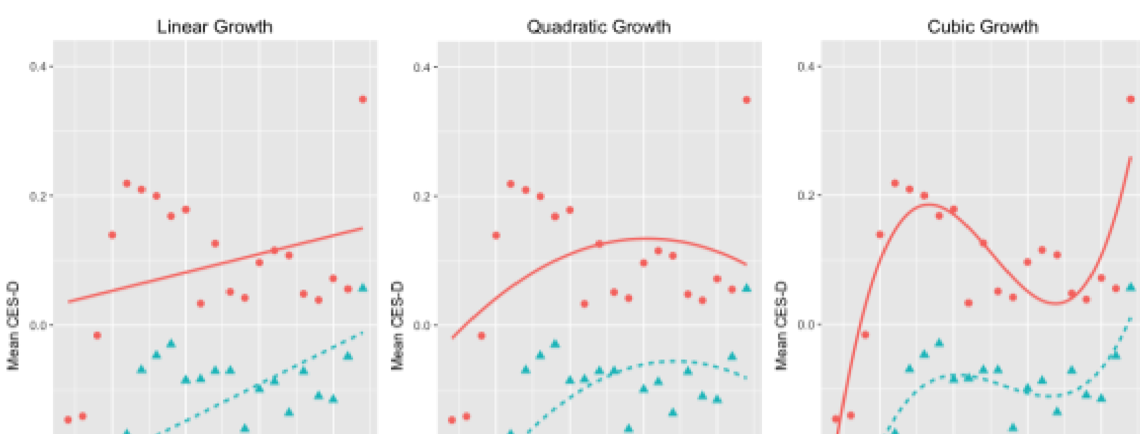

Table 3

provides the comparisons of model fit for the different functional form of depressive symptom trajectories. All models in this table are limited to a random intercept and estimated using maximum likelihood (ML). The unconditional model yielded an intra-class correlation coefficient (ICC) of 0.38, demonstrating a relatively strong clustering effect within individuals over time. The linear growth model did not significantly improve the model based on the likelihood-ratio (LR) test ($\Delta\chi^2$ = 2.89, *p*=.089) or show large improvements based on the other fit statistics including Akaike's Information Criterion, or AIC (Akaike 1974), with lower relative values indicating a better fitting model. Inclusion of the quadratic term for age resulted in a significant improvement in fit in the LR test ($\Delta\chi^2$ = 178.10, p<.001). Lastly, the inclusion of the cubic term for age resulted in significantly better fit than the previous model ($\Delta\chi^2$ = 197.72, p<.001). Overall, a cubic function best described the change in depressive symptoms over time, supporting the patterns in the visual inspection of the data.

Table 2: Models for Determining Functional Form and Random Effects Structure

Fixed Effects Model Fitting	AIC	LL	DF	Constant	Age	Age^2	Age^3
Unconditional Model	151290.6	-75642.3	0	-0.002	-	-	-
Linear Growth Model	151289.7	-75640.9	1	-0.010	0.0010	-	-
Quadratic Growth Model	151113.6	-75551.8	2	**-0.117**	**0.033**	**-0.002**	-
Cubic Growth Model	150917.9	-75453.0	3	**-0.296**	**0.119**	**-0.012**	**< 0.001**
Random Effects Model Fitting	AIC	LL	DF	Δ -2LL	Δ DF	*P*	
Random Intercept	150975.4	-75481.7	2	-	-	-	-
Random Slope for Age	150417.5	-75200.8	4	561.8	2	0.000	-
Random Slope for Age and Age^2	150315.5	-75146.8	7	108.0	3	0.000	-

Estimates with p < .05 bolded. AIC = Akaike's Information Criterion.

Table 3 also presents the results for determining the random effects components, estimated using restricted maximum likelihood (REML), which is preferable for estimating the random effects components (Fitzmaurice et al. 2012). We allowed the models to freely estimate the variance of each random effect and its covariance with the other random effects, rather than specifying these to be independent or have some other covariance pattern. Each model sequentially improved on the fit from the previous model, using likelihood ratio tests and AIC. We did not estimate models with a random slope for the cubic term for age, as we did not have enough observations per person to estimate this model. We therefore fit all models with random intercepts, a random slope for age, and random slopes for age^2, and the covariance between these estimates, allowing us to differentiate the between and within person variance in change over time.

Table 4 contains all of the estimates for the multilevel models evaluating the change in depressive symptoms contingent on neighborhood and individual level covariates. All continuous predictors were grand-mean centered. Because these analyses include both survey weights and robust standard errors, log-likelihoods and the corresponding likelihood ratio tests are not used. In order to assess improvements in model fit, the AIC is provided. We only present the estimates for the neighborhood variables of interest and sex (all other results available upon request).

Table 3: Multilevel Growth Models for Change in Depressive Symptoms Over Time

	Model 1: Unconditional Growth Model	Model 2: Neighborhood Structural Characteristics	Model 3: Neighborhood Disorder	Model 4: Individual Level Covariates	Model 5: Sex Effects for Change over Time
Intercept	**-0.303**	**-0.302**	**-0.303**	**-0.119**	**-0.138**
Linear Slope	**0.111**	**0.110**	**0.110**	**0.100**	**0.087**
Quadratic Slope	**-0.011**	**-0.011**	**-0.011**	**-0.010**	**-0.007**
Cubic Slope	**< 0.001**	**< 0.001**	**< 0.001**	**< 0.001**	**< 0.001**
Neighborhood Disadvantage: Intercept	-	**0.062**	-0.016	-0.025	-0.025
Neighborhood Disadvantage: Linear Slope	-	< 0.001	0.013	0.004	0.003
Neighborhood Disadvantage: Quadratic Slope	-	-0.0002	-0.001	> -0.001	> -0.001
Neighborhood Disadvantage: Cubic Slope	-	< 0.001	< 0.001	< 0.001	< 0.001
Neighborhood Advantage: Intercept	-	**-0.065**	-0.033	-0.023	-0.022
Neighborhood Advantage: Linear Slope	-	0.017	0.014	0.012	0.012
Neighborhood Advantage: Quadratic Slope	-	-0.001	-0.001	> -0.001	> -0.001
Neighborhood Advantage: Cubic Slope	-	< 0.001	< 0.001	< 0.001	< 0.001
Neighborhood Disorder: Intercept	-	-	**0.110**	**0.059**	**0.059**
Neighborhood Disorder: Linear Slope	-	-	-0.015	-0.010	-0.009
Neighborhood Disorder: Quadratic Slope	-	-	0.001	< 0.001	< 0.001
Neighborhood Disorder: Cubic Slope	-	-	< 0.001	< 0.001	< 0.001

Female: Intercept	-	-	-	**0.166**	**0.206**
Female: Linear Slope	-	-	-	-	0.026
Female: Quadratic Slope	-	-	-	-	**-0.006**
Female: Cubic Slope	-	-	-	-	**< 0.001**
AIC	252959816.6	252637850.9	252494884.8	244853408.2	244620361.4
Observations	61,090	61,090	61,090	61,090	61,090
N	18,740	18,740	18,740	18,740	18,740

Estimates with p < .05 bolded. All models include survey-weights to adjust for Add Health's complex sampling design. Estimates with more than 3 decimal places listed as < 0.001 (or > -0.001 in the case of negative estimates)

Model 1 reflects the unconditional growth model. The weighted initial status ($\beta =-.303, p <.001$) and rates of change over time in depressive symptoms for the linear ($\beta =.11q, p <.001$), quadratic ($\beta =-.011, p <.001$), and cubic ($\beta =.0004, p <.001$) terms are all significant. Model 2 builds on the unconditional growth model and includes the measures for neighborhood disadvantage and neighborhood advantage. We can see both neighborhood disadvantage ($\beta =.062, p <.05$) and neighborhood advantage ($\beta =-.065, p <.01$) have significant influences on baseline values in the expected directions. However, neither is related to change in depressive symptoms over time.

Model 3 adds additional parameters to Model 2 and introduces the measure for neighborhood disorder on top of the measures for neighborhood advantage/disadvantage. Once disorder is included, the effects for neighborhood disadvantage and neighborhood advantage become non-significant. Neighborhood disorder is positively associated with initial values of depressive symptoms ($\beta =.110, p <.001$), though not the change in depressive symptoms over time. Individuals living in more disordered neighborhoods during adolescence suffer greater levels of depressive symptoms, though they do not differ significantly in change over time from their counterparts living in less disordered neighborhoods.

Model 4 includes all of the individual level covariates, including race-ethnicity, family SES, and family composition, on top of the variables for neighborhood context. Neighborhood disorder remains significantly associated with baseline depressive symptoms even after the inclusion of individual level influences such as family SES, race, and family composition. However, the effect of neighborhood disorder is reduced by approximately half ($\beta = .059, p < .05$). Female respondents also report greater level of depressive symptoms at baseline ($\beta = .166, p < .05$), consistent with previous research (Adkins et al. 2009). While some of the relationship between neighborhood disorder and depressive symptoms can be explained by the composition of these neighborhoods; it appears that neighborhood context has implications for mental health over the early life course (Table 4).

Model 5 adds the effect of sex on change over time. Female respondents did not differ in change over time related to the linear slope of age ($\beta = .026, p = .129$). However, they did have significantly steeper declines ($\beta = -.006, p < .01$) and later life increases ($\beta = .0002, p < .01$) relative to their male counterparts based on the evidence from the interactions with the quadratic and cubic slopes for age. The effect of neighborhood disorder was relatively unchanged and remained associated with depressive symptoms at baseline ($\beta = .059,\ p < .05$). The final model (results available upon request) tested whether or not the influence of neighborhood disorder differed by sex. Both interactions and stratified analyses revealed that males and females did not differ in either the influence of neighborhood disorder on baseline or depressive symptoms change in these symptoms over time. Additionally, the AIC for Model 5 was the lowest, revealing it to be the best fitting model.

Comparison of the variance components in Model 1 to those in the final model provides an estimate of the between-person variance explained by all of the variables in the final model. We see a proportional reduction in variance of 0.272 between the variance in the random intercepts from Model 1 (σ_{11} = 0.538) and Model 5 (σ_{11} = 0.289), telling us the final model accounts for that roughly 27 percent of the variance in the initial status of depressive symptoms. Moving on to the variance in linear growth, we see a reduction of 3.9 percent (σ_{22} = 0.0101 in Model 1 to σ_{22} = 0.0096 in Model 5). Finally, there was a reduction of 5.3 percent in the variance in random slopes for the quadratic growth term, between the initial (σ_{33} = 1.710*10^{-5}) and final models (σ_{33} = 1.610*10^{-5}). Overall, the final model explained a small-to-moderate proportion of the variation in depressive symptoms across the early life course.

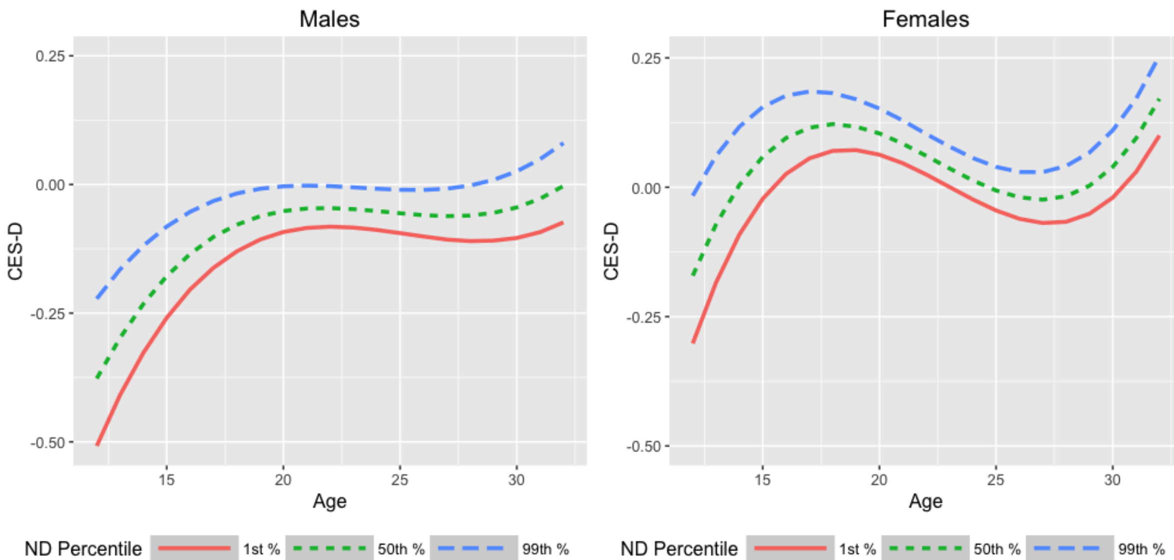

*Figure SEQ Figure * ARABIC 2: Predicted Trajectories of Depressive Symptoms by Neighborhood Disorder and Sex*

Figure 2 presents predicted CES-D from Modle 5. Scoress are conditioned on sex and neighborhood disorder (ND) percentile. All other covariates were fixed at their mean.

Figure 2 presents the predicted scores for depressive symptoms across ages 12 to 32 by sex, conditioned on neighborhood disorder at the 1st, 50th, and 99th percentile. The most noticeable characteristic in these predicted trajectories for both males and females is the shape they take over time. Depressive symptoms peak in late adolescence, around the age of 18, and then decline as respondents approach college age. For both males and females, depressive symptoms start to rise again as they move deeper into adulthood. Looking at the role of neighborhood disorder within male and female respondents, we can see that individuals from highly disordered neighborhoods start with greater levels of depressive symptoms early on. These differences remain throughout the early life course. This suggests that while neighborhood conditions in early adolescence may not influence change in depressive symptoms over time, they do have significant influences on the overall levels of depressive symptoms throughout the early life course.

Discussion

The goals in this research were to examine: 1) whether neighborhood characteristics were related to trajectories of depressive symptoms net of individual level factors, 2) which aspects of neighborhoods are more important, and 3) whether the effects of neighborhoods on trajectories of depressive symptoms were equal across sex, using a nationally representative sample spanning the period of early adolescence into adulthood. In doing so, we provide some evidence for the important role that neighborhoods play in shaping patterns of depressive symptoms across the early life course.

Neither neighborhood disadvantage nor neighborhood advantage - whether on initial status or on change over time - remained associated with depressive symptoms after accounting for individual level covariates such as family SES or race-ethnicity. Only the relationship between neighborhood disorder and initial levels of depressive symptoms remained once all individual level covariates were introduced into the model. Additionally, this effect was reduced by roughly half, suggesting that much of the influence of neighborhood disorder can be explained by the characteristics of individual living in these disordered neighborhoods. Though neighborhoods in early life are important in regards to depressive symptoms throughout the life course, much of the influence they have is on how they shape proximal conditions, such as those related to family SES or family composition.

The relationship between neighborhood disadvantage/advantage, identified as being important in previous longitudinal research on neighborhood effects (Wheaton and Clarke 2003), and depressive symptoms disappears when measures of neighborhood disorder were included. This is not to say that these neighborhood structural characteristics are not important. Because disorder is thought to be the result of structural disadvantage and advantage (Sampson et al. 1997), the impact that these neighborhood structural characteristics have on depressive symptoms works through the ways in which they influence the social conditions in a neighborhood.

These results for which neighborhood conditions are important are consistent with social disorganization theory and replicate findings from previous cross-sectional research: neighborhood disorder often explains (at least in part) the relationship between neighborhood socioeconomic conditions and depression (Mair et al. 2010b, Ross 2000). While socioeconomic conditions are no doubt important, the social environment created by the breakdown in local institutions and the resulting fear and alienation seem to have more immediate consequences for mental health. However, in addressing the social environments associated with neighborhood disadvantage, focusing exclusively on these environments will not address the underlying inequalities that lead to their emergence or persistence (Cerdá et al. 2014). As posited by social disorganization theory, neighborhood social environments are the direct result of neighborhood structural conditions, especially those related to disadvantage (Sampson and Groves 1989, Sampson et al. 1997). Addressing the structural origins of these issues will likely benefit in both improving population health and reducing health disparities.

The last question focused on sex differences in response to neighborhood disorder. While females started with greater levels of depressive symptoms early on and these differences were maintained across the early life course, disorder did not operate differently across sex. These findings are inconsistent with recent evidence that neighborhood conditions operate differently for young boys and girls (Browning et al. 2013). However, our analyses differed slightly in that we considered the differential impact of neighborhood disorder on depressive symptoms over time across sex, and did not examine the impact of neighborhood collective efficacy. Future research should examine whether collective efficacy buffers the influence of disorder in longitudinal models and whether this effect is consistent across sex.

Other interesting patterns emerged. The shape of the trajectories, as can be seen in Figure 3, shows that depressive symptoms seems to peak in late adolescence and then drops off approaching the period in which respondents are around college aged and beginning to enter the workforce, similar to the findings of previous analyses using Add Health (Adkins et al. 2009). However, the inclusion of the fourth wave indicates a quadratic curve no longer fit the data. The period spanning the mid-to-late twenties in to their early thirties was marked by an increase in depressive symptoms. This runs counter to previous cross-sectional (Miech and Shanahan 2000, Mirowsky and Ross 1992) and longitudinal (Walsemann, Gee and Geronimus 2009) research examining the age-depression relationship, where depression is often on the decline from late adolescence into midlife. Research examining age and depression from cross-sectional data can confound age and cohort effects (George 2014). Our results may reflect developmental changes, while much of the previous research has provided information about differences across age cohorts. Additionally, previous longitudinal work has focused primarily on adulthood through mid-life (Walsemann et al. 2009) and does not include how depression changes through adolescence and early adulthood.

In addition to age and cohort differences, these increases in depression could reflect the timing of data collection. Because the data for Wave IV were collected during 2007-2009, respondents were likely answering these questions during the height of the Great Recession. There is evidence that economic crises have a significant impact on population mental health (Zivin, Paczkowski and Galea 2011). The future addition of Wave V of Add Health will allow researchers to determine whether this uptick in depressive symptoms during adulthood is a discernible pattern or not. This cubic shape could also reflect a methodological issue. Because of the smaller number of individuals at the upper end of the age continuum in Wave IV, the small number of observations may have artificially inflated the mean CES-D value at those later ages. We dropped all observation past the age of thirty as an additional robustness check. The cubic model remained the better fitting model, even after removing these potential outliers, suggesting that it is unlikely that the later increase in depressive symptoms is the result of some methodological issue.

Several important limitations should be considered when interpreting these results. Causal inference is difficult in the study of neighborhoods where the possibility of selection into neighborhoods is based on certain characteristics of the neighborhood or the individual. We have attempted to overcome that in part by examining long term patterns beginning in adolescence when respondents are less likely to have control over their current neighborhood. Selection effects are still possible given that psychiatric conditions are moderately heritable and genetic liability could be the reason both parents and children selected into their current neighborhood. However, recent work using qausi-causal designs has shown that when we consider not only the immediate neighborhood, but also the surrounding neighborhood conditions, moving to a more advantaged neighborhood is beneficial for mental health (Graif, Arcaya and Diez Roux 2016). Additionally, moving out of disadvantaged neighborhoods earlier in life is related to greater earnings and educational attainment when compared to moving during adolescence (Chetty, Hendren and Katz 2016). Though we cannot claim the influence of neighborhood conditions are causal in the current analysis, there is growing evidence that neighborhoods do have some causal effect on a variety of outcomes.

Second, we did not examine mechanisms through which neighborhood conditions influence depressive symptoms. Drawing on both social disorganization theory and the stress process, we would expect that part of this relationship may reflect the greater likelihood of exposure to stressful conditions and less resources to deal with them for those living in disadvantaged and disordered neighborhoods. These neighborhoods are characterized by greater threats, such as crime and violence (Sampson et al. 1997). Experiencing this type of violence in adolescence likely has a causal effect on depression in adulthood (Kimmel 2014). Coming from a disadvantaged and violent neighborhood also reduces the likelihood of graduating high school (Harding 2009), reducing the health promoting resources offered by greater education. Future research should incorporate these possible mechanisms through which individual and neighborhood level covariates exert their influence on mental health, especially those that can vary across including time. Additionally, allowing neighborhood conditions to vary over time would allow us to assess whether there are different effects of point in time and cumulative exposure to these conditions, which are relevant to other behavioral outcomes such as alcohol use (Cerdá et al. 2010).

Finally, some of the measures used in this paper are not without criticism. We considered only one, highly gendered outcome. Because sex differences in mental health can be contingent upon the outcome used in analysis (Aneshensel, Rutter and Lachenbruch 1991), future research should consider additional outcomes that are more prevalent among males, such as substance use or other externalizing disorders (Kessler et al. 2005). We also relied on neighborhood characteristics drawn from census data. While these measures have the benefit of being free of subjective bias, the boundaries they encompass may be artificial and not reflect the precise "neighborhood" within which respondents lived. Future research can overcome these limitations of neighborhood measures by using a variety of methods, including both the ecometrics approach and/or spatial analyses that take the conditions of nearby neighborhoods into consideration.

Our analyses have made several important contributions to the literature on neighborhoods and long-term trajectories of mental health. Neighborhood conditions in adolescence place some at elevated risk of depression over the life course. These differences remain constant, at least until early adulthood, as neighborhood conditions do not influence change over time, an important null finding. While individuals from more disordered neighborhoods do not experience steeper growth in depressive symptoms over time, they also do not experience steeper decline later in the life course and disparities are maintained across time. When we consider the relative impact of disorder, disadvantage, and advantage on trajectories of depression, it is only neighborhood disorder that remains associated. Any influence of advantage or disadvantage is mediated through the relationship they have with disorder. Continued understanding of how these early life experiences lead to disparities in mental health over time allows greater understanding of the dynamic nature of mental health over the life course. It also provides information as to critical periods in which prevention and intervention efforts may be most effective. Future work comparing different outcomes and different aspects of neighborhoods will provide us with a clearer picture of the patterns within existing social arrangements.

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Appendix A

Models for Neighborhood Disorder (ND):

Table 5: Items for Ecometric Model of Neighborhood Disorder

Item	Question	Respondent	Responses	Frequency (%)
ND1	Do you usually feel safe in your neighborhood?	Child	0) No	2,425 (11.69%)
			1) Yes	18,182 (87.65%)
ND2	In this neighborhood, how big a problem is litter or trash on the streets and sidewalks?	Parent	1) No problem at all	9,509 (54.09%)
			2) A small problem	6,887 (39.18%)
			3) A big problem	1,165 (6.63%)
ND3	In this neighborhood, how big a problem are drug dealers and drug users?	Parent	1) No problem at all	10,282 (58.42%)
			2) A small problem	5,339 (30.34%)
			3) A big problem	1,642 (9.33%)
ND4	How well kept is the building in which the respondent lives?	Interviewer	1) Very well kept	11,038 (53.23%)
			2) Fairly well kept	6,301 (30.38%)
			3) Poorly kept	2,077 (10.02%)
			4) Very poorly kept	1,002 (4.83%)
ND5	How well kept are most of the buildings on the street?	Interviewer	1) Very well kept	7,315 (35.27%)
			2) Fairly well kept	6,092 (29.38%)
			3) Poorly kept	1,639 (7.90%)
			4) Very poorly kept	455 (2.19%)
ND6	When you went to the respondent's home, did you feel concerned for your safety?	Interviewer	0) No	19,495 (94.01%)
			1) Yes	992 (4.78%)

All items with more than two categories (four items in total) were dichotomized in order to have consistent indicators for the multilevel model. Both items from the parent interview were recoded so that the “No problem at all” category was coded as 0 and both the “A small problem” category and the “A big problem category” were coded as 1. For the two items from the interviewer related to housing quality, houses and surrounding buildings identified as very well kept or fairly well kept were coded as 0. House and building identified as poorly kept or very poorly kept were coded as 1. The child item asking whether the child felt safe in their neighborhood was reverse coded so that 1 indicated feeling unsafe. We chose to dichotomize these so that all indicators were in the same metric and could be estimated in the same multilevel logistic regression. Ordinal items were reduced to absence/presence. The result was six indicators where ones indicated the presence of some physical or social disorder (alpha = .73) and showed moderate clustering within neighborhoods (ICC = .223).

In order to determine ND scores for each neighborhood, we fit a three-level model with items nested within individuals, nested within neighborhoods. After fitting the model the predicted value of the random intercept of each neighborhood (otherwise known as Empirical Bayes estimates or posterior means) was used as that neighborhoods ND value. These values were standardized to ease interpretation. The coefficients in the model represent item severity. The greater the value is from zero, the more severe the indicator. A quick check of the items showed that the two focused on neighborhood safety (ND1 and ND6) were the most severe, with items pertaining to physical conditions (ND4 and ND5) demonstrating less overall severity, as to be expected. The only item that was not significant pertained to parents rating of how much a problem litter and trash was in their neighborhood (ND2), perhaps reflecting that this is not an ideal indicator for disorder.

Reliability of the ND scale for each neighborhood was calculated by comparing the between neighborhood variance to the sum of the between neighborhood variance, the within neighborhood variance weighted by the number of individuals within each neighborhood, and one over the product of the mean number of items per individual in each neighborhood, the average proportion of items coded 1 times the average proportion of items coded zero per neighborhood, and the number of individuals in that neighborhood (Equation

10 in Raudenbush and Sampson 1999). Overall the scale showed modest reliability, with an average reliability of .67 (SD = .22) across neighborhoods.

Table 6: Three-level Logistic Regression Model for Neighborhood Disorder

Item	Difficulty	SE	95% CI	
ND1	2.5198	0.0423	2.4368	2.6028
ND2	0.0722	0.0369	-0.0002	0.1445
ND3	0.3740	0.0372	0.3010	0.4469
ND4	2.2000	0.0408	2.1200	2.2801
ND5	2.3908	0.0442	2.3040	2.4775
ND6	3.6928	3.6928	3.5917	3.7940
Variance: Neighborhood	1.2649	0.0776	1.1215	1.4266
Variance: Individual	1.1138	0.0402	1.0378	1.1953
N of Items	100,987			
N of Individuals	18,738			
N of Neighborhoods	2,344			

Graded Response Models (GRM) for CES-D

Table 7: Parameter Estimates for CES-D GRM (Waves I-IV)

Item		Wave I		Wave II		Wave III		Wave IV	
		Coef	*P*	Coef	*P*	Coef	*P*	Coef	*P*
CESD-1	Discrim.	1.507	0.000	1.536	0.000	1.629	0.000	1.431	0.000
	Cut >=1	0.321	0.000	0.183	0.000	0.207	0.000	0.259	0.000
	Cut >=2	2.079	0.000	2.042	0.000	2.046	0.000	2.209	0.000
	Cut >=3	3.238	0.000	3.266	0.000	3.183	0.000	3.353	0.000
CESD-2	Discrim.	2.545	0.000	2.693	0.000	2.710	0.000	2.829	0.000
	Cut >=1	0.621	0.000	0.581	0.000	0.768	0.000	0.765	0.000
	Cut >=2	1.658	0.000	1.643	0.000	1.832	0.000	1.876	0.000
	Cut >=3	2.481	0.000	2.434	0.000	2.507	0.000	2.517	0.000
CESD-3	Discrim.	0.672	0.000	.692	0.000	0.837	0.000	1.063	0.000
	Cut >=1	-1.093	0.000	-0.939	0.000	0.263	0.000	-0.188	0.000
	Cut >=2	1.070	0.000	1.299	0.000	1.764	0.000	1.488	0.000
	Cut >=3	3.247	0.000	3.299	0.000	3.574	0.000	3.318	0.000
CESD-4	Discrim.	1.189	0.000	1.228	0.000	1.375	0.000	1.121	0.000
	Cut >=1	-0.473	0.000	-0.510	0.000	0.055	0.000	-0.541	0.000
	Cut >=2	1.631	0.000	1.609	0.000	2.002	0.000	1.844	0.000
	Cut >=3	3.102	0.000	3.157	0.000	3.209	0.000	3.319	0.000
CESD-5	Discrim.	3.323	0.000	3.285	0.000	4.036	0.000	3.596	0.000
	Cut >=1	0.266	0.000	0.298	0.000	0.664	0.000	0.555	0.000
	Cut >=2	1.419	0.000	1.470	0.000	1.685	0.000	1.708	0.000
	Cut >=3	2.172	0.000	2.214	0.000	2.331	0.000	2.335	0.000
CESD-6	Discrim.	1.016	0.000	1.143	0.000	0.921	0.000	0.889	0.000
	Cut >=1	-0.436	0.000	-0.441	0.000	-0.093	0.000	-0.903	0.593
	Cut >=2	2.163	0.000	1.969	0.000	2.632	0.000	2.037	0.000
	Cut >=3	3.955	0.000	3.647	0.000	4.402	0.000	3.904	0.000
CESD-7	Discrim.	1.086	0.000	1.109	0.000	1.366	0.000	1.583	0.000
	Cut >=1	-0.198	0.000	-0.232	0.000	0.211	0.000	-0.008	0.000
	Cut >=2	1.422	0.000	1.500	0.000	1.466	0.000	1.352	0.000
	Cut >=3	3.373	0.000	3.464	0.000	3.310	0.000	3.419	0.000
CESD-8	Discrim.	2.474	0.000	2.584	0.000	2.751	0.000	2.774	0.000
	Cut >=1	0.013	0.222	0.057	0.000	0.224	0.000	0.017	0.138
	Cut >=2	1.763	0.000	1.781	0.000	1.753	0.000	1.817	0.000
	Cut >=3	2.625	0.000	2.597	0.000	2.559	0.000	2.643	0.000

CESD-9	Discrim.	1.173	0.000	1.200	0.000	1.139	0.000	1.048	0.000
	Cut >=1	0.664	0.000	0.738	0.000	1.371	0.000	1.237	0.000
	Cut >=2	2.889	0.000	3.009	0.000	3.344	0.000	3.494	0.000
	Cut >=3	4.148	0.000	4.181	0.000	4.446	0.000	4.663	0.000

CES-D Items Consistent across Waves I-IV in Add Health

How often was each of the following true during the last week?

CES-D 1: You were bothered by things that usually don't bother you.

CES-D 2: You felt that you could not shake off the blues, even with help from your family and your friends.

CES-D 3: You felt that you were just as good as other people (reverse coded).

CES-D 4: You had trouble keeping your mind on what you were doing.

CES-D 5: You felt depressed.

CES-D 6: You felt that you were too tired to do things.

CES-D 7: You enjoyed life (reverse coded).

CES-D 8: You felt sad.

CES-D 9: You felt that people disliked you.

Responses:
1. Never
2. Sometimes
3. A lot of the time
4. Most/all of the time