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Linear Mixed-Effects Models: Applications to the Behavioral Sciences and Adolescent Community Health

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Linear Mixed-Effects Models: Applications to the Behavioral Sciences

and Adolescent Community Health

by

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A thesis submitted in partial fulfillment
of the requirements for the degree of
Master of Science in Public Health
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psychological disorders

Dedication

I dedicate this thesis to my entire family, the true essence of my heart. Without their love, support and continued sacrifice, I would not have found the strength or motivation to complete a Master's level degree. Thank you to my beautiful mother, the force behind everything I do and everything I am. This is for her, Papá Carlos, Madelyn, Abuelo, Abuela, Tío Alex, Tío Mario, Tío Jorge, Rosibel, Daysi, Roman, Hani, Kyra and those family members separated by distance. I would not be where I am today without any of you. I recognize I am in a unique position to further my education. To my fellow dreamers in and out of the United States, this is also for you.

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Abstract

Linear mixed-effects (LME) modeling is a widely used statistical method for analyzing repeated measures or longitudinal data. Such longitudinal studies typically aim to investigate and describe the trajectory of a desired outcome. Longitudinal data have the advantage over cross-sectional data by providing more accuracy for the model. LME models allow researchers to account for random variation among individuals and between individuals.

In this project, adolescent health was chosen as a topic of research due to the many changes that occur during this crucial time period as a precursor to overall well-being in adult life. Understanding the factors that influence how adolescents' mental well-being is affected may aid in interventions to reduce the risk of a negative impact. Self-esteem, in particular, has been associated with many components of physical and mental health and is a crucial focus in adolescent health. Research in self-esteem is extensive yet, sometimes inconclusive or contradictory since past research has been cross-sectional in nature. Several factors associated with self-esteem development are considered. Participation in religious services has also been an interest in research for its impact on depression. Depression development and its predictors are evaluated using LME models. Along with this line, this project will address the research problems identified through the following specific topics (i) to investigate the impact of early adolescent anxiety disorders on self-esteem development from

adolescence to young adulthood; (ii) to study the role of maternal self-esteem and family socioeconomic status on adolescent self-esteem development through young adulthood; and (iii) to explore the efficacy of religious service attendance in reducing depressive symptoms. These topics present a good introduction to the LME approach and are of significant public health importance.

The present study explores varying scenarios of the statistical methods and techniques employed in the analysis of longitudinal data. This thesis provides an overview of LME models and the model selection process with applications. Although this project is motivated by adolescent health study, the basic concepts of the methods introduced have generally broader applications in other fields provided that the relevant technical specifications are met.

Chapter 1

Introduction

1.1   Longitudinal Studies

Longitudinal data require that subjects in the study be repeatedly measured across time (Diggle, Heagerty, Liang, & Zeger, 2002; Hedeker & Gibbons, 2006; Vonesh & Chinchilli, 1997). This is the crucial difference between longitudinal data and cross-sectional data, which measures only a single outcome for each individual (Diggle et al., 2002). An advantage of longitudinal studies is having more information on each subject. With this extra information, researchers are able to observe a trajectory for the subjects. Individual trajectories show how the response variable changes over time for the respective individual. In gathering trajectories for all subjects, an overall trend and its relationship to covariates of interest may then be assessed. Cross-sectional data does not allow for distinguishing these changes over time within individuals (Diggle et al., 2002). More elegantly stated, repeated measurements from the same subject provide more independent information than a single measurement from a single subject as in cross-sectional studies (Hedeker & Gibbons, 2006). For this reason, longitudinal studies are more powerful than cross-sectional studies (Hedeker & Gibbons, 2006). Often, the goal of longitudinal analysis is to investigate the effects of covariates both on the overall level of the response

(outcome) and on changes of the response over time (Skrondal & Rabe-Hesketh, 2008).

Another characteristic of longitudinal data are that the data are clustered or considered two-level data (Skrondal & Rabe-Hesketh, 2008). In other words, values or measurements are nested within the individual as measurements are obtained at different time points. In general, individuals are considered at level 2 and the repeated observations within individuals are at level 1. Higher levels may exist beyond the individual level, but are not the focus of this thesis. Longitudinal data are a special case of multilevel or hierarchical data in that the measurements are in chronological order and consist of a large number of small clusters (Skrondal & Rabe-Hesketh, 2008). Longitudinal data are also characterized by missing (unbalanced) data and time-dependent covariates (Davis, 2002).

Clustered observations from the same subject are likely correlated (Diggle et al., 2002). This correlation implies a violation of the independent observations assumption from traditional statistical methods and must be accommodated. Some consequences of ignoring the correlation include incorrect inferences about regression coefficients, inefficient and less precise estimates, and less protection against biases due to missing data (Diggle et al., 2002).

The outcome measured in longitudinal data may be continuous, binary, ordinal, or categorical in nature. Longitudinal data may be collected prospectively or retrospectively; prospective data, as in clinical trials, are typically preferred to minimize recollection bias (Diggle et al., 2002). Longitudinal studies may be

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applied to social sciences such as psychology and economics as well as the biological sciences and clinical trials for evaluating new drugs (Diggle et al., 2002; Vonesh & Chinchilli, 1997). Multilevel modeling has become increasingly popular, particularly in the area of education (Singer, 1998). For more examples of uses of longitudinal data outside of this thesis, please refer to Diggle et al. (2002) and Vonesh and Chinchilli (1997).

1.2   Longitudinal Analysis

The two most commonly used approaches to analyzing longitudinal data are referred to as marginal models (population-averaged) and random-effects (subject-specific) models. The marginal model describes the relationship between the outcome variable and explanatory variables with a population-average regression, as in a cross-sectional study (Diggle et al., 2002). This approach is sometimes called the population-averaged model as it attempts to reduce the repeated values to a summary statistic such as the mean or population average. This approach is not as practical in the presence of time-varying covariates (Diggle et al., 2002). As previously mentioned, the repeated measurements are likely correlated since they are obtained from the same subject. To account for within-subject correlation in the marginal model, the mean and covariance are modeled separately (Diggle et al., 2002). Parameter estimates for population-averaged models depend on the degree of heterogeneity in the population and this may vary between populations (Skrondal & Rabe-Hesketh, 2008).

The random-effects model, on the other hand, considers that regression coefficients vary across individuals (Diggle et al., 2002); a process that stems from the assumption that repeated observations are correlated. In basic terms, there is an average regression coefficient from which each individual deviates given person-specific conditions. For example, when measuring height from a sample of youth at baseline, height will vary across individuals. Collected across several time points beyond baseline, the measurements will also vary across individuals. This is natural and expected. Therefore, a basic height model with an intercept and slope results from an average height at baseline and an average slope. These averages are common to all individuals. Some individuals may be above, below or at the average. The random-effects model is interested in how much each individual deviates from these common regression coefficients. Also of interest is how subjects vary between each other and how measurements for each subject vary. These deviations are often referred to as between-subject variations and within-subject variations. The random-effects model takes care of both. Hence, it is possible to estimate individual-level and population-level growth curve parameters. This approach is the focus of this project and is further discussed in subsequent chapters with applications to adolescent health.

A third approach referred to as a transition model has also been used and is a function of covariates and of past responses (Diggle et al., 2002). The transition models are not relevant to the data presented in this thesis and is not discussed in detail. For more information, please see Diggle et al. (2002). Population-averaged models are particularly useful in public health and

epidemiology (Skrondal & Rabe-Hesketh, 2008; Zeger, Liang, & Albert, 1988). The approach used will depend upon the research question and objective of the study.

1.3 Additional Chapters

The focus of this thesis is to enhance an understanding of longitudinal data analysis using the linear mixed-effects modeling approach. Applications of linear mixed-effects modeling concentrate on adolescent health research. The methodology, however, is applicable to other fields of study given that the relevant technical specifications are met. It is important to note that all outcome measures are continuous. As such, this thesis will focus only on linear mixed-effects modeling for the continuous outcome. Adolescent health is so closely linked to future outcomes that examining the factors influencing adolescent well-being is crucial to minimizing potential negative impact. The motivation for this thesis is to apply as useful a statistical approach as linear mixed-effects modeling to a topic of significant public health importance.

This chapter has given a summary of the characteristics of longitudinal studies. It has also briefly gone over common approaches to analyzing longitudinal data. A summary of the content presented in the remaining main body of this thesis is presented below.

1.3.1 Focus of Chapter 2

This chapter further discusses the linear mixed-effects modeling approach. Assumptions and considerations for use of the approach are explained. A general model is specified. Additionally, the data exploration and model building process are discussed. The emphasis of this chapter is to explain

the tools available and steps taken to perform a linear mixed-effects modeling analysis on longitudinal data. The dataset used and data collection procedures will be described in detail.

1.3.2 Focus of Chapters 3, 4, and 5

These chapters will build on previous research and discuss relevant findings pertaining to adolescent health. Adolescent self-esteem is the outcome of Chapters 3 and 4. The objective of these chapters is to model self-esteem trajectory through young adulthood and assess the influence of factors of interest. Chapter 3 focuses on the impact of anxiety disorders while Chapter 4 focuses on the impact of maternal self-esteem, socioeconomic status, gender and the relation between these factors on self-esteem growth. The goal of Chapter 5 is to assess the impact of church attendance on depressive symptoms score development from adolescence through young adulthood.

1.3.3 Focus of Chapter 6

The main purpose of this chapter is to summarize findings from the research presented in Chapters 3 - 5. New contributions to adolescent health are emphasized. The relevance of linear mixed-effects modeling to these findings is underscored. Limitations in the modeling approach and further potential research are discussed.

Chapter 2

Linear Mixed-Effects Model and Data Description

2.1   Model Specification and Assumptions

Longitudinal data, a special case of repeated measures data, are characterized as having both between-subject and within-subject variation, time-dependent covariates and missing data (Davis, 2002). Linear mixed-effects model can accommodate these complex features of longitudinal data whereas traditional methods are limited by statistical assumptions. More importantly, the approach allows for explicit modeling of the variation between subjects and within subjects. Furthermore, mixed-effects modeling have become increasingly popular and more accessible through statistical software such as SAS (Singer, 1998).

The term "mixed-effects" refers to the expression of the model into fixed-effects and random-effects. The linear mixed-effects model assumes that the observations follow a linear regression where some of the regression parameters are fixed or the same for all subjects, while other parameters are random, or specific to each subject (Verbeke & Molenberghs, 2009). Laird and Ware (1982) describe a two-stage model concept in which the random-effects make up the second stage of the model. Meanwhile, population parameters, individual effects, and within-person variation make up the first stage of the model (Laird & Ware, 1982). The general form of the linear mixed-effects model after combining the

two stages is as follows (Davis, 2002; Laird & Ware, 1982; Verbeke & Molenberghs, 2009):

$$\begin{cases} Y_i = X_i\boldsymbol{\beta} + Z_i\boldsymbol{b_i} + \boldsymbol{\varepsilon_i}, \quad i = 1, \dots, N, \\ \\ \boldsymbol{b_i} \sim N(\mathbf{0}, \boldsymbol{D}) \\ \boldsymbol{\varepsilon_i} \sim N(\mathbf{0}, \sigma^2\boldsymbol{I}) \\ \boldsymbol{b_1}, \dots, \boldsymbol{b_N}, \boldsymbol{\varepsilon_1}, \dots \boldsymbol{\varepsilon_N} \; are \; independent \end{cases}$$

Where i represents each individual subject of which there are N number of subjects. The response vector for subject i is denoted as $\boldsymbol{Y_i}$ and is of n_i dimensions; X_i and Z_i denote the $(n_i \times p)$ and $(n_i \times q)$ dimensional matrices of known covariates; $\boldsymbol{\beta}$ represents the fixed-effects as a p-dimensional vector; $\boldsymbol{b_i}$ is the q-dimensional vector representing the random-effects and $\boldsymbol{\varepsilon_i}$ represents a vector of error components of n_i dimensions.

The assumptions that the linear mixed-effects model must satisfy are that the random-effects follow a normal distribution with mean zero and general covariance matrix D (Davis, 2002; Laird & Ware, 1982; Verbeke & Molenberghs, 2009); the error terms also follow a normal distribution with mean zero and covariance of $\sigma^2\boldsymbol{I}$ where $\boldsymbol{I}$ is the identity matrix. Finally, the random-effects are independent of each other and of the error terms (Davis, 2002; Laird & Ware, 1982; Verbeke & Lesaffre, 1996). In other words, the covariance between the random-effects and the error terms is zero (Zeger et al., 1988). In the remaining chapters, the general model will be applied to specific examples and will be rewritten appropriately.

2.2 Exploratory Data Analysis

The first step to analyzing longitudinal data is to explore the data given. Observe patterns through graphical displays and summary statistics that are relevant to the research question. Diggle et al. (2002) recommends illustrating relevant raw data as much as possible, identifying both cross-sectional and longitudinal patterns that may be of interest, and identifying outliers or unusual observations.

Making a scatterplot of the outcome over the time variable is an excellent starting point. From this plot, the researcher may be able to assess the overall direction of the raw data (increasing, decreasing or constant). It is important to note if the trend is linear or nonlinear. The variation between individual responses and how this variation changes across time may also be observed. If the trend is similar across subjects, then this is an indication that the model will be an easy fit. However, the variation between responses of a single individual may not be clear in this initial plot, particularly if there are a large number of subjects. In this case, a standardized residual plot is recommended (Diggle et al., 2002). Between-subject and within-subject variation are sources of correlation. The lowess curve-fitting method can be used to estimate the mean response profile as a function of time (Diggle et al., 2002). In the case of large datasets where a general trend is unclear, a useful tool is the individual profile plots. For the examples in the remaining chapters, this was one of the preferred methods for examining trends and choosing an appropriate model.

Once a general trend, if any, has been established, trends by various groups may be of interest. For instance, if the research question calls for

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examining gender differences, then a scatterplot dividing individuals by male and female groups is appropriate. It should be noted how these group trends differ from each other and from the overall trend observed in the initial scatterplot. If the research question requires investigating the relationship between the outcome and a covariate other than time, then a scatterplot between these two variables is appropriate. For details and examples on graphing this relationship, see Diggle et al. (2002).

Additionally, a scatterplot matrix and a correlation matrix should be part of the exploratory data analysis. A brief discussion of this can be found in Diggle et al. (2002) and Verbeke and Molenberghs (2009). Variability trends within subjects and between subjects will help in choosing a covariance structure for the model as explained in the next section.

2.3   Model Building Process

Model selection will depend partly on the results of the exploratory data analysis and partly on the research question. As mentioned previously, the focus of this thesis is on linear mixed-effects modeling for continuous outcomes. In the continuous case, subjects do not have to be measured at the same time points (Hedeker & Gibbons, 2006). In practice it is natural that not all subjects are followed up uniformly, but with linear mixed-effects modeling this is not a problem. Furthermore, this approach can accommodate both time-invariant and time-variant covariates in the model (Hedeker & Gibbons, 2006). The ability to handle missing data in a single response variable is another advantage (Hedeker & Gibbons, 2006; Laird & Ware, 1982).

A basic model should be approached based on the results of the exploratory data analysis. Does the outcome behave linearly or nonlinearly over time? If the trend appears to be linear, then the basic model is to be linear. The basic model does not include other covariates and is generally simply a starting point from which to build the final model. The random-effects should be decided prior to running the basic model. A random intercept model is one in which subjects are expected to have subject-specific intercepts, but the same slopes within groups such as in treatment groups if no significant differences are seen (Verbeke & Molenberghs, 2009). Conversely, a random intercept and slope model is one in which both intercept and slope differences are expected. Verifying the assumptions is important for any statistical testing. The methodology for assessing the normality of random-effects, however, is limited (Jiang, 2007; Verbeke & Lesaffre, 1996). For more information, please see Jiang (2007).

Once the random-effects have been established, the fixed-effects should be added to the model to complete the mixed-effects model. The fixed-effects will depend on the research question and topic of interest. The researcher may begin with a full model containing a large number of covariates of interest. Through model comparison, significance testing and relevance of the covariates, a final model may be achieved. Demographic covariates such as race and gender may be included in the model as control factors, if these are important. A covariate such as a particular treatment may be considered as a main effect. If, for instance, the research interest is whether a treatment has an effect both on

where each person starts (intercept) and their rate of change (slope), then both the treatment covariate as a main effect and an interaction term between the treatment effect and the time variable would have to be added in order to examine the effect from each term. From practical experience, if two covariates are found to be statistically significant, then this may be a good indication to attempt an interaction between the same two covariates, given the interest and relevance to the research. However, if the interaction term is not statistically significant, then it is best to remove it from the model and continue building a final model. Interaction terms are explored in some of the examples in the subsequent chapters. For general guidelines on model building and selecting fixed and random-effects, please refer to (Verbeke & Molenberghs, 2009).

The maximum likelihood (ML) and restricted maximum likelihood (REML) are the two common methods for parameter estimation. These methods are based on maximizing the marginal likelihood function (Verbeke & Molenberghs, 2009). However, the estimates from the ML method for a large number of parameters may be biased and thus, not always a feasible option (Diggle et al., 2002). The REML method should be less biased (Diggle et al., 2002). Jiang (2007) notes that as a sample size increases, the number of fixed-effects allowed in the model may increase as well. Still, when using the REML method and building a model, care should be taken not to add too many covariates. The flexibility of the linear mixed-effects model may hamper its ability to estimate parameters (Lindstrom & Bates, 1988). If more parameters need to be estimated, then the computational burden greatly increases. The algorithm for parameter

estimation is usually done using a Newton-Raphson-based procedure (Verbeke & Molenberghs, 2009). For a detailed discussion of the Newton-Raphson algorithm, please refer to Lindstrom and Bates (1988). The Wald chi-square test or the likelihood ratio test can be used for hypotheses testing (Vonesh & Chinchilli, 1997). The Wald test, however, may be unreliable (Verbeke & Molenberghs, 2009), especially for small samples.

The likelihood ratio test may be one form of assessing goodness-of-fit for nested models under the normality assumption (Vonesh & Chinchilli, 1997). Nested models, in the context of model selection, suggest a comparison between a full and a reduced model, in which the reduced model is "nested" within the full model. For non-nested models, the Akaike's information criteria (AIC) are recommended (Vonesh & Chinchilli, 1997). The AIC is to be used in model selection and not as a formal test of statistical significance (Verbeke & Molenberghs, 2009). The generally accepted rule of thumb is to select the model with the lower AIC value (Lindsey, 1999). This is the criterion used for model selection in subsequent chapters.

More importantly is the selection of the covariance matrix. In fact, choosing an appropriate covariance structure is the first step in model selection (Hedeker & Gibbons, 2006). When choosing a covariance structure, all covariates of interest should be included in the model since the significance tests of the covariates depend on the covariance structure (Hedeker & Gibbons, 2006). The covariates in the model are to remain the same through the testing of different covariance structures for a proper comparison. Testing can be done

using the AIC criterion. Some common variance-covariance matrices include (Hedeker & Gibbons, 2006; Vonesh & Chinchilli, 1997):

(1) Independence (constant variance)

(2) Compound symmetry

(3) First-order autoregressive

(4) Toeplitz or banded

(5) Unstructured

(6) Random-effects

The unstructured form assumes each parameter in the variance-covariance matrix is different. In contrast, the compound symmetry structure requires only two parameter estimations: one for the diagonals and one for the off-diagonals. Another structure is called variance components and is the default structure in SAS statistical software. Variance components appear to be a special case of compound symmetry in which the off diagonals are zero.

Pu and Niu (2006) argue that selecting the random-effects in the model is equivalent to selecting the covariance structure and is essential for making valid inferences in the mean structure. The covariance matrix of the random-effects is thought to summarize the intra-cluster correlation (ICC) (Peng & Lu, 2012). The ICC will indicate how much of the unexplained variance in the outcome is due to individual heterogeneity. If there are a large number of random-effects components, then this leads to a complex covariance matrix and can increase computational burden (Peng & Lu, 2012). Selecting the unstructured covariance matrix would require greater computational power and usually involves reduced

efficiency and validity (Lindsey, 1999). In contrast, compound symmetry is more easily computed, but may not accurately reflect the dataset. Furthermore, covariance structure misspecification invalidates inferences about the mean response profile resulting from a structure that is too restrictive (Pu & Niu, 2006). While there is no general rule in selecting a covariance structure for the model, feasibility and goodness-of-fit are ways of identifying the appropriate one (Ware, 1985). As noted by Ware (1985), in some cases the likelihood ratio test can be used to compare nested models for selecting a covariance structure. This should also be done keeping the same fixed-effects, but different covariance structures as noted previously.

Missing data results when planned measurements are not observed. This may be due to random occurrence or when a subject drops out of the study, among other reasons. When data are said to be missing at random (MAR), it means that the probability of missingness does not depend on the values of the unobserved data given the observed data (Lindsey, 1999). There is no direct test available for verifying if data are in fact MAR (Potthoff, Tudor, Pieper, & Hasselblad, 2006). The multiple imputations method is one way of handling missing data under MAR (Allison, 2000). The general view, however, is that under the MAR assumption, likelihood-based methods to estimate parameters are still said to be valid (Rubin, 1976). The last observation carried forward method has been one proposed way of handling dropouts (Diggle et al., 2002). Each method has its limitations. More important than having missing data is to know the cause as this will help guide the researcher as to how to handle

missing data. Linear mixed-effects models, however, may not handle missing

values from multiple outcomes or additional covariates (Schafer & Yucel, 2002).

Strategies to manage this issue can be found in (Schafer & Yucel, 2002).

2.4   Data Description

The dataset used for analyses is based on the Children in the Community

(CIC) study. The CIC study is based on a randomly sampled cohort of 821

families with at least one child between ages 1 to 10 residing in one of two

upstate New York counties in 1975 (Kogan, Smith, & Jenkins, 1978). The study

sample is comprised of one randomly selected child per family and is

demographically representative of children living in the northeastern United

States at the time of the study. The regions were selected for their similarities in

racial distribution and socioeconomic status to that of the United States. It is one

of the few studies that have conducted systematic, interview-based assessments

of psychopathology in randomly-ascertained individuals over 30 years beginning

in childhood. Study procedures were conducted in accordance with appropriate

institutional guidelines and were approved by the Institutional Review Board of

the New York State Psychiatric Institute. A National Institute of Health Certificate

of Confidentiality has been obtained for these data. Written informed consent or

assent was obtained from all participants after the interview procedures were

fully explained. Additional information regarding study methods is available on

the study website: www.nyspi.org/childcom.

Data for the analyses performed in Chapters 3 and 4 rely on three waves

of data collected in 1983, 1986 and 1992. All three waves consist of data on 821

families. Demographic factors such as age, gender, race and socioeconomic status were collected. Offspring self-esteem was the outcome. Anxiety disorder status for the offspring was collected and analyzed in Chapter 3. Data on maternal self-esteem was also collected and used for Chapter 4 analyses. Offspring ages ranged from about 9 years to about 28 years of age with an overall average of 17 years (Table 2.1). Mean offspring age was 13 in 1983, 16 in 1986 and 22 in 1992. From Table 2.1 we can see that the gender of participants was about evenly distributed (49% female, 51% male). Participants were predominantly White. Average family socioeconomic status (SES) was 10±1 and was collected only at the beginning of the study. A more specific breakdown of the data can be found in Table 3.1 and Table 4.1. A detailed description of data collection procedures for all variables is discussed within Chapters 3 and 4.

Data for the analyses performed in Chapter 5 were drawn from the same population, but instead rely on four waves of data (1983, 1986, 1992 and 2003). Additionally, the dataset is restricted to 756 subjects. For this data, offspring age ranged from 9 years to about 40 years with an overall average of 21 years of age (Table 2.1). The mean age in 1983 was 13; 16 in 1986; 22 in 1992 and 33 years of age in the 2003 follow-up period. Gender for this subset of data was also evenly distributed (Table 2.1). Racial distribution also consisted of about 91% White and about 9% Black. Family SES was the same as for the previous dataset. The outcome of interest was depressive symptoms score. Covariates of interest include church attendance (yes/no) and frequency of church attendance

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(none, yearly, monthly, weekly). Control factors included recent negative events and lifetime trauma as time-varying covariates. A detailed description of these variables can be found in Chapter 5 and Table 5.1.

Table 2.1 **Mean and Standard Deviation (SD) of Demographic Characteristics of the Sample Population Based on the CIC Study by Dataset**

Variable	Chapter 3 and 4 Data Mean (SD)	Chapter 5 Data Mean (SD)
Age	17±4	20±8
SES	10±1	10±1
	N (%)	N (%)
Gender		
Male	418 (50.91)	375 (49.60)
Female	403 (49.09)	381 (50.40)
Race		
Black	73 (8.89)	69 (9.13)
White	748 (91.11)	687 (90.87)

The PROC MIXED procedure available in SAS 9.2, used for all analyses performed on these datasets, does not require complete data (Littell, 2006). The REML method is the default method in SAS and was chosen as the more appropriate method given the considerations described in the previous section. More on the analyses performed can be found within the subsequent chapters.

Chapter 3

Impact of Anxiety Disorders on Adolescent
Self-Esteem Development[1]

3.1   Background

Recent theoretical and empirical work has identified the transition from

adolescence to young adulthood as a period with distinct characteristics that is

important for the understanding of human development (Cohen, Kasen, Chen,

Hartmark, & Gordon, 2003). Adolescence is a developmental period marked by

rapid maturational changes, shifting societal expectations and conflicting role

demands. Self-esteem plays a critical role in this process. Studies on self-esteem

development from adolescence to young adulthood have found moderate

increases during adolescence and slower increases during young adulthood

(Erol & Orth, 2011). In contrast, other studies report that self-esteem declines

during adolescence, partially explained by adolescent concerns with self-image

and related issues associated with puberty, but increases gradually throughout

adulthood (Robins & Trzesniewski, 2005). From a theoretical standpoint,

changes in self-esteem coincide with major life events or transitions (Nisbet

Wallis, 2002). Nevertheless, there is little agreement regarding the development

of self-esteem through young adulthood due to few longitudinal-based studies

conducted on a non-clinical adolescent population (Aarons et al., 2008; Erol &

Orth, 2011). Given the negative implications of poor self-esteem, understanding

the self-esteem trajectory from adolescence to adulthood and what factors

influence its trajectory can aid in the development of interventions designed to

improve self-esteem.

Anxiety disorders are the most common of all the mental disorders

(Andrews et al., 2002). The prevalence rate in the general population has been

estimated at 11% and anxious people have contact with mental health

professionals at rates that are higher than any other mental disorders except

schizophrenia and bipolar disorder (Oakley-Browne, 1991). Estimates suggest a

lifetime prevalence of social phobia, a type of anxiety, ranging from 12% to 14%

and current prevalence between 7 and 8%. Social phobia is characterized by

marked and persistent fear of acting in an embarrassing or humiliating way in

social or performance situations that are observed or scrutinized by others

resulting in impairment in academic, career, and interpersonal function (Wittchen,

Fuetsch, Sonntag, Müller, & Liebowitz, 2000). Previous research concerning this

topic has focused on examining the association between demographic and

socioeconomic (SES) factors and self-esteem development (Block & Robins,

1993; Erol & Orth, 2011; Orth, Trzesniewski, & Robins, 2010). However, the

relationship between self-esteem and anxiety disorders is less frequently

acknowledged, discussed and understood in clinical literature (Nisbet Wallis,

2002). Greenberg et al. (1992) reported that anticipatory anxiety was buffered by

raised self-esteem. Studies (Ehntholt, Salkovskis, & Rimes, 1999; Marchand,

Goupil, Trudel, & Bélanger, 1995) found that subjects with anxiety disorders had lower levels of self-esteem, compared to non-clinical controls. Moreover, no research has examined the role of various categories of anxiety disorders on self-esteem development from a longitudinal perspective.

The purpose of the present study is to examine the relative impact of adolescent anxiety disorders on self-esteem development from adolescence to young adulthood. Adolescent anxiety disorders include overanxious disorder, obsessive compulsive disorder (OCD), simple phobia, social phobia, and separation anxiety disorder. Self-esteem was measured across three time points beginning from early adolescence and ending in adulthood.

3.2 Methodology

3.2.1 Data Collection

Data for the current study are based on 821 subjects (49% female, 51% male) interviewed in 1983 (wave 1), at a mean age of 13, for their anxiety disorders assessment and self-esteem. Follow-up measures of self-esteem were obtained in 1986 (mean age of 16) and 1992 (mean age of 22). Participants ranged from 9 years of age to about 28 years of age, with an average of 17 years of age.

Anxiety disorders were assessed with the diagnostic interview schedule for children (Costello, Edelbrock, Duncan, & Kalas, 1984). In 1983, the Diagnostic Interview Schedule for Children (DISC)-I was administered separately to the child and a parent, usually their mothers. Home interviews were carried out by two interviewers who were blind to the responses of the other respondent and to any prior data. Data from parent and child were combined by computer

algorithms in two ways. First, continuous scales were created for each disorder defined by *Diagnostic and Statistical Manual of Mental Disorders* (DSM) of the American Psychiatric Association (APA, 1987) by summing responses to disorder-specific questions on symptoms and associated impairment for each respondent.

By and large these scales have acceptable internal consistency reliability, ranging from 0.6 to over 0.9 (Cohen & Cohen, 1995), despite the absence of concern about such reliability in the definition of these disorders. DSM-III-R diagnoses for adolescents were made based on criteria met by either youth or parent report on the DISC-I but also required that the sum of the mother and adolescent symptom scales for the disorder be at least one standard deviation above the sample mean. This decision to consider either respondent's symptom indication as positive is consistent with the consensus of the field that sensitivity is thereby ensured (Bird, Gould, & Staghezza, 1992), while the use of the additional criterion based on the pooled scales enhances the specificity of the diagnoses. The type of anxiety disorder was noted as overanxious disorder, OCD, simple phobia, social phobia and separation anxiety disorder.

Self-esteem was measured in 1983 (mean age of 13), 1986 (mean age of 16) and 1992 (mean age of 22). Four items indexed global self-esteem in each protocol: (i) I feel that I have a number of good qualities; (ii) I feel that my life is very useful; (iii) I am a useful person to have around; and (iv) I feel that I do not have much to be proud of (reversed). The items were rated from 1 (false) to 4 (true), and the internal consistency of the scale formed by summing them was

0.64 in adolescence and 0.69 in young adulthood (Berenson, Crawford, Cohen, & Brook, 2005).

Covariates include gender, race, and SES. Family SES was measured as a standardized sum of standardized parental education, occupational status, and family income. Gender was included as a control variable and investigated with regard to potential influence on self-esteem and the relationships between adolescent anxiety disorder and self-esteem.

3.2.2 Data Analysis

A linear mixed-effects (LME) model (Laird & Ware, 1982) was used to model the self-esteem trajectory over time, with age considered as the time variable. This approach was taken given that the continuous outcome, self-esteem, was measured repeatedly over time (Laird & Ware, 1982). Self-esteem measurements for each subject were expected to be correlated. Hence, the LME model is most appropriate for taking into account both within-subject variation and between-subject variation. We were interested in predicting both self-esteem on average and its trajectory. The various factors that shape an adolescent's self-esteem are not only unique, but also dynamic and ever-evolving (Baldwin & Hoffmann, 2002). For this reason, self-esteem growth varies across individuals. Hence, in our model, both the intercept and slope were considered as random-effects. These random-effects in the LME model allow for estimation of parameters both at the intra-individual level and at the inter-individual level (Singer, 1998). In the present study, self-esteem, family SES, and age are

continuous variables. Gender, race, anxiety disorder status and anxiety type are categorical variables.

First, a basic unconditional LME model was assessed, which included no variables other than age to estimate the self-esteem trajectory. Age was centered at the mean (17 years) when placed into the model for all analyses for ease of interpretation (Singer, 1998). Based on Figure 3.1, a linear trend appears to be appropriate. For some individuals, self-esteem seems to decrease while for others it increases. This is expected given that the data contains subjects diagnosed with mental health disorders such as depression, anxiety, and other conditions which may negatively affect self-esteem.
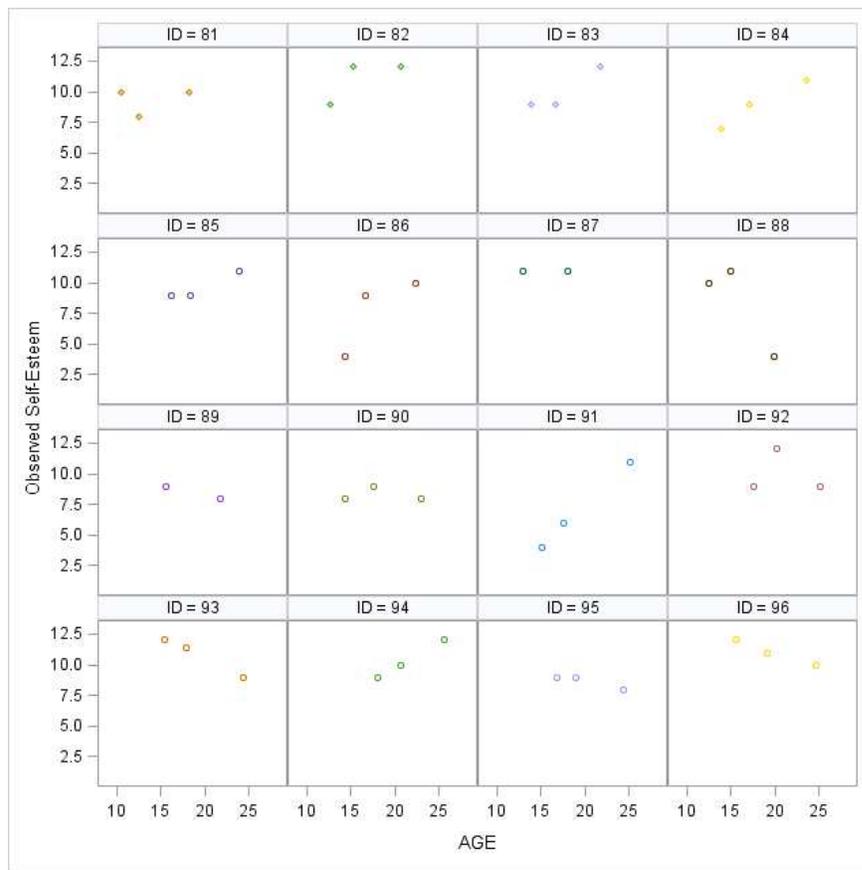
Figure 3.1   Individual Observed Self-Esteem Score for 16 Representative Subjects

A plot of the observed average self-esteem over time shows an overall increasing trend. Figure 3.2 plots the observed average self-esteem for subjects with at least an anxiety diagnosis and for those who have no mental health disorder (also referred to as the healthy group). The healthy group is coded as 0 (shown in blue) while the anxiety group is coded with a 1 (shown in red). Both groups appear to have their ups and downs, but the important thing to note, as hypothesized, the healthy group has a much higher observed average self-esteem at every age. The present model seeks to quantify these differences and model the self-esteem trajectory while controlling for demographic factors of interest.
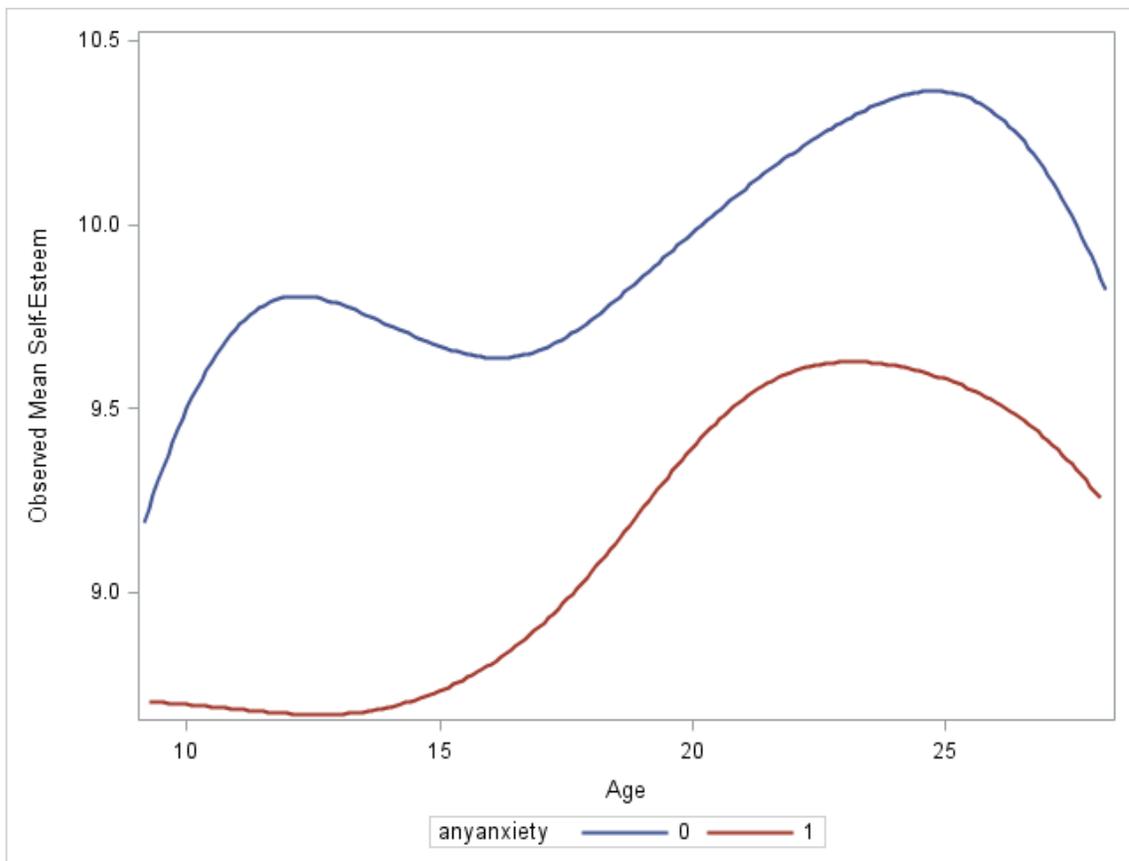
Figure 3.2   Observed Mean Self-Esteem by Anxiety Disorder Status

The basic unconditional LME model (3.1) with random-effects for both intercept and slope is given as follows:

$$y_{ij} = (\beta_0 + b_{0i}) + (\beta_1 + b_{1i})age_{ij} + e_{ij}, \qquad (3.1)$$

where $e_{ij} \sim N(0, \sigma^2)$. Gender, race and SES were then added to the model as fixed covariates to determine any potential influence on self-esteem development.

In order to assess if average self-esteem and its trajectory depended on adolescent anxiety disorder after controlling for demographic factors as described above, we can express the **model for any anxiety disorder with interaction** (3.2) as follows:

$$y_{ij} = \beta_{0i} + \beta_{1i}age_{ij} + \beta_4 SES_i + \beta_5 race_i + \beta_6 gender_i + e_{ij}, \qquad (3.2)$$

$$\begin{cases} \beta_{0i} = \beta_0 + \beta_1 anxiety_i + b_{0i} \\ \beta_{1i} = \beta_2 + \beta_3 anxiety_i + b_{1i} \end{cases},$$

The first set of analyses compared any anxiety disorder (n=225) to the reference group consisting of participants with healthy adolescents (n=427). Average and slope differences were tested. If the slope difference was not significant, then the final model excluded this term. The final model was also based on an assessment of various variance-covariance structures for the random-effects. The Akaike's Information Criteria (AIC) was used for model selection with the lower AIC values indicating a better fit. For this particular dataset, the unstructured variance-covariance matrix was selected as the best fit. This variance-covariance matrix for the random-effects was used for all subsequent models and does not impose any structure on the variances for intercepts or slopes (Singer, 1998).

The second set of analyses involved the five different classifications of anxiety disorders – overanxious disorder (n=111), OCD (n=43), simple phobia (n=90), social phobia (n=65), and separation anxiety disorder (n=67). Youth in these groups are considered to have at least the specified classification of anxiety disorder, but may have other mental health disorders not discussed in the present study. Each anxiety disorder group was compared to those without the specified disorder. All anxiety classifications were included in the model to control for co-morbidity impact. The model specification is similar to that of model (3.2) with five anxiety terms as fixed-effects, representing each group of anxiety disorders. Interaction effects were also assessed for each category before deciding on a final model. This includes interaction effects between gender and SES, gender and age and any other combination of factors in the model. More importantly, in order to assess any slope differences from the different anxiety disorders, each anxiety category was tested for any interaction effect with age, one at a time until any interaction effect was found, if any. Furthermore, to determine the relative impact of each anxiety category, an effect size (ES) was calculated. While a null hypothesis implies no relationship between variables, an effect size measures the degree to which this null hypothesis is wrong (Grissom & Kim, 2005). In order to calculate the effect size for each anxiety category, we used the coefficient of each anxiety disorder and divided it by the overall standard deviation for self-esteem in all subjects.

3.3   Results

3.3.1 Descriptive Statistics

About 51% of the participants were male and 49% were female; over 91% were White and about 9% of the subjects were Black. Over 27% of all participants had at least one anxiety disorder, not distinguishing from other Axis I disorders. About 14% of all participants were reported to have at least overanxious disorder; about 5% have OCD; 11% have simple phobia; 8% reported social phobia; 8% with separation anxiety. Average observed self-esteem at waves 1, 2 and 3 were 9.33±2.14, 9.34±2.0 and 9.98±1.8, respectively. Males had a higher observed self-esteem (9.70±1.92), on average, than females (9.39±2.10). On average, self-esteem was highest in participants with no mental disorders – about 9.9 compared to about 9.0 in participants with any anxiety disorder (Table 3.1). Among the categories of anxiety disorders, participants with at least social phobia appeared to have the lowest observed mean self-esteem while participants with at least separation anxiety disorder had the highest followed by participants with at least OCD.

3.3.2 Statistical Modeling Results

Based on the basic unconditional growth model, self-esteem increased over time by about 0.08 units each year (Table 3.2, Figure 3.3). Subjects with any anxiety disorder (n=225), on average, have a self-esteem score of 0.714 (ES= -0.35, p<0.01) units lower than subjects with no mental health disorders (n=427) (Table 3.2, Figure 3.4). No slope differences were found among these two groups (Table 3.2). Average gender differences were found in the basic model with covariates (controlling for age, race and SES). However, there were

no significant gender differences in the effect of any anxiety on self-esteem. No

race or SES differences in the effect of anxiety on self-esteem were found.

Table 3.1   Mean and Standard Deviation (SD) of Self-Esteem Measures by Demographic and Anxiety Disorder Status

	Wave 1 (1983)	Wave 2 (1986)	Wave 3 (1992)
Demographic Characteristics			
Total Sample (N=821)	9.33 (2.14)	9.34 (1.99)	9.98 (1.84)
Gender			
Females (N=403)	9.05 (2.27)	9.17 (2.11)	9.94 (1.80)
Males (N=418)	9.60 (1.97)	9.50 (1.87)	10.01 (1.88)
Race			
Black (N=73)	9.19 (2.28)	9.51 (2.36)	10.03 (1.82)
White (N=748)	9.34 (2.13)	9.32 (1.96)	9.97 (1.84)
Anxiety Disorder Status			
Healthy/no mental health disorder (N=427)	9.76 (1.93)	9.64 (1.87)	10.18 (1.74)
Any anxiety disorder (N=225)[1]	8.71 (2.20)	8.82 (2.06)	9.52 (2.07)
Among Anxiety Disorders[2]			
Overanxious Disorder (N=111)	8.51 (2.28)	8.85 (2.10)	9.29 (2.12)
Obsessive-Compulsive Disorder (N=43)	9.12 (2.12)	9.11 (1.77)	9.03 (2.21)
Simple Phobia (N=90)	8.70 (2.30)	8.55 (1.94)	9.47 (2.11)
Social Phobia(N=65)	8.24 (2.14)	8.31 (1.92)	9.33 (1.86)
Separation Anxiety Disorder (N=67)	8.85 (2.19)	9.20 (1.99)	9.87 (2.11)

(1) Individuals with at least one anxiety disorder including those with any combination of anxiety disorders

(2) Individuals have at least the specified anxiety disorder as compared with individuals without specified anxiety disorder

Social phobia, overanxious disorder, OCD, and simple phobia predicted

self-esteem among the study population. Social phobia, overanxious and simple

phobia classifications of anxiety disorders lowered self-esteem, on average, with social phobia having the most negative impact on average self-esteem relative to the other anxiety disorder types. Subjects with at least social phobia had an average self-esteem score about 0.62 units lower than subjects without social phobia (ES=-0.30, p<0.01; Table 3.3, Figure 3.6).

Overanxious disorder had the second highest impact on average self-esteem, with a score of about 0.38 lower than the reference group (ES=-0.17, p<0.05; see Table 3.3, Figure 3.6). Simple phobia had the least impact at 0.37 units lower (ES=-0.17, p<0.05; Table 3.3, Figure 3.6). No statistical evidence was found to suggest a difference in average self-esteem between participants with separation anxiety disorder and participants without separation anxiety (p=0.08; Table 3.3, Figure 3.6).

Similar to the findings for subjects with any anxiety disorder, no significant gender or race differences were found for the classifications of anxiety disorders. On the other hand, the model controlling for co-morbidity of the various classifications of anxiety disorders suggests that higher SES was significantly associated with higher self-esteem, on average.

Self-esteem in participants with OCD changed over time when compared to non-OCD controls, decreasing by about 0.1 units per year (p<0.05; Table 3.3, Figure 3.5). However, other anxiety disorder types were not found to have a slope difference (Table 3.3).

The relative impact and ranking of the anxiety disorder types varies when assessing the average difference versus the slope difference (Table 3.3). OCD

had the highest impact on the slope difference, and social phobia (ES=-0.30, p<0.01; Table 3.3) had the greatest impact on the average self-esteem.
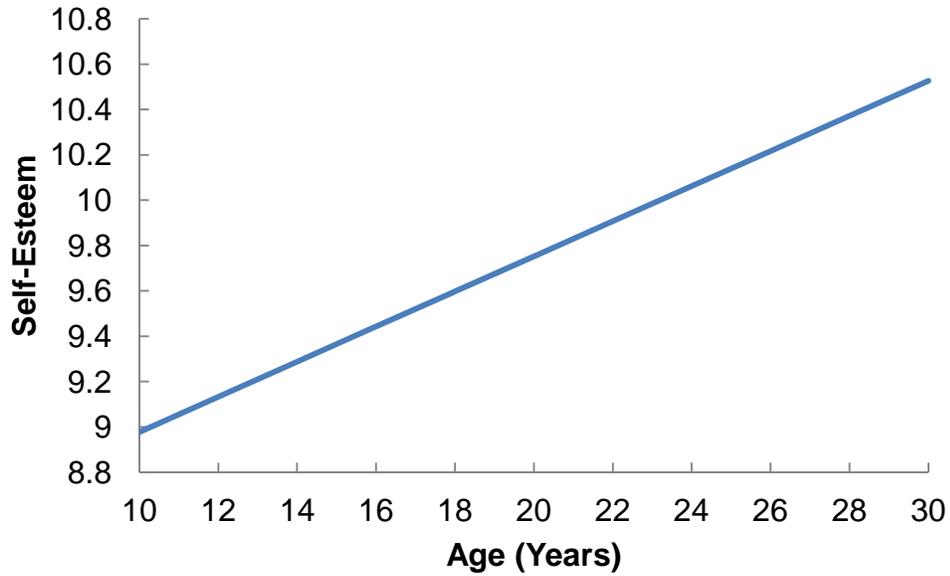
Figure 3.3   Predicted Self-Esteem Based on Basic Unconditional Model
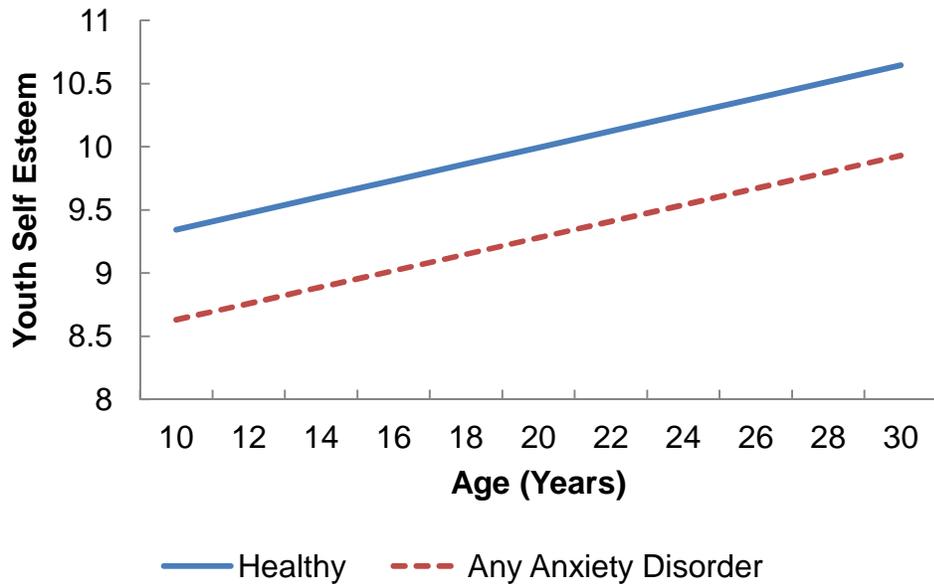
Figure 3.4   Self-Esteem Change in Youth by Anxiety Disorder Status (Any Anxiety Disorder versus Healthy Youth/No Mental Disorder) Based on the Model for Any Anxiety Disorder

Table 3.2   Impact of Adolescent Anxiety on Self-Esteem from the Ages of 13 to 22 Years[1]

Parameters	Basic Unconditional Model			Basic Model with Demographic Covariates		
	Coefficient	p-value	95% CI	Coefficient	p-value	95% CI
Intercept	9.52	<0.01	(9.41, 9.63)	7.76	<0.01	(6.72, 8.81)
Age	0.08	<0.01	(0.06, 0.10)	0.08	<0.01	(0.06, 0.10)
Gender				0.27	<0.01	(0.07, 0.48)
Race				-0.32	0.11	(-0.70, 0.07)
SES				0.19	<0.01	(0.08, 0.30)
	Model for Any Anxiety Disorder(s)[2]			Model for Any Anxiety Disorder(s) with Interaction[2]		
	Coefficient	p-value	95% CI	Coefficient	p-value	95% CI
Intercept	8.76	<0.01	(7.53, 9.98)	8.78	<0.01	(7.56, 10.01)
Age	0.07	<0.01	(0.05, 0.09)	0.05	<0.01	(0.03, 0.08)
Anxiety	-0.71	<0.01	(-0.96, -0.47)	-0.73	<0.01	(-0.98, -0.49)
Anxiety × Age				0.04	0.10	(-0.01, 0.08)

(1) Age was centered at 17 for all models; disorder was coded as 1 (0 for healthy adolescents)
(2) Models include Gender, Race and family SES as control variables

Table 3.3   Relative Impact of Categories of Anxiety on Self-Esteem from the Ages of 13 to 22 Years (Based on the Model Controlling for Categories of Anxiety Disorders with OCD Slope Effect)

Variable	Coefficient	p-value	95% CI	Effect Size
Social	-0.62	<0.01	(-1.03, -0.20)	-0.30
Overanxious	-0.38	<0.05	(-0.71, -0.06)	-0.17
Simple	-0.37	<0.05	(-0.73, -0.02)	-0.17
OCD	-0.21	0.39	(-0.68, 0.26)	-0.10
OCD × Age	-0.11	<0.05	(-0.19, -0.02)	
Separation	0.36	0.08	(-0.04, 0.77)	0.17
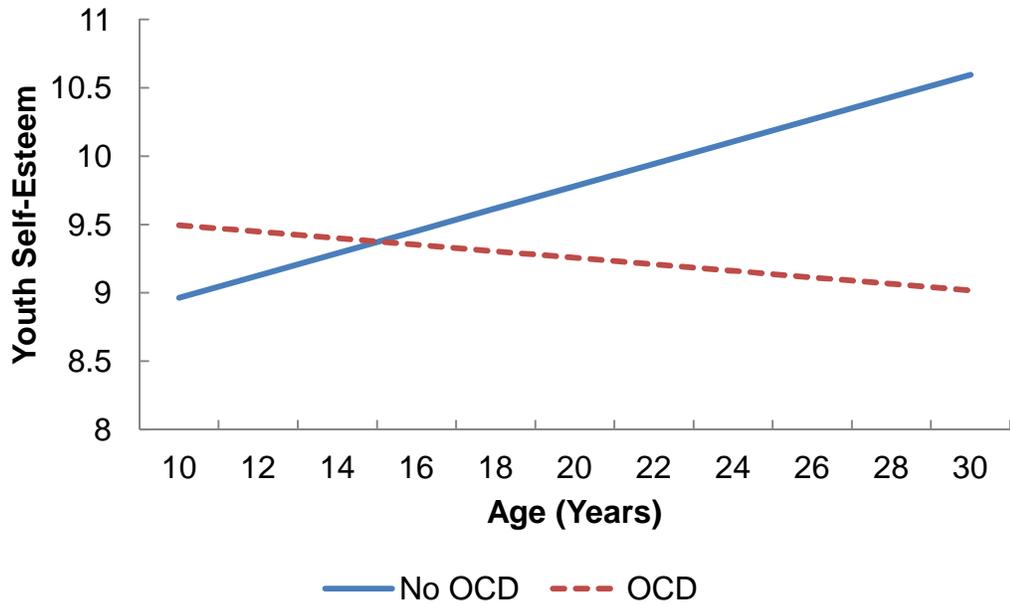
Figure 3.5   Self-Esteem Change in Youth by OCD Status (At Least OCD versus without OCD) Based on the Model for Controlling for Categories of Anxiety Disorders with OCD Slope Effect
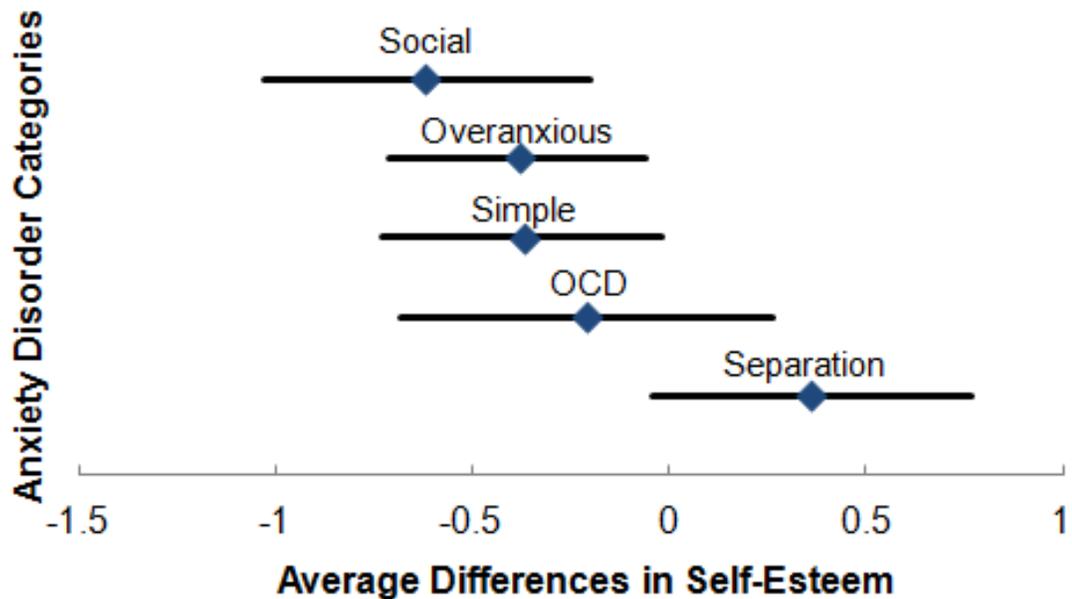
Figure 3.6   Mean Effects with 95% Confidence Interval per Anxiety Disorder Category Based on the Model Controlling for Categories of Anxiety Disorders with OCD Slope Effect

3.4 Implications of Research

Many longitudinal studies have found that self-esteem increases over time, particularly from early adolescence to young adulthood (Erol & Orth, 2011; Gentile, Twenge, & Campbell, 2010; McCarthy & Hoge, 1982; Orth et al., 2010). Our findings based on three waves of data collected over about one decade are consistent with these studies. Baldwin and Hoffmann (2002) found a curvilinear relationship for self-esteem development. A meta-analysis performed on 86 published articles found that self-esteem declines during adolescence and increases gradually throughout adulthood (Robins & Trzesniewski, 2005). However, many of the studies from the meta-analysis were based on cross-sectional data and assess group mean difference rather than change over time.

Two studies that have linked anxiety disorder with decreased self-esteem were conducted in clinical settings (Ehntholt et al., 1999; Nisbet Wallis, 2002). These studies found a relationship between anxiety and self-esteem, but did not examine the impact of anxiety disorders on self-esteem development through young adulthood. Both studies were conducted on adult participants. The sample analyzed in the present study consists of community individuals with a variety of anxiety and mental health disorders as well as individuals without the assessed disorders, making the results relevant to the general population. Subjects with any anxiety disorder were found to have a significantly lower self-esteem, on average, than healthy subjects. Nisbet Wallis (2002) reported that adult anxious clients suffered from poorer self-esteem. In fact, following an intervention to

improve the state of anxiety in adult anxious clients, adult anxious clients became less anxious and showed increased self-esteem as a result (Nisbet Wallis, 2002).

Adolescence, as a transitory state, is subject to increased responsibility that may lead to additional stress thereby affecting self-esteem (Baldwin & Hoffmann, 2002). Adolescents who experience greater stress are typically depressed or anxious with evidence suggesting decreases in self-esteem for these adolescents (Baldwin & Hoffmann, 2002). The present study agrees with this conjecture. There are no known longitudinal-based studies using categories of adolescent anxiety disorders to prospectively predict self-esteem development through young adulthood.

Of the anxiety disorders, social phobia had the greatest impact relative to the other anxiety disorders. The National Institute of Mental Health defines social phobia as a "strong fear of being judged by others and of being embarrassed." Social acceptance by peers and parental figures play an important role in adolescent development and self-identity (Berenson et al., 2005; La Greca & Harrison, 2005). Adolescents who associate with peers or groups labeled as having low-status typically report lower self-esteem than others (La Greca & Harrison, 2005). Additionally, affiliation with peers of "high-status" may be associated with less social anxiety (La Greca & Harrison, 2005; Zimmerman, Copeland, Shope, & Dielman, 1997). For this reason, it makes sense that adolescents with social phobia experience lower self-esteem, on average, than subjects without social phobia. The findings from the present study agree with those from Geist and Borecki (2006), a cross-sectional study suggesting that the

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degree of social distress is indicative of an individual's perceived locus of control and level of self-esteem.

Separation anxiety disorder tends to be more common in children while social phobia tends to affect adolescents (Beesdo, Knappe, & Pine, 2009). Separation anxiety typically occurs at about 12 through 18 months of age and usually does not persist beyond childhood (Beesdo et al., 2009). Hale et al. (2008) showed that symptoms of separation anxiety disorder decreased for all adolescent participants over the course of a 5-year prospective community study. The same study showed that symptoms of social phobia, on the other hand, remained fairly stable over time further supporting the idea that social phobia plays a significant role in adolescent development (Hale et al., 2008). It is not surprising then that no evidence was found in the present study to suggest that separation anxiety disorder predicts self-esteem development in adolescents while social phobia does so overwhelmingly. Future research may consider investigating how separation anxiety disorder may influence childhood self-esteem development through adolescence. For the purposes of the present study, separation anxiety disorder appears to have no impact on self-esteem development from adolescence through young adulthood. However, Lewinsohn et al. (2008) found that separation anxiety disorder in childhood is a risk factor for the development of mental disorders such as panic disorder and depression during young adulthood. Thus, the potential impact of this disorder should not be ignored.

The present study showed that OCD adolescents exhibit a self-esteem decline over time. Obsessive thoughts leading to significant functional impairment are characteristic of OCD individuals (Cameron, 2007). High obsession individuals have been shown to evaluate their self-worth based on moral standing, social skills and acceptance, and physical attraction (Doron & Kyrios, 2005). With rising pressures experienced during adolescence and the increasing role of peer acceptance, one's evaluation of self-worth becomes more complex. As a result, the potential for perceived failure is extensive during this time of transition into adulthood. OCD individuals are particularly vulnerable to situations and intrusive thoughts that may trigger their insecurity relating to competence in areas they value highly (Doron & Kyrios, 2005). Perceived failure may then trigger more anxiety and misgivings on self-worth. OCD individuals have been found to be significantly more ambivalent toward self-perceptions than non-clinical individuals leading to contradicting thoughts on one's self-worth and in turn, one's self-esteem (Bhar & Kyrios, 2007). Obsession with self-worth, thus, may make adolescents with OCD much more prone to lowered self-esteem than individuals without OCD. It is likely that this type of anxiety and obsessions, left untreated, may become worse over time negatively impacting self-esteem development.

Among other factors hypothesized to influence self-esteem, no gender differences were found in the effect of any anxiety disorder on self-esteem. Orth et al. (2010) found minor differences between men and women in young adulthood. Meanwhile, Erol and Orth (2011) found no significant differences

between males and females in a longitudinal study of over 7,000 participants. In contrast, Block and Robins (1993) showed that self-esteem in males tends to increase while in females it tends to decrease through young adulthood. Their study suggests that males are more likely to be in control of their personal anxiety level. Social acceptance has a greater influence in females than in males as females tend to be in touch with how others may be judging them more so than their male peers (Berenson et al., 2005). There were no significant gender differences in the effect of the co-morbidity model. When considering gender as a main effect, however, females were found to have lower self-esteem, on average. These findings are consistent with other studies (Birndorf, Ryan, Auinger, & Aten, 2005; Robins, Trzesniewski, Tracy, Gosling, & Potter, 2002).

In summary, the present research investigated the development of self-esteem from adolescence to young adulthood using longitudinal data from the CIC study. As mentioned previously, studies have been inconsistent in determining self-esteem trajectory. Findings from the present study are consistent with the research (Erol & Orth, 2011; Gentile et al., 2010; McCarthy & Hoge, 1982; Orth et al., 2010) indicating that self-esteem increases from adolescence to young adulthood. The present study advances the topic by analyzing longitudinal data from a large community-based sample whereas prior research is based predominantly on clinical or cross-sectional studies. Our results suggest that distinct anxiety disorders differ in their impact on the development of self-esteem. Roberts (2006) advocates that self-esteem should be incorporated into treatment of mental health disorders, and states that poor

response to treatment of individuals with mental health disorders goes hand in hand with low self-esteem. Accordingly, raising self-esteem is a key ingredient in therapeutic attempts to elicit adaptive behavior in individuals with a mental health disorder (Roberts, 2006).

By understanding the relationship between self-esteem and mental disorders clinicians may be prompted to use an intervention with a focus on raising self-esteem. These interventions may vary by class of mental health disorders and even further, based on the results of the present study, vary by classification of anxiety. For instance, clinicians may consider developing different interventions for adolescents with social phobia or OCD than for those with separation anxiety disorder targeting raising self-esteem. The literature has also suggested that mental health problems are associated with physical health problems (Aarons et al., 2008; Trzesniewski et al., 2006); low self-esteem individuals are more likely to experience secondary symptoms (Rosenberg, 1962). The implications of this research are practical in the efforts to make adolescence a smooth transition for youth. Whether used for clinical treatment or further research, the present study serves to supplement the body of research on self-esteem in adolescents; it also serves as the first study to use various categories of anxiety disorders to predict self-esteem trajectories from adolescence through young adulthood.

Chapter 4

Impact of Family Socioeconomic Status and Maternal Self-Esteem on Adolescent Self-Esteem Development[2]

4.1   Background

Adolescence is a critical transitional period in the path of development, and is filled with a multitude of pressures from social acceptance to academic achievement that both challenge and provide opportunities for the development of self-esteem. This period brings with it a combination of successes and failures, building characteristics and skills that may be of relative importance as the adolescent begins to compare his/her self with peers. Unlike childhood, when values and self-worth are explored passively and identified with parental figures or objects, adolescence is the period when a basic or global level of self-esteem is solidified (Mruk, 2006). Thus, investigating self-esteem development during this period is essential to understanding how adolescents and young adults may cope with significant and challenging life events. Low self-esteem has been shown to be a predictor of depression in adolescence (Orth, Robins, & Roberts, 2008), poor physical health and higher levels of criminal behavior in adulthood (Trzesniewski et al., 2006); as such, identifying which common factors are associated with poor self-esteem is critical to healthy development.

While the literature agrees that age is a factor in predicting self-esteem, findings regarding the developmental course of self-esteem, particularly during the transition from the adolescent years to the young adult years, have been inconsistent. Some studies have found increases in self-esteem during adolescence (Birkeland, Melkevik, Holsen, & Wold, 2012; Erol & Orth, 2011; Huang, 2010) while others have found declines (Block & Robins, 1993; Robins & Trzesniewski, 2005). Self-esteem change can be viewed in two distinct ways: (1) average differences across groups and (2) individual differences (Birkeland et al., 2012). Those separate approaches to self-esteem analysis partially explain the lack of consensus among studies (Erol & Orth, 2011). In addition, few studies are based on longitudinal data and differences in sample composition make it difficult to compare findings and generalize results to diverse populations (Robins et al., 2002).

A growing body of research has sought to determine risk factors for low self-esteem. Studies based on cross-sectional data show that female gender and lower family socioeconomic (SES) status may be related to lower self-esteem (Bachman, O'Malley, Freedman-Doan, Trzesniewski, & Donnellan, 2011; Birndorf et al., 2005; Block & Robins, 1993; Kling, Hyde, Showers, & Buswell, 1999; McClure, Tanski, Kingsbury, Gerrard, & Sargent, 2010; Veselska, Geckova, Reijneveld, & van Dijk, 2011). However, others have found no gender differences or even minimal SES impact (Mullis, Mullis, & Normandin, 1992; Rhodes, Roffman, Reddy, & Fredriksen, 2004). Instead Rhodes et al. (2004) reported that interactions among social class and school SES were more influential

speculating that racial and ethnic similarities among individuals in a school setting gather support from one another regardless of family SES. Still, gender and family SES are generally regarded as influential in adolescent self-esteem development. While gender and SES have been examined individually as main effects, gender differences within SES groups have not been the focal point of previous self-esteem research. If gender differences can be established, then gender-specific factors may aid in drawing a greater consensus in the factors influencing self-esteem development.

Parental influence on adolescent self-esteem development adds to the complexity of the model. Mruk (2006) states that parental involvement is one of the first antecedents of self-esteem and usually presented as a positive impact. Gecas and Schwalbe (1986) speculate that positive parental support and interest conveys a degree of self-worth to the offspring. The literature tends to indicate that maternal support particularly affects self-esteem in female offspring. Furthermore, Elfhag, Tynelius, and Rasmussen (2010) found that girls resembled their mothers' global self-worth based on a cross-sectional data of children under 12 years of age. However, it is unclear if maternal self-esteem as a time-varying covariate can predict offspring self-esteem from adolescence to young adulthood. Any gender or family SES differences influenced by maternal self-esteem remain to be seen. The purpose of the present study is to further examine the impact of maternal self-esteem, family SES, gender, and any significant interactions between these factors on self-esteem development in offspring from adolescence to young adulthood.

4.2   Methodology

4.2.1   Data Collection

Maternal self-esteem was measured in 1983 (at mean age 40), 1986 (at mean age 43) and 1992 (at mean age 49). Self-esteem score ranged from 0 to 9 on a 3-item measure. Three items indexed global self-esteem (Coopersmith, 1967) in each data collection: (1) I feel satisfied with myself; (2) I tend to see myself as a defeated person (reversed); (3) I see myself as a very respected and successful person. The items were rated from 0 (false) to 3 (true), and the internal consistency of the scale formed by summing them was 0.62, 0.63, and 0.69 in 1983, 1986, and 1992, respectively.

Offspring self-esteem was measured in 1983 (mean age of 13), 1986 (mean age of 16) and 1992 (mean age of 22). Four items indexed global self-esteem in each protocol: (1) I feel that I have a number of good qualities; (2) I feel that my life is very useful; (3) I am a useful person to have around; and (4) I feel I do not have much to be proud of (reversed). The items were rated from 1 (false) to 4 (true), and the internal consistency of the scale formed by summing them was 0.64 in adolescence and 0.69 in young adulthood (Berenson et al., 2005).

Family SES was measured as a standardized sum of standardized measures of father's educational level, mother's educational level, family income, father's occupational status, and mother's occupational status (if employed). Although many studies use only one or two of these measures, a history of research on SES indicates that the best measure combines these components (Cohen et al., 2008).

4.2.2 Data Analysis

Linear mixed-effects modeling (LME), also known as individual growth modeling, was chosen as a method for analysis given the longitudinal nature of the data presented (Laird & Ware, 1982). Offspring self-esteem, the dependent variable, is continuous and measured repeatedly over time. The purpose is to fit a population model to estimate the effects of maternal self-esteem, gender, and family SES on mean level and age change trajectory for offspring self-esteem. The data were collected over three separate time points spanning across 10 years, where offspring age is used as the time variable. Thus, variations in self-esteem over time are expected for each individual. Variations between individuals are also expected. Given these assumptions, both the intercept and slope are considered as random-effects for all models tested. Random-effects in the multi-level model allow for estimation of parameters affected by differences within individuals and between individuals (Laird & Ware, 1982; Singer, 1998). In other words, the random-effects provide information on the variation in individuals' means and variation in individuals' slopes. Meanwhile, fixed-effects estimate population average effects of predictors. Growth modeling allows for the estimation of both fixed-effects and random-effects. Age is centralized in all models tested for ease in interpretation of results (Singer, 1998).

From plotting the individual offspring self-esteem scores, we observe a general upward trend. Figure 4.1 is a snapshot of the raw data taken from 16 subjects representative of the sample. We may infer that self-esteem increases linearly over time. A plot of the mean self-esteem over time for all subjects

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confirms a general upward trend that may be modeled linearly (Figure 4.2(a)). From Figure 4.2(b), we observe a similar trend for males and females. Males tend to have slightly higher self-esteem during adolescence (males indicated by a 1 and in red), but females catch up to males at some point during young adulthood (females indicated by a 0 and in blue).

Since we are interested in the gender and SES effect, we also plot the observed mean self-esteem scores for the low and high SES groups (Figure 4.3). In general, all that is observed is a general upward linear trend for both groups.
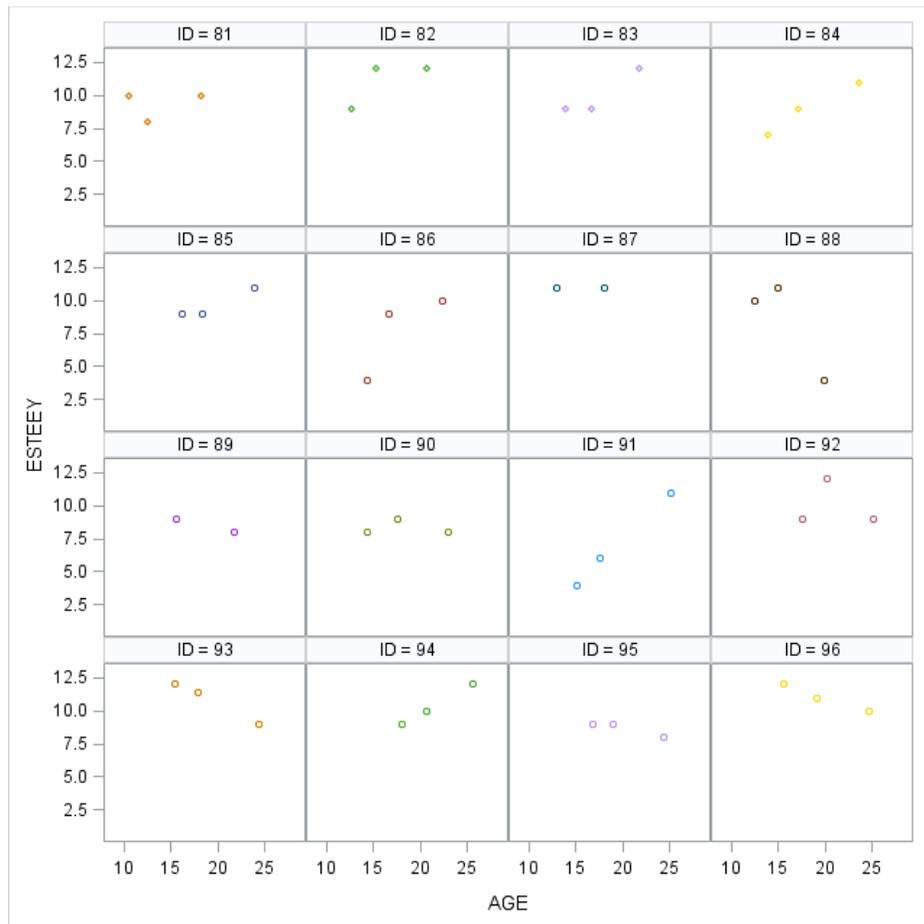
Figure 4.1   Individual Observed Offspring Self-Esteem Score for 16 Representative Subjects
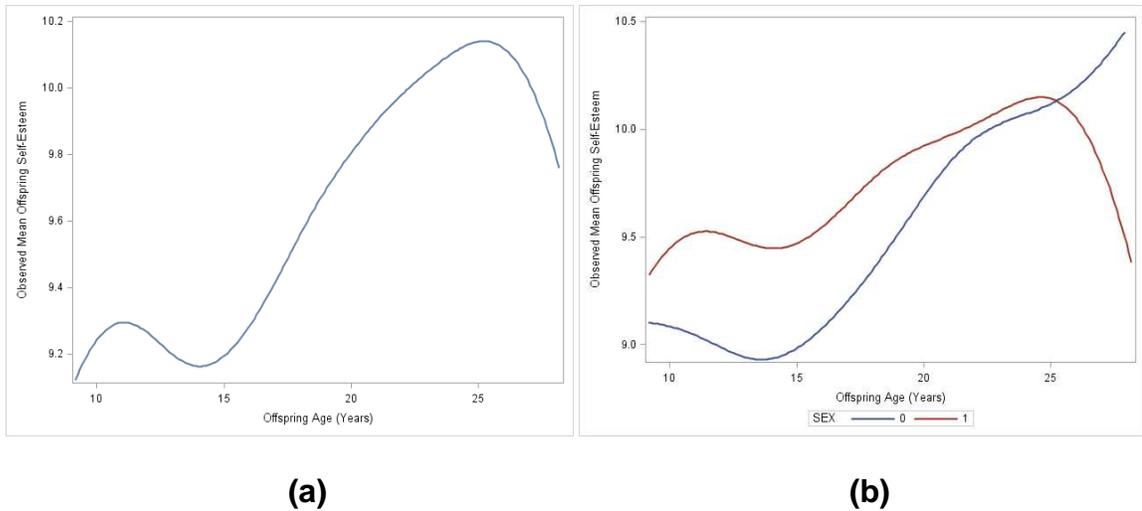
Figure 4.2   Observed Mean Offspring Self-Esteem by Age: (a) All Subjects, (b) By Gender
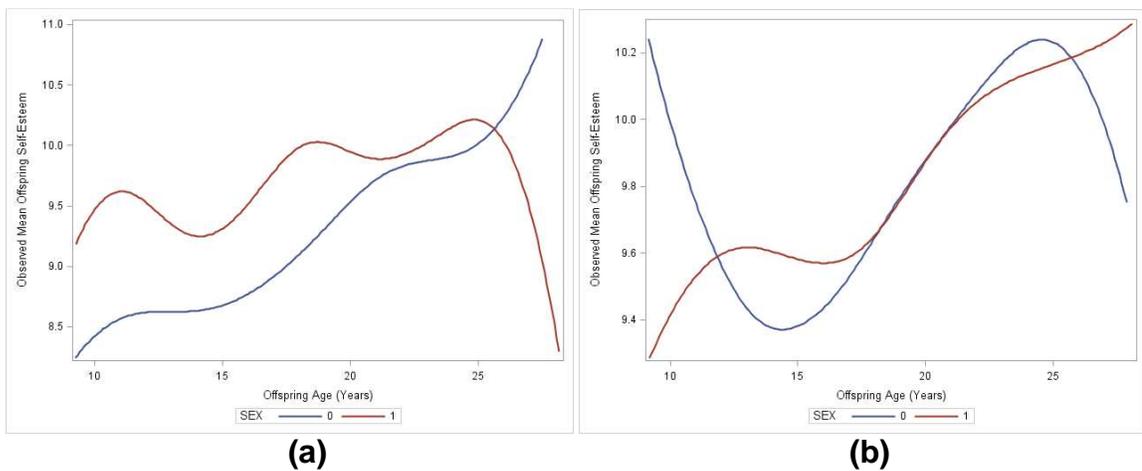
Figure 4.3   Observed Mean Offspring Self-Esteem by SES and Gender: (a) Low SES, (b) High SES

The data exploration above helps in choosing a basic model for offspring self-esteem development. The basic model examines the linear age changes in offspring self-esteem. No other predictors were included in the model. Age, as mentioned previously, is centered at the mean (17 years) when placed into the model for all analyses to facilitate interpretation. In other words, estimates represent offspring self-esteem mean values at age 17. *The basic linear mixed-*

effects model (4.1) with random-effects for both intercept and slope is given as follows:

$$y_{ij} = (\beta_0 + b_{0i}) + (\beta_1 + b_{1i})age_{ij} + e_{ij}, \qquad (4.1)$$

where $e_{ij} \sim N(0, \sigma^2)$. Our initial main model includes all covariates of interest: gender, SES and maternal self-esteem (MSE). These covariates are considered fixed covariates to estimate their effects on offspring self-esteem. Offspring age and maternal self-esteem are the only time-varying covariates. As with age, maternal self-esteem and family SES, both continuous variables, are centered at their means (6.72 and 10, respectively). In the case of SES, a score of 10 or above is considered high SES while a score of less than 10 indicates low family SES status. For clarification, females are the reference group in the gender variable. Thus, results in the next section are presented from the female reference point. This **main effects model** (4.2) may be expressed as follows:

$$y_{ij} = \beta_{0i} + \beta_{1i}age_{ij} + \beta_2 SES_i + \beta_3 gender_i + \beta_4 MSE_i + e_{ij} \qquad (4.2)$$

$$\begin{cases} \beta_{0i} = \beta_0 + b_{0i} \\ \beta_{1i} = \beta_1 + b_{1i} \end{cases},$$

From the main effects model, interaction terms were then examined. Interactions between maternal self-esteem and family SES, family SES and gender, maternal self-esteem and gender, and slope differences by gender and family SES are considered. A significant interaction term is one that yields a p-value of less than α=0.05. Various combinations of interaction terms were also considered. The Akaike's Information Criteria (AIC) obtained from the SAS output was used to assess if the models were a good fit. A lower AIC was desirable.

A final interaction model was built and is discussed in the next section. The unstructured variance-covariance matrix for the random-effects was selected as the best fit for this dataset based on the AIC values. The unstructured option indicates a separate variance or covariance component for the intercepts and slopes (Singer, 1998). All models used the unstructured covariance.

4.3 Results

4.3.1 Descriptive Statistics

Table 4.1 shows that the average offspring self-esteem is 9.3 (at wave 1), 9.4 (at wave 2) and 10.0 (at wave 3), respectively. Offspring self-esteem increased from 9.3 to 10.0 during the 10 year follow-up. Although average self-esteem in female offspring at each time point (9.0, 9.2, and 9.9) is lower than average male self-esteem (9.6, 9.5, and 10.0), the difference becomes smaller over time. For example, at wave 1, the difference is 0.6; while it is only 0.1 at wave 3. The average self-esteem for high SES females (9.5, 9.4, and 10.2) is much higher than the average self-esteem for low SES females (8.7, 9.0, and 9.7). The average self-esteem for low SES males (9.6, 9.4, and 10.0) is much higher than the average self-esteem for low SES females (8.7, 9.0, and 9.7). Maternal self-esteem remained relatively stable over the 10 year period.

Table 4.1   Mean and Standard Deviation (SD) of Self-Esteem Measures by Demographic Characteristic (Total N=821)

	Wave 1 (1983)	Wave 2 (1986)	Wave 3 (1992)
Offspring			
All Subjects (N=821)	**9.3 (2.1)**	**9.4 (2.0)**	**10.0 (1.9)**
Females (N=403)	9.0 (2.3)	9.2 (2.1)	9.9 (1.8)
Low SES (N=220)	8.7 (2.4)	9.0 (2.2)	9.7 (1.9)
High SES (N=183)	9.5 (2.0)	9.4 (1.9)	10.2 (1.6)
Males (N=418)	9.6 (1.9)	9.5 (1.9)	10.0 (1.9)
Low SES (n=223)	9.6 (1.9)	9.4 (2.0)	10.0 (1.9)
High SES (n=195)	9.7 (2.0)	9.6 (1.7)	10.0 (1.9)
Mother			
All Subjects (N=821)	**6.7 (1.6)**	**6.8 (1.6)**	**6.7 (1.7)**

4.3.2   Statistical Modeling Results

The basic unconditional model revealed that regardless of gender, adolescents at age 17 have an average self-esteem of 9.52 ($p<0.001$) that increased by 0.08 units per year ($p<0.001$) (Table 4.2). In the main effects model, males at age 17 reported an average self-esteem about 0.29 units higher than females ($p<0.01$) (Figure 4.4). With every unit increase in maternal self-esteem, offspring self-esteem increases by 0.10 ($p<0.001$) after adjusting for offspring age, gender and family SES (Figure 4.5). Our main model also suggests that family SES, based on a continuous measure, significantly influences offspring self-esteem by a 0.16 unit increase ($p<0.01$) with each unit increase in family SES (Table 4.2). This is equivalent to stating that high SES (+1SD) adolescents will show an increase in self-esteem by 0.16 standard deviations. Meanwhile, self-esteem will decrease in low SES (-1SD) adolescents by 0.32 standard deviations.

Table 4.2 **Developmental Trajectories of Offspring Self-Esteem between Ages 9 and 28 as Related to Gender, Family SES and the Trajectory of Maternal Self-Esteem**

Parameters	Basic Model			Main Effects Model			Interaction Model		
	Coefficient	SE	p value	Coefficient	SE	p value	Coefficient	SE	p value
Intercept	9.52	0.05	<.0001	9.66	0.07	<.0001	9.69	0.07	<.0001
Offspring age [1]	0.08	0.01	<.0001	0.07	0.01	<.0001	0.05	0.01	0.0002
Gender				-0.29	0.11	0.0055	-0.34	0.11	0.0012
Maternal self-esteem [2]				0.10	0.03	0.0005	0.10	0.03	0.0002
Family SES [3]				0.16	0.05	0.0037	0.04	0.08	0.6269
Interaction [4]:									
Offspring age × Gender							0.05	0.02	0.0071
Offspring age × SES							-0.02	0.01	0.0481
Gender × SES							0.26	0.11	0.0136

(1). Offspring's age was centered by the mean age of 17;
(2). Maternal self-esteem was centered by the mean (6.72);
(3). Family SES was centered by the mean of 10;
(4) Gender was coded 1=female and 0=male, no three ways or other two ways interactions were found significant.

Table 4.3 **Offspring Self-Esteem by Family SES Status***

Parameters	Low Family SES (N=443)			High Family SES (N=378)		
	Coefficient	SE	p value	Coefficient	SE	p value
Intercept	9.1	0.11	<.0001	9.67	0.11	<.0001
Offspring age	0.09	0.01	<.0001	0.06	0.01	<.0001
Gender	-0.56	0.15	0.0002	-0.01	0.15	0.9546
Maternal self-esteem	0.11	0.04	0.003	0.10	0.04	0.0221

* Offspring's age was centered by the mean of 17; gender was coded 1=female and 0=male; Maternal self-esteem was centered by the mean of 6.72; SES score < 10 (mean SES score) coded as low family SES, SES score ≥ 10 coded as high family SES

In the interaction model, gender and SES differences play a significant role. As Table 4.2 indicates, average female self-esteem is 0.34 units lower than males; a similar observation noted from the main effects model. Although, female self-esteem is lower on average, it increases at a higher rate than males (0.10 vs. 0.05, $p<0.01$, Table 4.2, Figure 4.4). As shown in Figure 4.4, by young adulthood, female self-esteem trajectory crosses that of the male trajectory.
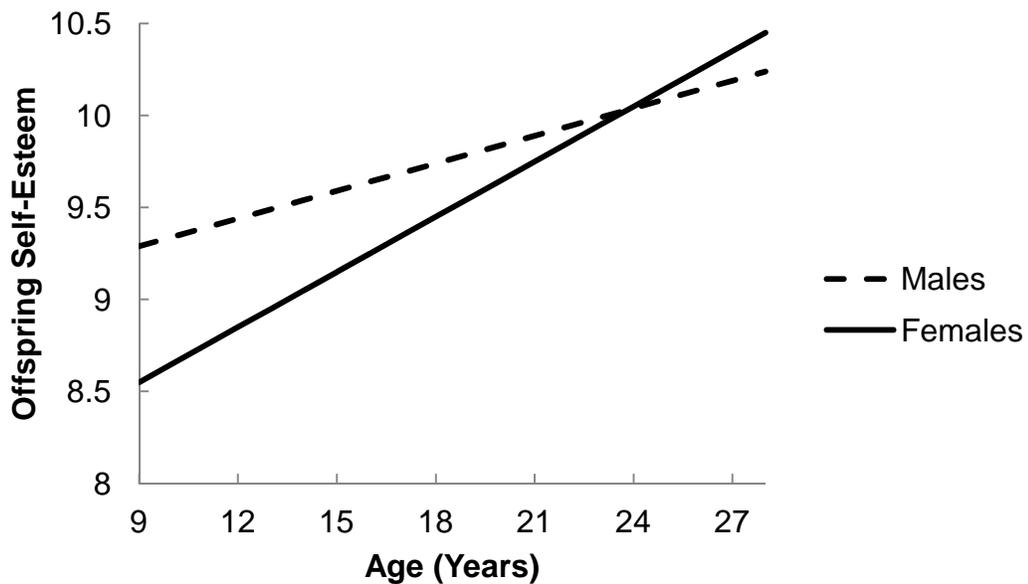
Figure 4.4   Predicted Offspring Self-Esteem Development by Gender

From the interaction model, we may conclude that gender differences are also found by family SES. Among females, a one unit increase in SES yields an average self-esteem increase of 0.26 units (Table 4.2). However, as time progresses, increases in family SES inhibit self-esteem growth by 0.02 units. As in the main effects model, maternal self-esteem had the same effect on offspring self-esteem development (one unit increase in maternal self-esteem yields an average of 0.10 unit increase in offspring self-esteem, Table 4.2, Figure 4.5).
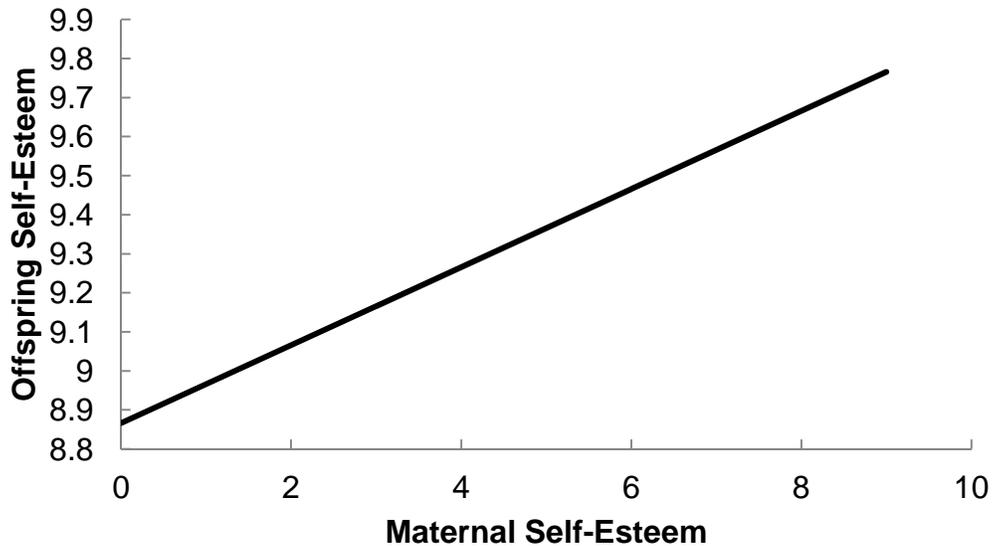
Figure 4.5   Predicted Offspring Self-Esteem Development by Maternal Self-Esteem

Finally, to further examine the significant gender difference by family SES, we stratified SES by high and low. Table 4.3 helps to interpret the significant interaction between gender and SES seen in Table 4.2. Among both family SES groups, self-esteem increases with age. As in previous models, maternal self-esteem positively predicts offspring self-esteem by at least 0.10 units, on average (Table 4.3). In the low family SES group, we can see that average self-esteem is significantly lower in females (difference of 0.56, $p<0.001$, Table 4.3). However, among the high family SES group, the difference in gender is not statistically significant ($p>0.05$, Table 4.3). We conclude from Table 4.2 that a gender difference by SES exists and as seen from Table 4.3, this difference is only found among low SES subjects. Figure 4.6 is a graphical representation of the results from Table 4.3.
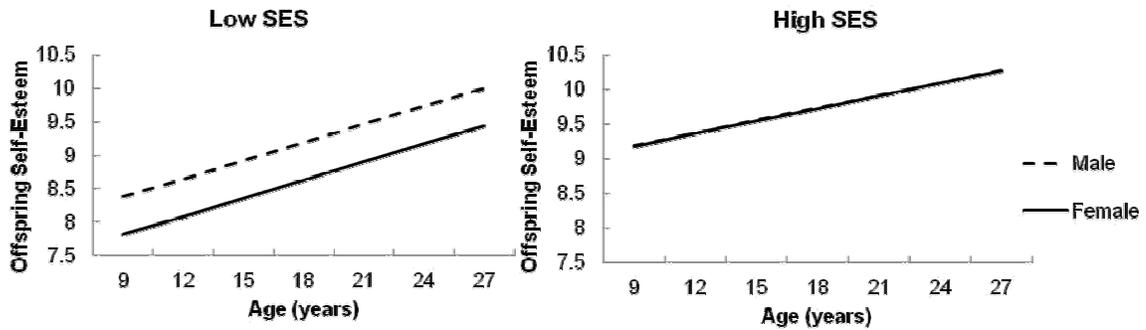
Figure 4.6   Predicted Offspring Self-Esteem Development by SES and Gender

4.4   Implications of Research

The main findings presented in the present study are that maternal self-esteem, family SES and gender are significant predictors of offspring self-esteem. The overall trend of the population self-esteem is positive and linear for both generations. The data suggests that females have significantly lower self-esteem, on average, with both male and female self-esteem increasing with age. However, female self-esteem tends to increase at a slightly faster rate than males. Further, gender differences were found only among low family SES subjects.

Ho, Lempers, and Clark-Lempers (1995) found that the parent-adolescent relationship suffers as a result of family economic hardships. Low-level SES families may experience more stress that may manifest in less parental support and increased discipline, both of which may affect offspring self-esteem. Given that females are affected more by perceived parental support, it makes sense that females in a low-level SES family have lower self-esteem than males. While there are no gender differences in the high-level family SES group, we did find that females from high-level SES families tend to have higher self-esteem

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compared to females from low-level SES families. However, the family SES effect on females becomes less influential as they age. Another explanation for gender differences is in the different effects puberty has on males and females. Baldwin and Hoffmann (2002) speculate that female dissatisfaction with their body image during the early stages of puberty may contribute to gender differences. Girls who base their self-esteem on appearance tend to have the lowest self-esteem (Jacobs, Bleeker, & Constantino, 2003). If the emphasis on appearance and body image during the middle adolescence period is strong as indicated, then females from a high family SES would arguably have the means of attaining an appearance to their liking. Meanwhile, females from a low SES family – already struggling with meeting various expectations from friends, family and school – may be unable to achieve their "ideal" body image thereby hindering self-esteem further. Consideration may also be given to domain-specific self-concepts rather than global self-esteem in order to fully comprehend gender differences (Jacobs et al., 2003). A lack of significant gender difference finding among high family SES subjects should not indicate that one does not exist.

Coopersmith (1967) was the first to notice a positive relationship between self-esteem levels in mothers and their children. Children tend to imitate their parents. Hence, a parent who positively copes with life's challenges will demonstrate a beneficial example to children in contrast to a parent who avoids dealing with difficulties (Mruk, 2006). Ruiz, Roosa, and Gonzales (2002) found significant associations between parenting style and child self-esteem. Our

findings support the evidence that mothers positively influence offspring self-esteem. Previous research supports the evidence that daughters are much more affected by maternal self-esteem than sons (Elfhag et al., 2010). This cross-sectional study concluded that while mothers' self-worth was correlated with both daughters and sons, daughters resemble their mothers' self-worth, whereas sons tend to resemble their fathers' self-worth.

Our findings also show that maternal self-esteem has a significant positive impact on offspring self-esteem, regardless of gender. No significant interaction by gender on the relationship between maternal self-esteem and offspring self-esteem from adolescence to adulthood were found. This may reflect developmental differences across childhood, and the years spanning the adolescence to adulthood transitional period. As parents influence a child's own perceptions of the world, values and self-beliefs, this influence may diminish as the child grows older. Effective parenting during adolescence comes from fostering an emotional attachment to parents as well as developing a sense of autonomy (Jacobs et al., 2003). Autonomy allows adolescents to make their own decisions and aids in solidifying an individual identity (Jacobs et al., 2003). While maternal self-esteem may affect offspring self-esteem during childhood, the extent of influence changes towards young adulthood. Late in adolescence, other factors may become more influential in adolescent development such that male and female self-esteem behave similarly when examining maternal self-esteem.

In summary, the present study suggests that maternal self-esteem positively predicts offspring self-esteem, regardless of gender and family SES

status. Gender differences require further research, particularly at varying levels of family SES. It is worth noting that the present study followed adolescents from average ages of 13 to 22. As adolescence is marked with many critical changes occurring within a short period, the factors affecting self-esteem development may also change frequently during this time period. This was seen with family SES having less of an impact on female offspring self-esteem over time. It is also seen in the gender effect. While females have a lower average self-esteem, given enough time, the models suggest female self-esteem catches up to male self-esteem. The turning points for these changes should be further researched.

The limitations of the present study require consideration. First, there is no data for paternal self-esteem. Further research should focus on understanding the dynamics of the household unit as a whole. Presence or absence of the either parent due to separation, divorce, delinquency, or other factors should be considered. Studying the role that fathers play in the family may reveal why no significant impact from maternal self-esteem was found on male offspring. Second, the present study was conducted with a sample in which a relatively high proportion is Catholic (54%) and Caucasian (91%), it is not clear whether the findings are applicable to other demographic groups within the U.S. population.

Despite these limitations, to the best of our knowledge, these are the only findings that provide details on self-esteem development for both offspring and mother in a community-based sample followed longitudinally over time and demographically representative of the region from which sampling took place.

The present study also has methodological strengths, including use of a prospective design, longitudinal self-esteem measures, a standardized summary measure of family SES, and the use of multilevel growth models for repeated measurement data. In addition, the study emphasized normative changes in youth self-esteem with age for both males and females, and findings highlight the influence of maternal self-esteem and family SES.

Chapter 5

Impact of Church Attendance on Depressive Symptoms Development[3]

5.1 Background

Several studies have investigated the relationship between religion and depression to determine whether a strong sense of spirituality or religion is implicated in lowered risk for depression. It is reported that people who routinely attend religious services are more likely to view life positively and are less likely to have symptoms of depression. Frequent church attendees are significantly more likely to report social support regardless of how often they attended services, suggesting that participating regularly in religious services may help enhance social interaction (Schnall et al., 2012).

Kasen, Wickramaratne, Gameroff, and Weissman (2012) reported that greater religiosity may contribute to development of resilience in certain high risk individuals. Increased religious attendance significantly reduced incidence of mood and psychiatric disorders, with a greater reduction in offspring whose parents had depression than in offspring of non-depressed parents. Offspring of depressed parents who reported that religion was important were 74% less likely to have a mood disorder than those who did not place importance on religious activity (Kasen et al., 2012). Findings suggest a decreased risk stronger in those

exposed to significant negative life events compared to those unexposed. (Kasen et al., 2012) findings support a positive longitudinal link between religious beliefs and mental health among high-risk individuals. A curvilinear trajectory of depressive symptom over time was observed in a recent study based on community-dwelling older adults: participants who attended religious services more frequently tended to have fewer depressive symptoms, whereas those with high levels of intrinsic religiosity usually experienced a steady decline in number of depressive symptoms (Sun et al., 2012).

While many studies have supported the benefits of religious involvement on mental health and overall well-being, other studies question the associations. Maselko and Buka (2008) reported that the rates of psychiatric illness among those who reported never attending religious services were not statistically different from those who either had always been religiously active or those who reported changing patterns of attendance. Another cohort study showed that depression may be a likely cause for people to stop attending religious services (Maselko, Hayward, Hanlon, Buka, & Meador, 2012). In this study, more than 90% of the participants reported religious involvement as a child, but only half reported involvement as adults. Women who developed early depression were more likely to stop going to religious services by their early twenties. This observation may imply that those who regularly attend religious services are a group with low rates of depression to begin with and not suggestive of religiosity reducing depression rates. Other studies have also found that depression has reduced religiosity (Atkinson & Malony, 1994; Koenig, 1993).

Many studies are based on cross-sectional data. Thus, it is not possible to establish causality as to whether depression leads to a lack of religious life or whether religious life protects against depression. Moreover, there is limited knowledge about how depression changes in individuals in relation to their religious involvement throughout their lives. Childhood is a period when parental influence on religiosity is strong, while adulthood is when religiosity is self-determined. The present study investigates the impact of church attendance on depression development in a community based longitudinal study.

5.2 Methodology

5.2.1 Data Collection

The data for the current study are based on 756 subjects (50.4% female, 49.6% male) interviewed at wave 1, a mean age of 13, for their church attendance and depressive symptoms. Follow-up measures of depression were taken in wave 2 (mean age of 16), wave 3 (mean age of 22) and wave 4 (mean age of 33). Participants ranged from about 9 years of age to about 40 years of age, with an average of 21 years. At each assessment, participants completed a five-point Likert-response item to rate frequency of their attendance at religious services from never to once a week or more (How often do you go to church or temple to attend religious services? Never, a few times a year, about once a month, 2 or 3 times a month, once a week or more).

To compare the difference between subjects who currently attend religious services and those who did not, church attendance was coded as 0 (did not go to church) and 1 (attended church). Subsequently, according to the frequency of

church attendance, the variable was re-coded as 0, 1, 2, and 3, which stand for "did not go to church", "went to church yearly", "went to church monthly", and "went to church weekly", respectively.

Major depression was diagnosed by the Schedule for Affective Disorders-Lifetime version (Kaufman, Birmaher, Brent, & Rao, 1997; Mannuzza, Fyer, Klein, & Endicott, 1986). Symptoms in adolescents were assessed using information from both parent and child. Depressive symptoms were measured at wave 1 (1983), wave 2 (1986), wave 3 (1992) and wave 4 (2003) and assessed with items covering most DSM (*Diagnostic and Statistical Manual of Mental Disorders)* depression criteria adapted from the System Checklist-90 (Derogatis, Lipman, Rickels, Uhlenhuth, & Covi, 1974); self-reported depressive symptoms have high reliability and validity (Angold, Costello, & Worthman, 1998). Responses to the questions were on a Likert scale of occurrence frequency over the preceding years. The measure of depressive symptoms was used in preference to a measure based on the diagnostic assessment due to the wording of the latter changed as necessary to the changing ages of the youth and the employment of a clinical diagnosis in the most recent. The scale does not reflect major depression disorder instead of symptoms of dysthymia (Cohen et al., 2008), which would require a definable depressive episode. Internal consistency reliability was 68 in early adolescence and increased steadily with age to 0.85 in the most recent assessment. Collected depressive symptom data were coded as a continuous variable with a range from 0 to 24 according to the symptom degree.

Covariates include gender, race, family socioeconomic status (SES), lifetime trauma and recent negative events. Family SES was measured as a standardized sum of standardized measures of father's educational level, mother's educational level, family income, father's occupational status, and mother's occupational status (if employed). Although many studies use only one or two of these measures, a history of research on SES indicates that the best measure combines these components (Cohen et al., 2008). Negative stress life events (SLE) refer to those that cause people to feel hassled, distressed, upset, guilty or scared. SLEs were reported by the youth for the period prior to each assessment. Relevant items include parental fighting, family loss of income, separation from a parent, loss of a close friend, suspension or expulsion from school, and death of a family member (Cohen et al., 2008). Cumulative trauma refers to events that could take away a sense of control and cause great emotional upheaval, such as history of child abuse or neglect, parental alcohol or substance abuse or dependence, parental arrest/imprisonment, parental death, death of a spouse, death of a child, army combat experience, close personal exposure to violent death, or family suicide. As implied by the variable name, these are the experiences that previous literature has identified as most likely to have long-lasting negative impact. Incidence was accumulated over the assessed years and employed as a time-varying covariate. Both SLEs and lifetime trauma were quantified based on possible stress intensity that they triggered, the mean score of recent negative events is 1.66 with a range of 36.5; the mean score for lifetime trauma is 0.98 with a range of 10.

In model building, gender and race were included as control variables and investigated with regard to potential influence on depressive symptoms and the relationships between religious service attendance and depressive symptoms.

5.2.2 Data Analysis

As in the previous examples, linear mixed-effects modeling (LME) was chosen to analyze the present longitudinal study. The main interest is in fitting a population model for the data assessing both average and slope differences of different comparison groups. LME models can accommodate the complexities and permit model specification determined by both within-subject variation and between-subject variation (Laird & Ware, 1982; Nakai & Ke, 2009). Age is the time variable of interest. Depressive symptoms score varies among subjects as they age. Hence, both the intercept and slope are considered as random-effects for all models. These random-effects in the multi-level model allow for estimation of all parameters within individual level and between individual levels (Singer, 1998). The outcome variable (depressive symptoms score) is continuous. Age was centralized at the mean when placed into the model for all analyses.

The analysis begins with a graphical representation of the raw data. Figure 5.1 is a plot of the depressive symptoms score over time for 16 of the individuals. Plots for all individuals were assessed, but only 16 representative subjects were selected for illustration. It appears that the depressive symptoms score for these subjects follow a quadratic curve. Furthermore, there is a general downward trend over time. Hence, a quadratic age term is considered for the initial models.
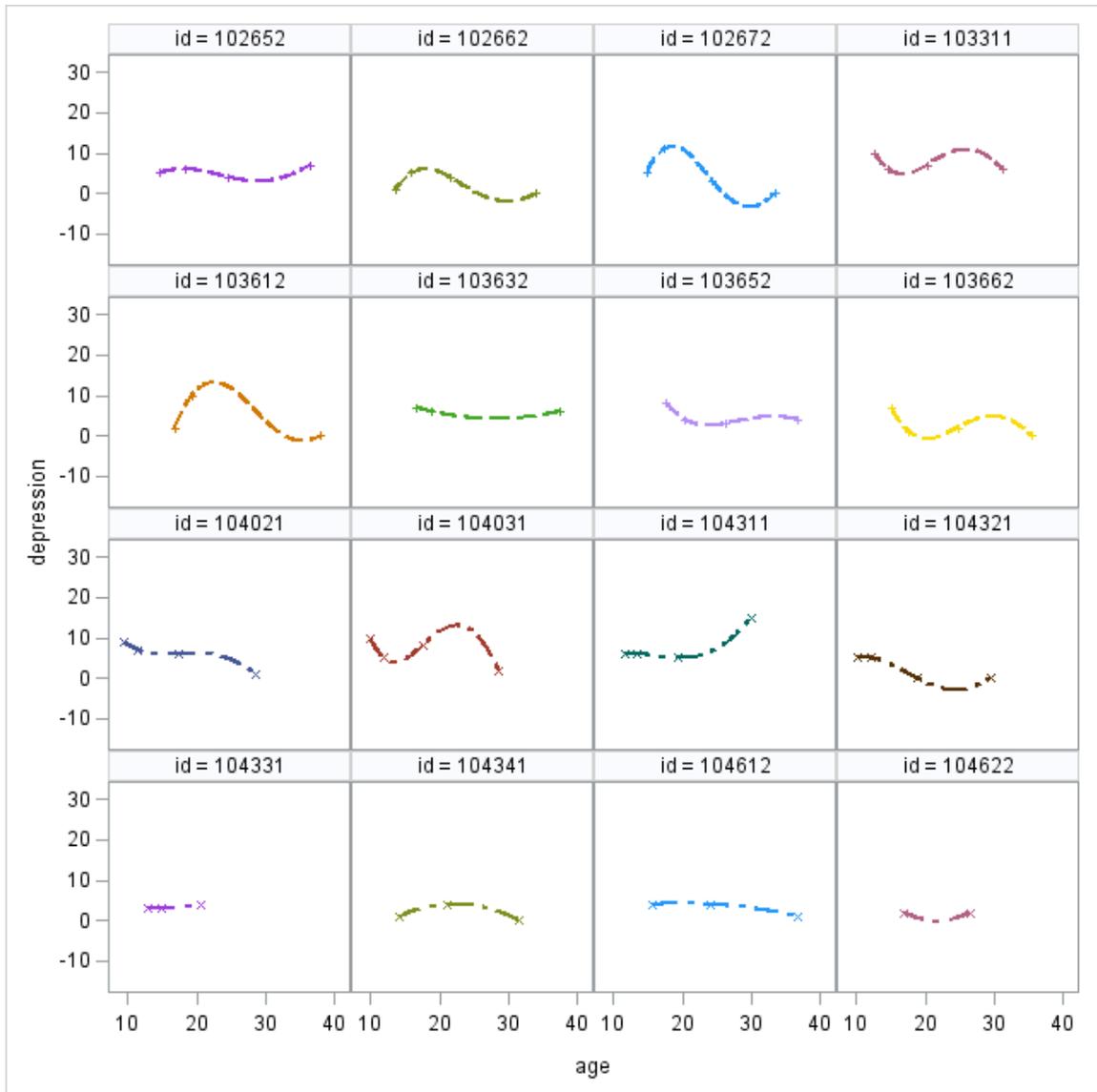
Figure 5.1   Individual Observed Depressive Symptoms Score by Age for 16 Representative Subjects

The observed average depressive symptoms score by age shown in Figure 5.2(a) further support testing of a model with a quadratic age term. Comparing the mean average depression scores (Figure 5.2(b)) between church attendees (indicated by a 1 and in red) and non-attendees (indicated by a 0 and in blue), the quadratic curvature is maintained for both groups.

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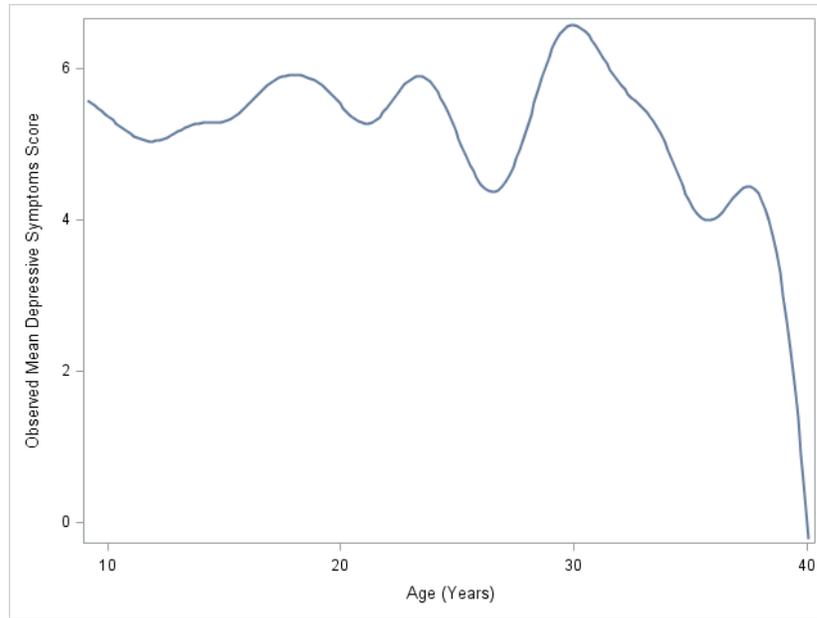
(a)
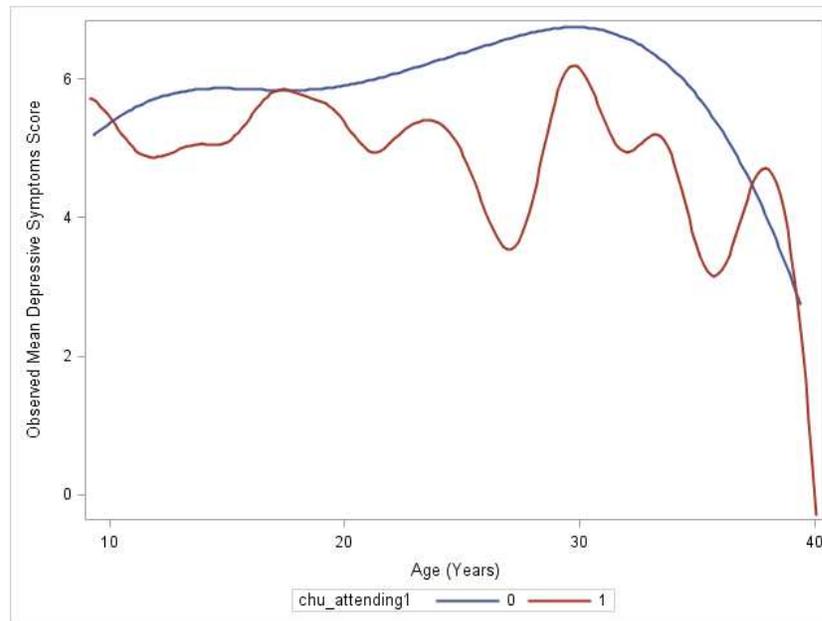
(b)

Figure 5.2   Observed Average Depressive Symptoms Score by Age: (a) All Subjects, (b) By Church Attendance

The model building process begins with a basic model. The basic model contains only age and no other covariates. While age is considered a random-

effect, there is no indication from the data that the quadratic age term also qualifies as a random-effect. After a trial of several models with and without a quadratic age term, comparing the Akaike's Information Criteria between each model, the conclusion for the best fit **basic unconditional growth model** (5.1) is as follows:

$$y_{ij} = \beta_{0i} + \beta_{1i} age_{ij} + e_{ij} \qquad (5.1)$$

$$\begin{cases} \beta_{0i} = \beta_0 + b_{0i} \\ \beta_{1i} = \beta_1 + \beta_2 age_{ij} + b_{1i} \end{cases}$$

Where $e_{ij} \sim N(0, \sigma^2)$, the random-effects $(b_{0i}, b_{1i}) \sim N(0, \Sigma)$ and Σ is a 2×2 variance-covariance matrix. The above model yields the predicted average depressive symptom for the sample population as well as the overall slope change by age. The next step is to add covariates of interest in order to assess if average depressive symptom and its trajectory depended upon church attendance.

As stated previously, church attendance was coded as binary (1 or 0) for each subject. Those who did not go to church were coded as 0 and any combination of more than a few times a year coded as 1. The **main effects model** (5.2) for church attendance (CA) is expressed as follows:

$$y_{ij} = \beta_{0i} + \beta_{1i} age_{ij} + \beta_3 CA_{ij} + e_{ij}, \qquad (5.2)$$

$$\begin{cases} \beta_{0i} = \beta_0 + b_{0i} \\ \beta_{1i} = \beta_1 + \beta_2 age_{ij} + b_{1i} \end{cases}$$

While the results indicated a good fit, other covariates were subsequently added to the model to assess any potential influence on depression development. Sex,

race, family SES, lifetime trauma and recent negative events were added to the model. Sex and race are categorical factors while SES, trauma and negative event (events) are continuous variables.

In order to assess if average depressive symptoms and its trajectory depended upon church attendance after controlling for other factors as described above, the **main effects model for church attendance with controls** (5.3) is expressed as follows:

$$y_{ij} = \beta_{0i} + \beta_{1i}age_{ij} + \beta_3 CA_{ij} + \beta_4 trauma_{ij} \qquad (5.3)$$

$$+\beta_5 events_{ij} + \beta_6 sex_i + \beta_7 race_i + \beta_8 SES_i + e_{ij}$$

$$\begin{cases} \beta_{0i} = \beta_0 + b_{0i} \\ \beta_{1i} = \beta_1 + \beta_2 age_{ij} + b_{1i} \end{cases}$$

To test the relationship between frequency of attending church and depressive symptoms, variable church attendance was coded as 0, 1, 2, 3 according to the frequency that subjects went to church. For frequency of church attendance, the variable was treated as a continuous or categorical variable. The correlation was analyzed without controlling or with controlling covariates. The models for frequency of church attendance tested are similar to models (5.2) and (5.3), with frequency of church attendance in place of church attendance. Interaction terms were tested as part of the model building process. However, no significant interaction effect between church attendance and other covariates on depressive symptoms were found. The variance-covariance matrix for the random-effects was chosen to be the variance components structure as the best fit for this dataset. In other words, a distinct variance component was assigned to each effect.

5.3   Results

5.3.1 Descriptive Statistics

The analysis is restricted to 756 subjects, including 49.6% males and 50.4% females, who were 13 years or older at the 1983 interview. About 90% of participants are White while Black (including a few other ethnic groups) subjects account for about 9% (Table 5.1). The frequencies of attendance at religious services and depressive symptoms at all time-points are shown in Table 5.1.

Table 5.1   Frequency of Church Attendance and Average Depressive Symptoms Score by Wave

	Church Attendance N (%)	Depressive symptom (Mean ± SD)
Wave 1 (1983)		
No	108 (14.32)	6.24 ± 3.73
Yes	646 (85.68)	5.30 ± 3.32
Yearly	191 (25.33)	5.36 ± 3.06
Monthly	151 (20.03)	5.45 ± 3.37
Weekly	304 (40.32)	5.19 ± 3.45
Wave 2 (1986)		
No	154 (20.56)	5.58 ± 3.34
Yes	595 (79.44)	5.14 ± 3.23
Yearly	214 (28.57)	5.29 ± 3.36
Monthly	139 (18.56)	5.15 ± 3.06
Weekly	242 (32.31)	4.99 ± 3.22
Wave 3 (1992)		
No	220 (29.45)	5.98 ± 3.90
Yes	527 (70.55)	5.27 ± 3.41
Yearly	289 (38.69)	5.42 ± 3.22
Monthly	117 (15.66)	5.10 ± 3.55
Weekly	121 (16.20)	5.07 ± 3.71
Wave 4 (2003)		
No	213 (31.65)	5.79 ± 6.54
Yes	460 (68.35)	4.83 ± 5.64
Yearly	247 (36.70)	5.00 ± 5.64
Monthly	109 (16.20)	4.85 ± 5.65
Weekly	104 (15.45)	4.41 ± 5.66

At wave 1 (1983), about 14% did not go to church and more than 85% accepted religious service by going to church (Table 5.1, Figure 5.3). Of those church attendees, 25.33% attended church yearly, 20.03% went monthly, and

40.32% weekly. The observed average depressive symptom score for subjects who attended church and who did not were (5.3 ± 3.32) and (6.24 ± 3.73), respectively. The average depressive symptom score for yearly, monthly, and weekly church attendance were (5.36 ± 3.06), (5.45 ± 3.37), (5.19 ± 3.45), respectively (Table 5.1, Figure 5.4).
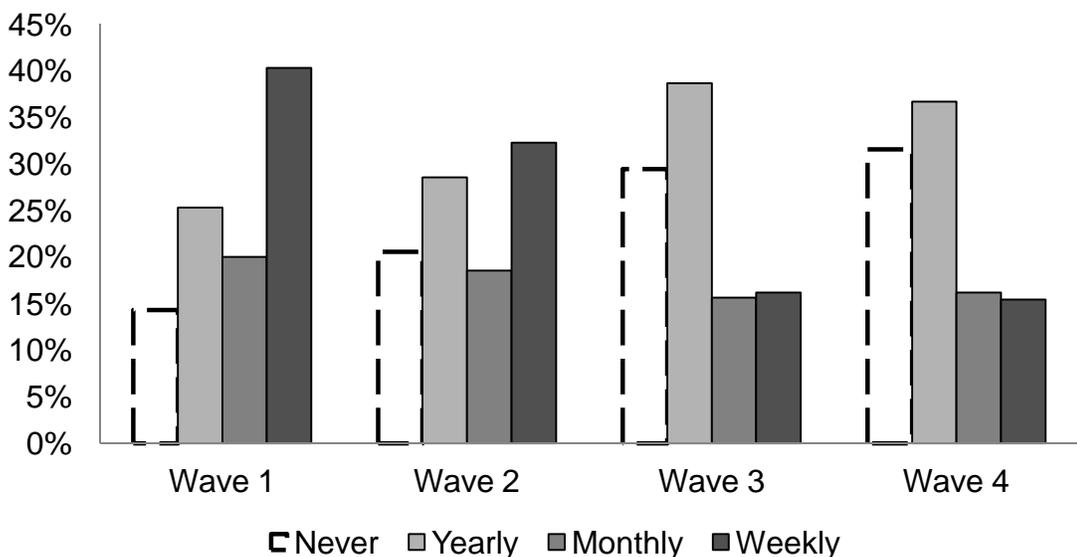
Figure 5.3   Observed Frequency of Church Attendance by Wave

At wave 2 (1986), 20.56% of participants did not go to church and 79.44% underwent religious service, of which, 28.57% attended church yearly, 18.56% attended church monthly, and 32.31% attended church weekly, respectively. The corresponding depressive symptom scores are (5.29 ± 3.36), (5.15 ± 3.06), (4.99 ± 3.22), respectively. Those who did not attend church had an average depression score of (5.58 ± 3.34) and the average score for all participants who attended church is (5.14 ± 3.23).

At wave 3 (1992), 29.45% of subjects, with an average depression score (5.98 ± 3.9), did not go to church; 70.55% subjects who did go to church had a

mean score of (5.27 ± 3.41) during the same period. Among church-attending subjects, 38.69% went to church yearly, 15.66% monthly, 16.2% weekly; their average depressive symptoms score were (5.42 ± 3.22), (5.1 ± 3.55), (5.07 ± 3.71), respectively.
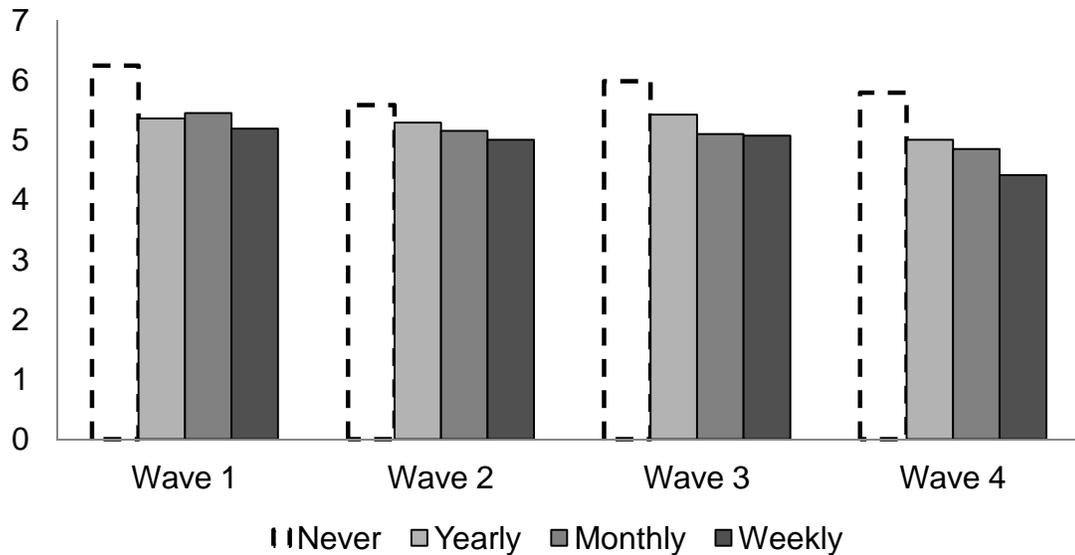
Figure 5.4   Observed Average Depressive Symptoms Score by Wave and Frequency of Church Attendance

During wave 4 (2003), the percentage of participants with no attendance was 31.65%. This group had an average depression score of (5.79 ± 6.54). Among 68.35% of participants who did go to church (average depression score: 4.83 ± 5.64), the proportions for the yearly, monthly, weekly church-attending subjects are 36.7%, 16.2% and 15.45%, respectively. Their corresponding average depression scores are (5 ± 5.64), (4.85 ± 5.65) and (4.41 ± 5.66), respectively.

From Figure 5.3, it is clear that while non-attendance and yearly attendance tended to increase, weekly attendance dwindled dramatically over

time. Despite these changes in attendance, average depressive symptoms score tended to decrease with time with weekly attendees showing the lowest average depressive symptoms score at each wave and non-attendees with the highest average score at each wave (Figure 5.4). The next section quantifies the magnitude by which each group's depressive symptoms score decreases with time based on the models in the previous section.

5.3.2 Statistical Modeling Results

The basic model in Table 5.2 demonstrates that the quadratic mixed-effects model fits the dataset very well. Without controlling for any covariates, on average, the depressive symptom score was 5.582 at the mean age of 20 with a linear increase of 0.012 units per year combined with a 0.004 unit deceleration in this increase (Basic Model from Table 5.2, Figure 5.5). As can be seen from Figure 5.5, the model shows a steady decrease in depressive symptoms score after about the age of 20.

To test the effect of church attending on depression development, church attendance (yes/no) was added into the model (Table 5.2, Figure 5.6). The results from this model indicate that attending church significantly predicts depressive symptom reduction even after controlling for demographic factors. Subjects who attended church reported 0.518 units lower on depressive symptoms than those who did not go to church (95% CI from -0.86 to -0.18, $p<0.005$). The predicted curve for relation of depressive symptom with church attendance versus non-attendance is demonstrated in Figure 5.6. The significant

average difference in depressive symptom score can be observed between attending church and not attending church.

Compared to not attending church, the more frequent the religious service attendance, the stronger the influence on depressive symptoms reduction. Yearly, monthly, and weekly church attendance reduced depression scores by 0.474 (95% CI from -0.841 to -0.106, $p<0.01$), 0.495 (95% CI from -0.933 to -0.057, $p<0.05$) and 0.634 (95% CI from -1.056 to -0.212, $p<0.005$) units, respectively, when compared with no church attendance (Table 5.2, Figure 5.7). While weekly attendance yields the lowest predicted depressive symptoms score, after about age 20, yearly attendance yields the lowest predicted average score (Figure 5.7). This may be due to the uneven distribution of subjects in each group since more subjects attended church yearly later in life. The most important thing to note is that church attendance will significantly reduce depressive symptoms score than non-attendance.

Table 5.2   Impact of Church Attendance on Depressive Symptoms Development

Parameters	Basic Model			Church Attendance versus Non-Attendance*			Frequency of Church Attendance*		
	Coefficient	p-value	95% CI	Coefficient	p-value	95% CI	Coefficient	p-value	95% CI
Intercept	5.582	<0.01	(5.37, 5.80)	4.618	<0. 01	(3.69, 5.10)	4.406	<0.01	(3.70, 5.11)
Age	0.012	0.40	(-0.02, 0.04)	-0.042	<0.01	(-0.07, -0.02)	-0.045	<0.01	(-0.07, -0.02)
Age×Age	-0.004	<0.05	(-0.01, -0.002)	-0.005	<0.01	(-0.01, -0.003)	-0.005	<0.01	(-0.01, -0.002)
Attendance				-0.518	<0.01	(-0.86, -0.18)			
Frequency:									
Weekly							-0.634	<0.01	(-1.06, -0.21)
Monthly							-0.495	<0.05	(-0.93, -0.06)
Yearly							-0.474	<0.01	(-0.84, -0.11)

* Model includes gender, race, SES, lifetime trauma, and negative life events as covariates
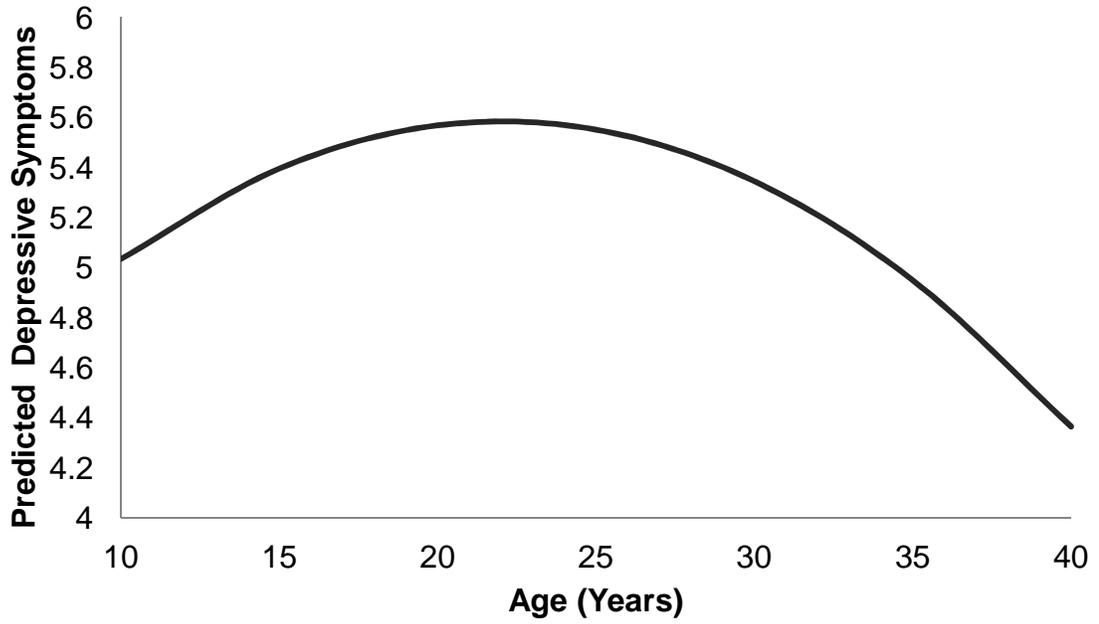
Figure 5.5   Predicted Depressive Symptoms Score by Age
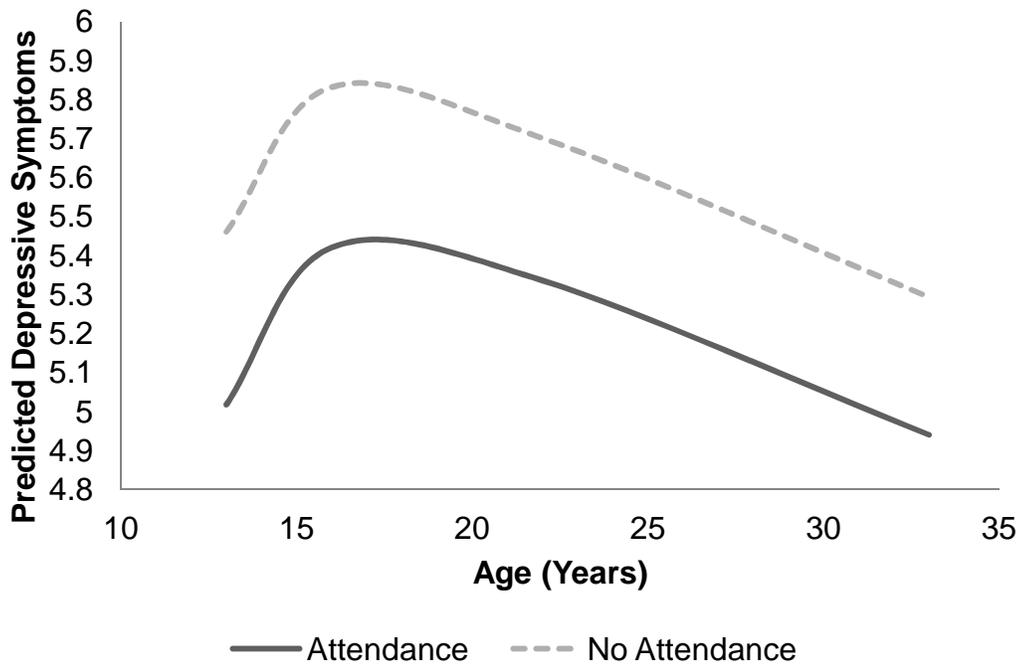
Figure 5.6   Predicted Depressive Symptoms Score by Church Attendance
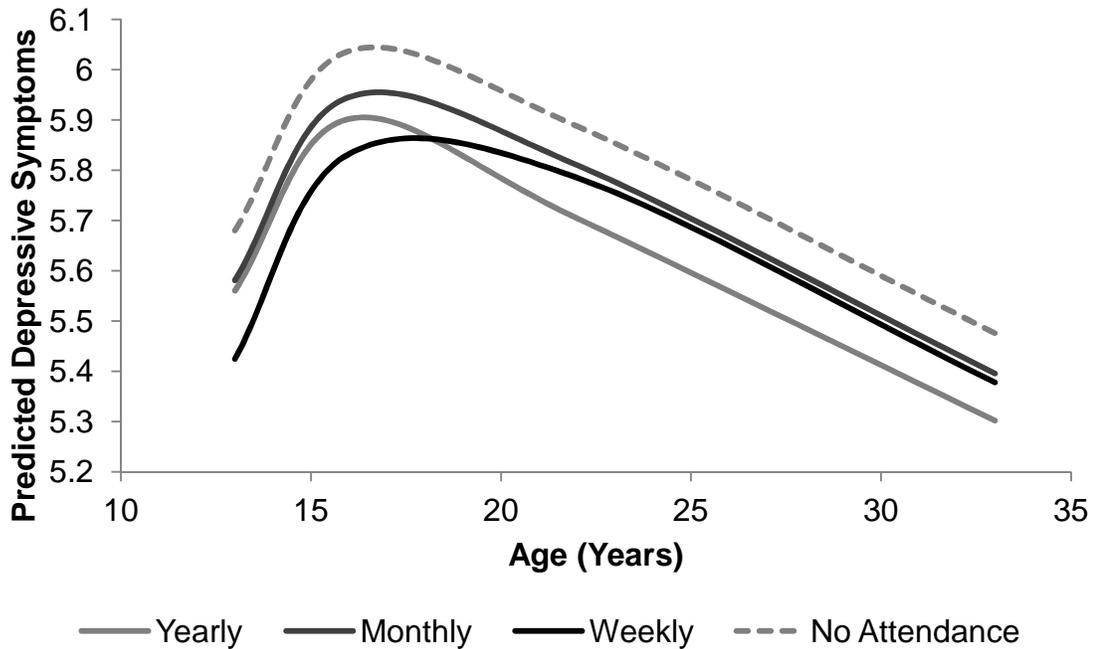
Figure 5.7   Predicted Depressive Symptoms Score by Frequency of Church Attendance

5.4   Implications of Research

There is a significant impact of major depression on population health status with a high prevalence in the population resulting in poor quality of life in those affected (Blazer & Kessler, 1994; Wells & Trust, 1989; Wulsin, Vaillant, & Wells, 1999). To identify protective factors against depression, scientists have investigated the relationship between religion and psychological well-being (Pargament & Saunders, 2007), which may link the needs of clients with the expertise of providers.

The study presented in this chapter is a community-based longitudinal study, which follows subjects from adolescence to adulthood. The findings indicate that church attendance significantly predicts depressive symptoms score development. Participants with a weekly church attendance have a much lower

mean score of depressive symptoms than those who did not attend. This result was observed throughout the period of assessment suggesting that religiosity may suppress depression development.

Maselko, Gilman, and Buka (2009) reported that onset of major depression could lead to a discontinued religious service attendance; the choice of ending religious activities may be a contributor to inverse correlations between religious participation and psychopathology. In the present study, it was noted that a higher proportion of subjects went to church weekly at the first collection of data while the percentage of subjects without attending church was the lowest (14.3%) at the same time point. Subsequent time periods revealed that the percentage of subjects who do not attend church increases with age and becomes 31.5% by the end of the study. Meanwhile, average depressive symptoms decreased over time. Although there is a decline of church attendance later in the study, there is no evidence to support decreased church attendance resulting from depression in our study. If depression had caused subjects to stop attending religious services, then these subjects would have higher depression scores at later time points in comparison with those non-attending participants at earlier time points. Among all non-attending subjects, however, those at wave 1 have the highest scores; the mean score is insignificantly lower during the three follow-up waves (Table 5.1). This decline may instead reflect factors such as a lack of motivation or boredom during the services, among other factors.

A main limitation in the present study is that no other aspect of religiosity was measured except attendance. In addition, the sample is primarily White,

which inhibits the generalizability of results. However, the use of a predominantly homogenous sample strengthens the internal validity of the study by reducing potential bias. Due to the many factors associated with major depression, we are unable to infer a causal relationship between religious service and depression symptom. Causality should be the focus of future studies.

Although our findings are insufficient to rule out a causal role of religious activity in major depression onset, they do raise substantive questions about whether religious involvement is the precursor to good health. Church attendance not only predicts depressive symptoms, but the frequency of attendance is also related to the score with higher attendance resulting in fewer symptoms. The mechanisms of how religion inhibits depression development or improves depressive symptoms are not so clear. Some of the literature suggests that religion makes people happier and less stressed (Ramirez et al., 2012). Religious-activity-related social contact could enhance one's ability to deal with stress and offer support to people who experience depression by giving them spiritual support to overcome various challenges (Berman et al., 2004; Patel, Shah, Peterson, & Kimmel, 2002). The positive aspects of religion could help people to accept failure and negative experiences as a part of life, and to make peace with them. When like-minded people come together through religion, they may share similar faith and beliefs forming a strong social core for supporting one another. This may not only help prevent depression, but also help in the recovery of depressed persons.

Depression is a common mental health problem. It is important to recognize its risk factors. The results of the present study demonstrate that both negative events and lifetime trauma are significantly associated with depressive symptoms development. Almost all negative life events appear to have a modest, but significant relationship with depression. The total number of negative events and the total number of daily hassles were reported to have the strongest relationship with depression (Kraaij, Arensman, & Spinhoven, 2002). Trauma, another risk factor, is sometimes considered as a seed of depression (Buodo, Novara, Ghisi, & Palomba, 2012). Trauma can occur from war, rape, murder, accidents, and even well-intentioned medical procedures. Depression is sometimes triggered by an identifiable event such that exposure to traumatic events is followed by full or partial posttraumatic stress disorder (Breslau, Davis, Peterson, & Schultz, 2000). The association between lifetime trauma, negative events and depressive symptoms development was found independent of religious service attendance.

Collectively, our main finding is that religious activity could suppress depressive symptom development in a community-based analysis. Such an effect is independent of demographic variables and family SES status, and thus it could benefit us to consider the impact of religious service on depression, when developing a psychological intervention for subjects in need. The present study adds to the body of research suggesting that religiosity reduces depressive symptoms. Further studies should consider causal inference between religiosity and depression.

Chapter 6

Summary and Conclusion

Longitudinal data have the feature that measurements are repeatedly collected for the same subject, often not in a consistent or uniform manner for all subjects. This inconsistency may result in an unbalanced design or missing data. The repeated measurements are correlated, violating the assumptions of independent observations from many traditional statistical methods. Linear mixed-effects modeling are a powerful approach to modeling longitudinal data. This approach has the ability to model both between-subject and within-subject variability through random-effects. It can also provide information on individual trajectories as well as population trajectories and can handle missing data. Both time-invariant and time-variant covariates can be accommodated in the model.

The use of linear mixed-effects modeling in our research allowed for significant contributions in adolescent health. In Chapter 3, we found that adolescents with an anxiety disorder a significantly lower average self-esteem than healthy adolescents. Furthermore, self-esteem trajectory varied by type of anxiety disorder with social phobia having the greatest relative impact. Adolescents with an obsessive-compulsive disorder showed a decline in self-esteem. Mental health information was obtained for all subjects in this study. Some subjects were known to have personality disorders, substance abuse, depression, anxiety, or a combination of any of these conditions. Prior to focusing

on subjects with an anxiety disorder as the comparison group, several models were performed to examine the impact of other disorders and any combination of disorders. All potential confounders were ruled out with minimal significant findings to report. For instance, mood disorders, including depression, were placed in the same model as anxiety disorders. In this model, anxiety was found to be significant while mood disorders were not found to have any significant impact on self-esteem development despite having an impact as a main effect. After several trials we felt that the most important findings came from anxiety disorders. Perhaps this was due to a larger subset of the group having an anxiety disorder in comparison with other conditions. At any rate, anxiety disorders were found to have a significant impact on self-esteem development when compared to the healthy group. No previous research on a longitudinal community-based study examining the impact of different anxiety types has been found.

Our main findings from Chapter 4 suggest that gender differences in self-esteem are found only in low family socioeconomic status adolescents. Females tend to have a lower average self-esteem, but their self-esteem increases at a faster rate. In this study we found that maternal self-esteem positively impacts adolescent self-esteem. While many prior studies examining the influence of parental self-esteem on adolescent self-esteem have been cross-sectional and had established a correlation, in our study we were able to quantify the effect of maternal self-esteem on adolescent self-esteem development. In this study, one of the major limitations was not having information on paternal self-esteem. Granted there are single parent households, but some of these single parents

are fathers. Hence, including various family dynamics may improve the accuracy of the results. Maternal self-esteem was found to be an important indicator of offspring self-esteem. We were fortunate to have this information available aside from demographic factors such as gender and socioeconomic status which have been examined much more extensively than maternal data.

Findings from the study presented in Chapter 5 indicate that those who attend church have a significantly lower mean depressive symptoms score. Additionally, the number of times an individual attends church significantly predicts their depressive symptoms score. The more often church is frequented, the lower the score. Depressive symptoms in adolescents follow a curvilinear trend where it increases slightly in adolescence, but begins to decrease as they get older. This trend was observed independent of demographic covariates and time-dependent factors such as negative events and lifetime trauma. There are many factors that affect depression. We strongly felt that any major influences were considered in the model. However, no model is perfect. Certainly from this study, we cannot infer causality. Since church attendance and frequency of church attendance were time-dependent, including additional survey questions about attendance may give clues as to why attendance changes or does not change over time.

The generalizability of the results from each of these studies may be inhibited due to the uneven proportion among race. At the same time, the use of a homogeneous sample reduces potential bias in terms of the internal validity of the studies. Although the sample was randomly selected and careful to choose

locations that were representative of demographics in the general population at the time, we recognize having a predominantly White sample as a limitation. The inclusion of participants from all racial and ethnic groups may be a focus in future studies.

From a developmental research standpoint, there are several limiting factors in describing patterns of change. One limitation is the ability to measure the outcome of interest, particularly in psychological attributes (Burchinal, Nelson, & Poe, 2006). Another limitation involves the sample size and number of repeated measurements collected per subject. Longitudinal research is typically done over a long period of time and hence, can be very expensive and lengthy as human development may be a slow process for some while faster for others. For this reason, only a few repeated measurements may be collected. Thus, the accuracy of the model and the ability to detect a change is limited with little information (Burchinal et al., 2006). While our research consisted of three or four waves of data, it still provides more information on individuals than that of a cross-sectional study. With more data, there is no doubt that the accuracy of our models would improve. Some other limitations to the studies presented in this thesis involve covariates not collected that may be relevant to the research. In spite of these limitations in study design, developmental researchers agree that linear mixed-effects models provide the best estimation of individual growth curves as compared with other growth curve methods. Linear mixed-effects models also have the most power to identify predictors of developmental change (Burchinal et al., 2006).

Regarding the statistical modeling approach used, limitations are partly in the hands of the researcher and partly in the tools and knowledge available to select the best model. Linear mixed-effects modeling, as with other statistical methods, is not without its disadvantages. We chose this approach for the studies presented due to the nature of the data. We felt that this was the most appropriate approach for the data in question. While verification of assumptions is emphasized in traditional statistical methods, this may not be the case in linear mixed-effects modeling. For instance, limited techniques exist for verifying the normality assumption for the random-effects and the error terms (Jiang, 2007; Verbeke & Lesaffre, 1996). The impact that ignoring these assumptions has on model accuracy is unclear (Verbeke & Lesaffre, 1996). Jiang (2007) discusses methods in the form of diagnostic plots and goodness-of-fit tests to assess the distribution of the random-effects and error terms. In practice, however, this is a process that is easily overlooked and will continue to be the case until widely accepted guidelines are proposed.

Model selection is rarely a perfect and bias-free process. With linear mixed-effects modeling, researchers have to be concerned not only with selecting appropriate covariates for the model, but also choosing the best covariance structure for the random-effects. The latter may prove to be more difficult than anticipated. As Peng and Lu (2012) note, the estimation of the covariance matrix involves an optimization problem for which the often used Newton-Raphson and so-called EM algorithm may fail. The researcher must balance the relevance of covariates and the appropriateness of the covariance

structure with the number of parameters to be estimated as a result. As stated previously, a larger number of parameters reduce the efficiency of the estimates. In our research, there were structured covariance matrices that may not have been considered. However, given the nature of the data, it is unlikely that a stricter structure would have been the best fit.

Given the limitations in the modeling approach and the study design, we are confident in the final models presented. We feel that our findings significantly contribute to adolescent health and provide practical evidence that may be used in developing interventions or in further research.

References

Aarons, G.A., Monn, A.R., Leslie, L.K., Garland, A.F., Lugo, L., Hough, R.L., & Brown, S.A. (2008). Association between mental and physical health problems in high-risk adolescents: A longitudinal study. *Journal of Adolescent Health, 43*(3), 260-267.

Allison, P. D. (2000). Multiple Imputation for Missing Data: A Cautionary Tale. *Sociologiccal Methods & Research, 28*(3), 301-309.

Andrews, G., Creamer, M., Crino, R., Hunt, C., Lampe, L., & Page, A. (2002). *The Treatment of Anxiety Disorders: Clinician Guides and Patient Manuals*: Cambridge University Press.

Angold, A., Costello, E.J., & Worthman, C.M. (1998). Puberty and depression: the roles of age, pubertal status and pubertal timing. *Psychological medicine, 28*(1), 51-61.

Association, American Psychiatric. (1987). *Diagnostic and Statistical Manual of Mental Disorders* (revised 3rd ed.). Washington, D.C.: American Psychiatric Association.

Atkinson, B.E., & Malony, H.N. (1994). Religious maturity and psychological distress among older Christian women. *The International Journal for the Psychology of Religion, 4*(3), 165-179.

Bachman, J.G., O'Malley, P.M., Freedman-Doan, P., Trzesniewski, K.H., & Donnellan, M.B. (2011). Adolescent self-esteem: Differences by race/ethnicity, gender, and age. *Self and Identity, 10*(4), 445-473.

Baldwin, S.A., & Hoffmann, J.P. (2002). The dynamics of self-esteem: A growth-curve analysis. *Journal of Youth and Adolescence, 31*(2), 101-113.

Beesdo, K., Knappe, S., & Pine, D.S. (2009). Anxiety and anxiety disorders in children and adolescents: developmental issues and implications for DSM-V. *The Psychiatric Clinics of North America, 32*(3), 483.

Berenson, K.R., Crawford, T.N., Cohen, P., & Brook, J. (2005). Implications of identification with parents and parents' acceptance for adolescent and young adult self-esteem. *Self and Identity, 4*(3), 289-301.

Berman, E., Merz, J.F., Rudnick, M., Snyder, R.W., Rogers, K.K., Lee, J., . . . Wolpe, P.R. (2004). Religiosity in a hemodialysis population and its relationship to satisfaction with medical care, satisfaction with life, and adherence. *American journal of kidney diseases, 44*(3), 488-497.

Bhar, S.S., & Kyrios, M. (2007). An investigation of self-ambivalence in obsessive-compulsive disorder. *Behaviour research and therapy, 45*(8), 1845-1857.

Bird, H.R., Gould, M.S., & Staghezza, B. (1992). Aggregating data from multiple informants in child psychiatry epidemiological research. *Journal of the American Academy of Child & Adolescent Psychiatry, 31*(1), 78-85.

Birkeland, M.S., Melkevik, O., Holsen, I., & Wold, B. (2012). Trajectories of global self-esteem development during adolescence. *Journal of adolescence, 35*(1), 43-54.

Birndorf, S., Ryan, S., Auinger, P., & Aten, M. (2005). High self-esteem among adolescents: Longitudinal trends, sex differences, and protective factors. *Journal of Adolescent Health, 37*(3), 194-201.

Blazer, D.G., & Kessler, R.C. (1994). The prevalence and distribution of major depression in a national community sample: the National Comorbidity Survey. *Age (years), 151*(7), 979-986.

Block, J., & Robins, R.W. (1993). A Longitudinal Study of Consistency and Change in Self-Esteem from Early Adolescence to Early Adulthood. *Child development, 64*(3), 909-923.

Breslau, N., Davis, G.C., Peterson, E.L., & Schultz, L.R. (2000). A second look at comorbidity in victims of trauma: The posttraumatic stress disorder-major depression connection. *Biological Psychiatry, 48*(9), 902-909.

Buodo, G., Novara, C., Ghisi, M., & Palomba, D. (2012). Posttraumatic and Depressive Symptoms in Victims of Occupational Accidents. *Depression Research and Treatment, 2012*. doi: doi:10.1155/2012/184572

Burchinal, M. R., Nelson, L., & Poe, M. (2006). IV. Growth Curve Analysis: An Introduction to Various Methods for Analyzing Longitudinal Data. *Monographs of the Society for Research in Child Development, 71*(3), 65-87. doi: 10.1111/j.1540-5834.2006.00405.x

Cameron, C. L. (2007). Obsessive–compulsive disorder in children and adolescents. *Journal of Psychiatric and Mental Health Nursing, 14*(7), 696-704. doi: 10.1111/j.1365-2850.2007.01162.x

Cohen, P., Chen, H., Gordon, K., Johnson, J., Brook, J., & Kasen, S. (2008). Socioeconomic background and the developmental course of schizotypal and borderline personality disorder symptoms. *Development and psychopathology, 20*(2), 633-650.

Cohen, P., & Cohen, J. (1995). *Life values and adolescent mental health*. Mahwah, NJ: Lawrence Erlbaum.

Cohen, P., Kasen, S., Chen, H., Hartmark, C., & Gordon, K. (2003). Variations in patterns of developmental transmissions in the emerging adulthood period. *Developmental Psychology, 39*(4), 657-669.

Coopersmith, S. (1967). *The antecedents of self-esteem*. San Francisco, CA: W.H. Freeman.

Costello, E.J., Edelbrock, C.S., Duncan, M.K., & Kalas, R. (1984). Testing of the NIMH Diagnostic Interview Schedule for Children (DISC) in a clinical population: Final report to the Center for Epidemiological Studies, NIMH. *Pittsburgh, University of Pittsburgh*.

Davis, C. S. (2002). *Statistical Methods for the Analysis of Repeated Measurements*. New York, NY: Springer.

Derogatis, L. R., Lipman, R. S., Rickels, K., Uhlenhuth, E. H., & Covi, L. (1974). The Hopkins Symptom Checklist (HSCL): A self-report symptom inventory. *Behavioral Science, 19*(1), 1-15. doi: 10.1002/bs.3830190102

Diggle, P., Heagerty, P., Liang, K.Y., & Zeger, S. (2002). *Analysis of Longitudinal Data*. New York, NY: Oxford University Press.

Doron, G., & Kyrios, M. (2005). Obsessive compulsive disorder: A review of possible specific internal representations within a broader cognitive theory. *Clinical psychology review, 25*(4), 415-432.

Ehntholt, K.A., Salkovskis, P.M., & Rimes, K.A. (1999). Obsessive–compulsive disorder, anxiety disorders, and self-esteem: an exploratory study. *Behaviour research and therapy, 37*(8), 771-781.

Elfhag, K., Tynelius, P., & Rasmussen, F. (2010). Self-Esteem Links in Families with 12-Year-Old Children and in Separated Spouses. *The Journal of psychology, 144*(4), 341-359.

Erol, R.Y., & Orth, U. (2011). Self-esteem development from age 14 to 30 years: A longitudinal study. *Journal of personality and social psychology, 101*(3), 607-619.

Gecas, V., & Schwalbe, M.L. (1986). Parental behavior and adolescent self-esteem. *Journal of Marriage and the Family, 48*(1), 37-46.

Geist, C.R., & Borecki, S. (2006). Social avoidance and distress as a predictor of perceived locus of control and level of self-esteem. *Journal of clinical psychology, 38*(3), 611-613.

Gentile, B., Twenge, J.M., & Campbell, W.K. (2010). Birth cohort differences in self-esteem, 1988–2008: A cross-temporal meta-analysis. *Review of General Psychology, 14*(3), 261-268.

Greenberg, J., Solomon, S., Pyszczynski, T., Rosenblatt, A., Burling, J., Lyon, D., . . . Pinel, E. (1992). Why do people need self-esteem? Converging evidence that self-esteem serves an anxiety-buffering function. *Journal of Personality and Social Psychology, 63*(6), 913-922. doi: 10.1037/0022-3514.63.6.913

Grissom, R. J., & Kim, J. J. (2005). *Effect Sizes for Research: A Broad Practical Approach.* Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Hale, W. W., Raaijmakers, Q., Muris, P., Van Hoof, A., & Meeus, W. (2008). Developmental trajectories of adolescent anxiety disorder symptoms: A 5-year prospective community study. *Journal of the American Academy of Child & Adolescent Psychiatry, 47*(5), 556-564.

Hedeker, D., & Gibbons, R.D. (2006). *Longitudinal Data Analysis*. Hoboken, NJ: John Wiley & Sons, Inc.

Ho, C.S., Lempers, J.D., & Clark-Lempers, D.S. (1995). Effects of economic hardship on adolescent self-esteem: A family mediation model. *Adolescence, 30*(117), 117-131.

Huang, C. (2010). Mean-level change in self-esteem from childhood through adulthood: Meta-analysis of longitudinal studies. *Review of General Psychology, 14*(3), 251-260. doi: 10.1037/a0020543

Jacobs, J.E., Bleeker, M.M., & Constantino, M.J. (2003). The self-system during childhood and adolescence: Development, influences, and implications. *Journal of Psychotherapy Integration, 13*(1), 33-65.

Jiang, J. (2007). *Linear and generalized linear mixed models and their applications*. New York, NY: Springer Science + Business Media.

Kasen, S., Wickramaratne, P., Gameroff, MJ, & Weissman, MM. (2012). Religiosity and resilience in persons at high risk for major depression. *Psychological Medicine, 42*(3), 509-519.

Kaufman, J., Birmaher, B., Brent, D., & Rao, U. (1997). Schedule for Affective Disorders and Schizophrenia for School-Age Children-Present and Lifetime Version (K-SADS-PL): initial reliability and validity data. *Journal of the American Academy of Child & Adolescent Psychiatry, 36*(7), 980-988.

Kling, K.C., Hyde, J.S., Showers, C.J., & Buswell, B.N. (1999). Gender differences in self-esteem: a meta-analysis. *Psychological bulletin, 125*(4), 470-500.

Koenig, H.G. (1993). Religion and aging. *Reviews in Clinical Gerontology, 3*(2), 195-203.

Kogan, L.S., Smith, J., & Jenkins, S. (1978). Ecological validity of indicator data as predictors of survey findings. *Journal of Social Service Research, 1*(2), 117-132.

Kraaij, V., Arensman, E., & Spinhoven, P. (2002). Negative Life Events and Depression in Elderly Persons A Meta-Analysis. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences, 57*(1), 87-94.

La Greca, A.M., & Harrison, H.M. (2005). Adolescent peer relations, friendships, and romantic relationships: Do they predict social anxiety and depression? *Journal of Clinical Child and Adolescent Psychology, 34*(1), 49-61.

Laird, N.M., & Ware, J.H. (1982). Random-effects models for longitudinal data. *Biometrics, 38*(4), 963-974.

Lewinsohn, P.M., Holm-Denoma, J.M., Small, J.W., Seeley, J.R., & Joiner Jr, T.E. (2008). Separation anxiety disorder in childhood as a risk factor for future mental illness. *Journal of the American Academy of Child and Adolescent Psychiatry, 47*(5), 548-555.

Lindsey, J. K. (1999). *Models for repeated measurements* (2nd ed.). New York, NY: Oxford University Press.

Lindstrom, M.J., & Bates, D.M. (1988). Newton—Raphson and EM Algorithms for Linear Mixed-Effects Models for Repeated-Measures Data. *Journal of the American Statistical Association, 83*(404), 1014-1022.

Littell, R. C. (2006). *SAS for Mixed Models* (pp. 834). Retrieved from http://lib.usf.edu, eBook Collection (EBSCOhost) database

Mannuzza, S., Fyer, A.J., Klein, D.F., & Endicott, J. (1986). Schedule for Affective Disorders and Schizophrenia—Lifetime Version modified for the study of anxiety disorders (SADS-LA): rationale and conceptual development. *Journal of psychiatric research, 20*(4), 317-325.

Marchand, A., Goupil, G., Trudel, G., & Bélanger, L. (1995). Fear and Social Self-esteem in Individuals Suffering from Panic Disorder with Agoraphobia. *Scandinavian Journal of Behaviour Therapy, 24*(4), 163-170.

Maselko, J., & Buka, S. (2008). Religious activity and lifetime prevalence of psychiatric disorder. *Social psychiatry and psychiatric epidemiology, 43*(1), 18-24.

Maselko, J., Gilman, SE, & Buka, S. (2009). Religious service attendance and spiritual well-being are differentially associated with risk of major depression. *Psychological medicine, 39*(6), 1009-1017.

Maselko, J., Hayward, R.D., Hanlon, A., Buka, S., & Meador, K. (2012). Religious service attendance and major depression: a case of reverse causality? *American journal of epidemiology, 175*(6), 576-583.

McCarthy, J.D., & Hoge, D.R. (1982). Analysis of age effects in longitudinal studies of adolescent self-esteem. *Developmental Psychology, 18*(3), 372-379.

McClure, A.C., Tanski, S.E., Kingsbury, J., Gerrard, M., & Sargent, J.D. (2010). Characteristics associated with low self-esteem among US adolescents. *Academic pediatrics, 10*(4), 238-244.

Mruk, C.J. (2006). *Self-esteem research, theory, and practice: Toward a positive psychology of self-esteem*: Springer Publishing Company.

Mullis, A.K., Mullis, R.L., & Normandin, D. (1992). Cross-sectional and longitudinal comparisons of adolescent self-esteem. *Adolescence, 27*(105), 51-61.

Nakai, M., & Ke, W. (2009). Statistical Models for Longitudinal Data Analysis. *Applied Mathematical Sciences, 3*(40), 1979-1989.

Nisbet Wallis, D.A. (2002). Depression, anxiety and self-esteem: A clinical field study. *Behaviour Change, 19*(2), 112-120.

Oakley-Browne, M.A. (1991). The epidemiology of anxiety disorders. *International Review of Psychiatry, 3*(2), 243-252.

Orth, U., Robins, R.W., & Roberts, B.W. (2008). Low self-esteem prospectively predicts depression in adolescence and young adulthood. *Journal of Personality and Social Psychology, 95*(3), 695-708.

Orth, U., Trzesniewski, K.H., & Robins, R.W. (2010). Self-esteem development from young adulthood to old age: A cohort-sequential longitudinal study. *Journal of personality and social psychology, 98*(4), 645-658.

Pargament, K.I., & Saunders, S.M. (2007). Introduction to the special issue on spirituality and psychotherapy. *Journal of Clinical Psychology, 63*(10), 903-907.

Patel, S.S., Shah, V.S., Peterson, R.A., & Kimmel, P.L. (2002). Psychosocial variables, quality of life, and religious beliefs in ESRD patients treated with hemodialysis. *American Journal of Kidney Diseases, 40*(5), 1013-1022.

Peng, H., & Lu, Y. (2012). Model selection in linear mixed effect models. *Journal of Multivariate Analysis, 109*, 109-129. doi: 10.1016/j.jmva.2012.02.005

Potthoff, R.F., Tudor, G.E., Pieper, K.S., & Hasselblad, V. (2006). Can one assess whether missing data are missing at random in medical studies? *Statistical Methods in Medical Research, 15*(3), 213-234.

Pu, W., & Niu, X.F. (2006). Selecting mixed-effects models based on a generalized information criterion. *Journal of multivariate analysis, 97*(3), 733-758.

Ramirez, S.P., Macêdo, D.S., Sales, P.M.G., Figueiredo, S.M., Daher, E.F., Araújo, S.M., . . . Carvalho, A.F. (2012). The relationship between religious coping, psychological distress and quality of life in hemodialysis patients. *Journal of Psychosomatic Research, 72*(2), 129-135.

Rhodes, J., Roffman, J., Reddy, R., & Fredriksen, K. (2004). Changes in self-esteem during the middle school years: A latent growth curve study of individual and contextual influences. *Journal of School Psychology, 42*(3), 243-261.

Roberts, J.E. (2006). Self-esteem from a clinical perspective. *Self-esteem issues and answers: A sourcebook of current perspectives*, 298-305.

Robins, R.W., & Trzesniewski, K.H. (2005). Self-esteem development across the lifespan. *Current Directions in Psychological Science, 14*(3), 158-162.

Robins, R.W., Trzesniewski, K.H., Tracy, J.L., Gosling, S.D., & Potter, J. (2002). Global self-esteem across the life span. *Psychology and aging, 17*(3), 423-434.

Rosenberg, M. (1962). The association between self-esteem and anxiety. *Journal of Psychiatric Research; Journal of Psychiatric Research, 1*(2), 135-152.

Rubin, D. B. (1976). Inference and missing data. *Biometrika, 63*(3), 581-592.

Ruiz, S.Y., Roosa, M.W., & Gonzales, N.A. (2002). Predictors of self-esteem for Mexican Anmerican and European American youths: A reexamination of the influence of parenting. *Journal of Family Psychology, 16*(1), 70-80.

Schafer, J.L., & Yucel, R.M. (2002). Computational strategies for multivariate linear mixed-effects models with missing values. *Journal of computational and Graphical Statistics, 11*(2), 437-457.

Schnall, E., Kalkstein, S., Fitchett, G., Salmoirago-Blotcher, E., Ockene, J., Tindle, H.A., . . . Wassertheil-Smoller, S. (2012). Psychological and social characteristics associated with religiosity in women's health initiative participants. *Journal of religion and health, 51*, 20-31.

Singer, J.D. (1998). Using SAS PROC MIXED to fit multilevel models, hierarchical models, and individual growth models. *Journal of educational and behavioral statistics, 23*(4), 323-355.

Skrondal, A., & Rabe-Hesketh, S. (2008). Multilevel and related models for longitudinal data. In J. d. L. E. Meijer (Ed.), *Handbook of Multilevel Analysis* (pp. 275-299). New York, NY: Spring Science + Business Media.

Sun, F., Park, N.S., Roff, L.L., Klemmack, D.L., Parker, M., Koenig, H.G., . . . Allman, R.M. (2012). Predicting the trajectories of depressive symptoms among southern community-dwelling older adults: The role of religiosity. *Aging & mental health, 16*(2), 189-198.

Trzesniewski, K.H., Donnellan, M.B., Moffitt, T.E., Robins, R.W., Poulton, R., & Caspi, A. (2006). Low self-esteem during adolescence predicts poor health, criminal behavior, and limited economic prospects during adulthood. *Developmental psychology, 42*(2), 381-390.

Verbeke, G., & Lesaffre, E. (1996). A linear mixed-effects model with heterogeneity in the random-effects population. *Journal of the American Statistical Association, 91*(433), 217-221.

Verbeke, G., & Molenberghs, G. (2009). *Linear Mixed Models for Longitudinal Data*. New York, NY: Springer.

Veselska, Z., Geckova, A.M., Reijneveld, S.A., & van Dijk, J.P. (2011). Socio-economic status and physical activity among adolescents: The mediating role of self-esteem. *Public health, 125*(1), 763-768.

Vonesh, E. F., & Chinchilli, V. M. (1997). *Linear and nonlinear models for the analysis of repeated measurements*. New York, NY: Marcel Dekker, Inc.

Ware, J.H. (1985). Linear models for the analysis of longitudinal studies. *The American Statistician, 39*(2), 95-101.

Wells, K.B., & Trust, P.M. (1989). The functioning and well-being of depressed patients: results from the Medical Outcomes Study. *Journal of American Medical Association, 262*(7), 914-919.

Wittchen, HU, Fuetsch, M., Sonntag, H., Müller, N., & Liebowitz, M. (2000). Disability and quality of life in pure and comorbid social phobia. Findings from a controlled study. *European Psychiatry, 15*(1), 46-58.

Wulsin, L.R., Vaillant, G.E., & Wells, V.E. (1999). A systematic review of the mortality of depression. *Psychosomatic medicine, 61*(1), 6-17.

Zeger, S.L., Liang, K.Y., & Albert, P.S. (1988). Models for longitudinal data: a generalized estimating equation approach. *Biometrics, 44*(4), 1049-1060.

Zimmerman, M.A., Copeland, L.A., Shope, J.T., & Dielman, T.E. (1997). A longitudinal study of self-esteem: Implications for adolescent development. *Journal of youth and Adolescence, 26*(2), 117-141.

Appendix A:

SAS Model Code for Chapter 3

```
/*new_age is centered age variable*/
*Basic unconditional model;
proc mixed data = esteem covtest;
model ESTEEY = new_age/solution cl ddfm = kr;
random intercept new_age/ type=un subject=id;
run;

*Basic model with demographic covariates;
proc mixed data = esteem covtest;
model ESTEEY = new_age sex race SESP /solution cl ddfm = kr;
random intercept new_age/ type=un subject=id;
run;

*Impact of anxiety on self-esteem as a main effect (any anxiety group vs. healthy group);
proc mixed data = healthy covtest;
model ESTEEY = new_age sex race SESP anyanxiety/solution cl ddfm = kr;
random intercept new_age/ type=un subject=id;
run;

*Impact of anxiety on self-esteem with interaction effect (any anxiety group vs. healthy group);
proc mixed data = healthy covtest;
model ESTEEY = new_age sex race SESP anyanxiety new_age*anyanxiety/solution cl ddfm = kr;
random intercept new_age/ type=un subject=id;
run;

/*Relative impact of categories of anxiety on self-esteem*/
proc mixed data = individual covtest;
model ESTEEY = new_age sex race SESP overanxious ocd simple social separation/solution cl ddfm = kr;
random intercept new_age/ type=un subject=id;
run;

/*Relative impact of categories of anxiety on self-esteem with interaction term*/
proc mixed data = individual covtest;
model ESTEEY = new_age sex race SESP overanxious ocd simple social separation ocd*new_age/solution cl ddfm = kr;
random intercept new_age/ type=un subject=id;
run;
```

```
/*Basic unconditional model after choosing best covariance structure
new_age is centered age variable*/
proc mixed data=esteem covtest;
model ESTEEY = new_age/solution;
random intercept new_age /type=un subject=id;
run;

/*Main effects model
c_ESTEEP is centered maternal self-esteem
c_SES is centered family SES*/
proc mixed data=esteem noclprint covtest;
class sex;
model ESTEEY = new_age sex c_ESTEEP c_SES /solution ddfm=kr;
random intercept new_age / type=un subject=id G V;
run;

/*Final interaction model*/
proc mixed data=esteem covtest;
class sex;
model ESTEEY =new_age
        sex sex*new_age
        c_ESTEEP
        c_SES   c_SES*sex   c_SES*new_age/solution ddfm=kr;
random intercept new_age /  type=un subject=id G V  ;
run;

/*Offspring self-esteem by family SES status*/
*Low family SES;
proc mixed data=esteem covtest;
where SEC=0;
class  sex;
model ESTEEY = new_age sex c_ESTEEP/solution ddfm=kr;
random intercept new_age/ type=un subject=id G V;
run;

*High family SES;
proc mixed data=esteem covtest;
where SEC=1;
class sex;
model ESTEEY = new_age sex c_ESTEEP/solution ddfm=kr;
random intercept  new_age/  type=un subject=id G V;
run;
```

Appendix C:

SAS Model Code for Chapter 5

```
/*Basic model where age20 is the centered age variable*/
proc mixed data=depression covtest;
model depression = age20 age20*age20 /solution cl;
random intercept age20 / sub=id;
run;

/*Church attendance versus non-attendance with covariates*/
proc mixed data=depression covtest;
class sex race;
model depression = age20 age20*age20 chu_attending1 sex race ses recentle
cmtraum/solution cl;
random intercept age20 / sub=id;
run;

/*Frequency of church attendance with covariates*/
proc mixed data=depression2 covtest order=data;
class sex race chu_attending3;
model depression = age20 age20*age20 chu_attending3 sex race ses recentle cmtraum
/ solution cl;
random intercept age20 / sub=id;
```