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The relationship between maltreatment and self-regulation trajectories: A multimethod approach

Grayson Sturgis

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THE RELATIONSHIP BETWEEN MALTREATMENT AND SELF-REGULATION TRAJECTORIES: A MULTIMETHOD APPROACH

By

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The Relationship Between Maltreatment and Self-Regulation Trajectories: A Multimethod Approach

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Table of Contents

Table of Figures

Table of Tables

Abstract

Typically, the ability of individuals to regulate their behaviors and emotions improves over time. However, prior research has not examined possible heterogeneity in self-regulation skills from birth to age 16. This study examined trajectories of self-regulation using growth mixture modeling and tested the relationship between child maltreatment (i.e., number of maltreatment allegations) and trajectory group membership, growth parameters, and group formation. Subjects *(N* = 1354*)* were drawn from the Consortium for Longitudinal Studies of Child Abuse and Neglect (LONGSCAN). Tests of unconditional models (i.e., those without covariates) with 1-5 classes supported a 4-class solution (consistently good, consistently poor, improving, and worsening). Tests of conditional models with total number of maltreatment allegations serving as a covariate supported a 2-class solution (improving and worsening). Tests of conditional models that incorporated a time-varying covariate found multiple well-fitting models with no clear 'winner.' A goal of this study was to examine the relationship between number of maltreatment allegations and self-regulation using three data analytic techniques (1-step, R3 step, and Time-Varying). Findings indicated that incorporating the number of maltreatment allegations in the model altered the optimal number of classes and was predictive of class membership. Importantly, this study showed that, in order to have a complete understanding of the relationship between number of maltreatment allegations and self-regulation, a variety of data analytic techniques are required.

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The Relationship Between Maltreatment and Self-Regulation Trajectories: A Multimethod Approach

Data from the Administration for Children & Families (ACF), a division of the Department of Health & Human Services, indicate that 3.5 million children were the subject of an investigation for child maltreatment in fiscal year of 2017. Of those cases investigated, 674,000 children were determined to be victims of maltreatment (U.S. Department of Health & Human Services, 2019). Based on US Census estimates, the population of the United States in 2017 was approximately 325 million. This yields a population prevalence of child maltreatment reports of slightly over 1%. It is important to note, however, that the exact prevalence of child maltreatment in the United States is challenging to determine given the substantially different estimates obtained using different assessment techniques. For example, researchers at Yale estimate that 12.5% of children in the United States experience some form of maltreatment before age 18 (Wildeman et al., 2014). These statistics become more disquieting when considering the effects of maltreatment on a child's development. As summarized by Dvir, it is known that exposure to trauma during childhood is correlated with a plethora of developmental, psychosocial, and medical impairments throughout life (Dvir, Ford, Hill, & Frazier, 2014). Dvir and colleagues go on to suggest that difficulty with emotional regulation is a core feature across many of these impairments and may account for elevated risk.

Self-regulation can be defined as the ability to modulate negative emotions and experience positive emotions (Ford, 2013). It is an integral developmental skill without which individuals are at increased risk for anxiety and mood disorders (Dvir et al., 2014).

Questions remain, however, regarding the developmental trajectory of self-regulation skills. Whereas many may believe that the developmental trajectory of self-regulation is best described by a single uniform improving trend (Griffin, Lowe, Acevedo, & Botvin, 2015) an alternative possibility is that there are multiple subgroups of individuals (or classes) that differ in trajectory of self-regulation skills. These classes can be identified and studied through the statistical method of Growth Mixture Modeling (GMM). For example, Montroy, Bowles, Skibbe, McClelland, and Morrison (2016) found three distinct self-regulation trajectories between ages three and seven years old. One goal of the current study is to identify the optimal number of self-regulation classes in a large sample of maltreated/at risk children between the ages of 4 and 16.

Growth Mixture Modeling also allows researchers to investigate the impact of covariates/auxiliary variables on the optimal number of classes and the shape of those trajectories. There are three techniques for incorporating covariates/auxiliary variables into the modeling process, each of which yields different information. However, most researchers make use of only one method of covariate incorporation and consequently it is impossible to be certain as to whether the results obtained reflect 'reality' or the method used. As such, a second goal of this paper is to examine the relationship between time (birth to age 16) and self-regulation ability (measured on a dysregulation scale) while incorporating the covariate of number of childhood maltreatment allegations using three different methods. Thus, this paper can be conceptualized as a 'content paper'. As such, one goal of this study is to examine the relationship between number of maltreatment allegations and self-regulation using three data analytic techniques. In addition, this paper can be conceptualized as a 'methods paper' in which the aim is to see how the findings can change depending on which method of covariate inclusion is used.

Review of Literature

Historical Underpinnings of Maltreatment

The study of trauma and its effects is, like modern experimental psychology, relatively new compared to other sciences. It was not until the late 19th century when French neurologist Jean Martin Charcot, through his studies of hysteria in women, recognized the roots of their distress as psychological instead of physiological, as was widely believed at the time (Ringel & Brandell, 2012). His work went on to investigate dissociative states resulting from past traumatic events among women. The sentiment that past traumatic events influence future psychological states has persisted in the field of psychology. It was not until the discovery of Battered Child Syndrome in the 1960s that these concepts were applied to children (Miller-Perrin & Perrin, 2014). This condition describes serious physical injuries received from a caregiver much like the current definition of physical abuse. However, while this is certainly a form of child maltreatment that pervades a number of households, Battered Child Syndrome only describes one form of maltreatment – physical abuse. For this reason, the field of child maltreatment has continued to expand its scope in order to account for the effects of more diverse (and sometimes less conspicuous) forms of maltreatment such as educational maltreatment.

Broadly, the term child maltreatment refers to physical abuse, sexual abuse, or neglect (Messman-Moore & Bhuptani, 2017). Child maltreatment will be defined in this paper using the Modified Maltreatment Classification System (English & LONGSCAN Investigators, 1997), which was used in the Consortium of Longitudinal Studies of Child Abuse and Neglect (LONSCAN).

Under these guidelines, maltreatment is defined as actions falling into one or more of the categories described in the following sections. What follows are detailed descriptions of each form of maltreatment included in LONGSCAN along with numerical ratings of severity for each event type.

Physical abuse includes any physical injury inflicted upon a child by a caregiver or responsible adult by means that were not accidental, such as striking the child with a belt or shaking a child to the point of "shaken baby syndrome." This category is divided into the following nine subcategories: 1. assault (hitting or kicking) of a child's head, neck, or face; 2. assault of the torso (defined as the area from a child's neck to legs and excluding buttocks); 3. striking of the buttocks; 4. hitting/kicking of a child's extremities; 5. violent handling of a child such as dragging, pushing, or throwing; 6. choking, smothering, or any other action meant to cut off the ability to breathe; 7. burns or scalding; 8. nondescript abuse, is reserved for instances in which allegations do not state where or how a child was hurt. Additionally, if more than three body parts of the child are harmed, all three are be catalogued separately under their respective codes. The severity levels for each of the preceding subcategories are as follows*: 1 = no marks are found on the child in question*, 2 = *minor marks such as cuts or scratches are found*, 3 = *numerous or nonminor marks*, 4 = *injuries necessitating emergency treatment/hospitalization of less than 24 hours*, 5 = *hospitalization of more than 24 hours*, and 6 = *permanent disability, disfigurement, or fatality of the child*. In addition to the 8 categories already listed, there is a 9th subcategory of physical abuse that refers to the shaking of a child. The severity levels for this physical abuse category are as follows: *1 = child over the age of two is shaken with no marks resulting, 2 = child over the age of two is shaken resulting in bruises; 3 = child under the age of two is shaken resulting in no marks; 4 = doctor noticed or suspected as a result of examination* *that a caregiver was shaking or had shaken a baby; 5 = child was hospitalized with Shaken Baby Syndrome; and 6 = child dies, is brain damaged, or has a broken neck due to having been shaken*.

Sexual abuse is constituted by sexual contact or attempted sexual contact between a caregiver or responsible adult and a child for the sexual or financial gratification of the adult. It should be noted that both physical and psychological means of coercion may be utilized by the perpetrator. The severity scale of sexual abuse consists of the following: *1 = child is exposed to but not directly involved in explicit sexual stimuli or activities, 2 = direct requests were made for sexual contact with the child and/or the genitalia of the caregiver were exposed to the child in order to sexually gratify the caregiver or stimulate the child, 3 = child is touched or made to touch the caregiver for the caregiver's sexual gratification including instances of mutual sexual touching, 4 = penetration of the child, attempted or otherwise, 5 = forced (including with the use of restraints, physical or otherwise, weapons, etc.) penetration or intercourse/prostitution of the child in any form.*

Emotional Abuse is defined as persistent or extreme thwarting of a child's emotional needs, as well as parental acts considered insensitive to a child's developmental level to the point of harmfulness. As stated by the LONGSCAN website, though all acts of maltreatment carry emotionally damaging effects, the category of "emotional maltreatment" remains separate in order to maintain the conceptual integrity of the categories (English & LONGSCAN Investigators, 1997). This category is divided into 27 subcategories/severity levels, and are as follows: *11*[1] *= caregiver forces child to assume a level of responsibility inappropriate for their age on a regular basis (taking care of younger siblings, etc.), 12 = caregiver undermines child's*

[1] The numeric values are provided in order to help readers easily locate entries in the LONGSCAN user manual and do not reflect severity.

relationships with significant individuals besides the caregiver (frequently verbally degrading other parents, etc.), 13 = caregiver ridicules or calls child names ("loser", "wimp", etc.) 14 = caregiver purposefully fails to acknowledge a child's bids for attention (an infant's crying, etc.), 15 = caregiver uses intimidation tactics as a disciplinary method or pressures a child to keep a secret pertaining to a family situation, 21 = caregiver prohibits age-appropriate socialization (not permitting a child to interact socially with their school-age friends, etc.), 22 = caregiver places a child in a role of being forced to take care of them as opposed to vice versa , 23 = caregiver intentionally undermines child's burgeoning sense of maturity via infantilization, etc., 24 = caregiver intentionally refuses or fails to notice a child's bids/needs for positive regard (affection, verbal or physical, etc.) to the extent that this lack of attention becomes pattern-based, 25 = child is exposed to a caregiver's extreme (albeit nonviolent) marital conflict, 31 = caregiver blames a child for family and or marital issues, 32 = child is set up to feel inadequate and/or fail due to excessive expectations placed upon them by a caregiver 33 = caregiver makes a serious and convincing threat of injury to a child, 34 = caregiver engages in derogatory name calling towards child, 35 = caregiver binds child's hands and feet for a period approximately 2-5 hours during which the child is not attended, 36 = caregiver exposes child to inappropriate, unpredictable, or extreme behavior (violence toward family members, etc.), 37 = caregiver demonstrates patterns of hostility or negativity towards a child, 41 = caregiver threatens suicide or abandonment in front of child, 42 = child is exposed to extreme marital violence which results in serious injury of a caregiver, 43 = caregiver blames child for the death or suicide of another member of the family, 44 = caregiver confines/isolates child for a period lasting between 5 and 8 hours, 45 = child is bound by restrictive methods or placed in a close confinement (where movement is difficult and light/ventilation is severely limited) situation for less than 2 hours, 51

= caregiver makes a suicidal attempt in the presence of a child, 52 = caregiver makes a homicidal attempt or realistic homicidal threat towards child without physical harm resulting, 53 = caregiver abandons child for a period of 24 hours or more without indication of returning or a method of location, 54 = use of extremely restrictive methods upon a child and/or placement into close confinement for a period of more than 2 hours, 55 = child being placed in confinement for a period exceeding 8 hours.

In addition to these forms of child abuse, LONGSCAN assessed a number of forms of neglect. These typically include acts of omission that place the child at risk for adverse outcomes.

Physical neglect-Lack of supervision refers to instances in which the minimum level of supervision required for a child's safety is not provided by a caregiver, or is provided by a supervisor with the potential to do a child harm, and is divided into 3 subcategories, each of which is assigned a severity scale, and are as follows: 1. caregiver fails to provide an adequate level of supervision to a child rated from *1 = lack of supervision lasts for a short period of time with no immediate environmental dangers, to 5 = caregiver fails to supervise child for periods of more than 12 hours,* 2. failure to provide supervision of a child in a possibly harmful environment rated from *1 = child of preschool age allowed to play outside unsupervised, to 5 = child is placed into or not removed from a life-threatening situation including a caregiver driving while intoxicated with a child in the car,* 3. child is left under the care/supervision of a substitute caregiver rated from *1 = child is left in the care of an individual of questionable competency (a preadolescent babysitter, mildly impaired elderly relative, etc.) for less than 3 hours, to 4 = child is allowed to be in the presence/care of a caregiver with a known violent past and/or known history of sexual acts against children.*

Maltreatment will be operationalized within this paper as the sum of Physical Abuse, Sexual Abuse, Emotional Abuse, and Neglect.

Prevalence of Childhood Maltreatment

A broad array of studies has been conducted to assess for the prevalence of child maltreatment. The estimates obtained are often a function of the assessment method that was used. As outlined in the introduction, based on a combination of Child Protective Services reports and US Census data, the estimated prevalence of child maltreatment is approximately 1%. However, substantially higher prevalence estimates have been found in self-report studies of adults and young adults in the US and the United Kingdom. Scher, Forde, McQuaid, and Stein (2004) used phone interviews to assess for the prevalence of maltreatment in a sample of 967 adults from the metropolitan Memphis, Tennessee area. Approximately 40% of men and 30% of women reported having been the victim of physical abuse, physical neglect, emotional abuse, emotional neglect, or sexual abuse. Approximately 13% of respondents reported multiple types of maltreatment. Due to the limited geographical area of this study, it is difficult to extrapolate national prevalence.

Similarly high prevalence rates of childhood trauma have been found in larger surveys of adults. For example, Edwards, Holden, Felitti, and Anda (2003) assessed maltreatment history in 8,667 adults enrolled in a health maintenance organization. It was found that 21.6% of respondents had experienced sexual abuse, 20.6% had experienced physical abuse, and 14% had witnessed a maternal caregiver experience a violent act. Moreover, of the respondents who had experienced one type of abuse, 34.6% had experienced more than one type throughout childhood.

Hussey, Chang, and Kotch (2006) estimated the national prevalence of childhood maltreatment. Study participants consisted of a representative sample of 10,828 young adults who were followed from adolescence into adulthood as a part of the National Longitudinal Study of Adolescent Health. In this sample 45% reported at least one instance of supervision neglect (42% of whom reported three or more instances), 11.8% reported at least one instance of physical neglect (42% of whom reported three or more instances), 28.4% reported at least one instance of physical abuse (50% of whom reported three or more instances), and 4.5% reported contact sexual abuse (36% of whom reported three or more instances).

Researchers at Yale (Wildeman et al., 2014) developed synthetic cohort life tables to estimate confirmed cumulative childhood maltreatment prevalence by age 18. In developing these tables, they used information gathered by the National Child Abuse and Neglect Data System (NCANDS), which includes every child living in the United States with a confirmed history of maltreatment (N = 5,689,900 from 2004-2011). Findings from this study indicate that by 18 years of age, 12.5% of all U.S. children will experience a confirmed case of maltreatment. The prevalence estimates were similar for girls (13%) and boys (12%). However, there were substantial ethnic differences in prevalence estimates. Only 10.7% of White children were estimated to experience confirmed maltreatment, while 20.9% of Black children, 14.5% of Native American children, and 13% of Hispanic children were estimated to experience confirmed maltreatment. The rate for Asian/Pacific Islander children was noticeably lower than that of all other ethnic groups, with only 3.8% of children estimated to experience confirmed maltreatment. Additionally, this study found that the earliest years of life pose the greatest risk for maltreatment, with 2.1% of children experiencing a confirmed instance of maltreatment by age 1, and 5.8% by age 5. It is important to note that the prevalence rates provided in this study reflect *projections* of prevalence. The authors note that their findings, indicating an estimated prevalence of 12.5%, is far greater than the 1% of confirmed cases annually. In addition, however, these projections are for confirmed cases of childhood maltreatment and consequently it is possible that the figures may be underestimates of maltreatment based on self-reports.

Comparable prevalence estimates were obtained in a study conducted in the United Kingdom (Radford, Corral, Bradley, & Fisher, 2013). In this study, a representative sample of 2,275 children (age 11 and under) and adolescents (age 11-17), 1,761 young adults (age 18-24), 2,160 caregivers of children aged two months to ten years old, and the caregivers of those interviewed who were age 11-17 were assessed through computer assisted interviews. It was found that 8.9% of children, 21.9% of young people, and 24.5% of young adults indicated experiencing some form of maltreatment from a parent or guardian. There was a significant gender disparity for young adults, with 22.7% of males and 26.5% females reporting some type of maltreatment. The reasons for this similarity across countries are unclear but may be due to the similarities in culture, history, and development level of the two nations. When examined across individual studies, it is clear that child maltreatment is an all-too-frequent event. It is increasingly important to understand the long-term consequences of child-maltreatment. In a systematic review of the literature, Gilbert et al. (2009) found that child maltreatment is associated with a broad array of adverse outcomes including poorer educational performance and lower earnings, increased risk for internalizing and externalizing symptoms, poorer physical health, increased risk for engaging in criminal/aggressive behavior, and in extreme cases death. Though ample evidence exists affirming the multiple adverse outcomes of maltreatment, this study will focus on difficulties with self-regulation.

Self-Regulation

Self-regulation is defined by Ford (2013) as the deployment of psychobiological capacities to maintain the safety, integrity, development, well-being, and goal attainment of the individual and their core relationships. This can include involuntary, reflexive mechanisms for emotion regulation, deliberate efforts, and altering one's behaviors to modify unpleasant affects. Consequently, it involves modifying behavior to alter unpleasant affect and conversely, unpleasant affect can result in altered behavior. As such, this term will be operationalized within this paper as the ability to properly control one's affect and behaviors. In this paper, self-regulation is measured using the Childhood Behavior Checklist (CBCL) Dysregulation Profile Index.

By way of background, initially, Biederman et al. (2009) proposed the sum of T-scores in three syndromes scales from the Childhood Behavior Checklist (Achenbach, 1991) could be used to identify juvenile bipolar disorder. The scale was composed of the following scales: Aggressive Behavior, Anxious/Depressed and Attention Problems. However, the utility estimates (i.e., sensitivity and specificity) were unacceptably low (Volk & Todd, 2007). Recently, this scale has been renamed as the 'CBCL-Dysregulation Profile' (CBCL-DP) index, as it better detects children with 'a persisting deficit of self-regulation of affect and behavior' (Holtmann et al., 2011). This profile can be used as both a marker for risk of poor adulthood functioning and an identifier of difficulty in self-regulating behavior and affect (Bellani, Negri, & Brambilla, 2012). One method of assessing longitudinal dysregulation trajectories is the use of a statistical technique known as growth mixture modeling.

Brief description of GMM and Examples of its Use

As previously mentioned, Growth Mixture Modeling (GMM) is a statistical analysis method that allows for the identification of multiple trajectories or classes within a population. Growth mixture modeling can be conducted in a number of statistical software packages including Mplus, SPSS (AMOS) and R. Traditional growth modeling assumes that one trajectory is sufficient to describe a population. By contrast, growth mixture modeling assumes that there are mixtures of subgroups within a population. Each subgroup is characterized by unique growth parameters (e.g., slope and intercept). When conducting GMM the adequacy of fit of models with an increasing number of classes is tested. The goal is to identify the best fitting model, which includes the optimal number of classes used to adequately describe the sample. The number of classes to retain is determined by comparing models with different numbers of classes along a number of fit indices. The result of these analyses is an unconditional model – one with no covariates. Multiple studies have used GMM to examine changes in self-regulation over time.

A Growth Mixture Modeling analysis was performed on 1,386 children between the ages of three to seven years old (Montroy et al., 2016). The study was composed of three diverse samples as part of a longitudinal study examining trajectories of self-regulation development. The samples varied by socioeconomic class and geography. Two samples were collected from parts of Michigan, and the third from a rural part of Oregon. The results suggest that children's self-regulation skills develop along one of three trajectories: "early developers" who demonstrated both higher levels of initial self-regulation ability and more rapid gains in ability when compared to peers, "intermediate developers" who demonstrated low initial self-regulation ability levels but rapid gains, and "later developers" who demonstrated low initial self-regulation ability levels as well as slower gains in ability. While the proportion of children in each trajectory varied by sample, the presence of the three trajectories did not. Multiple predictors of class membership were found. These predictors are gender, expressive vocabulary, and mother's education level. It is important to note, however, that other studies have arrived at different conclusions regarding the optimal number of classes.

A four-class model was found to be best-fitting in a longitudinal study of 1,574 students from grade 5 to grade 11. The sample was diverse in terms of racial/ethnic composition, socioeconomic status, and maternal education level. The study focused on examining possible predictive variables for intentional self-regulation (ISR) patterns (Bowers et al., 2011). Self-regulation was assessed using the Selection, Optimization, and Compensation (SOC) questionnaire (Freund & Baltes, 2002). The SOC was administered in paper-and-pencil format until grade 7, at which point participants were also allowed to use a computer questionnaire. As previously mentioned, the researchers found that a four-class model best fit the collected data. These classes were "Steady Decline", "Elevated", Pronounced Decline", and "Late Onset." Those in the "Steady Decline" class experienced a slow decrease in ISR over time. The majority of participants were in this class. Those in the "Elevated" group experienced increasing ISR after grade 8/age 14. Those in the "Pronounced Decline" group experienced a drastic drop in ISR after grade 8/age 14. Those in the "Late Onset" group experienced low ISR rates in earlier grades followed by nearly average ISR in later grades.

Brief Description of Three Strategies for Examining the Impact of Covariates/Auxiliary Variables

This study utilized three strategies for examining the impact of covariates/auxiliary variables after identifying the best fitting unconditional model: 1-step procedure, 3-step procedure, and time-varying procedure. The 1-step procedure, also known as the traditional method of covariate incorporation, examines the way in which a covariate can influence the number, size, and shape of trajectory groups. This method allows the covariate to affect the growth parameters such as slope and intercept, and the number of classes. As such, incorporation of a covariate using this technique can yield models that differ drastically from the unconditional models of the same data.

The 3-step procedure, also known as the R3step method, is used to test the relationship between a covariate and group membership probability without altering the trajectories found from the unconditional model. This method is used after a well-fitting unconditional model has been identified. Both the 1-step and R3step techniques assume that the covariate is a fixed or time-invariant value.

The third strategy involves assessing the covariate at multiple time points in parallel with the growth variable. Incorporating the variable as a time-varying covariate is a method used to examine dynamic relationships between covariates and growth variables.

Purpose of the LONGSCAN

The Consortium of Longitudinal Studies in Child Abuse and Neglect (LONGSCAN) aims to comprehensively explore consequences of child maltreatment as well as risk and resilience factors. LONGSCAN was comprised of five research sites (Hunter & Knight, 1998). While each of these sites have different specific research goals, between-site collaboration allows the consortium to look into additional issues and increases chances for result replication. These results can be extended across many social, economic, and ethnic subgroups as well. LONGSCAN conducts this research by "follow[ing] the 1300+ children and their families until the children themselves become young adults" (Larrabee & Lewis, 2015). The children, their teachers, and their caregivers completed comprehensive assessments every two years from child ages 4-18, except for age 10. In between these assessments, bi-annual telephone interviews were conducted to track important life events, check in on families, etc. The data on maltreatment were gathered from numerous sources such as through reviewing records from Child Protective Services.

Hypothesis

This paper has two components. The first is to identify the optimal number of trajectory classes needed to adequately describe self-regulation skills in this sample. Though this study is not conducive to a classical directional hypothesis, heterogeneity in self-regulation ability over time is anticipated. A previous GMM examining self-regulation development trajectories among children aged three to seven years old (Montroy et al., 2016) found a 3-class model best represented the sample. A study of slightly older children (aged 5-11 years old) found that a 4-class model (Steady Decline, Elevated, Late Onset, and Pronounced Decline) fit best (Bowers et al., 2011). In studying the disruptions in normal functioning over time of adults handling loss, Bonanno (2004) also identified a 4-class model (Chronic, Delayed, Recovery, and Resilience). As the latter two studies have samples more closely resembling the sample used in this paper in terms of age, we can expect to see a 4-class model as well, including two stable classes (low and high) and two classes that change over time (increasing and decreasing).

The second component is to examine the impact of trauma exposure on symptom trajectory using the three different techniques for incorporating covariates that were described previously. This portion is really an examination of the methods used rather than outcomes. I expect to find somewhat different results across the three techniques. As such, it could be said that the hypothesis is that the method of covariate incorporation can have a significant effect on the shape of the data, without predicting exactly how.

Method

Description of Sample[2]

The sample was composed of 1,354 children who were maltreated or at elevated risk for maltreatment. There were a comparable number of males (48.5%) and females (51.5%). Slightly over half of the sample was Black (53.2%) and roughly a quarter was White (26.1%). The average number of maltreatment allegations was quite high (5.28).

Study Design

The data for the current study were collected by the Consortium for Longitudinal Studies of Child Abuse and Neglect (LONGSCAN). The study included five sites with common data collection strategies, definitions, measures, training, data entry, and data management. Three of these sites are primarily urban (East, Midwest, and Northwest), one of them is primarily suburban (Southwest), and one is was a mix between urban, suburban, and rural (South). The presence of multiple collection sites allows for a systematic variation of maltreatment histories and/or risk level for maltreatment among participants. The participants were assessed comprehensively every two years from age 4 to age 18 via interviews. These interviews were administered face-to-face for ages 4-8, and by Audio Computer-Assisted Self-Interview (A-

[2] The version of the dataset used for this study includes data collected between July 1991 and January 2012

CASI) software from age 12-18. Caregivers were also given yearly telephone calls to collect information about the child's behavior and to increase subject retention. Data pertaining to maltreatment was collected from a variety of sources including Child Protective Service records.

Measures

Child Behavior Checklist

The Childhood Behavior Checklist (CBCL) is a paper-and-pencil measure consisting of 120 items designed to assess the behaviors, competencies, and problems of children aged 6-18 years old (Achenbach, 1991). The measure is completed by a parent or primary caregiver. Each item is scored using the following anchors: 0 = *behavior is not present*, 1 = *behavior is sometimes shown*, or 2 = *behavior is frequently demonstrated*. The CBCL has eight psychopathology scales, three broad band scales, and three competency scales. The psychopathology scales measure the following symptoms: Anxious/Depressed, Aggressive Behavior, Attention Problems, Social Problems, Somatic Complaints, Thought Problems, Rule-Breaking Behavior, and Withdrawn/Depressed. The broad scales measure Externalizing symptoms, Internalizing symptoms, and a Total Problems scale can also be computed. The three competency scales are labeled: Activities, Social, School, and Total Competency. The measure of self-regulation used in the current study was derived from the CBCL.

Child Behavior Checklist Dysregulation Profile

The CBCL (Achenbach, 1991) dysregulation profile (CBCL-DP) is composed of the sum of T-Scores on three "syndrome" subscales of the CBCL: Anxiety/Depression, Aggressive Behavior, and Attention Problems (Bellani et al., 2012). The Anxiety/Depression scale assesses internal emotions including loneliness, feelings of worthlessness, guilt, nervousness, and fearfulness (Wadsworth, Hudziak, Heath, & Achenbach, 2001). The Aggression scale assesses defiance, disobedience, poor frustration tolerance, angry moods, fights, and screaming (Spencer et al., 2011). The Attention Problems scale assesses immaturity, difficulty concentrating, difficulty sitting still, daydreaming, impulsivity, and nervousness (Achenbach & Ruffle, 2000). This profile was defined following research demonstrating that various hypothesized CBCL presentations can be conceptualized as overlapping manifestations of an underlying self-dysregulation construct (Ayer et al., 2009).

The subscales included in the CBCL-DP have solid psychometric properties. The Attention Problems subscale has an 8-day test-retest reliability Cronbach's alpha value of .86, a 12-month stability Pearson r value of .70, and a cross-informant agreement on scale Pearson r value of .73 (Achenbach & Rescorla, 2001). The Anxious/Depressed subscale has an 8-day test-retest reliability Cronbach's alpha value of .84, a 12-month stability Pearson r value of .68, and a cross-informant agreement on scale Pearson r value of .68. The Aggressive Behavior subscale has an 8-day test-retest reliability Cronbach's alpha value of .94, a 12-month stability Pearson r value of .82, and a cross-informant agreement on scale Pearson r value of .82.

Several studies provide support for the validity of the CBCL-DP. An 18-month longitudinal study followed 247 children between the ages of 3.5 and 5.5 (Geeraerts et al., 2015). The children were assessed at the beginning of the study using the CBCL, and at the end using multiple parent and teacher assessments. Confirmatory Factor Analysis (CFA) found that the Dysregulation Profile was significantly correlated with General Level of Functioning, Inhibition, Observed Anger Modulation Problems, Observed Behavior Regulation Problems, Observed Inattentiveness, Observed Hyperactivity/Impulsivity, as well as syndrome clusters that include a behavior/emotional dysregulation element [i.e., Oppositional Defiant Disorder (ODD), Conduct

Disorder (CD) and ADHD]. The CFA also included correlations between the criteria measured in the study and the DP syndrome subscales individually. The Anxious/Depressed factor was correlated positively with parent-reported emotional reactivity and ‘irritable’ symptoms of ODD, and negatively with observed anger modulation problems, behavior regulation problems, hyperactivity/impulsivity, and inattentiveness. Aggressive behavior was correlated positively with ODD and CD clusters. The Attention Problems factor was correlated positively with ADHD symptoms and negatively with general functioning, observed anger modulation problems, and reported irritable ODD symptoms. The results of the study indicate that the dysregulation profile can be best understood as a “broad syndrome of dysregulation” (Geeraerts et al., 2015).

A different study utilized the dysregulation profile to analyze adolescent outcomes in 80 children with disruptive behavior disorders (Masi, Pisano, Milone, & Muratori, 2015). These children were followed from ages 8-9 until ages 14-15. A higher score on the dysregulation profile corresponded to a higher risk of mood disorders and ADHD in adolescence. Though this study found no association between a dysregulation profile and substance use, conduct disorder, or hospitalizations in adolescence, Holtmann et al. (2011) did find that higher dysregulation profile scores in childhood corresponded to a heightened risk for substance use, overall functioning and suicidality. The authors found that a dysregulation profile was not a precursor to comorbidity in general or to a specific pattern of comorbidity, which is compatible with the definition given by Masi et al. (2015) previously.

The CBCL-DP is also reliable across informant types. By comparing scores on the CBCL, Youth Self-Report (YSR), and Teacher Report Form (TRF), researchers were able to measure the level of agreement between parents/guardians, the children, and teachers respectively in terms of which children met the DP criteria (Althoff, Rettew, Ayer, & Hudziak, 2010). Kappa values for the boys in the DP latent class ranged from 0.14 (for TRF vs. CBCL) to 0.28 (for TRF vs. to YSR). As such, across-informant agreement is significant and in the slight to mild range (Landis & Koch, 1977). Through chi-square comparisons, researchers found statistically significant nominal associations across all informant groups barring TRF vs. YSR for girls. Chance-corrected Kappa values suggested more modest levels of agreement among informant groups but were in line with component subscales for which Pearson correlations were between .16 and .52. (Achenbach & Rescorla, 2001).

Traditionally, a score that is two or more standard deviations above the average on each of the three CBCL-DP subscales (i.e., attention problems, aggression, and anxiety/depression) is defined as the threshold for dysregulation (Masi et al., 2015). In other words, if the sum of the T-scores for the three scales is 180 or greater, the profile is elevated. However, when calculating T-Scores, LONGSCAN truncated the lower end of the distribution at T = 50. In addition, when using the traditional strategy for determining elevation (i.e., over or under 180 T) significant information is discarded. This has implications for conducting GMM. Therefore, for the current study, continuous dysregulation scores were computed by taking the sum of the raw scores for each of the three subscales.

Maltreatment

Maltreatment data are collected from multiple sources, including Child Protective Services (CPS) and state Central Registry records, at least every two years. The data with which this paper will be working has been collected from Child Protective Services files at the county level. CPS Maltreatment reports were coded using LONGSCAN's modification of the Maltreatment Classification System (MMCS). The MMCS is a coding system that was developed to help promote definitional clarity regarding research definitions of child maltreatment (Manly, 2005). The MMCS was a modification of the MCS (Runyan et al., 2005) which added greater specificity to intermediate severity codes, dropped the original chronicity codes, and disaggregated a variety of neglect codes. The use of a consistent system across data collection sites is vital given that definitions of trauma type can differ across state and county lines. To use the MMCS, the accepted allegation narrative as well as the summary narrative of the allegation investigation of a given Child Protective Services report are taken by a trained abstractor with the multiple points of abstraction serving to standardize scoring between sites. Based on this review, the coder first determines the maltreatment type for an event or episode. The broad categories of maltreatment in the MMCS were described in detail earlier in this paper and broadly include physical abuse, sexual abuse, physical neglect, supervisory neglect, emotional/psychological maltreatment, moral-legal/educational maltreatment, and drug/alcohol use. After identifying an abuse type, the coder then chooses a code based on the severity of the maltreatment. To eliminate the risk of missing previous CPS referrals, abstractors complete lifetime reviews each time child files are searched. Each child can have multiple observations (CPS referrals) which can in turn contain multiple allegations (coded subtypes of maltreatment). In this study, the maltreatment value of a participant is the sum of Physical Abuse, Sexual Abuse, Emotional Abuse, and Neglect allegations.

Data Analysis

The first step of this analysis was to identify the best-fitting unconditional latent class model. The adequacy of fit of unconditional models with 1-5 classes was tested. Decisions about the best fitting model is based on a combination of statistical indices of best fit as well as logical and theoretical considerations. The first of these indices is the Bayesian Information

Criterion or BIC (Schwarz, 1978). This index is used to choose between two alternative models. Lower BIC values generally denote models with better fit. When comparing two models, a change in BIC values of 10 or more points is the threshold for judging the alternative model (model with lowest BIC) to be clearly superior. An alternative fit index is the sample-size adjusted BIC (A-BIC) which includes a 'penalty' component which discourages increasing the number of estimated parameters simply to improve the fit of the model. Comparing models on the basis of A-BIC as I have done has been found to favor more simplistic models regardless of whether or not the model is rejected by a standard hypothesis test (Weakliem, 1999).

Entropy has been defined by Wang et. al. as "a standardized index of model-based classification accuracy" in which higher values correspond to individuals being assigned to latent classes more accurately (Wang, Deng, Bi, Ye, & Yang, 2017). This value is scaled from 0 to 1, with a score of .8 or above widely considered to be indicative of a well-fitting model.

I subjected the unconditional models to three types of likelihood ratio tests (LRT); Lo-Mendell-Rubin (LMR), Vuong-Lo-Mendell-Rubin (VLMR), and Bootstrap. For each LRT, the fit of a model is compared to the fit of a model with one fewer class to ensure that fit is significantly better (Tofighi & Enders, 2008). The LMR LRT utilizes a weighted sum of chi-squares as an approximate reference distribution. In using this type of LRT, one runs the risk of falsely accepting a model with too many classes if the assumption of multivariate normality of outcomes is violated.

The Bootstrap Likelihood Ratio Test (Bootstrap LRT) is a second test for comparing the adequacy of fit of a model with K classes to a model with K - 1 classes. A significance test for the LRT can also be generated using bootstrap resampling (McLachlan, 1987; McLachlan & Peel, 2000). Initially, X number of bootstrap sub-samples are drawn from the sample. An approximate probability value is subsequently calculated. A small probability value (i.e., $p \leq .05$) indicates that the K - 1 class model should be rejected in favor of the model with at least k classes (Tofighi & Enders, 2007).

According to Jung and Wickrama (2008), a model should have no less than 1% of a given sample in any one class. As such, ensuring that the Smallest Class Percentage of a given model meets this threshold is a factor in the selection process.

Results

Description of Sample

The mean Dysregulation T-score of the sample varied over time from 166.32 (raw score: 17.12) at age four to 165.87 (raw score: 14.66) at age 16. The highest mean Dysregulation T-score was a 169.27 (raw score: 17.43) at age 12. Assuming an average Dysregulation T-score to be 150 (a T-score of 50 on each of the three subscales), I would consider the sample mildly dysregulated. If the mean T-score was at or above 180 at any point in time, the sample would be considered highly dysregulated at that time. The percentage of the sample for whom dysregulation T-scores were above 180 increased steadily from age 4 to 12 (barring a slight decrease between ages 8 and 10), and fell from ages 12 to 16, as seen in Table 1.

Table 1. Dysregulation T-Scores Dichotomized

Age	Valid *N*	% Above 180	*N* Above 180
4	1220	19.8	242
6	1218	23.1	281
8	1124	24.8	279
10	1015	23.0	233
12	951	25.4	242
14	930	23.5	219
16	867	20.6	179

One way of conceptualizing maltreatment over time is by observing the number of maltreatment reports in discrete two-year epochs of time from birth to age 16 (barring the first 0-4-year span). The largest concentration of maltreatment referrals by far occurred between birth and age 4, with a mean of 2.52 (SD = 3.90). This was more than 3.5 times that of the next most concentrated timespan, 4-6. Though we could reasonably expect a larger proportion of referrals within a four-year timespan than the following two-year spans, we would expect, at most, double the number of referrals as next highest concentration. The mean and standard deviation of referrals decrease steadily over the ensuing timespans with 14-16 having a mean of .26 and a SD of .98. See Table 2.

Table 2. Maltreatment Referrals (Non-Cumulative)

Timespan	Mean	*SD*
0 to 4	2.52	3.90
4 to 6	0.63	1.83
6 to 8	0.54	1.58
8 to 10	0.52	1.54
10 to 12	0.43	1.35
12 to 14	0.37	1.36
14 to 16	0.26	0.97

A second way of conceptualizing maltreatment exposure is by calculating cumulative exposure (AKA a running total) at each age range. Naturally, the mean and *SD* continue to grow overtime, starting at a mean of 2.52 (*SD* = of 3.90) for the 0-4 span and ending with a mean of 5.28 and *SD* of 7.8 for the 0-16 span. See Table 3.

Table 3. Running total of Maltreatment Referrals (Cumulative)

Timespan	Mean	*SD*
0 to 4	2.52	3.90
0 to 6	3.16	4.71
0 to 8	3.69	5.33
0 to 10	4.21	5.85
0 to 12	4.64	6.32
0 to 14	5.02	6.81
0 to 16	5.28	7.08

Tests of Unconditional Latent Class Models

The first step was to evaluate the adequacy of fit of unconditional models with 1-5 latent classes. To assess the adequacy of fit of the 1-class model, I measured Root Mean Square Error of Approximation (RMSEA), Chi-Square Model of Fit, Comparative Fit Index (CFI) and the Tucker Lewis Index (TLI). RMSEA is a measure of model misfit and ranges from 0 to 1, with lower values indicating better model fit. The 1-class model's RMSEA value of .09 is considered too large and suggests the consideration of a model with a greater number of classes (Browne & Cudeck, 1992). Chi-Square Model of Fit tests for a significant difference between the hypothesized model and the actual relationship among items. The 1-class model is highly significant in this measure with a p-value of 0.00. Since a hypothesized model which maps closely onto the actual data is preferred, significance in this measure suggests consideration of a model with a greater number of classes. The Tucker Lewis Index is a measure of agreement between the model and the actual covariance matrix (Bentler, 1990). This index ranges from 0 to 1, with higher values indicating a stronger agreement. Generally, a TLI value of .95 or higher is considered acceptable. The 1-class model's TLI value of 0.94 suggests consideration of a model with a greater number of classes. In combination, the fit indices for the 1-class model present a mixed picture. Therefore, I tested models with 2-5 classes. Based on a combination of fit indices and practical considerations, the 4-class model was accepted. As shown in Table 4, the 4-class model yielded the second lowest A-BIC value (54407), highest Entropy value (.82), and has a significant p value for the Bootstrap LRT ($p < .0005$) and p values for the remaining two Likelihood Ratio Tests that approached significance (VLMR: $p < .07$, LMR: $p < .08$, Bootstrap: $p < .00005$). In addition, the smallest class in the 4-class model was sufficiently large (3.0%) to retain. Based on this combination of findings, I concluded that the 4-class model outperformed all other models tested. The classes are labeled Consistently Poor (3.6%), Improving (6.9%), Worsening (9.8%), and Consistently Good (79.8%). See Figure 1.

Table 4. Tests of unconditional models with 1-5 classes

# of Classes	A-BIC	Entropy	Smallest Class %	VLMR LRT	LMR LRT	Bootstrap LRT
1	54733	RMSEA =. 09	Chi-Square of Model Fit: $p = 0.00$	CFI: 0.93 TLI: 0.94	N/A	N/A
2	54524	0.80	13.5%	$p < 0.00005$	$p < 0.00005$	$p < 0.00005$
3	54459	0.75	4.0%	NS	NS	$p < 0.00005$
4*	54407	0.82	3.6%	$p < 0.07$	$p < 0.08$	$p < 0.00005$
5	54352	0.79	2.3%	NS	NS	$p < 0.00005$

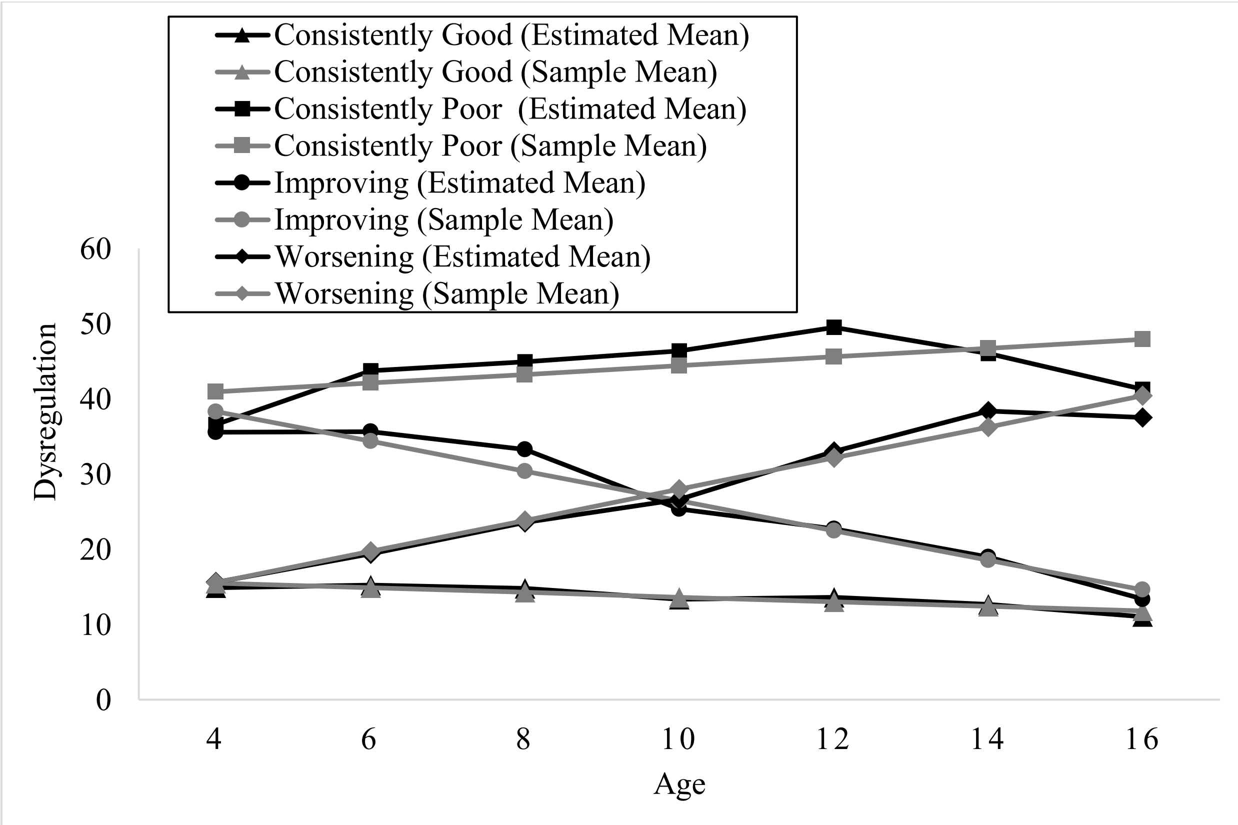

Figure 1. Sample and estimated means 4-class model

Findings from 3-step Procedure

The R3Step procedure preserves the initial 4-class model and examines whether the number of maltreatment allegations predicts class membership. This method allows for the addition of covariates (i.e., number of maltreatment allegations) without changing class membership from the unconditional model (Vermunt, 2010). Results indicated that the Consistently Good group was significantly different from the Consistently Poor, Improving, and Worsening groups. I convey this information in two ways. Firstly, I use the logit coefficient. For the purposes of this paper, the logit coefficient signifies that the log-odds of membership in the reference class compared to the log-odds of membership in the class in question increases by the value of the coefficient for every additional maltreatment allegation. Secondly, I use odds ratios (OR) which represent the logit coefficients as a percent change in class membership odds per additional maltreatment allegation. For example, when comparing the consistently good and worsening classes with the worsening class as the reference, the log-odds of membership in the worsening class as opposed to the consistently good class decreases by 5.09, or by 9% (1.09 - 1 = .09) with each additional maltreatment allegation.

Using the consistently good class as a reference, I found a significant logit coefficient between the consistently good and consistently poor (3.57; OR = 1.07), improving (3.94; OR = 1.08), and worsening (5.09; OR = 1.09) classes. See Table 5.

Table 5. R3 Step Maltreatment as a Predictor of Class Membership

Panel A

Predictor	Consistently good Estimate/SE (OR)	Consistently Poor Estimate/SE (OR)	Improving Estimate/SE (OR)	Worsening Estimate/SE (OR)
Tot. Maltreatment	-5.09****	-0.68	-0.41	Reference
Allegations (0-16)	(1.09)	(1.01)	(1.1)	class

Panel B

Predictor	Consistently good Estimate/SE (OR)	Consistently Poor Estimate/SE (OR)	Improving Estimate/SE (OR)	Worsening Estimate/SE (OR)
Tot. Maltreatment	Reference	3.57*****	3.94*****	5.09*****
Allegations (0-16)	Class	(1.07)	(1.08)	(1.09)

Panel C

Predictor	Consistently good Estimate/SE (OR)	Consistently Poor Estimate/SE (OR)	Improving Estimate/SE (OR)	Worsening Estimate/SE (OR)
Tot. Maltreatment	-3.57****	Reference	0.33	0.68
Allegations (0-16)	(1.07)	Class	(1.01)	(1.01)

Panel D

Predictors	Consistently good Estimate/SE (OR)	Consistently Poor Estimate/SE (OR)	Improving Estimate/SE (OR)	Worsening Estimate/SE (OR)
Tot. Maltreatment	-3.94****	-0.33	Reference	0.41
Allegations (0-16)	(1.08)	(1.01)	Class	(1.01)

*****$p < .0005$

Findings from 1-Step Procedure

Muthén (2004) argues that failure to include covariates in the initial modeling process can result in model misspecification and distorted results. Therefore, I tested conditional models with 1-5 classes in which the covariate (number of maltreatment allegations) can influence placement in a category as well as slope, intercept, and the optimal number of classes. Using this approach yielded a substantially different results which supported the viability of a model with two classes. The Entropy value of the 2-class model was 0.80, which was the highest value of the five models and reflected good classification rates. The smallest class in the 2-class model exceeds the minimum threshold of 1%. The 2-class model fits the data significantly better than the one class model based on VLMR, LMR, and Bootstrap Likelihood Ratio Tests (VLMR: p = 0.0005, LMR: p = 0.0005, Bootstrap: p < .00005). See Figure 2. The 3-class model had p-values significant at less stringent cutoff points for the VLMR and LMR Likelihood Ratio Tests, suggesting inferior fit to the 2-class model. The one anomalous finding is that the A-BIC value of 63593 was higher than the 3-class and 4-class models suggesting poorer fit. See Table 6. The two classes of the resulting model were labeled Improving (86%) and Worsening (14.4%). The worsening class has an intercept of 15.40 and a slope of -0.79. The Improving class has an intercept 24.19 and a slope of 2.71.

Table 6. Tests of conditional models with 1-5 classes – relationship between trauma exposure and S, I, and class membership

# of Classes	A-BIC	Entropy	Smallest Class %	VLMR LRT	LMR LRT	Bootstrap LRT
1	54641	RMSEA =. 08	Chi-Square of Model Fit: $p = 0.00$	CFI: 0.94 TLI: 0.94	N/A	N/A
2*	63593	0.80	14.3%	$p < 0.0005$	$p < 0.0005$	$p < 0.00005$
3	63534	0.77	4.0%	$p = 0.16$	$p = 0.16$	$p < 0.00005$
4	63481	0.79	2.2%	$p =0.18$	$p = 0.18$	$p = 0.11$

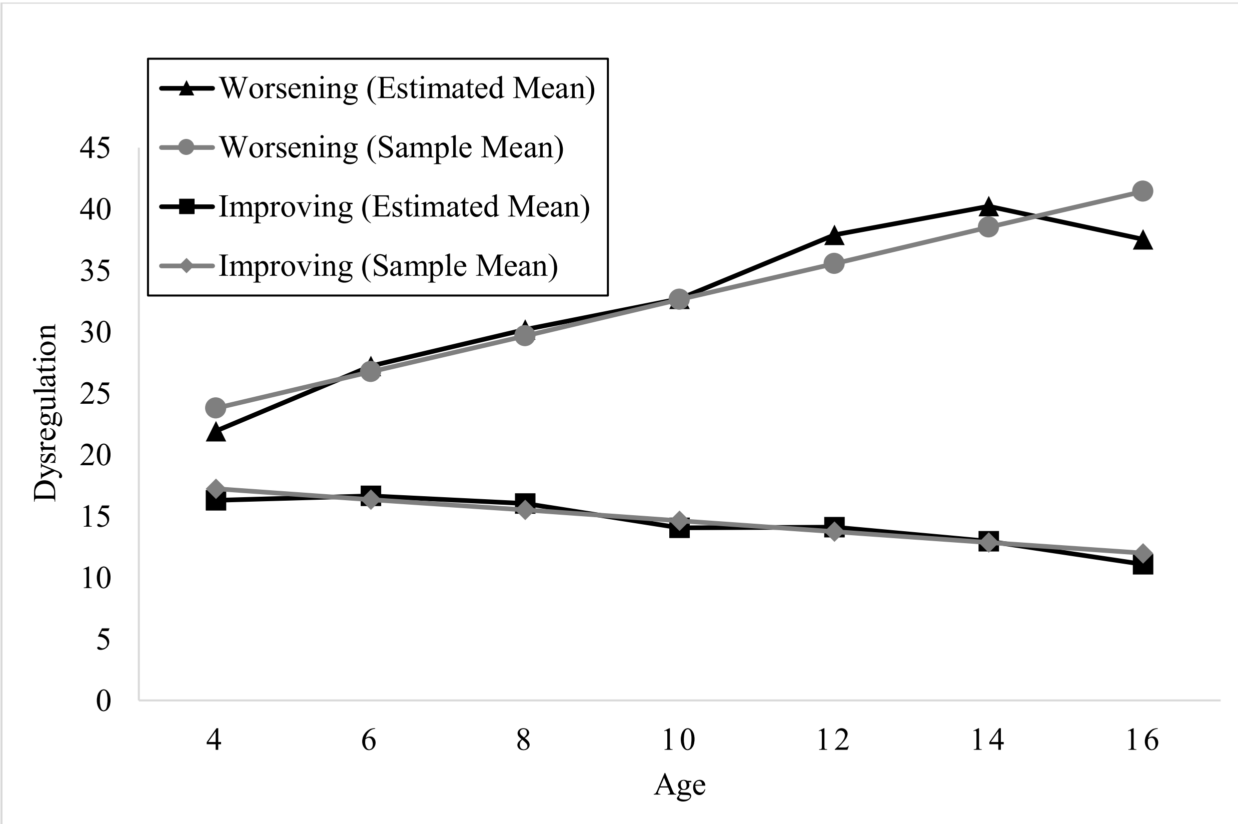

Figure 2. Sample and estimated means for the 2-class conditional model

Findings Using Maltreatment as a Time-Varying Covariate

Thus far, a single value has reflected the number of maltreatment allegations. A third alternative for examining the effect of a covariate on dysregulation trajectories is to conduct a multi-process GMM in which maltreatment is assessed at each age (4-16) as a running total. So, maltreatment at age four is the sum of all maltreatment allegations between birth and age four. Maltreatment at age six is the sum of all maltreatment allegations between birth and age six. See Table 3. Tests of models with 1-4 classes indicated that all models fit the data well. For example, for the 1-class model, the CFI value was 0.99 indicating excellent fit. Models with two to four classes yielded excellent entropy values (0.99) indicating reliable placement of subjects in classes. Tests directly comparing models with k classes against models with k – 1 classes (i.e., Lo-Mendell-Rubin Adjusted LRT Test (LMR-LRT) were non-significant. Given that all models fit exceptionally well, the failure to find a single 'best'-fitting model is not surprising. The exception was for the Parametric Bootstrapped Likelihood Ratio Test, which supported models with greater numbers of classes. For illustrative purposes Figure 3 reflects the 2-class conditional model in which the covariate is time varying. For the low slightly improving class (6.5% of sample), individual regressions of the running total of maltreatment at time X_1 with the corresponding dysregulation score at time X_1 reveal no significant relationships for the low slightly improving class. By contrast, for the high slightly worsening class (93.5% of sample) the relationship between cumulative maltreatment at age 14 and dysregulation at age 14 was significant ($p < .0005$) as was the relationship between cumulative maltreatment at age 16 and dysregulation at age 16 ($p < .0005$). Relative to the corresponding 2-class conditional model in which the covariate was reflected in a single value, the time-varying values reflect a downward shift in the higher class and an increase in the proportion of membership in the lower class.

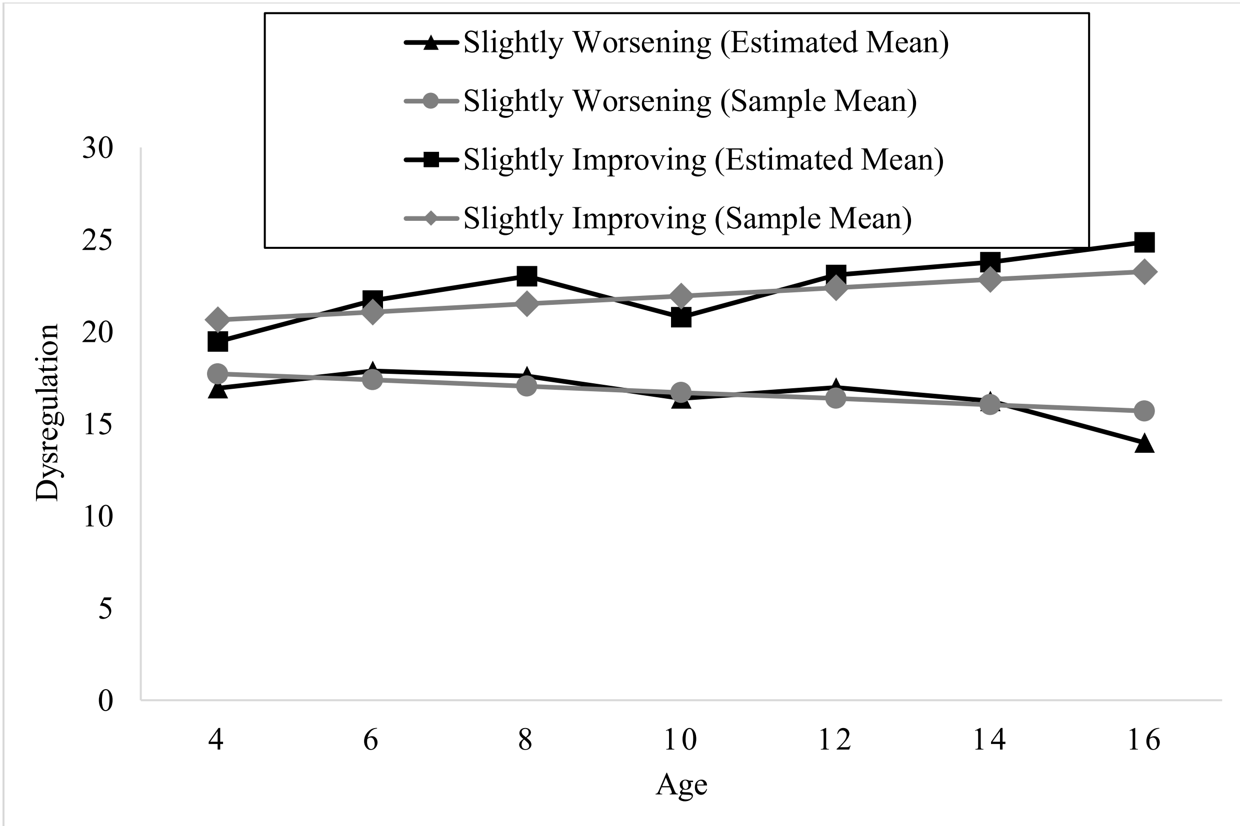

Figure 3. Sample and estimated means for the 2-class conditional model with a time-varying covariate

Discussion

My reasons for undertaking this research were twofold. First, the percentage of the population that has encountered childhood maltreatment is sizable. This means that the probability of interacting with an individual between the ages of 4 and 16 with delayed self-regulation ability is larger than many people may assume. This lack of age-appropriate self-regulation ability may be falsely associated with personal moral shortcomings instead of the symptom of maltreatment that it is. Though work is being done to minimize exposure to maltreatment in children, the fact remains that a substantial portion of the population has been maltreated and must be understood and accepted. For educators and caregivers, understanding the ways in which children who have experienced maltreatment may differ developmentally from other children is an important component of properly teaching and interacting with them. For those in administrative positions, increased general awareness of the differing trajectories of self-regulation skills may help normalize this variance and encourage a more open-minded approach to the structuring of activities and discipline within institutions populated by children, adolescents, and teenagers. Second, it is paramount that those directly and indirectly involved in the field conceptualize the profound degree to which the decisions made by a researcher with regards to data analysis method can affect the results and conclusions that are drawn.

The results show that self-regulation development trajectories between the ages of 4 and 16 are heterogeneous, supporting the idea that two children can demonstrate significantly different developmental trajectories in response to exposure to maltreatment. The results also support the idea that results can be strongly affected by the choice of statistical method that is employed. With regards to the hypotheses posited earlier in the paper, evidence is mixed. The first hypothesis which predicted heterogeneity in self-regulation ability over time has strong support from each model with which I worked, as a 1-class model did not emerge as best-fitting through any method of covariate incorporation. The second hypothesis which predicted "a 4-class model…including two stable classes (low and high) and two classes that change over time (increasing and decreasing)" was partially supported. This was the exact pattern of classes that emerged in the unconditional model. However, after covariate inclusion (i.e., 1-step and time varying), the 4-class model was not superior to the two conditional models which allowed for changes in class assignment. The third hypothesis which predicted that "the method of covariate incorporation can have a significant effect on the shape of the data" is strongly supported by the results, as the 4-class unconditional model differed from both 2-class conditional models in terms of number of classes, slope, and intercepts. The time-varying and time-invarying models also differed from each other in terms of slope, intercepts, and percentage of sample in each class.

Incorporating a similar covariate through differing methods can change the model of best fit drastically. This has strong implications for conclusions drawn from studies using GMM, specifically that those which use only one method of covariate incorporation may be inadequate to fully describe a relationship between variables. The results suggest that multiple methods of covariate incorporations must be utilized in order to draw a more complete conceptual picture of any relationship analyzed through GMM.

Analytical Considerations

Despite the value of a large, well-organized longitudinal study such as those performed by LONGSCAN, use of this database poses its own risks, as made clear by the database's user guide. First, the longitudinal nature of the data itself violates the independent observations assumption, as the participants have been previously exposed to the experiment for every assessment barring the first. Second, the variation of participant ages and visit timings can also lead to unwanted variation in data. Lastly, should individuals within similar ecological contexts (SES, caregiver psychological disorder) be more similar to each other than across contexts, individual differences may be distorted in the processing of averaging the effects. Through manipulating sample size, class separation, and a multitude of additional variables, Hu, Leite, and Gao found that unconditional models outperform those with a covariate assuming that both the sample size and degree of separation between classes are sufficiently large (Hu, Leite, & Gao, 2017).

It should also be kept in mind that the dysregulation data were based on caregiver reports of dysregulation on the CBCL. Consequently, it is always possible that well-intentioned caregivers minimized (or amplified) symptoms. The maltreatment data were based on referrals to CPS for suspected physical abuse, sexual abuse, emotional abuse, and neglect allegations. While this remains the most effective method of collecting data of this type, reliance on CPS data has a number of well-known limitations. For example, mandated reporters such as teachers can underreport the abuse they encounter and CPS may only investigate the most serious cases (Miller, Perrin, 2014). Self-report assessments regularly arrive at higher estimates of maltreatment, which may be a consequence of instances of maltreatment which do not meet the standards of severity for CPS referral (Negriff, Schneiderman, & Trickett, 2017). Of course, self-report by young children, such as those in this sample, is problematic. Very young children are simply unable to accurately report maltreatment. Moreover, underreporting due to fear (rational or otherwise) of retribution by caretakers, failure to fully understand that one was subjected to maltreatment make the use of self-report data untenable. Similarly, sole reliance on caregivers' reports of maltreatment are equally problematic given the motivation to underreport or deny the full extent of their living situations, parenting practices, etc.

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Appendix: Additional MMCS Maltreatment Categories

Failure to provide refers to a caregiver failing to provide necessary components for the proper care of a child, and is composed of five subcategories, each of which has a unique severity scale, and are as follows: 1. failure to provide food rated from *1 = caregiver fails to ensure food is available for regular meals, resulting in a child under 10 having to prepare their own meals and/or missing meals due to negligence, to 5 = severe malnourishment symptoms (infant weight loss and severe nonorganic failure-to-thrive),* 2. failure to provide clothing rated from *1 = failure to provide a child with clothes that are clean and allow free movement, to 2 = clothing given by a caregiver is inappropriate for the weather*, 3. failure to provide shelter rated from *1= caregiver makes no attempts to clean living space (remove refuse, clean cookingware, etc.)/ potentially hazardous living situations, (inability for a child to escape during an emergency), to 4 = caregiver fails to arrange for adequate shelter within prolonged period.* 4. failure to provide adequate medical care rated from *1 = caregiver often fails to take child for medical checkups, immunizations, and/or fails to attend to a mild behavioral problems brought to their attention by professionals, to 5 = caregiver has abused drugs or alcohol during the term of a pregnancy to the point of giving birth to a child with fetal alcohol syndrome or a congenital drug addiction, child fatality/disablement due to gross inattention to medical needs, failure to seek help with regards to a potentially fatal emotional issue (suicide attempts, etc.)* 5. failure to provide hygiene [*sic*] rated from *1 = caregiver frequently fails to bathe the child and/or a child only infrequently* *brushing their teeth with obvious signs of tooth dental damage, to 4 = extremely unsanitary living conditions including the presence of human waste in the living area.*

Moral-legal maltreatment includes failure of a caregiver to demonstrate the minimum degree of care in assisting a child integrate with the expectations of society, as well as exposing a child to or involving a child in illegal activities that may foster delinquent/antisocial behavior within them. Moral-legal maltreatment is divided into five severity levels and are as follows: *1 = caregiver allows a child to be present for activities for which the child does not meet the age requirement, 2 = caregiver participates in illegal activities with the knowledge of a child, 3 = caregiver fails to intervene in a child's known illegal behaviors, 4 = caregiver involves child in misdemeanors or forces child to participate in illegal behaviors, or gives drugs/ alcohol to child, 5 = caregiver involves child in a felony.*

Educational maltreatment is categorized by a failure to demonstrate minimum the degree of care in helping a child gain an education and/or become properly socialized through regular school attendance, and is divided into five severity levels which are as follows: *1 = caregiver allows child to stay home from school with no acceptable reasoning for up to 15% of the reported school period, 2 = caregiver allows child to miss school from 15%-25% of the reported period, 3 = child is permitted to avoid and/or kept out of school for 26%-50% of the year, or up to 16 consecutive days, 4 = caregiver keeps child out of school for more than 50% of the reported school period, or for a period exceeding 16 consecutive days while still maintaining school enrollment, 5 = caregiver encourages child under the age of 16 to drop out of school or does not send child to school at all.*

Drug/alcohol-related maltreatment refers to alcohol/drug use by a caregiver having an adverse effect upon a child, such as a caregiver staying out to drink. All cases in this category are assigned a blanket severity value of 6.