Development of Emotion Regulation and Parental Socialization during Early Childhood

Dissertation

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By

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Abstract

Children's development of emotion-regulation skills and abilities is a major task of early childhood. A large research corpus has been developed on this topic, but much remains to be learned about how children develop regulatory abilities. Particularly as there is a diverse set of influences on children's development of regulatory abilities, ranging from intrapersonal to genetic to environmental, continued research into children's development of regulation is and likely will continue to be needed indefinitely. The current dissertation attempts to make some headway into this problem and examined several aspects of how children develop self and emotion regulation abilities.

The first chapter includes a general introduction to understanding children's development of emotion regulation and details how the current dissertation will advance the field. The second chapter presents an empirical study that examined the role of respiratory sinus arrhythmia (RSA) in children's negative reactivity. Importantly this study examined non-linear effects of RSA on negative reactivity using generalized additive models. Results suggest that RSA is related in a non-linear manner to children's negative reactivity both concurrently and longitudinally.

The third chapter tested measurement invariance of the Challenging parenting behavior questionnaire across mothers and fathers. Data was collected using Amazon Mturk and included parent's ratings of their own challenging parenting behavior as well as child anxiety. Measurement invariance of challenging parenting behavior was found across mothers and fathers. Fathers were also found to have higher latent means of challenging parenting behavior. Finally, a structural equation model of the effect of challenging parenting behavior on child anxiety was developed. It was found that several aspects, particularly rough-and-tumble play, of challenging parenting behavior by fathers were related to decreased child anxiety.

The fourth chapter utilized statistical learning techniques to select variables from a large list of candidate variables, stratified into demographic maternal personality and psychopathology, maternal parenting, and child characteristic groups, and then modeled the effect of these variables on children's negative reactivity to tasks designed to induce negative emotions. Models were developed using both a random forest and penalized regression methodology. Results suggested several variables that are of interest to children's development of regulation ability. Further, it was found that penalized regression generally outperformed random forest in finding and relating variables to children's regulation. The fifth and final chapter provides a conclusion and a discussion of the results of the current dissertation.

Dedication

For everyone that has helped me in my journey, thank you.

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Publications

Chan, M. H., Gerhardt, M., & Feng, X. (2019) Longitudinal measurement invariance of MIDUS depressive affect and positive affect items. *European Journal of Psychological Assessment* <u>https://doi.org/10.1027/1015-</u> 5759/a000529

- Gerhardt, M., Feng, X., Wu, Q., Hooper, E. G., Ku, S., & Chan, M. H. (2020). A naturalistic study of parental emotion socialization: Unique contributions of fathers. *Journal of family psychology: JFP: journal of the Division of Family Psychology of the American Psychological Association (Division 43)*. https://doi.org/10.1037/fam0000602
- Hooper, E. G., Wu, Q., Ku, S., Gerhardt, M., & Feng, X. (2018). Maternal emotion socialization and child outcomes among African Americans and European Americans. *Journal of Child and Family Studies*, 1-11.
- Ku, S., Feng, X., Hooper, E. G., Wu, Q., & Gerhardt, M. (2019). Interactions between familial risk profiles and preschoolers' emotionality in predicting executive function. Journal of Applied Developmental Psychology, 63, 76-86.
- Lee, J. K., Schoppe-Sullivan, S. J., Feng, X., Gerhardt, M. L., & Dush, C. M. K. (2019). III. Longitudinal measurement invariance across fathers' and mothers' reports of maternal gatekeeping behavior. Advancing Research and Measurement on Fathering and Children's Development, 35.

- Wu, Q., Feng, X., Gerhardt, M., & Wang, L. (2019). Maternal depressive symptoms, rumination, and child emotion regulation. European child & adolescent psychiatry, 1-10.
- Wu, Q., Feng, X., Hooper, E. G., Gerhardt, M., Ku, S., & Chan, M. H. M. (2019). Mother's emotion coaching and preschooler's emotionality: Moderation by maternal parenting stress. Journal of Applied Developmental Psychology, 65, 101066.
- Wu, Q., Hooper, E., Feng, X., Gerhardt, M., & Ku, S. (2019). Mothers' depressive symptoms and responses to preschoolers' emotions: moderated by child expression. Journal of Applied Developmental Psychology, 60, 134-143.

Fields of Study

Major Field: Human Development and Family Science

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Chapter 1. Introduction

Emotion regulation is the ability to modulate one's own actions, responses, and internal states in response to emotion in order to achieve one's goals (Fletcher et al., 2013; Fliek et al., 2015). Emotion regulation is used throughout the lifespan in a variety of situations including family life, peer relations, academic settings, workplace settings and more (Fletcher et al., 2013; Fliek et al., 2015). Unsurprisingly, given the variety of situations emotion regulation is used for, there is a great deal of research that examines emotion regulation at different points in the lifespan (Fletcher et al., 2013; Fliek et al., 2015). There are also many aspects to emotion regulation including but not limited to emotional, behavioral, and physiological regulation. Understanding all three of these aspects of regulation in young children is important to gain a more complete picture of their emotion regulation (Fletcher et al., 2013; Fliek et al., 2015). As emotion regulation is related to a number outcomes including, better mental health, social skills, peer relations, and academic performance (Fletcher et al., 2013; Fliek et al., 2015) furthering our understanding of all aspects of emotion regulation is an important task. A better understanding of how emotion regulation develops will also benefit practitioners as they can better target their interventions and protocols to help children develop emotion regulation skills.

The development of emotion regulation skills is a major task for young children in their first five years of life (Fletcher et al., 2013; Fliek et al., 2015). Children acquire

emotion regulation strategies and abilities through their caregivers early in life. The following studies examined several pathways through which children's emotions are socialized (Berk & Meyers, 2016). Through engaging in parenting behaviors such as teaching children how to regulate their emotions (Fletcher et al., 2013; Fliek et al., 2015) and modeling appropriate reactions and behaviors (Fletcher et al., 2013; Fliek et al., 2015) parents socialize their children to regulate and express their emotions in a socially appropriate way. These parenting behaviors and actions help to lay the foundation for children's emotion regulation, skills that are essential to success in social and academic settings, as well as general mental wellbeing (Berk & Meyers, 2016). Children also have emotion regulation skills that are thought of as being inherent to them (Fletcher et al., 2013; Fliek et al., 2015). It is widely accepted that aspects of temperament, such as effortful control, are related to children's ability to regulation their emotions (Fletcher et al., 2013; Fliek et al., 2015). Temperament is generally regarded as an inborn trait, and while it contains an environmental component that can somewhat alter traits over time, much of temperament is genetic (Berk & Meyers, 2016).

An important implication of children having environmental influences on their emotion regulation abilities, in addition to internal influences on their regulatory behaviors, is that understanding children's development of regulation requires understanding multiple aspects of emotion regulation. This is formalized in the Tripartite model which includes both parental socialization and children's characteristics (Fletcher et al., 2013; Fliek et al., 2015). This has led to a number of studies that focus on various aspects of emotion regulation and how it develops (Fletcher et al., 2013; Fliek et al., 2015).

The Multifaceted Nature of Emotion Regulation

Children's emotion regulation is multifaceted and involves many different aspects. There is thought to be a physiological component to emotion regulation (Berk & Meyers, 2016). One aspect of physiological regulation that has received a good deal of study is vagal tone. Vagal tone is the result of the vagus nerve exerting its influence on the heart to either up or down regulate emotions (Fletcher et al., 2013; Fliek et al., 2015). The vagus nerve is involved in regulation by either increasing or decreasing its influence on the heart. When action is required, for example if children feel threatened, the vagus nerve can withdraw its influence from the heart. This supports children in engaging the flight or fight response to either escape from the threat or to fight the threat (Fletcher et al., 2013; Fliek et al., 2015). Alternatively, after a threat has been dealt with, or the individual is otherwise overstimulated, the vagal brake can be engaged to calm the individual (Berk & Meyers, 2016). By engaging and disengaging the nervous system the vagus nerve can assist in the regulation of self and modulate behaviors to be more socially appropriate (Fletcher et al., 2013; Fliek et al., 2013; Fliek et al., 2015).

The activity of the vagus nerve can be indexed by respiratory sinus arrhythmia (RSA), which can be measured non-invasively using an electrocardiogram (Fletcher et al., 2013; Fliek et al., 2015). RSA has been shown to relate to children's regulatory capacities as well as their behaviors (Gerhardt et al., 2020; Wu, Feng, et al., 2019; Wu, Hooper, et al., 2019). This implies that vagal tone is indeed used in emotion regulation capacities. Further, this suggests that children with better physiological regulation may be better able to regulate themselves in a variety of situations. Understanding the manner in which vagal tone relates to behavior can be quite complicated as there have been non-

linear associations between vagal tone and behavior found (Berk & Meyers, 2016). Further work may be required in order to fully understand how vagal tone relates to behavior and how this relationship may change at different levels of vagal tone.

Another important aspect of children's emotion regulation is their behavioral regulation. There are a number of different behaviors that children may engage in to regulate their negative emotions. Children that distract themselves from a negative stimulus are better able to regulate their negative emotions, conversely children who focus on the negative stimulus are less able to regulate their negative emotions (Fletcher et al., 2013; Fliek et al., 2015). Similarly, children who have parents who themselves express more positive emotion and teach their children how to regulate their emotions are better able to modulate their behavioral responses to negative stimuli (Fletcher et al., 2013; Fliek et al., 2015). Children's responses to negative emotional stimuli is an important aspect of their development of emotion regulation (Gerhardt et al., 2020). As it is inevitable that everyone will encounter negative emotions throughout their lives, successfully regulating these negative emotions, and behavioral responses to negative emotions, is exceedingly important to successful emotional development (Berk & Meyers, 2016).

Parental Roles in the Development of Emotion Regulation

Parents are widely accepted to have a major role in children's development of emotion regulation (Fletcher et al., 2013; Fliek et al., 2015). While researchers have explored this topic in many different studies there is still a great deal that we do not know about children's development of emotion regulation. New hypotheses for how children develop emotion regulation skills and refinements of hypotheses are still being

proposed and developed as well as new models of development (Fletcher et al., 2013; Fliek et al., 2015). Recently, a great deal of attention has been placed on father's roles in children's development of emotion regulation. Historically, fathers' roles have not received as much attention as mothers' roles, but with increasing father involvement, and findings that fathers are important to many aspects of children's development including emotion regulation, research into fathers has increased recently (Cabrera et al., 2014). One major area of interest is fathers' challenging their children and the role this has in teaching children emotion regulation (Paquette, 2004). It has been found that fathers that challenge their children teach them emotion regulation skills (Bögels & Phares, 2008; Dumont & Paquette, 2013). Considering the many benefits that are derived from emotion regulation abilities understanding how these abilities develop is of vital performance (Berk & Meyers, 2016).

There are a number of influences on children's development of emotion regulation, two major influences are children's individual characteristics and parentchild interactions (Morris et al., 2007). It has been well established that children who are higher in effortful control, an aspect of temperament that is partly the ability to modulate one's behaviors, are better able to regulate themselves (McCrae et al., 2000; Spinrad et al., 2007). It is also known that parent's behavior can help modulate children's behavior and temperament as well as parenting interacting with these characteristics to produce children's behavior (Reuben et al., 2016). Other aspects of children's temperament and personality are also important for children's emotion regulation behaviors (Shiner & DeYoung, 2013; Stifter & Braungart, 1995). Children higher in negative affectivity experience more negative emotions and are more likely to have mental health problems

such as depression and anxiety later in life (Watson et al., 1988). Further, higher levels of negative affectivity are related to worse emotion regulation in children (Chen et al., 2014). Finally, children with higher levels of effortful control or conscientiousness are better able to regulate their behavior in response to negative emotions and inhibit or engage in behaviors that reduce negative emotions (Eisenberg et al., 2014; Spinrad et al., 2007).

The interactions that children have with their parents are also important for children's development with different types of parental interactions relating to different aspects of the development of emotion regulation (Cabrera et al., 2017; Lunkenheimer et al., 2007; StGeorge et al., 2015; Wu, Feng, Hooper, et al., 2019). We know that parents that engage in emotion coaching have children who are better able regulate their own emotions (Wu, Feng, Gerhardt, et al., 2019; Wu, Feng, Hooper, et al., 2019). It is also known that parent's play behavior with children is related to their development (Cabrera et al., 2017). Children who engage in play activities with their parents develop better regulation skills and are even less likely to sustain physical injuries (StGeorge et al., 2015).

Challenges in Studying Emotion Regulation

Understanding and accepting that emotion regulation is multifaceted means that studies involving multiple systems of emotion regulation (e.g., behavioral, physiological) are required. Additionally, this means that studies of emotion regulation should attempt to systematically consider individual and familial influences. Considering the various aspects of emotion regulation and how they are employed by children allows studies to gain a more complete understanding of emotion regulation. Including more aspects of emotion regulation also has the added effect of reducing the presence of third variable effects. This would allow researchers to produce models and understandings of emotion regulation that are more accurate and better understand the processes involved.

A limitation of studies that is necessitated by monetary and modeling constraints is that they only study one or at most a couple of aspects of emotion regulation development. Given the wide range of variables that are known to relate to children's development of emotion regulation the ability to only model the effects of one or a few of these variables may be cause for concern. Determining which variables to use and how to model their effects can drastically change results (Shadish et al., 2002). Some modeling techniques can help resolve this issue to an extent, many of these techniques fall under the category of statistical learning models (James et al., 2013).

Another difficulty in studying physiological and behavioral emotion regulation simultaneously is that there is the possibility of non-linear effects between physiological regulation and behavioral regulation (Kogan et al., 2013). There is evidence that vagal tone, a commonly studied physiological regulatory tool, has a non-linear effect on behavior such that moderate levels of vagal tone are most beneficial for optimal functioning (Kogan et al., 2013; Miller et al., 2017). Some research has suggested that moderate vagal tone is related to the best regulation ability and the most prosocial behavior (Kogan et al., 2013; Miller et al., 2017). Further complicating the matter there is also evidence that males and females have differences in vagal tone and the vagal response to stressors (Snieder et al., 2007). This non-linearity makes studying physiological effects a complicated endeavor as not only must the relationship between

vagal tone and regulation need be modeled, but this model must differ at different levels of vagal tone.

Examining the influence of parents' behaviors is another important aspect of studying emotion regulation (Dyer, 2015). One common method to measure parenting and children's behavior is self-report questionnaires. There are hundreds of questionnaires, some well understood and tested while others are less well tested, that measure a wide variety of constructs from temperament to parental depression; many of which have been in use for years or decades and are well understood (Chiorri et al., 2016; Edwards et al., 2010; Goldsmith & Rothbart, 1996; Putnam & Rothbart, 2006; Radloff, 1977). However, newer constructs and questionnaires are not as well understood and require psychometric evaluation and testing before widespread use. Particularly in the case of fathers, there is a dearth of established questionnaires (Volling et al., 2019). Oftentimes questionnaires and measures that have been developed and tested for use with mothers are used for fathers under the potentially faulty assumption that maternal and paternal parenting is the same (Volling et al., 2019). There is empirical evidence that suggests that mothers and fathers engage in parenting in different ways and measures should be adapted and developed for each parent (Paquette & Bigras, 2010; Volling et al., 2019). A construct that is relatively new, lacks an extensively tested questionnaire for, and may differ between mothers and fathers, is challenging parenting behavior (Majdandžić et al., 2018). Particularly as this is hypothesized to have a multifactor structure studies are needed to examine this structure and examine measurement invariance (Dyer, 2015).

A difficulty presented by the multitude of factors that relate to emotion regulation is that modeling can be quite difficult. There are limits to a model's ability to be flexibly used in a variety of situations and produce useful and reliable estimates (Shadish et al., 2002). Further, as a consequence of the wide variety of variables related to emotion regulation, selecting appropriate variables for inclusion in a model can be challenging and have large consequences for models and conclusions drawn from those models. Various modeling techniques have different strengths and drawbacks, consideration of which modeling technique is best suited for the task at hand is an important part of researcher's work, and is related to what research questions can be answered by a study (Shadish et al., 2002). One limitation of many modeling methods is that a limited number of variables can be included (Shadish et al., 2002). This limitation in modeling reduces the possible hypotheses that can be tested and the research that can be done.

Understanding how these variables interact with one another to produce behavior is further complicated by other external variables that can affect family functioning. Maternal depression is known to effect mother's ability to teach emotion regulation skills as well as creating an emotional environment that may be detrimental to children's development of emotion regulation (Goodman et al., 2011). This means that to understand parenting behavior, children's characteristics, and children's behavior requires an understanding of how several variables interact with one another. This is even more complicated as other variables such as family income, coparenting, and many other variables are also related to behavioral outcomes (Ku et al., 2019; Schoppe-Sullivan et al., 2013). While it is possible to collect information on all of these variables

in a single study, modeling all of these variables can be challenging or impossible depending on a variety of factors including sample size, model selected, and number of time points collected (Shadish et al., 2002).

The Current Dissertation

Structure

The overall goal of this dissertation is to advance our understanding of the role of mothers and fathers, as well as children's own regulatory resources, in the development of children's emotion regulation utilizing state of the art methods. These studies examined the emotion socialization process, the role of parenting, and individual characteristics related to children's development of emotion regulation. This dissertation is comprised of three individual studies that all build upon one another to address the question of children's development of emotion regulation.

The first study, presented in chapter 2 examined the non-linear relations between children's physiological and behavioral regulation in challenging situations when they were 6, 15, and 24 months old (Vernon-Feagans et al., 2018). Data for this study were drawn from the Family Life Project (FLP; Vernon-Feagans et al., 2018). This large longitudinal study includes measures of a wide variety of variables that are of interest to researchers, the third study only utilized a small portion of the variables. Children's vagal tone was measured at baseline when children were resting and during a Bayley exam, a measure of cognitive functioning (Bayley, 1969). The Bayley exam was thought to be a stressful experience for the children and allowed for changes in vagal tone from baseline to be measured.

To test the non-linearity of the relationship between children's RSA and their behavior generalized additive models (GAM) were used (Wood, 2017). These models allow for the relationship between the predictor, RSA, and the outcome, children's negative expressed emotion, to vary at different levels of RSA. Models for each concurrent timepoint (6, 15, and 24 months) and each longitudinal relationship (6 to 15, 6 to 24, and 15 to 24) were run using children's baseline RSA and the difference between the baseline and Bayley RSA. These models also included linear terms so the effects of other linear variables can be examined alongside the non-linear effects of RSA (Snieder et al., 2007).

The second study, presented in chapter 3, tested the measurement invariance of the challenging parenting behavior questionnaire across mothers and fathers (Majdandžić et al., 2018). The challenging parenting behavior questionnaire is a newly developed questionnaire that measures, as the name suggests, challenging parenting behavior. Challenging parenting behavior can be defined as actions that parents engage in that push children's limits in a fun manner (Majdandžić et al., 2014). Children's anxiety can be thought of as a consequence of children lacking the emotion regulation skills necessary to successfully regulate their anxiety. Challenging parenting behavior is thought to reduce children's anxiety and teach children these necessary regulation skills, but measurement of challenging parenting is not as well developed as some other questionnaires (Majdandžić et al., 2018). Questionnaires that have had extensive studies conducted upon them testing psychometric properties in a variety of contexts and a variety of populations are preferable as there is a higher level of confidence that these measures are valid, reliable, and invariant across reporters (Dyer, 2015). Specifically,

the challenging parenting behavior questionnaire has not been used in an American sample and has not been extensively studied in countries other than the Netherlands. There is some evidence that the questionnaire may readily expand beyond use in a Dutch language speaking population as measurement invariance was found in Australia (Majdandžić et al., 2018).

The data for this study were collected using Amazon Mechanical Turk (MTurk), an online platform that allows researchers to post questionnaires on a board. Use of MTurk for academic research purposes is quite common in social science and has been used for questionnaire development with parents of children (Parent & Forehand, 2017). This study collected data using MTurk because the population of possible test takers is large, data collection can be completed very rapidly, and data collection is cheap when compared with other methods (Parent & Forehand, 2017).

In chapter 4, the third study focused on the mother-child interactions and characteristics, such as children's temperament and emotion expression in children's homes, that are associated with children's development of emotion regulation skills. To achieve this, statistical learning techniques were used to predict children's regulation of emotion during frustrating and disappointing tasks. The study utilized random forests and penalized regression, which consider variables and interactions that may not be readily tested by researchers who manually specify models. This had the potential to identify important variables and interactions and improve our understanding of how mother-child interaction relates to children's development of emotion regulation skills. This study also has the potential to develop useful models that can predict children's later regulatory behaviors (James et al., 2013).

Data for this study is drawn from a longitudinal study conducted at a large Midwestern University, referred to as ACER. This study used several variables from the ACER study that have been largely, or completely, been unused thus far. The ACER study included observational ratings of children's and mother's behavior in a lab setting, mother reports of children's behavior and individual characteristics, and mother's report of their own individual characteristics. Several published studies have resulted from data collected by the ACER study but only a small portion of the information collected has been used (Gerhardt et al., 2020; Hooper et al., 2018; Ku et al., 2019; Wu, Feng, Hooper, et al., 2019; Wu, Hooper, et al., 2019).

Chapter 5 provides a general discussion and conclusion of the results from this dissertation taken across all three studies. It argues that these studies have advanced our knowledge of children's development of and use of emotion regulation. Chapter 5 also discusses the implications of these findings and what they might mean for future research. The chapter concludes with a recommendation for future directions for research and how the results of the studies for this dissertation can be used to inform these future studies. Ideally, the results of each of the studies can be used to produce better models and a more accurate understanding of children's development of emotion regulation.

Chapter 2. Nonlinear Relations of Children's Respiratory Sinus Arrhythmia to Regulation Outcomes

Social science has seen an increased interest in physiological markers of emotion regulation and how these relate to future behavior and mental health (Hastings et al., 2008; Laurent et al., 2017; Leonard, 2001; Perry et al., 2013; Porges, 2007; Sulik et al., 2015). There are good reasons for this trend as technological advances have allowed for more direct measures of nervous system functioning that are more easily implemented and economically viable. One popular physiological marker of emotion regulation is vagal tone. Vagal tone is a measure of neural regulation of the heart by the vagus nerve and is measured by the effect of the respiration cycle on cardiac activity (Moore & Calkins, 2004). Vagal tone is known to be related to the regulation of stressors, emotions and social interactions (Hering, 1910; Porges, 2007). The relation between vagal tone and regulation of emotions is quite complicated and much work remains to be done to understand this relationship (Porges, 2007). This is further complicated as there is evidence, as well as theoretical reasons, that vagal tone may relate to negative reactivity in a non-linear fashion (Kogan et al., 2013; Miller et al., 2017). The current study attempts to extend the understanding of if and how vagal tone may relate non-linearly to children's negative reactivity, negative emotion expression in response to negative stimuli such as fear and sadness.

While previous research has established that there is a relation between vagal tone and regulation of emotions there remains a great deal to discover about this relationship.

Recently there has been discussion of non-linear relationships between vagal tone and regulation of emotions (Kogan et al., 2013). However, work to further test this relationship and further elaborate on existing research is still needed. There have been studies that support a non-linear relationship but there are also studies that have found a linear relationship between vagal tone and behavior (Calkins, 1997; Kogan et al., 2013; Miller et al., 2017). Further, there have been theoretical models developed that explicitly state that development in general occurs rapidly followed by periods of relatively stability supporting the notion that the effect of RSA could be non-linear (Feldman, 2006). The goal of the current study is to examine if vagal tone relates to emotion regulation in a non-linear fashion during the rapid developmental change in autonomic regulation in infancy and toddlerhood.

Polyvagal Theory and Physiological Regulation

Vagal tone is a physiological measure of the functioning of the autonomic nervous system; it can be measured by respiratory sinus arrhythmia (RSA; Porges, 2007) the variability in heart rate that results from regular breathing and is considered a normal process (Hering, 1910; Porges, 2007). It is thought that by measuring RSA we can measure the role of the autonomic nervous system in the physiological regulation of behavior and emotion (Porges, 2007). Empirically there has been work connecting RSA to child emotion regulation and anxiety (Gentzler et al., 2009; Hastings et al., 2008), as well as other aspects of behavior such as altruism (Miller et al., 2017). The link between physiological regulation and various psychological outcomes including, depression, anxiety, and emotion expression, has not always been clear and consistent (Chida & Steptoe, 2009) and given the relatively recent interest in this topic much work remains to

be done. However, this area presents an exciting opportunity to move the field of psychology forward as well as the opportunity to promote interdisciplinary work with the field of biology.

One theory that has been put forth regarding physiological regulation is polyvagal theory (Porges, 2007). Polyvagal theory is primarily concerned with the 10th cranial nerve, the vagus nerve which is responsible for much of parasympathetic nervous system function (Slonim, 2014). Porges (2007) argues that the vagus nerve, through influencing heart rate, can alter emotional states and help regulate responses to stressors and demands. The vagus nerve can withdraw from influencing heart rate when action is needed, for example to run away from a threat. This process of removing the vagal influence from the heart is referred to as "vagal withdrawal" (Porges, 2007). Conversely, the vagus nerve can apply a "vagal brake" to reduce heart rate to calm an individual down after a stimulating event (Hastings et al., 2008). This system allows for physiological regulation of emotions and can both provide the response necessary to excite an individual to deal in danger (vagal withdrawal) and provide the ability to calm down and regulate emotions (vagal brake) to engage in a more prosocial way with others (Porges, 2007; Slonim, 2014). For example, if an individual is threatened by some environmental effect (e.g., a bear is chasing them) the vagus nerve will withdrawal (vagal withdrawal) to prepare the individual to either run or fight the threat (Hastings et al., 2008; Porges, 2007). If an individual is overly excited and needs to reduce their activity or arousal, for example if an overly excited individual needs to engage in appropriate behavior in a school setting, the vagus nerve will increase vagal tone which in turn reduces cardiac activity (vagal brake) and calms that individual down (Porges, 2007). RSA is commonly

used to measure the activity of the vagus nerve as it is non-invasive and is thought to be able to measure the vagus nerves responses to environmental conditions (Hastings et al., 2008; Porges, 2007; Slonim, 2014).

Since vagal tone is a physiological response it is present from birth and can be measured reliably (Porges, 2007). In comparison, concepts such as personality, social skills, and self-regulation are generally thought to be more difficult to observe in young children (Shiner et al., 2012). Since the use of ECGs is safe and does not rely on any level of self-report or observations that are later coded the measure is less likely to be biased or unreliable because of the reporter (Shadish et al., 2002). The ability to directly measure vagal tone, even at birth is a major advantage of this physiological measure of regulation.

There are a number of studies that have found that baseline vagal tone as measured by RSA is related to prosocial behavior (Miller et al., 2017), baseline and change in RSA to behavior problems, (Calkins et al., 2007) as well as emotion regulation (Hastings et al., 2008). Further it has been found that baseline and RSA change are related to peer relations (Graziano et al., 2007), and mental health issues (Gentzler et al., 2009). Understanding RSA and its relation to behavior is an important step to further understand emotion regulation (Tull & Aldao, 2015). The role of RSA in response to challenge is an important part of polyvagal theory, thus testing physiological responses to challenging situations provides an opportunity to further understand emotion regulation. Additionally, understanding parental behavior that may encourage better vagal responses in children is an important consideration in furthering this area.

RSA and Emotion Regulation during Infancy and Toddlerhood

Research into the role of vagal tone on behavior and regulation has supported the hypothesis that vagal tone is related to behavior, expression, and social interaction (Porges, 2007). It has been found that behavior problems can be predicted using infants' ability to engage their vagal control when challenged by the environment (Porges et al., 1996). Further, it has been found that both baseline and RSA in response to stressful situations is related to young children's ability to regulate their emotions (Gottman & Katz, 2002). Similar findings have been observed in infants with vagal tone relating to regulation when separated from their mothers (Oosterman & Schuengel, 2007). Multiple studies have found that lower baseline and less change in RSA in response to challenge is related to greater difficulties in behavioral regulation and work health outcomes (Calkins, 1997; Gangel et al., 2017; Porges, 2007). Additionally, children with low baseline RSA have been found to have more behavior problems (Forbes et al., 2006). Taking a more holistic look at the research shows that numerous studies have established that, baseline, response to challenge, and change from baseline in RSA in response to a stimulus, all have an important role in children's and infant's regulation and appropriate expression of emotions (Feldman, 2009; Porges, 2007; Tull & Aldao, 2015).

The previously discussed research considered linear effects of RSA but it also may be the case that the effect of RSA on behavior and regulation may be non-linear such that excessive vagal activity, either too much braking or too much withdrawal, may not be ideal. Intuitively the presence of non-linear effects in social science makes sense as it is unlikely that the effect of a variable remains the same at all levels of the variable. Further, there have been research findings that reactive RSA has a non-linear effect on behavioral outcomes and regulation in both infants and older individuals (Coulombe et

al., 2019; Feldman, 2006). Evidence that both reactive and baseline RSA is related to emotion regulation and negative emotions and expressions in a non-linear fashion has been found in several studies (Giuliano et al., 2015; Miller et al., 2017). There is also evidence that variation in heart rate is non-linear in infants from birth through 6 months of life (Schechtman et al., 1989). There have been findings that RSA may change in a nonlinear fashion when attempting to regulate negative emotions such as fear and anger in both infants and older children (Brooker & Buss, 2010; Miller et al., 2013). It is possible that infants that have either over or under active RSA may not be as successful in regulation their negative emotion.

The need to examine nonlinear effects of RSA in relation to children's regulation has been brought up in previous research (Blandon et al., 2008; Skoranski et al., 2017). Similarly, it has been found that moderate baseline RSA, rather than high or low RSA, is related with better individual wellbeing (Kogan et al., 2013). Additionally, children and infants with moderate levels of RSA have been found to be more prosocial and perform better on executive functioning tasks (Brooker & Buss, 2010; Marcovitch et al., 2010; Miller et al., 2017). Examining non-linear effects of RSA can also help to resolve conflicting findings. For example, RSA has been found to predict lower levels of depression, higher levels of depression, and not to predict depression (Kogan et al., 2013). As pointed out by Kogan and colleagues (2013) this could simply be due to some issue with the studies such as lack of proper controls, but it could also be indicative that the effect of RSA on depression is non-linear. The current study attempted to contribute to the understanding of nonlinear effects of RSA on children's emotion regulation.

Child Negative Reactivity and RSA

Infant's, toddler's, and older children's expression and regulation of their own negative emotion is widely studied and is related to several outcomes such as academic success, peer relations, behavior problems, and mental health (Morris et al., 2007; Porges et al., 1996; Rubin et al., 1995). One of the ways that infants and toddlers regulate their emotion is through their autonomic nervous system (Porges et al., 1996). As previously discussed, this system regulates responses to the environment by increasing or decreasing cardiac output (Porges, 2007). RSA has been found to relate to regulation in children from birth and this continues to be the case throughout the lifespan (Feldman, 2009; Porges, 2007). By measuring both children's RSA and negative reactivity the role of RSA in children's regulation of negative emotion can be further understood. Since expression and regulation of negative emotion are important to success in social interactions and general functioning understanding the role of RSA in children's negative expression can help further our understanding of children's emotional development. The current study examines the role of baseline, response to challenge, and change between baseline and response to challenge RSA in children's regulation of negative emotion during a negative valence task.

Child negative reactivity is used to measure emotion regulation as this is thought to be a behavioral manifestation of emotion regulation. Emotion regulation cannot be directly measured, thus a behavioral manifestation of emotion regulation in response to a task designed to induce negative emotion was used. It is thought that by observing behavioral responses an understanding of the individual's emotion regulation capacities can be developed. This strategy is common in studies of emotion regulation (Gerhardt et al., 2020; Wu, Feng, et al., 2019; Wu, Hooper, et al., 2019).

Current Study

This study will attempt to further understand the role of RSA in infant and toddler's ability to regulate their negative emotions and behavior in response to a cognitive task. Children's baseline RSA when they are resting, and their RSA during a challenging task, the Bayley exam, along with their change in RSA from the baseline to the Bayley task will be used to predict children's ability to regulate their negative emotions. Understanding the role of RSA in regulating negative emotions during stressful and difficult tasks will allow us to better understand how children develop regulation skills during difficult, frustrating, or scary situations.

Much of the current understanding of the relationship between RSA and physiological regulation is based on studies focusing on middle class individuals (Graziano et al., 2007; Perry et al., 2013; Sulik et al., 2015). To continue expanding the understanding of how RSA relates to children's physiological regulation we need to explore this relationship in less affluent communities. This is particularly true as recently proposed theories such as differential susceptibility suggest that individuals may differ in their susceptibility to the environment (Belsky & Pluess, 2009). Given that RSA is related to reactivity to the environment it is possible that individuals who have excessive vagal responses may be more susceptible to their environment. If an individual is predisposed to be susceptible to their environment as a result of their RSA then it stands to reason that we may see greater effects in lower SES environments as these typically have additional stressors (Belsky et al., 2007). The current study attempts to address this issue and furthers our understanding of the relation between RSA and negative emotion in lower SES children. Further, the current study controls for parental occupational prestige as this allows for some of the SES effects to be disentangled from the effect of RSA.

There is also a need to examine the developmental trend of the role of RSA and how this may change throughout the beginning of life. RSA is known to mature throughout an individual's life, with RSA in young infants only being detected during sleep (Longin et al., 2006). Further as an individual undergoes further maturation there is a general rise in heart rate variability measures indicating increased vagal control of the heart (Longin et al., 2006). This increased vagal control can result in increased vagal activity in regulating emotions as indexed by RSA. This trend of increasing heart rate variability and vagal control on the heart continues throughout infancy, toddlerhood, and into early childhood (de Rogalski Landrot et al., 2007). Furthering the understanding of developmental trends in how heart rate variability relates to behavior is an important goal of the current study. The current study can only provide a description of the change over time, there is insufficient information available to form a formal hypothesis.

There have also been findings that RSA has sex differences with females showing higher levels of heart rate variability compared with males (Snieder et al., 2007). Further, differences in RSA have been found with females having higher resting RSA than men, with some studies intentionally using only women in their sample so as to observe as large an effect as possible (Butler et al., 2006; Jönsson & Sonnby-Borgström, 2003). This relationship is somewhat less clear in children, however, a meta-analysis found that boys have higher heart rate variability than girls, although this is not universal and some studies found the opposite effect (Koenig et al., 2017). Given sex differences in heart rate variability are in opposing directions in children and adults it seems reasonable to

hypothesize that some development occurs that causes this change. Examining this developmental change is outside of the scope of the current study but future work may want to further examine the nature of this development. Regardless, understanding how RSA relates to regulation and behavior may be best understood by examining the unique effects of RSA on both males and females. Additionally, there is evidence that males and females are socialized to and express their emotions differently (Berk & Meyers, 2016). As such, to understand how RSA relates to behavior and expression effects on males and females should be examined separately. Taken together research has shown that RSA can both alter individual's behavioral regulation and be altered by individual's behavioral regulation and this effect may differ by sex (Porges, 2007; Tull & Aldao, 2015). By studying children's negative reactivity to the mask task in the current study it is thought that a further understanding of children's emotion regulation and the role of RSA can be achieved.

The first hypothesis for this study was that RSA will have a non-linear effect on children's negative reactivity. The second hypothesis was children with moderate levels of RSA will be better able to regulate their negative emotions compared with children who have either excessively high or excessively low levels RSA (Marcovitch et al., 2010). Finally, it was expected that the effect of RSA on children's negative expression will differ based on child sex.

Method

Participants

This study used data collected for the Family Life Project (Vernon-Feagans et al., 2018). This large secondary data set includes 1,292 children and their families from six

rural counties in North Carolina and Pennsylvania. The Family Life Project is 58% White and 42% African American; over half (51.9%) of the mothers were not married at the beginning of the study (Blair et al., 2011). The current study was only able to use 1,196 of these participants due to data only being available for participants who completed the requisite tasks. Further details on sample collection and procedures can be found in (Burchinal et al., 2008). In the current study 606 participants were male (50.7%) with 590 females. The mean score on the O*Net system occupational prestige system was 38.82. Occupations with similar prestige include: advertising salesman (39.29), paper tester in a pulp mill (39.74), and record keeper (37.50). Descriptive statistics for the sample used in the study can be found in table 1.1 and figure 1.1.

Procedure

Children completed several home visits while wearing an electrocardiogram (ECG) to measure their RSA. Children first had their baseline ECG recorded. The baseline ECG was recorded for a maximum of 5 minutes while the child sat quietly prior to engaging in the Bayley exam. After completing the baseline RSA portion children were given the Bayley exam (Bayley, 1969), a widely used measure of cognitive ability. In addition to measuring children's cognitive abilities the Bayley exam also served the dual purpose of causing stress to the child. RSA was collected for up to 15 minutes during the Bayley exam. In the cases where children disengaged for the Bayley exam the recording was removed from the final data. RSA is not available during tasks other than the Bayley exam and baseline measurement which occurred immediately before the Bayley exam.

Children's negative reactivity and regulation of fear were measured using a scary

mask task. This task has been widely used to induce mildly fearful stimuli to children (Goldsmith & Rothbart, 1996; Kochanska, 2001; Kochanska et al., 1998, 2001). This task was completed in the child's home and involved a research assistant wearing a series of 4 masks. Each mask was worn for approximately 10 seconds during which time the research assistant would say the child's name while moving their head back and forth, and finally leaning their head toward the child. The research assistant was to silently time themselves doing to mask task. The task was discontinued if the mother asked for the task to stop or if the child spent 20 seconds crying hard. This task was done when children were 6, 15, and 24 months old (Vernon-Feagans et al., 2018). This task was later coded for negative affect, among other behaviors, by a team of coders.

Measures

Demographics. Children's sex was reported by respondents as either male or female, for the current study males were dummy coded as 1 and females were coded as 0. Participants reported their occupation which was coded using the O*Net system. O*Net is a compilation of occupations that is maintained by the United States Department of Labor (Crouter et al., 2006). The current study used only the overall occupational prestige of the primary caregivers.

RSA. RSA was used to measure child vagal tone. Data were cleaned and analyzed using Mindware by a separate team of research assistants from those collecting the ECG data. The frequency band between .24 and 1.04 Hz was used to extract RSA from the ECG. The change in RSA between the baseline measure, when the child is resting, and the RSA during the Bayley cognitive task, when the child was experiencing more stress, is used to measure vagal tone. Additionally, the baseline RSA during rest and RSA

during the Bayley task (challenge) were used to measure children's vagal tone as well. Baseline RSA was collected prior to the children engaging in any activities when they were resting. Bayley RSA was taken while the child was taking the Bayley exam. RSA data were collected when children were 6, 15, and 24 months old.

Negative Reactivity. Children's negative reactivity to the scary mask task was coded by a team of coders. Four passes by separate teams of coders were done for every mask task as children could engage in multiple behavioral strategies and expressions simultaneously. There were three levels of negative reactivity coded, low negative reactivity, moderate negative reactivity, and high negative reactivity. Low negative reactivity was indicated by expressions and behaviors indicating slight discomfort including children being whiny, furrowing their brow, and pressing their lips together. Moderate negative reactivity was indicated by behaviors that indicated higher levels of negativity such as crying. The highest level of negative reactivity was indicated by behaviors such as screams, wails, and children's face turning colors. Reliability was good at all time points, K = 0.95 at 6 months, K = 0.89 at 15 months, and K = 0.90 at 24 months (Vernon-Feagans et al., 2018). These codes were converted to a percentage of the time of the scary mask task that a child expressed each of these. The current study weighted these expressions, multiplying low negative reactivity by 1, moderate negative reactivity by 2, and high negative reactivity by 3.

Data Analysis

Data were analyzed in R using the generalized additive model function from the mgcv package (Wood, 2017). Generalized additive models allow for nonlinear effects to be estimated in a flexible fashion (Wood, 2017). Rather than manually specifying the

functional form, for example a quadratic, the generalized additive model automatically uses a series of basis functions to fit the best line to the data (Wood, 2017). To limit overfitting the nonlinear terms were penalized which limits how wiggly the line can become (Wood, 2017). We further limited our models to using a maximum of 5 basis functions as results with more basis functions were excessively wiggly, making interpretation more difficult and may be fitting noise.

There were 143 missing patterns involving negative reactivity at 6 months, 293 at 15 months, and 370 at 24 months. Further analysis revealed data were missing completely at random ($\chi^2 = 717$, df = 691, p = .243). Missing data were estimated using the missForest package in R which has been shown to outperform other methods, including multiple imputation, in dealing with missing data (Stekhoven & Buhlmann, 2012). Since RSA and negative reactivity data were both collected when children were 6, 15, and 24 months of age this data were used. The RSA data collected at 35 months has no equivalent scary mask data and therefore was not used. Parental occupational prestige was used as a control variable in all models as this has been found to relate to children's regulatory abilities and behavior, this was of particular importance in this study as the Family Life Project aimed at collecting data from lower SES individuals (Berk & Meyers, 2016; Vernon-Feagans et al., 2018).

To test the first hypothesis that RSA has a non-linear effect on children's emotion regulation and expression a series of models was fit. First, a model containing only linear terms was fit, this is equivalent to a regular linear regression that are commonly used. This was done for each concurrent timepoint (6, 15, and 24 months) as well as each longitudinal time analysis (6 months predicting 15 months, 6 months predicting 24

months, and 15 months predicting 24 months) which results in 6 models being tested. These linear models were used as a baseline comparison to test if the non-linear models significantly improve fit. After the linear models were fit non-linear generalized additive models that allow the association between RSA and child negative expression to be nonlinear were fit for each timepoint. Using the ANOVA function in R the model fits were subjected to a chi-square test to see if the additional degrees of freedom needed to estimate the non-linearity of the RSA term significantly reduced deviance. A significant reduction in deviance, indicated by a significant chi-square value, suggests that the generalized additive model with a non-linear term, is a significant improvement over the linear model (Wood, 2017). After the ANOVA tests were completed to determine if the models were non-linear, the adjusted R-squared of the models was also compared between the models with the expectation that the model with the higher adjusted Rsquared was the better model. In the case that the AVONA results and the adjusted Rsquared results contradicted one another the ANOVA results were given preference as this was the direct test of model improvement. Finally, the significance of each non-linear term was directly tested with a significant p-value indicating that the non-linear term is significant. Using multiple tests to examine if the model is non-linear was valuable as it allowed us to be more confident in our results. It should be noted that non-linear terms can be penalized to being linear while still being significant, any models in which this proved to be the case were considered linear. This process was done for each measurement of RSA, baseline and change between baseline and Bayley, for each timepoint. This means that a total of 12 models were tested, 6 models with each of 2 RSA predictor variables.

To test the second hypothesis, that children with moderate levels of RSA regulate their negative emotions more effectively, models had the effects of their RSA graphed and interpreted. This was done even when the non-linear model was not a significant improvement over the linear model. Children's negative reactivity was graphed on the yaxis with RSA on the x-axis. To make interpretation simpler all variables were standardized. As the actual function of the term is quite complicated and involves many different functions at different levels of RSA, understanding the effect graphically is the standard method of model interpretation (Wood, 2017). Further, to prevent the line from becoming too wiggly the k-value, which is related to the number of basis functions that can be used was set to 5. The third hypothesis was also tested using the graphs of the effects of RSA on negative reactivity and comparing the male and female estimated effect.

The results of this analysis allowed us to further understand the role of RSA during stressful tasks. These analyses also allowed us to examine and test non-linearity of the effect of RSA. Since no constraints were set on the functional form of the model it was possible that new hypotheses can be generated because of this study. Results from this study can help us understand the role of vagal brake, baseline RSA, and RSA in response to a stressful situation in helping children to regulate their emotions in response to stressful situations.

Results

Examining the Non-Linear Associations between RSA and Negative Reactivity

Each of the 18 models of the effect of child RSA on negative reactivity was tested for non-linearity using a chi-square test to determine if the reduction in deviance was a significant improvement for the number of degrees of freedom exhausted. Of these models, 15 were found to be non-linear while 3 found to be linear. The three models that were found to be linear were the 6-month concurrent and 6-month predicting 15-month using change in RSA and the 15-month concurrent model using baseline RSA. All models had slight increases in adjusted R-squared but this alone was not enough to consider them non-linear. Full results of all model comparisons can be found in Table 1.2.

The results of these comparisons suggested that generally the association between RSA and behavior is non-linear. This means that the relation of RSA to behavior changes across different levels of RSA and that the use of linear models may not correctly capture the nature of these relations. Further, in all cases allowing for the effect of RSA to be non-linear improved the adjusted R-squared. Additionally, these effects are similar across different measures of RSA with a great deal of the changes in the way that RSA relates to behavior occurring near the mean.

All non-linear models were graphed, even those that were not significant improvements over their linear counterparts. A complete table of non-linear model results can be found in table 1.3, graphs of non-linear effects can be found in figures 1.2 and 1.3. Children's negative reactivity was relatively stable at low values then begins to decrease around the mean level of RSA. Eventually, slightly above the mean value of RSA, children's negative reactivity stops decreasing and stays relatively similar. Additionally, the male and female lines are similar to one another and follow similar trajectories suggesting that baseline RSA has a similar relation with boys' and girls' negative reactivity. The exception to this trend was the concurrent 6-month models. In these

models negative reactivity began to increase around the mean RSA value and continued to increase after the mean.

Another aspect of these models is how RSA between plus 1 standard deviation and minus 1 standard deviation relates to negative reactivity. There is some non-linearity in this region, but the relation of RSA and negative reactivity appears to be mostly linear in the baseline models. This is consistent with previous studies that have examined linear relations between RSA and behavior. After RSA levels went beyond plus and minus 1 standard deviation the trend often either stabilizes at what appear to be an asymptote or reverses direction. Results from the baseline models can be seen in figures 1.2.

The results for the models using change in RSA had a different trend in predicting children's negative reactivity. Recall that baseline RSA was subtracted from Bayley RSA, thus positive numbers on the x-axis indicate that RSA during Bayley test was higher than baseline RSA while negative numbers indicate the opposite. For models where the non-linear model was a significant improvement over the linear model, all except concurrent 6 months and 6 predicting 15 months, negative reactivity began to increase near the mean for change in RSA. Then once change in RSA reached higher positive numbers there was a decrease in negative reactivity, except for the 6-month RSA predicting 24-month reactivity model, which leveled off once it reached a maximum value. Again, the male and female results were similar further supporting that the effects of RSA on negative reactivity are similar for both males and females. These results are presented in figure 1.2C. Additionally, in all models the male and female confidence intervals overlap suggesting that the effects of RSA are consistently similar between males and females. The only exception to this was a very small difference near the mean

for the concurrent 6-month model for change in RSA. However, this model was not a significant improvement over the linear model and the difference is very small and covers a very small range of RSA. In all other cases the effect of RSA was not different between males and females at any level of observed RSA.

Similar to the baseline models, the association between RSA change and negative reactivity appear to be mostly linear between plus and minus 1 standard deviation for change in RSA. However, in the case of change in RSA this is the opposite direction one would expect based on past research. Children with Bayley RSA higher than baseline RSA had higher levels of negative reactivity. Further, the mean values of RSA are higher in baseline than in the Bayley task, which is also the opposite of what one would expect. It is possible that the Bayley task was not very effective in inducing stress in children this young. Further, infants may be more stressed by the appearance of strangers in their home and fitting of the ECG than by the Bayley task which could elevate their baseline RSA. Additional examination of this effect may be warranted.

Discussion

Results from this study supported our first hypothesis, it was found that RSA had a non-linear relation with children's negative reactivity in 15 of the 18 models tested. Of the models where the non-linear model was not found to be an improvement two of them involve the change in RSA from baseline to challenge at 6 months. It is possible that children at 6 months of age are not reactive to the Bayley task and are not stressed by it or the situation. As stranger anxiety is only starting to emerge around 6 months of age it is possible that children of 15 and 24 months of age have an additional stressor, the presence of the study staff, that 6 month old children do not (Berk & Meyers, 2016). The

other model that was not found to be non-linear used 15-month baseline RSA and concurrent negative reactivity. The non-linear model was a marginally significant improvement over the linear model suggesting that there could still be a non-linearity to this relationship. Alternatively, these findings may indicate that the systems relating RSA and negative reactivity may not be fully developed at 6 months or even 15 months. Given that heart rate variability is known to increase over at least the first 7 years of life (de Rogalski Landrot et al., 2007) there are developmental changes that may explain the difference between the 6-month-old results and older ages. All models involving 24month RSA were found to be non-linear, suggesting that as the vagal system becomes more mature it may have an increasingly non-linear relation with behavior. This is further supported by finding that 2 models using 6-month RSA and only 1 using 15-month RSA were linear, suggesting that vagal development is occurring throughout the period studied. Given this information this study supports the presence of a non-linear relationship between RSA and children's negative reactivity as well as developmental changes in how RSA relates to negative reactivity. It should also be noted that for the models that are found to be non-linear, the functional form of the line is complicated and differs somewhat between the models.

This study also found that the effect of RSA was not different between males and females. The confidence intervals for males and females overlapped for every nonlinear model at all observed levels of RSA. This suggests that while the effect of RSA on negative reactivity may be non-linear the effect is not different between males and females. This was somewhat unexpected when considered with previous findings that females have higher levels of heart rate variability (Snieder et al., 2007). Certainly, this

did not support our hypothesis that the effect of RSA on behavior would differ by sex. It is possible that sex differences in the role of RSA in behavioral regulation may not appear until later in life. One might expect that differences in vagal activity, that lead to differences in heart rate variability, give rise to differences in how RSA, a vagally controlled process, relates to negative reactivity. However, this was not the case and it was consistently found that there were no sex differences in how RSA related to negative reactivity. Future studies may want to examine if, and when, the effect of RSA on behavior become different between males and females. It is also possible that a larger sample may be required to observe sex differences. While the confidence intervals overlap there are regions where the overlap was limited and it is possible a larger sample would find sex differences in these regions. Regardless, given that the male and female lines have similar shapes and, with one very minor exception overlapped, effects of RSA from one another they will be discussed together for the remainder of this article.

There is not a universal shape to the lines in figures 1.21 to 1.22 nor are most of the lines approximations of the same common functions. Some of the lines appear to be cubic, while others look sinusoid, and still others appear to be an inverted parabola for part of the model and then become a flat line. The variety in functional form underlies the difficulty in modeling the effect of RSA on negative reactivity using explicit functional forms. By allowing the model to discover the functional form, rather than forcing the model to fit a specific functional form, the model fits the data better as it was less constrained. Further, as there is no functional form imposed upon the model, new potential relationships between RSA and behavioral and regulation outcomes can be discovered.

For the second hypothesis we found support that moderate levels of change in RSA in response to stress are related to better regulation and expression of negative emotions indicated by lower levels of negative expression. In all of the models that were found to be nonlinear using baseline RSA negative reactivity began decreasing near the mean value of RSA. While children with high baseline RSA were generally not more negative than children closer to average RSA, they also did not have lower negative reactivity. There were some small increases in negative reactivity at very high levels of RSA for several of the models, but these increases were small when compared to the overall model trend. Further, these increases were only at the highest RSA levels and could be the result of a small portion of the sample, the confidence intervals are quite wide at this point in the model. The exception to this trend were the concurrent 6-month RSA results for baseline, that did support that higher RSA levels were related to higher levels of negative reactivity. Both models saw large increases in negative reactivity starting near the average level of RSA. This supports previous findings that have suggested that higher RSA is not always desirable, and there may be diminishing returns, or even negative effects, from high RSA (Kogan et al., 2013).

The results from the models using change in RSA from baseline to Bayley were less uniform than the previously discussed results. The concurrent models that were found to be non-linear, 15 and 24 months, both saw increases in negative reactivity near the mean and decreases in negative reactivity as baseline RSA was larger in comparison to Bayley RSA (positive values on the x-axis). However, these models were different in their behavior below the mean. In the 15-month concurrent model female RSA below the mean did not change negative reactivity. However, male RSA below the mean was

related to a decrease in negative reactivity. In the concurrent 24-month model as female RSA approached -0.25 difference there was a decrease in negative reactivity. Beginning at -0.25 and continuing through the mean increases in baseline RSA compared with Bayley RSA were related to increases in negative reactivity in both males and females.

Both longitudinal models found to be non-linear had a similar pattern for both males and females. For the model predicting negative reactivity at 24 months using change in RSA at 6 months as baseline RSA becomes larger compared to Bayley RSA there was an increase in negative reactivity. Near the mean the increase was quite rapid, after baseline RSA becomes equal to Bayley RSA and when baseline RSA was higher negative reactivity stops increasing and the curve flattens out. The 15-month RSA predicting 24-month negative reactivity has a similar pattern except that both male and female negative reactivity decreases after crossing 0.

Taken together these results suggest that having higher resting RSA and higher RSA in response to challenging or stressful situations decreases negative reactivity. Additionally, having slightly larger RSA during a stressful or challenging task compared with resting baseline RSA also relates to lower levels of negative reactivity. Further, it can be seen that most of the change in negative reactivity as a result of RSA occurs near average levels of RSA. This is not unreasonable, that average levels of RSA might produce most of the changes in reactivity. As vagal tone, which RSA is measuring, is an evolved response to environmental stressors it should be able to affect behavior in most people (Porges, 2007). As most people are likely near the average it follows that RSA might have most of its effect near the mean as found in this study.

Of the 18 models tested 3 were not found to have non-linear effects, 2 involved

RSA measured at 6 months of age. It is possible that developmental changes during this age, which is well understood to be a time of rapid development and large changes, result in RSA beginning to effect children's behavior(s) more consistently (Berk & Meyers, 2016). Considering the known developmental changes that result in higher levels of vagal activity it seems reasonable to hypothesize that the effect of RSA on behavior changes during this time period (de Rogalski Landrot et al., 2007). Taken together these results may suggest that prior to achieving a certain level of development, which occurs sometime between 6 and 15 months of age, RSA is less strongly related to children's negative reactivity. Then, after children achieve this prerequisite level of development, the effect of RSA on negative reactivity is non-linear. This finding warrants more investigation but certainly finding both this developmental path and non-linearity of the effect of RSA would help us better understand child development.

Interestingly, the general trend of 6-month concurrent associations between RSA and negative reactivity are in the opposite direction of other time points. This is perhaps most pronounced in the baseline RSA models where higher levels of RSA are related to higher levels of negative reactivity. There are developmental changes in vagal activity during the entirety of the period studied, this could result in the present findings. With increasing heart rate variability as infants get older it is possible higher levels of RSA are more effective at regulating negative reactivity. This explanation would suggest that prior to achieving a requisite level of development there is insufficient vagal control to regulate negative reactivity. Further examination of how RSA relates to negative reactivity and other behaviors is warranted as well as further research into the developmental processes involved.

There are some important limitations to consider for this study. First, this study only used 3 time points that spanned 2.5 years. While this allowed us to test longitudinal effects of RSA on children's ability to regulate during the scary mask task having access to data when children were older would have improved the study. Particularly, all models that used 24 months as an outcome found non-linearity. The 24-month non-linear models also had larger improvements over their linear counterparts. It is possible that RSA has an increasingly non-linear relationship with behavior as children get older, this further emphasizes the need to collect data from older children. Secondly, the task used to test children's regulation, the scary mask, is not a typical experience that children are likely to encounter in daily life. This brings into question if the results of this study are ecologically valid and apply to children's everyday life (Bronfenbrenner, 1977). There was also an additional stressor that could be related to children's negative expression, strangers are conducting the tasks, this could be cause the children to be more negatively expressive. Collecting additional data when children are older and in school would solve both previously discussed limitations. This would allow for both a longer longitudinal perspective and for data to be collected from other sources such as teacher's ratings. This would also provide the opportunity to explore the relationship between children's RSA and more applied, everyday situations that require self-regulation, such as peer relations. Further, assessments of academic success would provide another outcome that is partially reliant upon ability to regulate oneself. This data is being/has been collected by the Family Life Project but is not yet available to the public. Future studies may want to consider utilizing this data in follow up studies.

This study also had a number of strengths. First, the use of generalized additive

models allowed for the presence of non-linear effects to be directly tested and for any non-linear effects found to be modeled. The shape of the relationship between the independent and dependent variables was allowed to be freely estimated which meant that the functional form of the model was not constrained by a specific function. Further, the Family Life Project has a large number of participants with RSA data and has a diverse sample in terms of race and SES. This further strengthens the findings of this study as they are based on a relatively diverse sample. Finally, the use of three different measures of RSA allowed us to further support the non-linear relationship between RSA and negative reactivity.

This study examined non-linear effects of RSA on children's negative reactivity during lab tasks at 6, 15, and 24 months of age. Support for non-linear effects of RSA at all ages were found, however these effects were not universally found in every model. This study extends our understanding of how RSA relates to children's negative reactivity and provides evidence of a non-linear effect of RSA on children's behavior. Results from this study have important implications for future studies that examine RSA. Researchers may want to consider modeling non-linear effects of RSA, particularly as children get older. Additionally, interventions that include measures of RSA may want to consider attempting to target optimal levels of heart rate variability rather than universally attempting to raise or lower heart rate variability. This study is an important early step in attempting to understand the non-linear and developmental changes in the relationship of RSA with behavior.

-	М	SD	Mdn	Min	Max	Range	Skew	Kurtosis
Female		~~~						
Baseline RSA 6months	3.93	0.46	3.88	2.93	4.91	1.98	0.06	-0.62
Baseline RSA 15months	4.24	0.46	4.13	3.14	5.34	2.20	0.43	0.24
Baseline RSA 24months	4.96	0.45	4.93	3.77	6.13	2.36	0.13	1.58
Change in RSA 6months	-0.12	0.28	-0.11	-0.82	0.55	1.37	0.00	-0.27
Change in RSA 15months	-0.17	0.21	-0.17	-0.72	0.39	1.10	-0.02	1.28
Change in RSA 24months	-0.01	0.18	-0.02	-0.50	0.50	1.00	0.33	2.21
Bayley RSA 6months	3.79	0.31	3.72	3.04	4.52	1.48	0.43	0.75
Bayley RSA 15months	4.14	0.40	4.06	3.20	5.08	1.88	0.34	0.49
Bayley RSA 24months	4.96	0.40	4.92	3.89	6.02	2.14	0.32	1.55
Negativity 6months	0.24	0.40	0.00	0.00	2.42	2.42	2.14	4.64
Negativity 15months	0.70	0.58	0.65	0.00	2.56	2.56	0.75	0.14
Negativity 24months	0.90	0.73	1.03	0.00	2.70	2.70	0.23	-0.96
Male								
Baseline RSA 6months	3.92	0.43	3.82	2.93	4.91	1.98	0.33	-0.48
Baseline RSA 15months	4.21	0.44	4.11	3.14	5.34	2.20	0.62	0.35
Baseline RSA 24months	4.92	0.44	4.9	3.77	6.13	2.36	0.09	1.90
Change in RSA 6months	-0.14	0.29	-0.1	-0.82	0.55	1.37	-0.17	-0.30
Change in RSA 15months	-0.16	0.21	-0.16	-0.72	0.39	1.10	-0.15	1.16
Change in RSA 24months	0.00	0.18	-0.01	-0.50	0.50	1.00	0.47	1.95

Table 2.1 Descriptive statistics of study variables

Continued

Male	М	SD	Mdn	Min	Max	Range	Skew	Kurtosis
Bayley RSA 6months	3.77	0.27	3.69	3.04	4.52	1.48	1.00	1.46
Bayley RSA 15months	4.13	0.35	4.06	3.2	5.08	1.88	0.61	1.08
Bayley RSA 24months	4.93	0.39	4.89	3.89	6.02	2.14	0.31	2.32
Negativity 6months	0.17	0.36	0.00	0.00	2.22	2.22	2.84	9.01
Negativity 15months	0.64	0.55	0.62	0.00	2.67	2.67	0.79	0.30
Negativity 24months	0.95	0.75	1.10	0.00	2.92	2.92	0.26	-0.87

Table 2.1 continued.

		Basel	ine RSA		Change in RSA						
	Δ Deviance	df	Linear Adjusted R ²	Non-linear Adjusted R ²	Δ Deviance	Df	Linear Adjusted R ²	Non-linear Adjusted R ²			
6 months concurrent	2.01	3.33*	.02	.32	0.11	0.62	.02	.02			
15 months concurrent	2.75	4.09	.02	.03	6.89	5.50**	.01	.02			
24 months concurrent	35.26	5.79**	.05	.10	26.75	5.72**	.34	.07			
6 predict 15 months	3.24	2.27*	.12	.13	1.04	1.84	.09	.10			
6 predict 24 months	24.74	6.84**	.09	.13	17.26	6.54**	.13	.15			
15 predict 24 months	13.30	5.66**	.19	.21	30.73	5.79**	.20	.25			

Table 2.2. Model Fit Comparison

Note. Δ = change in; **p < .001, *p<.05

		Baseline RS	SA	Change in RSA					
	edf	Ref df	F	edf	Ref df	F			
6 months concurrent	2.18(2.10)	2.71(2.63)	7.80 (4.41)	1.00(1.34)	1.00(1.62)	10.98 (3.85)			
15 months concurrent	2.84(2.18)	3.38(2.71)	5.57 (5.00)	3.71(3.05)	3.95(3.05)	4.51(2.61)			
24 months concurrent	3.48(3.70)	3.84(3.94)	14.29(19.94)	3.68(3.39)	3.94(3.79)	9.77(12.66)			
6 predict 15 months	1.00(3.75)	1.00(3.75)	64.30(9.32)	1.00(2.29)	1.00(2.84)	31.35(7.73)			
6 predict 24 months	3.58(3.71)	3.90(3.95)	24.03(8.12)	3.19(3.48)	3.68(3.86)	26.73(28.07)			
15 predict 24 months	3.70(3.47)	3.95(3.84)	21.94(21.22)	3.70(3.47)	3.95(3.84)	21.94(21.22)			

Table 2.3. Non-Linear Models

Note. Bold indicates p < .001; italicized indicates p < .05; Results for males are inside parentheses; edf = estimated degrees of

freedom; Ref df = reference degrees of freedom

Figure 2.1: Correlations of study variables by child sex

Male Correlation Matrix

5_												
neg_15mo											0.4	
neg_6mo 0.2											0.1	
	bay_RSA_24mo 0.1 -0.2											
	bay_RSA_15mo 0.7 0.2 -0.2										-0.2	
bay_RSA_6mo 0.7 0.7 0.1 0										-0.1	1.0 0.5	
cng_RSA_24mo 0 -0.1 0 0 0.2										0.2	- 0.0 -0.5	
cng_RSA_15mo 0.3							-0.1	-0.2	0	0.1	0.3	1.0
	0.6	0.4	-0.1	-0.4	-0.3	-0.1	0.1	0.3				
base_RSA_24mo -0.4			-0.3	-0.3	0.7	0.8	0.9	0.1	-0.2	-0.2		
base_RSA_	_15mo	0.8	-0.5	-0.5	-0.2	0.7	0.9	0.7	0.2	-0.1	-0.3	
base_RSA_6mo	0.8	0.7	-0.7	-0.4	-0.3	0.7	0.7	0.7	0.1	-0.2	-0.3	

neg_24mo

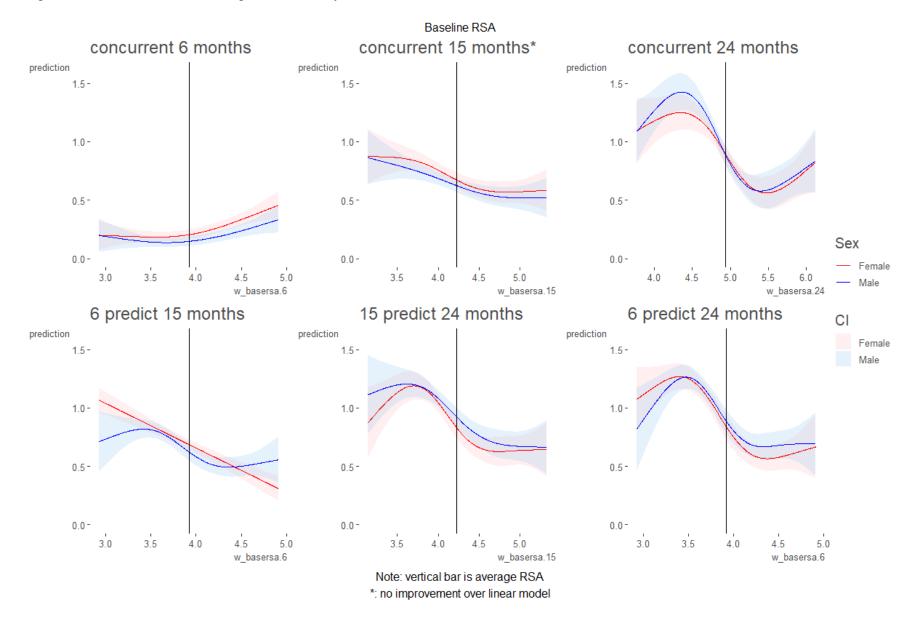
Figure 2.2: Correlations of study variables by child sex

Female Correlation Matrix

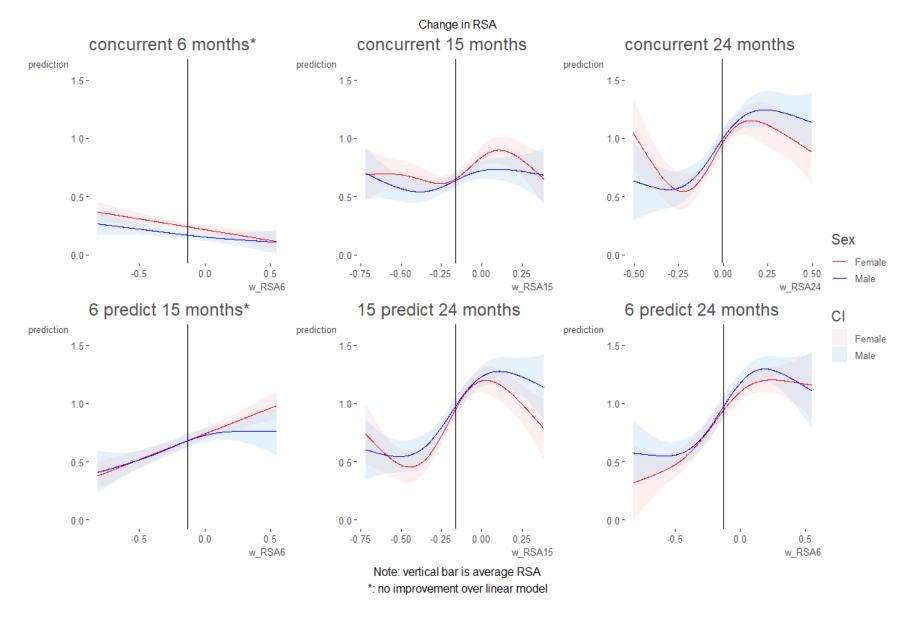
	neg_15mo											
	neg_6mo 0.3											
	bay_RSA_24mo 0 -0.2											
	bay_RSA_15mo 0.6 0.1 -0.1										-0.2	
	bay_RSA_6mo 0.8 0.7 0.1 -0.1										-0.1	- 1.0 - 0.5 - 0.0 0.5
cng_RSA_24mo 0 0 0 0.1								0.2	0.1			
cng_RSA_15mo 0.2						0	0	-0.1	0	0.1	0.2	1.0
cng_RSA_6mo 0					0.3	-0.1	-0.2	-0.2	-0.1	0.2	0.3	
base	base_RSA_24mo -0.2			-0.2	-0.4	0.6	0.6	0.9	0	-0.2	-0.2	
base_RSA_	base_RSA_15mo 0.6 -0.4		-0.3	-0.1	0.7	0.9	0.6	0.1	-0.1	-0.3		
base_RSA_6mo	0.7	0.6	-0.6	-0.3	-0.1	0.8	0.7	0.6	0.2	-0.3	-0.3	

neg_24mo









Chapter 3: Measurement Invariance of the Challenging Parenting Behavior Questionnaire and Child Anxiety

Parental socialization of children's emotion is a major area of interest in modern psychology with a number of different models that attempt to explain how socialization works (Eisenberg et al., 1998; Morris et al., 2007). One nearly ubiquitous aspect of these models is the inclusion of parental influences. Through parent's actions, teaching, behavioral modeling, and the climate parents create in the home children are socialized in how they should regulate and experience their emotions (Morris et al., 2007). This early learning is related to how children interact and behave in the social world as well as their experience of emotions (Lunkenheimer et al., 2007; Q. Wu et al., 2019). An area of emotion socialization that has been of interest to researchers is children's development of anxiety (Möller et al., 2014, 2016; Yap & Jorm, 2015).

Anxiety is a major health concern for children in the contemporary United States, 7.1% of children in the 3-17 years of age range have been diagnosed with anxiety (Ghandour et al., 2019). This is a major health crisis that has attracted a great deal of attention and research. Anxiety has been related to a number of issues including social problems and personal struggles that can persist through adulthood (Lazarus et al., 2016). Furthermore, this health issue is becoming increasingly common with large increases in the percent of children with a diagnosis of an anxiety (Ghandour et al., 2019). The issue of childhood anxiety has become prevalent enough that a simple internet search returns pages upon pages of websites published by governmental organizations, hospitals, child health organizations, and mainstream media. This has resulted in a great deal of effort to understand how child anxiety develops and develop treatments for these anxiety issues (McLeod et al., 2007; Wei & Kendall, 2014; Yap & Jorm, 2015).

Parent's role in children's development of anxiety has been and continues to be an active area of research (Lazarus et al., 2016; Möller et al., 2013). A recent focus of this research is the effect of fathers on children's development of anxiety. This is relatively understudied as much of the historical research has focused on mother's roles (Bögels & Perotti, 2011). In an attempt to further understand the development of anxiety a recent theoretical model has been proposed arguing that fathers have an important role in children's development of anxiety and that fathers can socialize their children to better deal with their anxiety (Bögels & Perotti, 2011). This model proposes that fathers have a more important role than mothers in children's development of anxiety (Bögels & Perotti, 2011). The model argues that from an evolutionary standpoint fathers typically would be the ones engaging with the outside dangers of the world, for example hunting. As a result of this experience and expertise in dealing with external dangers children will naturally look to fathers for guidance when dealing with external dangers (Bögels & Perotti, 2011). In modern society there are not many physical dangers for humans presented by the outside world, social interactions with other humans have taken the place of these previous physical dangers. As these social interactions have largely taken the place of physical danger Bögels & Perotti (2011) argue that children will naturally trust their fathers more when dealing with social interactions and other

situations that can provoke anxiety. Furthermore, this theory argues that part of the reason why research has found that father involvement generally has a beneficial effect on children's development is that children learn from their fathers how to appropriately exist and compete within the social sphere (Bögels & Perotti, 2011). This provides children with a competitive advantage in gaining access to resources and succeeding in various domains such as school and later work (Bögels & Perotti, 2011).

This hypothesis has received support with some studies finding that only fathers and not mothers are related to their children's anxiety, however studies have found the opposite (only mothers and not fathers are related to children's anxiety), and yet other studies have found that both parent's behavior are related to children's anxiety (Möller et al., 2015). Perhaps there are some unknown variables that would explain these contradictory findings, but researchers are presently unaware of what these variables might be. As has been pointed out by researchers these conflicting findings are both confusing and an area worth further exploring (McLeod et al., 2007). Reviews of research in this area generally support the idea that father's parenting is related to children's anxiety levels, however, there are relatively few studies in this area, a metaanalysis finding only 25 such studies (McLeod et al., 2007). Parenting, by either or both parents, explained 4% of the variance in child anxiety in this meta-analysis, which while not trivial, leaves 96% of the variance unexplained (Majdandžić et al., 2014; Paquette, 2004).

Child anxiety can also be viewed as dysregulation of emotion or lack of emotion regulation. If an individual is unable to successfully regulate their anxiety it can result in difficulties in many different daily activities including academic performance, peer

relations, and general mental health (Berk & Meyers, 2016). However, individual's that are better able to employ emotion regulation skills and strategies are better able to regulate their anxiety and better engage in various activities (Berk & Meyers, 2016). Through parent's actions they may be able to help their children develop the emotion regulation skills necessary to successfully regulate their anxiety (Berk & Meyers, 2016).

Challenging Parenting Behavior

One of the ways that has been hypothesized for fathers to teach their children to deal with anxiety is through challenging parenting behavior and rough-and-tumble play (Pellegrini & Smith, 1998). Rough-and-tumble play can be thought of as boisterous behaviors such as running and wrestling that happen in a play context (Legge, 2011). The idea of challenging an individual and this causing the individual to become stronger has been discussed for millennia. This has been expressed by philosophers as far back as the 3rd century BCE with Meng Tzu saying

When heaven is about to confer a great office on a man, it first exercises his mind with suffering, and his sinews and bones with toil; it exposes his body to hunger, and subjects him to extreme poverty; it confounds his undertakings. By all these methods it stimulates his mind, hardens his nature and supplies his incompetencies (Legge, 2011, p. 75).

A similar concept was expressed by Friedrich Nietzsche in his 1888 book *Twilight of the Idols* when he wrote: what doesn't kill me makes me stronger (Nietzsche, 2018). Recently the concept of antifragility has been put forth to discuss this same concept in a more scientific manner (Taleb, 2012). It is important to remember that antifragility, as discussed by Taleb (2012), is the idea that stressing systems (e.g., exposing them to

challenges) makes them stronger, not that they can survive stress (Lukianoff & Haidt, 2019). The concept of antifragility was quickly adapted into psychology as a possible method of teaching individuals how to deal with stress in their lives and better regulate their emotions (Lukianoff & Haidt, 2019). In a psychological sense antifragility would suggest that allowing individuals, including children, to face challenges is beneficial (Lukianoff & Haidt, 2019). Resolving these challenges, such as a conflict with peers, promotes children's development of self-regulation and social skills (Paquette, 2004). While this concept still requires additional testing and investigation it offers a promising framework for helping individuals regulate their emotions.

Building upon this idea of challenging individuals to make them stronger, through challenging parenting behaviors, fathers build their relationship with their children and socialize them to be able to behave appropriately in the competitive social world (Paquette, 2004). An important aspect of rough-and-tumble play is that the father shows both warmth and control; to qualify as rough-and-tumble play the father must both communicate affection towards their child and show dominance toward their child (i.e., the father is in control) (Paquette, 2004). However, it is important that fathers allow their children to enjoy themselves and have the exciting experience of winning the rough-and-tumble play (e.g., being on top in the dominant role), if both the child and father are not enjoying the play the experience will end and children will lose the opportunity to develop self-regulation through rough-and-tumble play (Paquette, 2004). Mothers are also capable of engaging in rough-and-tumble play but fathers have a greater tendency to engage in rough-and-tumble play with their children (Majdandžić et al., 2018).

Rough-and-tumble play is part of the larger construct of challenging parenting which are parenting behaviors that encourage children to push their limits, expose themselves to safe risks, and develop assertiveness (Majdandžić et al., 2014). In addition to rough-and-tumble play other aspects of challenging parenting have been posited to have a positive effect on children's development. rough-and-tumble play behaviors typically focus on physical activities, games, and challenges; verbal behaviors also constitute parts of challenging parenting behavior (Majdandžić et al., 2014). Some examples of verbal behaviors that fall under challenging parenting behavior are teasing or challenging children in performances or competitions (Lazarus et al., 2016; Majdandžić et al., 2014). These physical and verbal behaviors together are thought to make up the construct of challenging parenting behavior and are hypothesized to help children better regulate their anxiety (Majdandžić et al., 2014; Paquette, 2004).

Another important aspect of challenging parenting behavior is encouraging children to stand up for themselves and do tasks for themselves (Lukianoff & Haidt, 2019). For example, if a child wishes to play with another child, rather than the parent setting up the children to play with one another, the parent encourages their child to ask the other child themselves. Children engaging in activities for themselves allows them to develop the necessary abilities to overcome difficulties they may experience throughout their lives (Lukianoff & Haidt, 2019). Further, not providing these opportunities has been shown to be related to a number of mental health problems including increased anxiety (Lukianoff & Haidt, 2019). Parents who encourage their children to actively engage in the outside world, while the parents are present, provides children with the opportunity to practice necessary skills in a safe environment where the parent can

intervene if necessary (Fletcher et al., 2013; Fliek et al., 2015; Panksepp, 1993; Shannon et al., 2002; StGeorge et al., 2018).

Historically challenging parenting behavior has been a neglected aspect of parenting from a research standpoint but a greater interest in challenging parenting behavior has started to develop (Paquette, 2004). Challenging parenting behavior provides children an opportunity to experience struggles and challenges in a safe context and an opportunity to overcome them (Paquette, 2004; van der Bruggen et al., 2010). This teaches children how to regulate their emotions in response to situations that may produce anxiety or negative emotions associated with depression. (Paquette, 2004). Through the relationship with their fathers, children are proposed to develop competence in competitive social domains. To continue to develop the understanding of psychopathology in children researchers need to further understand the father-child relationship (Fliek et al., 2015; Panksepp, 1993; Paquette et al., 2013; Shannon et al., 2002; StGeorge et al., 2018; StGeorge & Freeman, 2017). In support of this perspective a number of empirical studies have found an important role for challenging parenting behavior in children's social skills, cognitive skills, anxiety, and depression (Majdandžić et al., 2018).

Challenging Parenting Behavior Questionnaire

Measurements of challenging parenting behavior are not common and are still being developed. One measure that has been proposed is the aptly named Challenging Parenting Behavior Questionnaire (Majdandžić et al., 2018). This questionnaire, as the name suggests, is designed to measure challenging parenting behavior by parental selfreport. The questionnaire is divided into 6 subscales: teasing, rough-and-tumble play,

encouragement of risk taking, social daring, competition, and modeling. The modeling subscale deals with behaviors the parent displays in front of their child but do not directly involve the child (e.g., I show my child that I take risks). The other five subscales are behaviors that are directed at the child or directly involve the child (e.g., I splash my child when we're in the swimming pool). This scale has undergone several revisions including a reduction from 43 items and seven subscales to the form used in this study containing 39 items and six subscales (Majdandžić et al., 2018).

This measure was originally developed in Dutch but has since been translated to English and has been shown to work well with an English-speaking Australian population (Majdandžić et al., 2018). The measure was found to have sufficient invariance across mothers and fathers to be considered invariant in the one study to examine the psychometric properties of the questionnaire in an English-speaking population (Majdandžić et al., 2016). Establishing measurement invariance is needed to be confident that differences in scores on a scale are the result of differences in levels of the construct and not differences in measurement (Majdandžić et al., 2018). However, a single study may not be enough to fully validate any questionnaire's appropriate test score uses. Further examining the CPBQ in other samples and other countries could provide more support for use of the questionnaire in future studies. Examining the questionnaire across cultures could help reveal cultural differences in parenting behavior as the one study that has already examine the questionnaire found (Majdandžić et al., 2018). Finally, this single study also found that there was a negative correlation between CPBQ scores and child anxiety; this finding also needs corroborated in studies of different populations (Vandenberg, 2002). It is of particular importance to establish

measurement invariance across mothers and fathers on this questionnaire as fathers are thought to have higher levels of challenging parenting behavior and establishing measurement invariance will help support these differences are from differences in levels of challenging parenting behavior, and are less likely to be a measurement issue (Chan et al., 2019).

Testing measurement invariance allows for researchers and practitioners to better understand the scales they use and what those scales are measuring (Vandenberg, 2002; Vandenberg & Lance, 2000). Measurement invariance can be thought of as having equivalent factor structures, factor loadings, and intercepts across groups (e.g., sex) or time (e.g., longitudinal studies) (Vandenberg & Lance, 2000). The general issue that measurement invariance is trying to address is whether respondents from different groups interpret and respond to questions in the same manner (Vandenberg & Lance, 2000). Establishing measurement invariance improves scales psychometric properties and increases the knowledge researchers have of the scale. Without testing measurement invariance, it is unclear if scales are measuring equivalently across groups. With evidence of measurement invariance and a strong understanding of a scale's properties researchers can be more confident in their scale and have a greater understanding of the construct they are measuring. This is important as with limited funding and participants time being limited researchers have a limited number of scales they can include. Being confident that the scales used in one's study will measure the intended constructs is important when resources are limited.

Examining measurement invariance when a scale is being used in a new context is important as there can be various influences that alter the manner a participant

understands or responds a question (Vandenberg & Lance, 2000). A scale that works in one country or with one participant group may not be as appropriate with another group or may differ in important ways (Rozin et al., 2010). Across countries that speak different languages the need to translate a questionnaire is obvious. Even the most careful and accurate translation should still be tested for measurement invariance as there are not always equivalent words and concepts across languages (Milfont & Fischer, 2010). However, even in cases where countries speak the same language, as is the case for Australia and the United States, both being primarily English-speaking countries, there is still a need to examine measurement invariance. Differences between the United States and Australia lead to the need to test a questionnaire's measurement invariance across those different contexts (Oppenheimer, 2004; Singelis et al., 1995).

Parents also engage in differential parenting practices by child sex. Children are found to prefer physical, rough-and-tumble type, play with their parents, compared with other types of play, but this difference is particularly pronounced in boys (Ross & Taylor, 1989). Additionally, rough-and-tumble play is particularly important for boys to learn to manage and regulate their emotions (Lafreniere, 2011). However, it is not the case that findings universally support differences in how parents socialize their children with some studies finding that socialization did not differ by child sex (Denham et al., 2010). Given the relative dearth of research into how challenging parenting behavior differences between boys and girls, particularly outside of rough-and-tumble play, additional work is needed to understand sex differences in challenging parenting behavior.

Oftentimes Western countries, which includes the United States, Netherlands,

and Australia are grouped into the category of individualistic cultures. This is a broad similarity between these countries and cultures but there are different types of individualism. Horizontal individualism, which is the type of individualism found in Australia and Dutch samples, emphasizes that people are individuals with the same status as others (Singelis et al., 1995). This contrasts with the vertical individualism that is found in American samples that emphasizes that people are individuals and are not of the same status of others (Harkness et al., 2000; Singelis et al., 1995). In vertical individualism there is an expectation of inequality, whereas this is not expected in horizontal individualistic cultures (Singelis et al., 1995). Behaviorally, this manifests in vertical individualistic cultures being more competitive (Singelis et al., 1995). These differences in the conceptualization and behavior associated with individualism indicates that one cannot assume that findings in a horizontal individualistic culture will apply in vertically individualistic cultures, or vice versa. While parents in the United States may generally share the belief that people are individuals with Australian and Dutch parents, U.S parents may consider status differences among children as expected and anticipate a higher level of competition for resources.

There are also differences in the way parenting is conceptualized and practiced within these countries. It has been found that Dutch parents place a greater emphasis on the ability for children to play by themselves when compared with American parents (Harkness et al., 2000). Australian parents also rate their children higher on problem behaviors when compared with American parents (Achenbach et al., 1990). This difference was found in ratings of specific behavioral and emotional problem items with Australian parents rating their children higher on 80 of 118 items (Achenbach et al.,

1990). Additionally, when given open ended questions about any complaints or issues children have not already specified by a questionnaire Australian parents reported more physical, school, and other additional complaints when compared with American parents (Achenbach et al., 1990). Further research has revealed that there are other differences between American and Australian parent's views on children's temperament with American children being rated higher on both relational and physical aggression (Russell et al., 2003). American children were also found to be more outgoing when compared with Australian children (Russell et al., 2003). Finally, American fathers were found to engage in more authoritative parenting compared to Australian parents, although this effect was not found in mothers (Russell et al., 2003). Given that aspects of authoritative parenting such as autonomy granting may be different between Americans and Australians it is possible that challenging parenting behaviors may not be the same. Additionally, this effect was only found for fathers so there could be sex differences challenging parenting. This suggests that there is not a uniform Western parenting style or parenting behaviors. This argument extends even further as, even within a single country, measurement invariance is tested across distinct groups (Vandenberg & Lance, 2000). This testing is necessary as even within a single country different groups can understand and respond to a question differently (Vandenberg & Lance, 2000). Thus, to be confident in measures across various stratification researchers should test measurement invariance, across countries and within countries. The best-case scenario being one in which a questionnaire being used for a study has been tested with exactly that population and the measurement invariance properties for that questionnaire are well understood.

Furthermore, without establishing measurement invariance it is unclear where differences between groups or over time may arise. If a researcher were to find differences in levels or responses of any construct between two groups, for example fathers and mothers, but has not established measurement invariance, it is unclear what is driving this finding. The difference that was found could either result from actual differences in the level of the construct the researcher is interested in, or from differences in how the individuals are interpreting the question. If measurement invariance is established, then it is known that any differences between fathers and mothers are the result of differences in their levels of the trait. Thus, to be confident in scales and where observed variance comes from measurement invariance must be established.

Current Study

The current study tested measurement invariance of the CPBQ in the United States. Parents completed an online questionnaire that included ratings of their own challenging parenting behavior, their child's anxiety, and demographic information. Data on both mothers and fathers were collected. As there has been a previously established factor structure for the CPBQ this structure was tested (Majdandžić et al., 2018). However, the previous work on this scale has been only done in one other English-speaking sample, Australia. Establishing measurement invariance of the scale in an American sample will allow researchers to be more confident in using this scale for American samples in the future.

In addition to testing measurement invariance of the CPBQ the current study also examined the relations between challenging parenting behavior and child anxiety. As

challenging parenting behavior has been hypothesized to reduce child anxiety understanding how the CPBQ relates to anxiety is important to the construct validity of the CPBQ (Lazarus et al., 2016; Majdandžić et al., 2018). There have also been some conflicting research findings regarding the effect of challenging parenting behavior on children's anxiety (Majdandžić et al., 2018). Furthermore, understanding how challenging parenting behavior relates to child anxiety, particularly if it can reduce child anxiety, could help with the ongoing issue of anxiety problems currently afflicting the United States. Parental education and income were controlled for in all SEM analyses as these demographic variables are known to be related to children's emotion expression and regulation (Berk & Meyers, 2016).

The current study tested four hypotheses. First, it was expected that the factor structure found in the previous studies in Australia and the Netherlands would be replicated. Second, it was expected that the CPBQ would show measurement invariance across mothers and fathers at configural, metric, and scalar levels. Configural invariance indicates that the scale has the same factor structure across mothers and fathers. Metric invariance tests whether the factor loadings are equivalent across mothers and fathers indicating that items are related to factors in the same way. Finally, scalar invariance is a test of equivalent intercepts across mothers and fathers, indicating that mean differences are found in the latent variable, but item intercepts are not different. If a scale is found to have all three of these it has demonstrated measurement invariance. Furthermore, this study hypothesized that the factor structure of the CPBQ would be the same as the structure previously found in Australian parents (Majdandžić et al., 2016). Thirdly, it was hypothesized that fathers would have higher latent means on challenging parenting behavior than mothers. The fourth and final hypothesis was that higher levels of challenging parenting behavior would be related to lower levels of child anxiety. As this effect might differ by sex, a model examining the difference between the effect of challenging parenting behavior on boys and girls was tested.

A major advantage of the current study is that regardless of whether the hypotheses were supported the results would be valuable. Given that the CPBQ is a newly developed questionnaire it has not been as extensively studied and examined as some other questionnaires. If it was found that mothers and fathers were invariant on the CPBQ it would be useful information that suggests that researchers can use this questionnaire with more confidence in American samples. If measurement invariance is not found, then that is also useful information that suggests this scale may need additional work in order to be used confidently in American samples. Similarly, there is a lack knowledge about how challenging parenting behavior relates to anxiety generally as the concept of challenging parenting behavior itself has not been extensively studied (Majdandžić et al., 2018).

Methods

Participants

Data were collected using Amazon Mechanical Turk (MTurk), an online marketplace that allows posting of academic surveys. To be included in the current study participants had to be a mother or father of a child who was 3 or 4 years of age. Additionally, the participant had to be currently residing in the United States. Further, to be allowed access to the MTurk platform the participant must apply to and be accepted by Amazon MTurk, the requirements to be accepted are not released by Amazon.

Participants were also required to have a minimum acceptance rate of 95% on other tasks they had completed on MTurk to help ensure higher quality data. Finally, a check to make sure the participants were in the United States and not using a virtual private network to appear they were in the United States was used. This was done to increase data quality further and ensure that the respondents were residing in the United States. A total of 355 mothers and 365 fathers completed the survey for a total of 720 participants. The participants had high levels of education with the median education level being a 4-year bachelor's degree for both mothers and fathers. The majority of both mothers (85%) and fathers (80%) were White, further both mothers and fathers had a median income between \$60,000 and \$69,999 per year. A correlation matrix is available in figure 2.1.

Procedures

Two links to two separate surveys hosted on Qualtrics was posted on MTurk. This was done to collect balanced numbers of mothers and fathers. Participants were paid \$2.00 for completing the survey which was credited to their MTurk account upon successful completion of the survey. Participants who met the criteria for inclusion completed the questionnaire and entered a code provided to them by Qualtrics into MTurk for payment after completion of the questionnaire. The questionnaire included 16 demographic questions, 29 questions about child anxiety, and 40 questions from the CPBQ regarding parent's own challenging parenting behavior. To check the quality of responses there was a free response question at the end of the survey that asked participants to describe their experiences taking this study in at least two sentences. Further, there was a question embedded in the demographics questionnaire that asked

participants to write out the number 9 in letters to catch bots trying to take the survey; in the anxiety questionnaire there was a question that asked the participant to select "very true" to check if the participant was paying attention to the questions. Finally, a question was embedded in the CPBQ asking participants to rate if they ever yelled at their child this question. The purpose of this question was to further check if participants were paying attention as it is very unlikely that they have never yelled at their child but this question was discarded as respondents would commonly say they never yelled at their child despite getting all other attention checks correctly. The quality of these responses was checked daily so that any potential issues could be identified quickly and rectified.

Measures

Challenging Parenting Behavior Questionnaire. The CPBQ is a 39-item Likert measure of parents' challenging parenting behavior (Edwards et al., 2010). The questionnaire has a series of statements that describe various activities that parents may engage in with their children. Some sample items from the CPBQ include: "When I play tag with my child, I make myself hard to catch", "I encourage my child to ask for himself/herself whether another child wants to play with him/her", and "I urge my child on when he/she is competing against other children". This scale has six subscales: teasing, rough-and-tumble play, risk taking, social daring, competition, and modeling. Parents are asked to rate these items based on their interactions with their child on a scale of 1 (not applicable) to 5 (completely applicable). The scale demonstrated good reliability with a coefficient omega of 0.94. Coefficient omega is considered a superior measure of reliability compared with coefficient alpha and can be used in cases where the underlying factor structure is not unidimensional (Revelle & Zinbarg, 2009).

Preschool Anxiety Scale. Anxiety was measured using a revised version of the preschool anxiety scale (Edwards et al., 2010). This questionnaire consists of 28 items that ask parents to rate how accurate a series of statements is of their children. The questionnaire has three subscales: generalized anxiety, social anxiety, and separation anxiety; additionally, there are 9 items that ask about specific fears (e.g., the dark). The current study used the three subscales of generalized, social, and separation anxiety, the specific fear items were not used. Sample items include: "Is afraid of meeting of talking to unfamiliar people", "Has difficulty stopping him/herself from worrying", and "Asks for reassurance when it doesn't seem necessary". Parents respond using a Likert scale ranging from 0 (not true at all) to 4 (very often true). The scale had good reliability with a coefficient omega of 0.96.

Demographics. Participants were asked several standard demographic questions including their sex, ethnicity, race, employment status, marital status, annual household income, and highest education completed. They were also asked about their 3-4-year old child's sex, birthdate, birth order, ethnicity, and race.

Data Analysis Plan

Data were analyzed in R using lavaan (Rosseel, 2012) for all hypotheses. All analyses were done using diagonally weighted least squares with robust standard errors (WLSMV), as this has been shown to perform better than maximum likelihood for ordinal data (Majdandžić et al., 2018). Upon fitting the initial model using the previously established six-factor structure it was found that there was an extremely high covariance between several of the factors causing a non-positive definite matrix. Additionally, several of the items were found to have issues such as negative variances

and small, nonsignificant, factor loadings. To further explore these findings a parallel analysis was run that suggested there were only 5 factors. An exploratory factor analysis was run using the suggested 5 factors from the parallel analysis. Then, using the new factor structure suggested by the exploratory factor analysis, a confirmatory factor analysis (CFA) was fit. This new factor structure fit better and did not have any problems with items or factor covariances. This model was used in all remaining analyses. First, measurement invariance at configural, threshold, metric, and scalar levels was tested in accordance with the first hypothesis. Models were considered invariant if the CFI change was less than 0.01 (Cheung & Rensvold, 1999). Change in RMSEA and chi-square were also used but these were considered secondary indicators of measurement invariance. This is particularly the case with chi-square which is known to be overly sensitive, particularly with larger sample sizes (Kline, 2015). To answer the third hypothesis latent means between mothers and fathers challenging parenting behavior were tested. Finally, to address the fourth hypothesis, child anxiety was regressed onto challenging parenting behavior in a structural equation model. As this was a cross-sectional study there was no missing data.

Results

Descriptive Statistics

Correlations between CPBQ items were generally found to be in the 0.1 to 0.2 range. Items in the preschool anxiety scale were more strongly correlated with one another generally ranging from 0.35 to 0.5. A correlation heatmap can be found in figure 2.1. Additionally, the CPBQ items generally had a decent distribution of responses although some items (e.g., 31) had few respondents endorsing either the highest or

lowest category. The story for the preschool anxiety scale is similar, with some items (e.g., 1) having very few respondents endorsing the highest or lowest category.

Measurement Invariance

All measurement invariance testing was done following the guidelines and terminology described by H. Wu and Estabrook (2016) and lavaan (Rosseel, 2012). The initial step for modeling was to fit a configural model using the 6-factor structure previously found (Majdandžić et al., 2018). The original 6 factors fit in this study were teasing, rough-and-tumble play, encouragement of risk taking, social daring, competition, and modeling. This factor structure was found to have two problems. First, the latent covariances among the factors were found to be very high and were causing a non-positive definite covariance matrix. Second, results could still be extracted from the model even with the non-positive definite covariance matrix but the model fit was poor with a CFI of 0.776 and a RMSEA of 0.096.

As a result of the poor fit and non-positive definite matrix, a parallel analysis was conducted to determine the number of factors and the results suggested 5 factors (see figure 2.2 for the scree plot with simulated data). Given this information an exploratory factor analysis using 5 factors was run. The exploratory factor analysis largely retained 5 of the original factors but split the modeling factor from the original structure. The items in the modeling factor were typically placed in the factor that was most similar to the content of their question. For example, one modeling item reads "my child sometimes sees me tease others", this item was loaded onto a factor called teasing. Another item on the teasing factor reads "I regularly tease my child for fun", since both of these items deal with teasing, it is not surprising they loaded onto the same factor. This factor structure also fit much better than the previous factor structure with a RMSEA of .042 and TLI of 0.922 (CFI is not output by the model). The factors are named similarly to the previous factors. The factors were named competitiveness/risk taking (ML1), autonomy (ML2), teasing (ML3), rough-and-tumble play (ML4), and bravery (ML5). In the appendix factors will be abbreviated ML1 through ML5 to keep output cleaner, otherwise factor will be referred to by their names. The complete exploratory factor analysis results can be found in table 2.2.

Using the factor structure found in the exploratory factor analysis a CFA was fit. To test invariance a guideline of CFI changes of less than 0.01 indicating invariance was used (Cheung & Rensvold, 1999). Additionally, χ^2 and RMSEA were considered as well but were secondary indicators of invariance. The first step was to try a configural invariant model across fathers and mothers. This model was found to fit better but still had some room for improvement (RMSEA = 0.072, CFI = 0.885). It was found that two of the items 7 and 32 had many crossloadings based on modification indices. However, item 7 was somewhat redundant with items 4 and 36 and had relatively small loadings. Item 32 had an issue with very few participants choosing that they rarely engaged in the behavior. The decision was made to cut these two items from the CFA. Removing these two items improved the model fit to acceptable levels (CFI = 0.904, RMSEA = 0.068). This model was then used to test threshold, metric, and scalar invariance.

Since the questions on the CPBQ are ordinal there are thresholds for all of the items. A model with the thresholds held constant across fathers and mothers and found that the thresholds were indeed invariant across fathers and mothers, $\Delta \chi^2(70) = 62.54$ p-value = 0.72, $\Delta CFI = 0.001$, $\Delta RMSEA = 0.002$. Unexpectedly, the threshold model

improved on the RMSEA of the configural model, but the change was still quite small. It is possible this is because the values are so close to one another that the degree of freedom that are gained by not estimating the thresholds in one group are enough to improve model fit. Next, metric invariance was tested and it was found that the model was invariant ($\Delta \chi^2(30) = 25.18$ p-value = 0.72, $\Delta CFI = 0.004$, $\Delta RMSEA = 0.002$). This model unexpectedly improved in terms of model fit compared to the threshold model with both CFI and RMSEA improving. Finally, a scalar invariance model was fit and was found to be invariant with the metric model ($\Delta \chi^2(30) = 93.73$ p-value < 0.001, ΔCFI = 0.002, $\Delta RMSEA = 0.000$). Unlike the previous models the model fit did not improve when fitting the scalar model. A table of changes in model fit for invariance testing can be found in table 2.2, factor loadings in the confirmatory factor analysis can be found in table 2.3.

After scalar invariance was established latent means between fathers and mothers were compared. Latent means were constrained to be equal across mothers and fathers, the same criteria of a change in CFI of greater than .01 indicating non-invariance was used. It was found that the latent means were not equivalent between fathers and mothers ($\Delta \chi^2(5) = 56.57$ p-value < 0.001, $\Delta CFI = 0.014$, $\Delta RMSEA = 0.004$). Fathers had higher latent means in all five challenging parenting behaviors except for autonomy which was not different between fathers and mothers. Complete results can be viewed in table 2.4.

Next, the effects of challenging parenting behavior across boys and girls were examined. First, invariance was tested between boys and girls. It was found that the scale was invariant at the configural, threshold, metric, and scalar levels. Using the scalar invariance model the regression effect of challenging parenting behavior on child anxiety was constrained to equality between male and female children. It was found that this was also invariant thus the effects of challenging parenting behavior were the same in boys and girls (Δ CFI = 0.001, $\Delta\chi^2(15) = 13.467$, p=0.57). Additionally, invariance for boys and girls was tested in a model of fathers only and a model of mothers only, both of these models were invariant at the scalar level as well. Full invariance testing results can be found in appendix B.

Finally, a model predicting child anxiety using the CPBQ was run. The scalar model was used to run this analysis as the CPBQ was found to have invariance at the scalar level. Latent variables of children's social anxiety, separation anxiety, and generalized anxiety were created and regressed onto the five factors used for the CPBQ. Parental education, parental income, and child sex were all included as covariates. None of the specific fears were used as they are all single items. This model fit well with a CFI of 0.922 and a RMSEA of 0.049. The non-robust CFI was better at 0.974 while the non-robust RMSEA was worse at 0.064.

In fathers, higher levels of social anxiety were significantly predicted by bravery (B = 1.052, SE=0.285, p < 0.001). Lower levels of social anxiety were predicted by autonomy (B = -0.498, SE = 0.217, p = 0.022). Bravery also predicted higher levels of generalized anxiety (B = 0.910, SE = 0.260, p < 0.001) but rough-and-tumble play predicted lower levels of generalized anxiety (B = -.712, SE = 0.334, p = 0.033). Higher levels of parental education predicted higher levels of generalized anxiety (B = 0.154, SE = 0.070, p = 0.026), while parental income predicted lower levels of generalized anxiety (B = -0.066, SE = 0.032, p = 0.041). Finally, bravery predicted higher levels of

separation anxiety (B = 0.204, SE = 0.075, p = 0.006). Parental education predicted higher levels of separation anxiety (B = 0.047, SE = 0.021, p = 0.023) while parental income predicted lower levels (B = -0.027, SE = 0.010, p = 0.006).

There were also several marginally significant predictors of anxiety among fathers. Rough-and-tumble play was related to lower levels of social anxiety (B = -0.649, SE = 0.346, p = 0.060). It was also found that teasing was related to higher levels of generalized anxiety (B = 0.522, SE = 0.303, p = 0.084). Finally, autonomy was found to be related to lower levels of separation anxiety (B = -0.096, SE = 0.058, p = 0.099) while teasing was related to higher levels of separation anxiety (B = 0.134, SE = 0.079, p = 0.089). All other challenging parenting behaviors were not significantly related to any type of anxiety.

The results in mothers were quite different from the results in fathers. No challenging parenting behavior was significantly related to any type of anxiety. However, there was a marginal relation between rough-and-tumble play and separation anxiety, with higher levels predicting lower separation anxiety (B = -0.334, SE = 0.182, p = 0.067). There was also a marginal relationship between teasing and separation anxiety with higher levels predicting higher levels of separation anxiety (B = 0.293, SE = 0.173, p = 0.091). Maternal competitiveness (B = 0.436, SE = 0.264, p = 0.099) and bravery (B = 0.595, SE = 0.357, p = 0.095) were both marginally related to social anxiety. Parental education was a significant predictor of increased social, separation, and generalized anxiety. Parental income was a significant predictor of decreased social anxiety and separation anxiety and marginally related to generalized anxiety. See figure 2.3 for a path diagram of the results, full output from the structural equation model using

scalar invariance can be found in appendix C.

Discussion

This study examined the measurement invariance of the CPBQ, a newly developed scale to measure challenging parenting behavior. Previous work had found that this scale was invariant between a Dutch and Australian sample, but the scale had not previously been tested in an American population. This study failed to support its first hypothesis, the factor structure previously found in a Dutch and Australian sample was not replicated in the current sample. The latent variables when using the previously established factor structure were too highly correlated and caused errors when running the analysis. An alternative factor structure was found and used for the remaining hypotheses. This was the first study to examine the CPBQ in an American population and therefore was somewhat exploratory. Future studies may be needed to further examine if the factor structure for the CPBQ is different in America. This study found support for its second hypothesis, the scale showed measurement invariance at the configural, threshold, metric, and scalar levels between mothers and fathers using the factor structure found in this study.

Latent mean invariance between fathers and mothers was not found suggesting that the average level of challenging parenting behavior is not the same between fathers and mothers. Since scalar invariance has been established, these latent mean differences are the result of differences in levels of challenging parenting behavior. Fathers had higher levels of encouraging children to be brave, engaged in rough-and-tumble play, competitiveness/risk taking, and teased their children more when compared with mothers which supported the third hypothesis. However, mothers and fathers did not

differ on their autonomy support.

It was also found that there was invariance across the effect of challenging parenting behavior between boys and girls. This suggests that even though there is evidence that boys engage in more rough-and-tumble play the effects of rough-andtumble play are similar in girls at least in regard to children's development of anxiety (Pellegrini & Smith, 1998). Considering that rough-and-tumble play was the only parental behavior to be found to reduce children's anxiety in both mothers and fathers, finding that the effects are not different in male and female children is valuable for programs aimed at reducing child anxiety. This result is particularly interesting as previous research has found that rough-and-tumble play is particularly important for boys (Lafreniere, 2011). There are several possible explanations of this finding. Perhaps previous research has underestimated the effects and value of rough-and-tumble play for female children. Alternatively, it is possible that as a result of parents reporting both their challenging parenting behavior and children's anxiety there is some type of reporter bias in this study. Future work may want to further examine the role of roughand-tumble play in both boys and girls. However, this result is consistent with past studies in finding that rough-and-tumble play is important for both boys' and girls' development and suggests that parents may want to engage in other challenging parenting behaviors with both their male and female children.

Regarding the fourth hypotheses somewhat mixed results were found. In mothers there were not any significant relations between any challenging parenting behavior and child anxiety. There was a marginally significant relationships with rough-and-tumble play predicting lower levels of separation anxiety but given the large sample size this

may not be of practical significance. Higher levels of separation anxiety were predicted by teasing at a marginal level. One should be cautious in interpreting these results as there were 720 participants, meaning there was decent power, and both results are only significant at a marginal level. However, these seem to suggest that mothers may want to limit their teasing behavior while ensuring they engage in rough-and-tumble play. Additionally, the robust CFI was worse than the non-robust CFI while the opposite case was observed for RMSEA. While these values all suggest at least decent model fit it is still strange that these model fit indices move in opposite directions from the non-robust to robust models. It is possible that this results from the much better baseline fit in the robust model. The subsequent robust models are not as much as an improvement over the baseline model thus the relative fit index becomes worse while the absolute fit index becomes better.

The structural equation modeling results for fathers were more complicated than the results for mothers. One aspect of challenging behavior, bravery, was found to predict significantly higher levels of all three aspects of anxiety. This was the only aspect of challenging parenting behavior that was related to all aspects of anxiety. It is possible that excessively encouraging children to be brave may result in them being excessively anxious. However, this result should be interpreted with caution as this was a cross-sectional study. It is possible that that children who are less socially anxious engage in many of the behaviors in the bravery factor without parental intervention. For example, one item in the bravery factor is "I encourage my child to approach unfamiliar people to ask them something". Socially anxious children are unlikely to engage in this behavior without prompting. Thus, parents may be encouraging their socially anxious

children to ask unfamiliar people questions while less socially anxious children may not need this encouragement. This means that the parent of a less socially anxious child rarely encourages their child to approach unfamiliar people and reports a low level on this question while the parent of a more socially anxious child does this often and reports a high level. A similar occurrence could lead to the generalized and separation anxiety results. Another possible explanation of the bravery results is that some parents may overencourage and overstimulate their children. This could be overwhelming to the children and lead to the increased anxiety. To disentangle these results longitudinal studies will be needed as these studies are able to control for previous levels of anxiety. Additionally, behavioral measures of challenging parenting behavior may be beneficial as this allows another perspective and is not subject to shared method variance. Longitudinal studies will also be able to test longitudinal invariance of the CPBQ which is also valuable.

Several challenging parenting behaviors by fathers also related to lower levels of child anxiety. Fathers who supported their children's autonomy had children with lower levels of social anxiety. Additionally, fathers who engaged in rough-and-tumble play with their children reported lower levels of generalized anxiety. This suggests that these parenting behaviors are generally beneficial for fathers to engage in. Particularly, rough-and-tumble play was found to reduce anxiety in children among both mothers and fathers, the only parenting behavior that was found to do so in both groups. The autonomy support results are quite interesting as autonomy support in fathers was found to reduce children's anxiety but was unrelated to child anxiety in mothers despite fathers and mothers having similar levels of autonomy support. Perhaps this suggests that there

is something different about autonomy support from fathers compared to mothers with respect to child anxiety and fathers have a particular importance as has been previously hypothesized (Möller et al., 2013).

While these results may seem somewhat mixed there is a clear pattern. First, it seems that teasing is consistently related to higher levels of child anxiety. Parents may want to be cautious about their teasing of their children. Second, it seems that roughand-tumble play is consistently related to lower levels of anxiety of child anxiety particularly when fathers engage in rough-and-tumble play but children also benefit from rough-and-tumble play with mothers. This is consistent with past research findings that rough-and-tumble play is beneficial for children's development and can help reduce child anxiety (Dumont & Paquette, 2013; Paquette, 2004; StGeorge & Freeman, 2017). Additionally, for fathers, encouraging children to be autonomous appears to be related to lower levels of child anxiety. Bravery was consistently related to higher levels of child anxiety among fathers. Finally, competitiveness/risk taking was consistently unrelated to any aspect of anxiety among either fathers or mothers suggesting this factor may not be an important aspect in reducing child anxiety. No aspect of challenging parenting behavior was related to higher levels of one type of anxiety and lower levels of another type of anxiety. These results suggest that the relationship between challenging parenting behavior and child anxiety is complicated and ubiquitously increasing or decreasing challenging parenting behavior may not be advisable. Also, certain types of challenging parenting behaviors may be more beneficial than others, more work should be done to further examine the differences between types of challenging parenting behavior.

An important consideration is that the factor structure used in this study is not identical to the factor structure used in the previous study (Majdandžić et al., 2018). Further, several items in the current study failed to load significantly onto any factor and were removed from the analysis. The previous factor structure used 6 factors compared to 5 factors in the current study. In fact, the previous factor structure fit the data poorly. The decision to use the alternative factor structure was, arguably, a sound decision; however, this precluded the possibility of finding the same factor structure as the previous study. Interestingly, the previous study found only partial scalar invariance compared while the current study found full scalar invariance. This could be related to the current study focusing on only one country, but it could also suggest that the 5-factor structure is more stable across mothers and fathers. This suggests that the scale may not be invariant across American and Dutch/Australian respondents and future work may want to examine this difference more directly.

One major source of the differences in the factor structure between the current sample and the previous work is the exclusion of the "modeling" factor found in previous studies. Items in this subscale deal with the child observing the parent engaging in behaviors such as the parent teasing others and the parent standing up for themselves. In the current study this modeling subscale was not found, instead these items grouped together with similar child items. For example, two of the items are "I regularly tease my child for fun", which was originally in the teasing subscale and "My child sometimes sees me tease others", which originally appeared in the modeling subscale, in the current sample these items both load onto a teasing/making things challenging subscale. This may suggest that the respondents in the current study focused on the

behavioral content of the question, teasing, and were not as focused on the target of the action.

Finding measurement invariance between mothers and fathers on the CPBQ supports the use of this scale in American samples that include both mothers and fathers. Researchers can be more confident in their measurement of challenging parenting behavior and that giving the CPBQ to both mothers and fathers is appropriate. Further, these results support that differences found between mothers and fathers on the CPBQ in the future, either in levels of challenging parenting or in the effect of challenging parenting parenting on the outcome(s) of interest, are not the result of measurement noninvariance. These findings also speak to the general quality of the scale which has been shown to be invariant in three separate countries and two languages.

This study also has several limitations. First, the data was collected entirely online and reports of both challenging parenting behavior and child anxiety were completed by the same individual. It is possible that this individual may be biased in some manner in their reporting of their challenging parenting behavior or their view of their child's anxiety. Additionally, this sample is Whiter and more educated than the national average and is not representative of the racially diversity nor differences in educational attainment that exist within the United States. Furthermore, Amazon's criteria to allow people to work on MTurk is proprietary so there is a possible unknown selection bias on who can access MTurk and therefore the survey. Finally, it is possible to intentionally misrepresent oneself on MTurk in order to qualify for various studies. However, this may be mitigated by the requirement that participants have over a 95% acceptance rate on previous MTurk tasks. Participants also risk access to their MTurk

account if found to be a poor-quality worker, for example lying about their demographics, and are repeatedly rejected from tasks they attempt.

There are also several strengths of the current study. The large sample has over 300 fathers and mothers to test measurement invariance of the CPBQ. Additionally, the sample is relatively racially similar to the U.S population with approximately 20% of the respondents in both the male and female groups not being White alone. Considering the most recent estimates by the United States Census Bureau put the White alone population at 76.5% of the U.S population this sample is relatively racially diverse and similar to the U.S population as a whole (U.S. Census Bureau, 2019). Examining measurement invariance across racial and/or ethnic groups, as well as longitudinally, is an important future direction for the CPBQ in America. While the majority of Americans are White there is still a large non-White population. The relationship between the CPBQ and anxiety could also differ across racial/ethnic lines and this should be further examined. This study also found that some aspects of challenging parenting behavior as measured by the CPBQ are related to children's anxiety providing some content validity.

Future studies may want to examine the factor structure of this scale in other contexts. Thus far, the scale has been examined and used only in WEIRD (Western, Educated, Industrialized, Rich, Democratic) countries. Other regions of the world could potentially benefit from examination of how challenging parenting behavior and the CPBQ relates to child anxiety. For example, several east Asian countries including South Korea (Yoo et al., 2016), Japan (Urao et al., 2016), and China (Han et al., 2019) all have high rates of child anxiety and are currently developing and testing various

interventions. It is unclear if challenging parenting behaviors are beneficial in these cultural contexts. Examining challenging parenting behavior in these contexts could help to better understand both challenging parenting behavior and how it relates to child development and child anxiety. Translating and testing the CPBQ in these countries has the potential to benefit these countries attempts to reduce child anxiety. Further, it permits for the general hypothesis regarding father's roles in anxiety as being more important than mothers to be tested (Bögels & Perotti, 2011).

A final important consideration for future studies of the CPBQ and challenging parenting behavior in general may be to consider other parent-child relationship variables. Previous studies have demonstrated that rough-and-tumble play is beneficial for children's development of anxiety regulation when parents engage in appropriate behavior (Fletcher et al., 2013; Fliek et al., 2015). Generally, parents need to assert dominance over their children and control the play so that children learn to regulate their behavior and what is appropriate (Fletcher et al., 2013; Fliek et al., 2015). In addition, many other parenting behaviors as well as the generally quality of the parent-child relationship may be important for how challenging parenting behavior relates to childanxiety. Some variables that may be of interest include the attachment type and quality between parent and child and parental emotion coaching philosophy. Future studies may want to examine these and other factors in conjunction with challenging parenting behavior to get a more complete and clearer picture of how children's regulation of anxiety develops.

This study found that the factor structure of the challenging parenting behavior questionnaire (CPBQ) may need to be further examined. The scale had a different

structure with only 5 factors found in the United States compared with the 6 factors found in previous studies. Further, several items had to be dropped both in this study and in the previous work that found measurement invariance across Dutch and Australian respondents (Majdandžić et al., 2018). The final model used in this study did demonstrate good fit. This suggests that the CPBQ may still need additional work and examination but has potential to be a useful measure. It should also be noted that the CPBQ explained between 28 and 34 percent of reported child anxiety by mothers and 42 to 47 percent of variance in father reported child anxiety, suggesting that the CPBQ could be a valuable tool to understand children's development of anxiety and parents' roles in child anxiety. The CPBQ offers a less studied and well-known direction for studies of parenting behavior and child anxiety. Future studies may want to consider including the CPBQ in their measurements especially when examining child anxiety.

Table 3.1: Exploratory Factor Analysis

	ML2	ML1	ML3	ML5	ML4
If I see something that is new or exciting to my child, I encourage him/her to approach it.	.71	07	.02	.14	.09
I encourage my child to say no if he/she doesn't want something.	.67	01	.07	08	05
If my child thinks that he/she can't do something, I encourage him/her to try again.	.66	.01	03	18	.05
I encourage my child to gain new experiences by, for example, eating something new or					
playing a new game.	.64	01	05	.00	.14
If my child wants to go on the seesaw or the swing, I let him/her ask for himself/herself if					
he/she may go on it.	.56	.09	.03	.07	.06
I encourage my child to ask for himself/herself whether another child wants to play with					
him/her.	.54	04	.01	.27	.04
I encourage my child to stand up for himself/herself.	.51	.41	01	03	12
I encourage my child to be the best.	.33	.30	14	02	.08
I encourage my child to compete against other children.	06	.79	.07	.04	.01
My child regularly sees me in situations in which I try to win games and competitions.	13	.64	.04	.13	.07
I urge my child on when he/she is competing against other children.	.12	.61	.03	05	.13
I show my child that I take risks.	.09	.46	.11	.18	.01

	ML2	ML1	ML3	ML5	ML4
encourage my child to perform for an audience by, for example, singing a song, dancing	, ,				
or doing something sporty.	.19	.43	.11	.09	04
show my child that I engage with situations that I find exciting or scary.	.14	.42	.01	.20	.14
challenge my child to contests, for instance running races or arm wrestling.	.03	.42	.05	.06	.32
f another child snatches something from my child, I encourage my child to get it back.	.25	.40	.05	02	04
encourage my child to stay the night with a friend.	05	.29	.27	.21	09
in the bath or in the swimming pool, I encourage my child to duck his/her head under					
water.	.08	.27	.16	.16	.08
regularly tease my child for fun.	.02	02	.95	04	02
My child sometimes sees me tease others.	01	.04	.70	0.10	.03
As a prank, I sometimes scare my child for fun, for instance, by popping up unexpectedly	<i>.</i> 05	.07	.37	.09	.37
play little tricks on my child.	15	.10	.30	0.20	.28
f my child comes to me because he/she is having a minor quarrel, I make him/her sort it					
out it by himself/herself.	.00	.07	.08	.57	03
encourage my child to approach unfamiliar people to ask them something.	06	.11	.14	.54	08
When I play tag with my child, I make myself hard to catch.	.00	.04	.14	.47	.23
encourage my child to do exciting things, such as jumping off high objects or climbing					
higher than he/she dares.	07	.24	.01	.46	.16

	ML2	ML1	ML3	ML5	ML4
If my child finds something scary, I encourage him/her to carry on regardless.	.27	.02	.08	.45	.02
I show my child how I stand up for myself.	.35	.22	10	.35	03
My child often sees me approach unfamiliar people.	.12	.24	.13	.31	10
I sometimes play "tag" with my child: I chase after him/her and say in a low voice that					
I'm going to grab him/her.	.24	.03	.05	03	.57
I sometimes play a game with my child in which I spin him/her around.	.16	.07	.02	.03	.46
I enjoy tickling my child.	.31	.00	01	05	.44
I pretend that I'm going to eat my child's sweets, for example, his/her cookies or dessert.	06	.17	.26	03	.43
I enjoy having pillow fights with my child.	04	.27	.09	.05	.40
I play boisterously with my child.	.05	02	.09	.31	.35
I splash my child when we're in the swimming pool.	.07	.18	.05	.10	.35
My child sometimes sees me horsing around (play boisterously/rough-and-tumble play)					
with others.	02	.24	.16	.14	.33

Note: competitiveness/risk taking (ML1), autonomy (ML2), teasing (ML3), rough-and-tumble play (ML4), bravery (ML5)

	df	χ^2	$\Delta\chi^2$	⊿df	CFI	ΔCFI	RMSEA	SRMR
Configural	1100	2987.2			.904		.068	.074
Threshold	1170	3012.2	62.547	70	.903	.001	.067	.074
Metric	1200	3055.7	25.179	30	.907	004	.064	.074
Scalar	1230	3196.4**	93.725	30	.905	.002	.064	.074

Table 3.2. Model fit comparisons for invariance across fathers and mothers

Note. p**<.001

SE Estimate Z **Competitiveness/Risk taking** I encourage my child to compete against other 1.24 0.09 14.54 children. My child regularly sees me in situations in 1.04 0.08 13.88 which I try to win games and competitions. I urge my child on when he/she is competing 0.99 0.08 12.88 against other children I show my child that I take risks. 1.02 0.08 12.44 I show my child that I engage with situations 1.10 0.08 13.17 that I find exciting or scary. If another child snatches something from my 0.65 0.06 10.67 child, I encourage my child to get it back. I encourage my child to perform for an 0.07 12.72 audience by, for example, singing a song, 0.84 dancing, or doing something sporty. I challenge my child to contests, for instance 14.46 1.10 0.08 running races or arm wrestling. I encourage my child to stay the night with a 0.66 0.06 10.59 friend. In the bath or in the swimming pool, I encourage my child to duck his/her head 0.84 0.07 11.69 under water.

Table 3.3. Table of Confirmatory Factor Loadings

Note. All factor loadings are significant (p < .001)

Continued

	Estimate	Std.Err	z-value	
Autonomy				
If I see something that is new or exciting to	1.00	0.10	10.04	
my child, I encourage him/her to approach it.	1.09	0.10	10.94	
I encourage my child to gain new experiences				
by, for example, eating something new or	0.86	0.08	11.29	
playing a new game.				
I encourage my child to say no if he/she	0.00	0.06	0.41	
doesn't want something	0.60	0.06	9.41	
If my child wants to go on the seesaw or the				
swing, I let him/her ask for himself/herself if	1.00	0.10	10.40	
he/she may go on it.				
I encourage my child to ask for				
himself/herself whether another child wants to	1.07	0.10	10.84	
play with him/her.				
I encourage my child to stand up for	1 10	0.12	0.64	
himself/herself.	1.12	0.13	8.64	
I encourage my child to be the best.	0.67	0.08	8.71	
Teasing				
I regularly tease my child for fun.	1.30	0.11	11.79	
My child sometimes sees me tease others.	1.36	0.12	11.76	
As a prank, I sometimes scare my child for	1 / 1	0.14	10.20	
fun, for instance, by popping up unexpectedly.	1.41	0.14	10.30	
I play little tricks on my child.	1.03	0.10	10.11	
Note. All factor loadings are significant ($p < .001$)				

Continued

0.82	0.07	12.60	
0.57	0.06	10.24	
0.60	0.06	11.00	
0.68	0.06	11.39	
0.00	0.00	10.10	
0.98	0.08	12.12	
0.89	0.07	12.33	
0.78	0.07	11.19	
1.11	0.09	12.86	
0.75	0.07	11.58	
	0.57 0.68 0.98 0.89 0.78 1.11	0.570.060.680.060.980.080.890.070.780.071.110.09	

 $\overline{\text{Note. All factor loadings are significant (p < .001)}}$

Continued

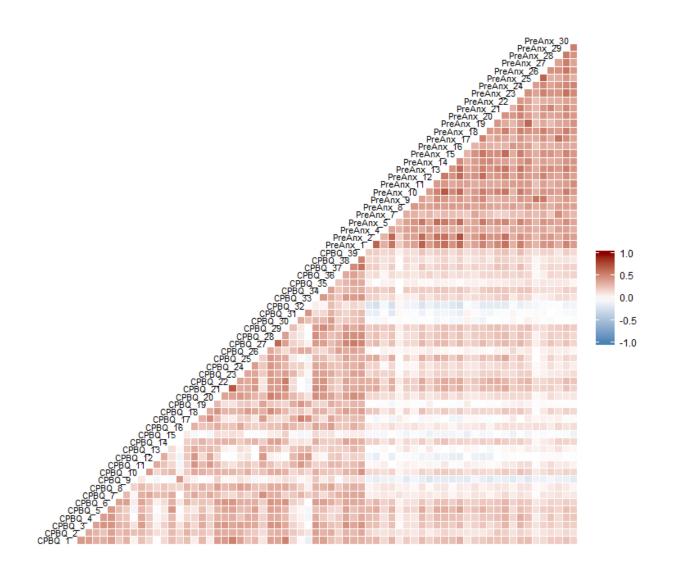
Estimate	SE	Z
0.70	0.07	10.00
0.72	0.07	10.83
0.50	0.05	10.00
0.70	0.06	10.93
0.01	0.07	10.00
0.81	0.07	10.99
1.05	0.09	12.35
1.10	0.00	10 10
1.13	0.09	12.40
0.83	0.07	11.19
	0.72 0.70 0.81 1.05 1.13	0.72 0.07 0.70 0.06 0.81 0.07 1.05 0.09 1.13 0.09

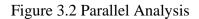
Note. All factor loadings are significant (p < .001)

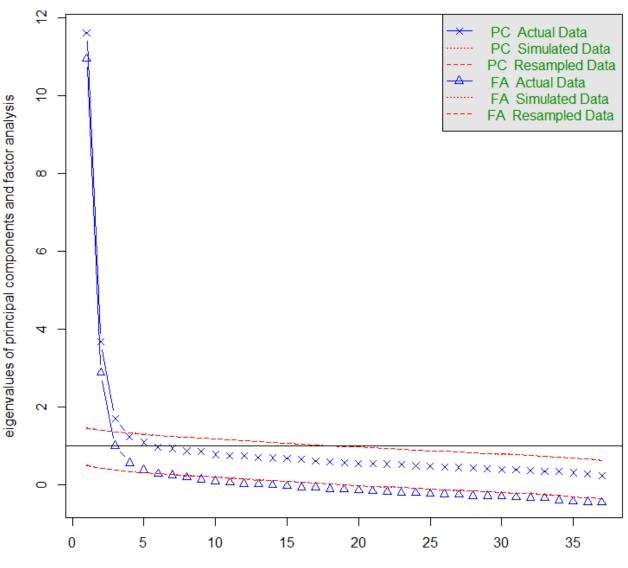
	Estimate	SE	Z	р
ML1	0.319	0.091	3.497	< 0.001
ML2	-0.138	0.090	-1.532	0.126
ML3	0.585	0.109	5.384	< 0.001
ML4	0.310	0.092	3.365	0.001
ML5	0.476	0.096	4.937	<0.001

Table 3.4: Latent mean comparisons

Figure 3.1 Correlation Heatmap

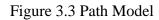


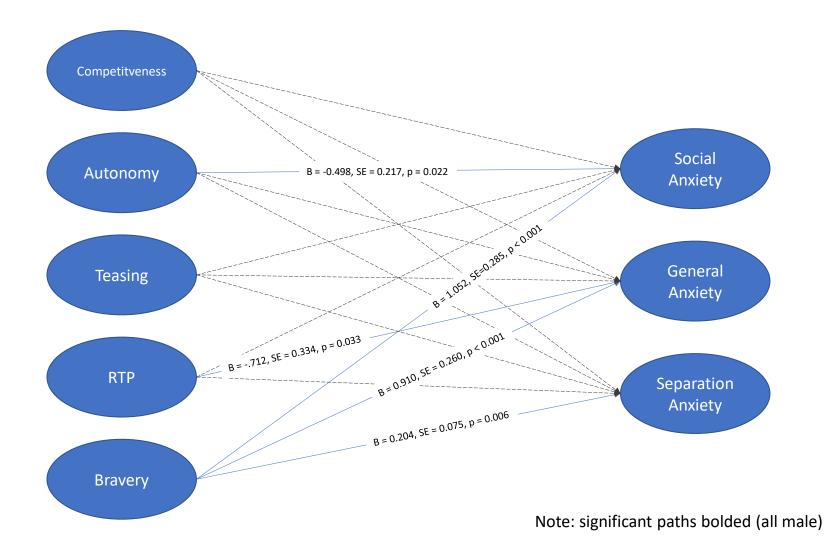




Parallel Analysis Scree Plots

Factor/Component Number





Chapter 4. Predictors of Children's Regulation during a Frustrating Task: A Statistical Learning Approach

The development of self-regulation of emotion is a major task for children (Morris et al., 2007). The preschool time period is particularly important to this process as this is when children are shifting from relying on their parents to regulate their emotions to self-regulation of emotions (Feng et al., 2017). Emotion regulation skills are important for children's success in many domains including: academics (Burge & Hammen, 1991; Spera, 2005), peer relations (Hooven et al., 1995), and even physical health (Sokol et al., 2017). Children acquiring the ability to regulate their negative emotions is important to their continued development and success (Berk & Meyers, 2016). Children that fail to acquire the ability to successfully regulate their negative emotions may engage in inappropriate behaviors or otherwise struggle in social situations (Feldman, 2006; Stormshak et al., 2000). Further, there are personal consequences of failing to appropriately regulate negative emotions including increased anxiety and depression (Yap et al., 2014; Yap & Jorm, 2015). Finally, successful regulation of negative emotion is important to success throughout life (Shallcross et al., 2013).

Mother-child interactions are an important aspect of the socialization of children's early social and emotional skills and are widely accepted to influence children's development (Hertz et al., 2017; Morris et al., 2007; Sulik et al., 2015). Researchers have established that maternal characteristics including: depression (Goodman et al., 2011), personality (Cumberland-Li et al., 2003; Ellenbogen & Hodgins, 2004), parent-child relationship quality (Jonason et al., 2014), attachment (Wolff & van Ijzendoorn, 1997), and parental stress (Crnic & Booth, 1991; Kendler et al., 2004; Rodell & Judge, 2009), are all related to children's development. Many of these areas have been studied for decades, are being studied in contemporary academia, and have been among the most successful areas of social science research in understanding child development (Wolff & van Ijzendoorn, 1997). It has been found that parental autonomy granting, allowing children an age appropriate level of decision making, is related to children having better academic achievement, lower levels of substance abuse, and higher levels of social competence (Silk et al., 2003). Additionally, it has been found that scaffolding is an effective manner of teaching children new skills and abilities that are in children's zone of proximal development (Berk & Meyers, 2016). There are numerous other areas in which interactions between mothers and children are known to be influential in children's development (Berk & Meyers, 2016); the important task of understanding how these interactions may influence children, in what context, and how they may influence each other remains inadequately explained.

Children's Development of Emotion Regulation

There are several models of how children learn emotion regulation skills, fortunately, many of these models are in general agreement about the processes involved (Morris et al., 2007). For the purposes of this study Morris and colleagues 2007 tripartite model of emotion socialization will be used. This model states there are 3 ways children learn emotion regulation skills. The first way children learn emotion regulation skills is through observation of their parent's behaviors (Morris et al., 2007). Through watching how their parents handle their emotions children are thought to learn strategies and the appropriate response to emotions (Morris et al., 2007). Naturally, an important aspect of this is the manner in which parents express their own emotions. If the children observe their parents engaging in socially inappropriate emotion expression or regulation of their own emotions, for example breaking things in response to anger, the children will also learn socially inappropriate emotion expression and regulation strategies.

Another mechanism of emotion socialization in the tripartite model is the family emotional climate created by parents (Morris et al., 2007). This is the general, overall mood and feeling of the home environment for children. Through this environment children's emotions are socialized and they are thought to learn about emotion expression (Morris et al., 2007). There are a number of aspects that are related to the overall emotional climate of the home. One aspect of the family emotional climate is the mental health of the parents. Parents who struggle with depression or anxiety may create a home environment that is negative and not conducive to children's development of successful regulation. This can reduce children's ability to learn how to regulate their emotions and make it more difficult for them to engage in appropriate emotion regulation. Another aspect of the home environment is the marital status of the caregiver(s) (Morris et al., 2007). Depending on the marital status of the child's caregiver(s) the home environment can be quite different. Additionally, parental psychopathology, such as depression, can influence the overall home environment resulting in a generally more negative home environment (Morris et al., 2007).

The third mechanism of emotion socialization the tripartite model discusses is parenting practices (Morris et al., 2007). The previously mentioned manners of emotion socialization are relatively passive on the part of the parents; however, parenting practices are active on the part of parents and require intentional behavior on the part of parents (Morris et al., 2007). Parenting practices include intentional behaviors on the part of parents to teach their children emotion regulation strategies. One method of parenting practice that has received some attention is the manner in which parents respond to their children's emotions (Gottman et al., 1996; Lunkenheimer et al., 2007). Parents who see their children's negative emotions as an opportunity to teach their children about emotions, rather than amplifying their negative emotions, can improve their children's self-regulation of negative emotions (Lunkenheimer et al., 2007).

Additionally, one aspect of a parent or home environment, parental mental health, can affect multiple pathways of emotion socialization. For example, depression can be related to all three aspects of the tripartite model. Parents with depression may display more negativity and fail to display appropriate emotional responses to various situations, children may learn inappropriate emotion regulation strategies through observing this behavior. Additionally, depression can be related to a lack of ability to engage in appropriate parenting practices. If the parent lacks appropriate emotion regulation skills themselves, it is difficult for them to engage in the best parenting practices with their children to teach appropriate emotion regulation skills. Further, people with depression generally have lower levels of emotion regulation skills themselves when compared to mentally healthy counterparts and are more likely to engage in ineffective strategies such as rumination (Rudolph et al., 2017; Wu et al., 2019). This provides part of the explanation for why children of depressed parents have more difficulties in a wide variety of domains and struggle with depression themselves (Feng et al., 2009; Goodman et al., 2011).

Another important aspect of the tripartite model are the parent's individual characteristics (Morris et al., 2007). There are a number of parent characteristics that are thought to influence parenting practices, the emotional climate parents create, and aspects of observation (Morris et al., 2007). One well known and studied area of individual differences is temperament and personality (Shiner & DeYoung, 2013), and while this is certainly part of the parenting characteristics that relate to how children learn emotion regulation skills there are many other parent individual characteristics that bear consideration. An important part of parent's individual characteristics that relate to their children's emotion regulation is parent's own expression of emotion. (McCrae & John, 1992). Parental characteristics can also influence how the previously discussed methods of emotion socialization are expressed, shown, taught, and relate to the overall familial climate.

Children's own characteristics are also an important aspect of how they regulate their own emotions (Morris et al., 2007). Of course, these are in part related to the parent's characteristics as there is a genetic component to aspects such as personality (Loehlin et al., 1998). Therefore, a parent who is high in the negative emotionality aspect of neuroticism is at a higher likelihood of having a child who is also high in this negative emotionality aspect of neuroticism which can, in turn, change the child's response to emotion socialization. Additionally, aspects of children's emotionality, such as their propensity towards feeling anger, is directly related to how much and often they must engage their emotion regulation strategies (Morris et al., 2007). Another way to think of children's individual characteristics in this model is as moderators of the effect of emotion socialization practices on children's emotion regulation behaviors.

With such a large number of potential variables and influences on children's emotion regulation studying all of these aspects in one study can be difficult. With 5 different domains that are theorized to be related to children's emotion regulation development, and each domain containing several aspects, the problem can quickly become intractable due to the number of variables that require consideration. A common strategy to deal with this issue is to only focus on only part of the model (e.g., Gerhardt et al., 2020; Hooper et al., 2018; Ku et al., 2019). An alternative possible solution is to use a data driven method to select the variables that should be used in the model. The current study utilizes this second option to determine which variables are most related to children's emotion regulation.

Based on the tripartite model there are numerous potential effects on children's development of self-regulation of negative emotion. A reality of many studies is that they only focus on one aspect of parent's role in child development in one specific task or paradigm. Traditional data analytic models, such as ordinary least squares regression, only allow researchers to examine the effects of, at most, several variables. Considering the number of factors that are included in the tripartite model this is a major shortcoming of traditional modeling techniques. A possible solution to this issue, employed by the

current study, is to utilize machine learning models which allow for inclusion of more variables than traditional methods. Considering the large number of possible predictors, two steps are needed in developing the machine learning models for the current study. First, a variable selection step to identify the most important and strongest predictors of children's development of self-regulation of emotion was needed. Then using the variables identified in the first step, models were developed to examine how those variables related to children's development of self-regulation of emotion. This study attempted to address both the issue of testing only one aspect of mother's role in children's development as well as examining interactions of these variables utilizing two methods known as random forest and penalized/regularization techniques.

Machine Learning

The goal of statistical learning methods is to understand data (James et al., 2013). Statistical learning analyses can be used in a wide variety of fields ranging from computer science, business, education, and psychology (James et al., 2013). There is a massive variety of statistical learning models that all have advantages and disadvantages (James et al., 2013). Machine learning is a specific type of statistical learning and can be broken down into two categories, supervised or unsupervised. Supervised methods use input(s) to predict, classify, or estimate an output (James et al., 2013). Unsupervised methods lack an output but are still useful to understand relationships and patterns that are present in the data (James et al., 2013). The current study used two supervised methods of machine learning random forest and penalized regression. Two different modeling techniques were used as they have advantages and disadvantages, particularly when used in relatively small psychology samples. Random forest models are generally very effective at predicting outcomes but may produce results that do not generalize well to new samples (James et al., 2013). Particularly in small samples with an outcome that is known to be difficult to predict, such as human behavior, random forests may generate a good solution only for the current dataset (James et al., 2013). This issue is somewhat mitigated by splitting the dataset and using training and test samples, as is common in many machine learning applications including random forests, however, there is still a concern about generalizing the results (James et al., 2013). Penalized regression as a modeling technique is generally less opportunistic than random forests and will not split the variables in the same way as a random forest (James et al., 2013). While it is possible that penalized regression may produce weaker predictive accuracy than random forests within samples, they may produce results that generalize to other samples more effectively (James et al., 2013).

Random Forests

There are a large variety of possible mother-child interactions, and aspects of those interactions, that could be related to children's development. Many researchers have examined many of these variables, for good reasons, but there are fundamental problems that are faced by researchers. First, systematically checking a large number of variables is both time consuming and introduces type I error (Shadish et al., 2002). Second, researchers may be biased, mistaken, or otherwise make poor decisions in selecting their variables. Third, testing many variables in a single model may limit the effect size or significance of the individual variables that are tested. Fourth, if the number of variables exceeds the number of participants in regression the model cannot be solved (Shadish et al., 2002).

Random forests can be utilized to model the variables that are most strongly related to an outcome. This resolves the previously stated issues as variables are systematically checked and a small number of variables are selected for inclusion in the final model. This method was originally proposed in 2001 and has generated over 50,000 citations as well as numerous different implementations of the algorithm (Breiman, 2001). Since the initial publication of the random forest method there have been alterations to the implementation and new use cases developed. This study utilized random forests to select variables that are most strongly related to an outcome.

Random Forest models are an ensemble machine learning method that involves growing many trees in an attempt to predict new data (Liaw & Wiener, 2002). The algorithm makes N bootstrap samples from the data (Liaw & Wiener, 2002). A tree will be grown for each of these samples; but rather than choosing the best predictor at each node the model chooses the best available predictor, the variable that best splits the data, from a random sample of M predictors (Liaw & Wiener, 2002). A tree is a series of splits of the data that attempts to correctly predict the value of an outcome variable. For example, a node (where the tree splits the data) in predicting probability to graduate college could be entrance exam scores. Students over a certain score would be sorted into group a, students below that score would be sorted into group b (not all splits are dichotomous). Then group a and group b resulted from this split are further split based on other variables. Each node is based on criteria that can be used to split the data that produces the best prediction at the next step. The combination of all of these nodes form the tree that is used to prediction. The tree is grown until the specified criteria is met, either sufficient purity (accuracy in prediction) in the terminal nodes or a sufficient number of nodes have been reached. Then the model takes the results from each of the N trees that have been grown, takes an average of the results, and attempts to predict new data (Liaw & Wiener, 2002). The VSURF package uses this process and then selects the variables that are most important to predicting the outcome.

As variable selection in random forests is automatic researchers are not forced to manually check a large number of variables. The testing of the variables and the model are systematic which reduces the time investment by the researcher and human error. Additionally, random forests have a built-in method that allows many different variable splits to be tested by randomly using a subset of the variables at each node which allows for many variables to be considered and for trees to be decorrelated (James et al., 2013). By decorrelating the trees, a better model fit is possible as trees will not make the same errors (James et al., 2013). Finally, the random forest model also models non-linear relationships between variables as well as interactions.

A second advantage of random forests is that they are less biased in their testing of variables. As the model randomly selects the variables used for each node, this aspect of the model cannot be biased by researchers (Liaw & Wiener, 2002). The issue of selecting which variables are available for the model is still present but the ability to use a large number of variables can help mitigate this issue. Moreover, random forests naturally model interactions between variables due to the method of growing trees (Liaw & Wiener, 2002). As the best variable is selected at each splitting of a node the constellation of variables that produces the classification at the bottom of the tree can be thought of as an interaction. Indeed, variables can be found to be of high importance through its role in interactions with other variables rather than being important in and of itself (Liaw & Wiener, 2002). This means that interactions that may not typically be examined by researchers are examined by the random forest model. For the current study this is useful as all aspects of the tripartite model (Morris et al., 2007) are at least given consideration in the model. While automatic variable selection may result in some aspects of the model being overrepresented or underrepresented in the final random forest this could suggest that these aspects of the model may be more strongly related to children's emotion regulation. Alternatively, this could also suggest that measures of some aspects of the model may be inadequate to accurately assess those aspects of the model.

Third, random forest models are well known to perform well in large p (where p is the number of variables) small n (where n is the number of data points or participants) problems (Chen & Ishwaran, 2012). This is a common difficulty that psychology and social science researchers face, collecting a large number of variables as it is more cost efficient to add more measures to a study, and lacking the tools to analyze this data. Random forests are known to effectively handle this situation; indeed, random forests performance gains over more typical methods are most dramatic in the large p small n situation (Chen & Ishwaran, 2012).

Fourth, many traditional analysis techniques are required to have more participants than variables in the model to have a closed form solution (Shadish et al., 2002). This is further exacerbated by the need for multiple participants per parameter estimated, even small participant to coefficient ratios are 10:1 (Kline, 2015). This means that if a researcher wants to test 100 variables, they would need a minimum of 1000 participants utilizing an ordinary least squares regression approach. However, utilizing random forests that same researcher could test all 100 of the variables in question, with a smaller sample, and be less concerned about issues of power or reliability of estimates (Chen & Ishwaran, 2012). The exact minimum sample size needed for random forests is unclear and sample size should be determined based on the goals of the study; however, larger sample sizes are preferable (Kim, 2009).

Penalized Regression and Regularization

Similar to random forests regularization models are very effective at variable selection (James et al., 2013). Regularization is often understood in relation to standard linear models which often use ordinary least squares regression (James et al., 2013). The remainder of this section will discuss regularization methods in relation to ordinary least squares, but the same logic applies to other estimators for linear models. In ordinary least squares variables X_1 to X_n are used to predict some outcome Y (Shadish et al., 2002). However, as the number of variables included in an ordinary least squares model approaches the number of participants there is data on (i.e., as p approaches n) the model fit becomes unreliable and has high variance (James et al., 2013). If the number of

predictors passes the number of participants the model no longer has a unique solution (James et al., 2013).

A method for dealing with this large p small n challenge is to employ shrinkage which is also referred to as regularization. Shrinkage involves reducing (shrinking) the coefficients from a model that contains all available predictors towards zero which reduces the variance and makes estimates more reliable (James et al., 2013). Two major types of regularization are ridge regression and lasso regression. Penalized regression involves reducing the coefficients relative to a tuning parameter, a hyperparameter that determines how aggressively the coefficients should be reduced. As the tuning parameter is set to larger values the coefficients are shrunk to smaller levels (James et al., 2013). However, in ridge regression all variables are included in the model and are not shrunk to 0. This is in contrast with lasso regression which will shrink coefficient estimates to 0 with a sufficiently high tuning parameter (James et al., 2013). There is also another type of regularization called elastic nets, which are a combination of ridge and lasso regression (Ahn et al., 2017).

No regularization method, lasso, ridge, or elastic net regression are always superior to each other, the appropriate shrinkage method depends on the data and the goals of the model (James et al., 2013). Lasso models have the advantage of being simpler and more concise given they reduce some coefficients to 0. However, in cases where coefficients are not 0 the lasso model may not perform as well as the ridge or elastic net model (James et al., 2013). Therefore, all of these models are useful and are used in statistical learning. When using these regularization techniques in a regression context the models will often be referred to as penalized regression models (Ahn et al., 2017).

The Current Study

The current study uses children's negative emotion expression during frustrating lab tasks to measure children's emotion regulation. Emotion expression is thought to be an external indicator of the ability to regulate (Morris et al., 2007), in this case, negative emotions. The tasks used are designed to frustrate and/or induce sadness in the child. It is posited that children who are better able to regulate their emotions will express fewer negative emotions during these tasks. Thus, it is thought that by observing expressed negative emotion children's emotion regulation can be derived.

A stratified variable selection technique to determine which variables were most strongly related to child self-regulation of negative emotion as indicated as negative emotion expression when alone in a laboratory setting. Variables were classified into one of four groups, demographics, children's temperament, maternal personality and mental health, and maternal parenting behaviors/mother-child emotion expression. Variables from each stratification were selected for a final model based on random forest and penalized regression techniques. Variables selected from the stratifications were used in combination to predict children's regulation and behavior both concurrently and longitudinally. Previous work has established that early interactions with mothers, early life experiences such as home environment, and children's characteristics such as temperament are all important to children's later ability to regulate themselves (Morris et al., 2007). However, it is unclear which variables are most strongly related to children's later emotion regulation outcomes. For many traditional modeling techniques, such as ordinary least squares regression, it is very difficult or even impossible to address the question of which variables are most important in relation to an outcome. This study used statistical learning techniques to screen variables and examine which variables are most strongly related to children's later regulation abilities. After determining the most important variables with the strongest relation to children's regulation a final model was run to evaluate the performance of the variables in predicting children's emotion regulation.

The use of both random forests and penalized regression to analyze the data provided multiple perspectives on how the variables relate to child negative expression. These models have different methods to fit data and determine which variables have the strongest relationship with children's negative expression. This provides multiple perspectives on how the variables of interest relate to children's negative expression. The models identifying different variables that are related to children's self-regulation of negative emotion could be greatly valuable to future research. It is possible that variables that are selected in the random forest are related to children's development of selfregulation of negative emotion in a more complicated fashion than variables identified in the penalized regression. The random forest model can capture non-linearity and interactions among the variables that it models, penalized regression does not readily capture these more nuanced relationships.

Both concurrent analyses, using the same timepoint, and longitudinal analysis were conducted. This was done as understanding both children's self-regulation of

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negative emotion in the short-term and long-term is valuable. The variables that are strongly related to children's self-regulation of negative emotion may not be the same in the short and long term. For example, parenting behaviors may slowly improve children's self-regulation of negative emotion (Gerhardt et al., 2020). Thus, to see the effects of parenting behavior longitudinal analyses are needed. Additionally, understanding which variables are important for children's self-regulation of negative emotion is also of value in helping children succeed.

This was a data driven study, thus there were no hypothesis regarding the final model. The goal was to determine which variables were most strongly associated with children's regulation and home behavior one year later. Both random forest and penalized regression models were used to examine which variables were most strongly related to children's regulation and behavior at home.

Method

This study draws its participants from a longitudinal study that focused on children's emotion regulation and attentional control. This study was approved by The Ohio State University institutional review board and is known as the Attentional Control and Emotion Regulation study (ACER). Participants were recruited using internet postings (primarily craigslist), flyers, word of mouth, and from daycares/schools in a large Midwestern city. To be eligible for this study mothers had to have a typically developing child who was between 3 and 3.5 years of age and be 21 years of age or older at the time of enrollment. Mother-child dyads came in three times, when the child was 3, 4, and 5 years of age. A total of 126 mother-child dyads that qualified for this study.

Procedures and Measures

The three timepoints for the first study (T1, T2, T3) are defined by the children's age during visits when they were 3 years old (T1), 4 years old (T2), and 5 years old (T3). At each timepoint mother-child dyads attend the lab for a visit. Dyads completed several tasks together designed to elicit emotion and observe the mother-child relationship, children also completed some tasks alone. In addition to the lab visit mothers also completed a survey that included questions about their mental health, emotion expression, and parenting behaviors. The questionnaire also asked mothers to report their children's behaviors and temperament, as well as demographics for them and their children. The procedure at all timepoints was mostly the same, with several emotion-eliciting tasks for child alone modified at T3 to ensure that the stimuli were novel to the child.

Predictors

Demographics. Mothers reported several common demographic variables about themselves and their children. Variables that relate to the child are the child's age, sex, and race (White vs. non-White). Mothers also reported demographic variables about themselves. This included their education, marital status, if they and their child were living with the child's biological father, and if the mother was White.

Maternal personality and psychopathology. Mother's reported their positive and negative emotionality using the Positive and Negative Affect Schedule (PANAS; Watson et al., 1988). The PANAS is a wellestablished measure of affect and includes 10 Likert items for positive emotionality and 10 Likert items for negative emotionality rated on a

scale of 1 to 5. Additionally, maternal depressive symptoms were measured using the Beck Depression Inventory (BDI; Beck & Steer, 1996). The BDI is a well-established measure of depressive symptoms and involves respondents rating 21 statements on a 4point Likert scale from least to most severe. Finally, mothers reported their anxiety on the State and Trait Anxiety (STAI; Spielberger et al., 1983) questionnaire. Participants rated their current anxiety level as well as their general anxiety level on 40 statements using a 4-point Likert scale.

Maternal behavior/parenting. Mothers also completed several questionnaires regarding their behavior and parenting. Mothers rated their rumination, distraction, and problemsolving behavior when they feel sad or depressed using the responsive style questionnaire (RSQ; Drabick et al., 2001). This questionnaire contains 38 Likert items rated on a 4point scale that ask participants to rate how often they engage in certain behaviors. Parenting stress, specifically frequency and intensity, were measured using the Parenting Daily Hassles (PDH; Crnic & Greenberg, 1990). This scale measures parents perceived hassles with parenting using 40 statements that are rated on Likert scales of increasing hassle. The number of points is not consistent across items ranging from 4 to 5. Mothers also rated their support and magnification reactions to children's emotion using the Response to Child's Emotions Questionnaire (RCE; Magai, 1997). This questionnaire includes 36 Likert items on a 5-point scale of how often mothers engage in certain behaviors in response to their child's emotions.

Observed mother/child emotion expression during interaction tasks. Child positive and negative emotion expression as well as mother's positive expression in the lab was

coded from videos of mothers and children interacting together in the lab. Positive expression was coded when participants had facial indicators of positive affect (e.g., smiling), or verbal indicators of positive affect (e.g., laughing, voice increasing in pitch). Children and mothers were also both coded for negative expressions. However, mothers' expression of negative emotion was so infrequent it was excluded from analysis. Child anger was coded when children had facial indicators of anger (e.g., clenched teeth) or verbal indicators of anger (e.g., yelling angrily). Child sadness was coded when children had facial indicators of sadness (e.g., pouting) or verbal indicators (e.g., whining or crying) (Hooper et al., 2015). While these were coded separately, they were combined into one composite variable for the current study as levels of both anger and sadness expression were generally low. Combining these variables increased variability in children's negative expression and reduced sparsity.

Several tasks were used to measure emotion expression in mother-child dyads. A free play task involving mothers and children playing with a set of toys together in whatever manner they chose. A collection of toys including Lincoln Logs, plastic food and cookware, and a dump truck were provided for the mother and her child. Participants were permitted to play with the toys for 5 minutes. Children were also asked to clean up these toys they were playing with in the clean-up task. This task lasted until all the toys were cleaned up or 5 minutes whichever was shorter. This task was designed to elicit negative emotion in children. A block task involving mothers and children playing with blocks and attempting to build pictures of structures provided to them for 5 minutes was also used. This task was designed to see how mothers and children interacted together.

Mothers and children also played with an Elmo doll at ages 3 and 4 or bubbles at age 5. These positive emotion tasks lasted for 5 minutes.

Child characteristics. Mothers also reported children's behavioral and temperamental characteristics at home. Children's negative affect, effortful control, and surgency were rated by mothers on the Child Behavior Questionnaire (CBQ; Rothbart et al., 2001). Mothers were asked to rate how often their children would react in certain ways to a series of 94 statements. All items were rated on a 7-point Likert scale. Children's externalizing and internalizing behavior were rated by mothers on the Child Behavior Checklist (CBCL; Achenbach & Ruffle, 2000). The CBCL contains 99 statements that are rated on a 4-point Likert scale.

Dependent variable

Children's self-regulation of negative emotion. Children's regulation of negative emotion was coded from video tapes in tasks designed to elicit anger and sadness separately. These tasks were combined to create a compositive measure of children's negative emotion. These tasks include the transparent box task (Goldsmith & Rothbart, 1996) at ages 3 and 4 which was designed to elicit anger in children. An attractive toy was placed into a transparent box which was subsequently locked. The child was given a set of keys with the instructions that if they could open the lock they could play with the toy. The experimenter then left the room. Unbeknownst to the child the keys they were provided with were incorrect and could not open the lock. After the experimenter returned, they would then open the box and allow the child to play with the toy. The broken toy task replaced the transparent box at age 5 but was still designed to anger the

child. Children were given a remote-control car, without any batteries, along with a large bag of batteries. They were told to put the batteries in the car, and if they could get it to work, they could play with the car. However, unbeknownst to the child none of the batteries they were provided with worked and it was impossible to get the car to work. After 5 minutes the experimenter would return and let the child play with a working car. The disappointing toy task involved the child choosing their favorite and least favorite toys from among a set of toys during the age 3 and 4 visits. The purpose of this task was to, as the name suggests, induce sadness in children. Several of these toys were either broken (e.g., half a ball), or were not a toy (e.g., a paperclip). After children selected their favorite and least favorite toy the experimenter left with all the toys. Later in the study visit, a different experimenter returned with the least favorite toy. The child was told this was their prize for doing so well. The experimenter would then sit in a chair and pretend to be busy with their own work. After 1 minute the experimenter would leave the room and the child would be left alone with the toy for 1 minute. At age 5 children did the impossible perfect circles task, designed to frustrate the child. This task involved the child being asked to draw "a perfect circle" on a sheet of paper at age 5. This task was designed to frustrate children. Regardless of what the circle looked like the child was given specific feedback about an aspect of the circle that was not ideal (e.g., it's too small, it's jagged, etc.). The child was then asked to draw another circle and told that this circle was also not perfect. This was done for 5 minutes at which point the experimenter would say that the child's most recent circle was pretty good.

Children's sadness, anger, and fear during these tasks was coded using the same rules as the predictor variables. Fear, the only variable not included in the predictor variables, was coded when children either had facial expressions that looked afraid, or verbally reacted in a fearful manner. These negative expressions across tasks were combined into a composite variable to provide a more stable evaluation of children's negative expression. This variable was calculated for age 3, 4, and 5 and used as the outcome for the analyses as appropriate.

Data Analysis

Data were analyzed using R (Team, 2008) and utilized the easyml, package for the statistical learning models (Ahn et al., 2017). All models used 70% of the sample for training and 30% for testing. Missing data were imputed using the missForest (Stekhoven & Buhlmann, 2012) package. The missForest imputation method grows random forests, it then utilizes these forests to impute the missing data. This method has been shown to outperform other multiple imputation methods such as multiple imputation by chained equations in a simulation study (Stekhoven & Buhlmann, 2012; Tang & Ishwaran, 2017). This method was particularly well suited to this study as the most drastic performance difference between the missForest imputation method and other imputation methods is when there are complex interactions in the data and a mix of continuous and categorical data types.

The first step for the random forest analyses was to determine which variables would be used in the model. This was done using the VSURF (Genuer et al., 2015) package which selected a subset of variables that were best at predicting the outcome. As a side note, after the variable selection step any number of models could be utilized, machine learning or otherwise, one is not restricted to using only random forests models. This study chose to use random forest models but other options such as linear regression, structural equation modeling, and multilevel modeling, were all possible considerations.

The modeling can be divided into two general categories, the concurrent analyses where variables from the same timepoint were used to predict the outcome, and longitudinal analyses where variables from the previous time point were used to predict the outcome 1 or 2 years later. This means that a total of 6 analyses were run, age 3,4, and 5 concurrent results, as well as age 3 predicting age 4, age 3 predicting age 5, and age 4 predicting age 5.

The set of variables selected were chosen as they do the best job of predicting the outcome and minimize redundancy. Variables were divided into stratifications based on content area. The stratifications used were: demographics, maternal personality and psychopathology, maternal behavior/parenting, observed mother-child emotion expression in the lab, and child characteristics. This drastically reduced the number of variables in each stratification that were later used in the analysis. The variables chosen from each stratification were combined into the final set of variables that were used for modeling in the random forest and penalized regression models. This was done separately for each of the 6 models described above. The random forest variable selection was done first and any variables that were not included in at least 2 models were not included in the penalized regression variable selection.

The majority of the variables that were included in the variable selection by random forest models were included in at least 2 models. The only exceptions to this were presence of a bio-father, if the child was White, RSQ distraction, RSQ problem solving, RCE support, CBQ surgency, and CBCL internalizing. There were also several variables that were included in 5 or more models. These include child sex, state-trait anxiety, child negative during lab tasks, and CBCL externalizing. A complete table of all variables included and excluded, along with estimates of their mean decrease in Gini index, from each model can be found in Table 3.1.

Utilizing the same set of stratifications as the random forest models, a series of 6 penalized regressions were run but penalized regression variable selection was independent from the random forest models and VSURF. Variables were selected using an elastic net with a mixing parameter of 0.5. This was done as larger parameters selected too few variables and smaller parameters selected too many. The penalized regression had a much more restrictive set of variables that were included in the final model. The only variable that appeared in more than 3 models was child sex. Additionally, no variables from the maternal mental health stratification were included in any model. The variable selection based on the penalized regression was far more restrictive. The penalized regression models had 38 data points in the test set and 88 in the training set. This splitting was done 1,000 times and estimates of model performance were estimated 1,000 times. A complete table of variables included and excluded, along with the associated log odds, can be found in table 3.2.

Results

Random Forest Models

Just as in the VSURF step a total of 6 analyses were run in the random forest analysis. Each model was estimated separately, one for each concurrent outcome and one for each longitudinal outcome. Each set of variables that was chosen based on the stratified variables selection was used for the corresponding random forest model. To evaluate model fit cross-validation was used, only model fit in the cross-validation sample, sometimes referred to as the test sample, was considered.

The age 3 concurrent random forest had a R-squared of .040 in the test sample. The variables that were found to be most important were child age, children's negative expression in mother-child interaction tasks, and parenting stress-frequency. In contrast mothers being White, mother marital status, and child sex were found to be of low importance. The age 4 concurrent random forest fit poorly with a R-squared of .005. The most important variables in this model also changed compared with the age 3 model as child negative emotionality and mother's positive expression during lab interactions were the most important variables. Child sex was again not an important variable. The age 5 concurrent random forest fit better than either the age 3 or 4 with a R-squared of .073 in the test sample. Child negative expression during the lab task and mother positive during lab interactions were the most important variables in this model. Maternal magnification of children's emotions and mother's positive affect were the next most important variables. The least important variables were the child being White, the mom being White, and the presence of a bio-father The age 3 predicting age 4 model had a R-squared of .008. The most important variable was mother's positive expression during lab tasks and child externalizing behavior. Child sex was the least important variable. The age 3 predicting age 5 model had an R-squared of .017. The most important variables in this model were child negative emotionality, child externalizing behavior, and parenting stress-intensity. Again, two demographic variables of child sex and maternal marital status were the least important variables. The age 4 predicting age 5 model a R-squared of 0.012. The most important variable was children's negative expression during the lab visit along with their age and child negative emotionality. Mothers being White and child sex were again the least important variables.

Given how poor the random forest models fit, explaining less than 1% of the variance in many cases, it was hypothesized that perhaps the stratification process was not removing enough unimportant variables. It is possible that the model is overfitting to the training data and is performing poorly in the test data. To address this issue, a second wave of variable selection by random forest was run on the variables selected from the stratification process in the previously described step. The random forest models from the variables selected from the second variables selection fit much better although not every stratification was included in the final model. Going forward these results will be referred to as the wave 1 random forest results. A table of the variables used in this second wave along with their mean decrease in Gini index can be found in table 3.3.

The age 3 concurrent model had a R-squared of .073. Additionally, all 4 variables included, parenting stress-frequency, parenting stress-intensity, child negative in the lab, and mother's depressive symptoms were important to the model. The age 4 concurrent model had a R-squared of .053 using maternal positive expression in the lab, child negative in the lab, and child externalizing behavior which were all important to the model. The age 5 concurrent model had a R-squared of 0.096, using child negative in the lab, mother positive in the lab, mother's positive affect, child externalizing behavior, child effortful control, child surgency, and child internalizing behavior. All of the variables were of similar importance except child negative expression during mother-child interaction tasks which was more important.

The age 3 predicting age 4 model had a R-squared of .012. Maternal state and trait anxiety, child externalizing behavior, child negative in the lab, Mother's positive affect, and mother's negative affect were included in the model. All variables were of similar importance except for mother's negative affect which was the least important. The age 3 predicting age 5 model had a R-squared of .063. parenting stress-intensity, child externalizing behavior, mother's depressive symptoms, mother's problem solving with children, and child sex were all included in the model. Child sex was the least important variable, other variables were of similar importance. The age 4 predicting age 5 model had a R-squared of .053. The most important variable was child negative in the lab, while the least important variable was child sex. Parenting stress-frequency, parenting stressintensity, and child externalizing behavior were also included in the model. Complete results from this set of analyses, along with the associated mean decrease in Gini index are available in table 3.3.

Penalized Regression

Variables from the variable selection step were modeled using a ridge regression as this would use all variables that were selected. The model fit was evaluated using cross-validation with only the fit in the test sample being considered. The age 3 concurrent penalized regression was found to fit well with a R-squared of .053. All of the variables included in this model, child negative emotionality, child externalizing behavior, and child effortful control were important to children's self-regulation of negative emotion. The age 4 concurrent model fit worse than the age 3 counterpart but better than the random forest age 4 concurrent model with a R-squared of .040. Child sex and maternal education were among the variables most strongly related to children's selfregulation of negative emotion. Marital status and child age were least strongly related to children's self-regulation of negative emotion. The age 5 concurrent model fit well with a R-squared of .073. The most strongly related variable was maternal magnification of children's emotions. There were not any variables that had a weak relation to children's self-regulation of negative emotion.

The age 3 predicting age 4 model had a R-squared of .058. Both variables included in this model, child sex and mother's positive affect, were strongly related to children's self-regulation of negative emotion. The age 3 predicting age 5 model fit worse with a R-squared of .026. Child sex and maternal education were the most strongly related variables. The least related variables were child negative emotionality, mother's

marital status, and child externalizing behavior. The age 4 predicting age 5 model had a R-squared of .063. All 3 variable in this model, child sex, child negative in the lab, and maternal education, were strongly related to children's self-regulation of negative emotion. All model fits for all models can be seen in appendix C.

Discussion

This study utilized random forests and penalized regression to predict children's ability to regulate themselves and their emotions in response to disappointing and frustrating tasks, both cross-sectionally and longitudinally. Several variables in the wave 1 random forest analysis were significant in a large number of different analyses and timepoints. One of the most consistent variables in predicting children's negative expression was children's sex. As child sex is well known to be related to emotion socialization and expression it is not surprising that this variable was consistently related, but it is still useful to know that these models back up empirical research. Additionally, children's externalizing behavior and temperamental negative emotionality as reported by mothers were consistently related to children's self-regulation of negative emotion. Finding that children's characteristics as reported by mothers are consistent predictors of children's concurrent and later self-regulation of negative emotion is quite valuable. This indicates that maternal reports on children's behavior are trustworthy and contain valuable information. The final variable that was related to self-regulation of negative emotion in all wave 1 random forest models was children's negative expression when they were with their mothers. Although it is not surprising that children's negative expression is consistent while alone and with their mothers, finding that the regulation of

negative emotion seems stable across different contexts is still valuable. Perhaps the reason that child regulation of negative emotion is related in both contexts is that the same variables are important in both contexts. This would suggest that characteristics inherent to the child are more important than context or mothers to children's self-regulation of negative emotion. Interestingly child negative expression in the interaction tasks in the lab was only included in one penalized regression model. Perhaps this suggests that the relation between child negative expression across contexts is non-linear and/or is largely important because of how it interacts with other variables.

Another interesting aspect of the models is the variables that were rarely or never included in any models. The presence of a bio-father, if the child was White, mother's ruminative response style, mother's problem-solving response style, mother's responding with support to children's emotions, children's temperamental surgency, and children's internalizing behavior were all significant in none or only one model. This is at odds with previous research and theoretical models which have suggested that rumination and support are related to child dysregulated emotion (Goodman et al., 2011). Perhaps these variables are simply unrelated to children's negative expression in lab contexts, but this finding does suggest that there may be more to understanding these variables in relation to children's self-regulation of negative emotion. Maternal mental health had some of the most consistently related variables, with mother's combined state and trait anxiety only being included in all models and PANAS negative emotionality by mothers was related to all concurrent negative expression by children in the lab. Considering how

widespread mental health issues are, for example approximately 1 in 6 U.S adults experience depression at some point in their lives, this study underscores the importance of solving the mental health crisis (Kessler et al., 2005). Mental health issues appear to affect not only the afflicted individual but also their children. To continue to improve the lives and development of children it may be necessary to first improve the mental health situation in the U.S.

There are several findings worth discussing from the random forest models. First, child sex, which was one of three variables to be included in every wave 1 random forest model was consistently among the least important variables. Further, variables included from the demographic stratification were generally among the least important in models they were included in. Perhaps this suggests that many of these demographic variables have a consistent effect on expressed negative emotion, but the effect is quite small and less important than parental behavior and other child characteristics. However, in the penalized regression models, child sex is not only one of the most consistent variables it also has some of the largest log odds. Other demographic variables in the penalized regression typically have some of the smallest log odds for models they are included in. Perhaps child sex is a strong predictor when straightforward linear relations are considered but is not as strong relative to other variables when non-linear relations are included. Child sex may also be related and interact with many other predictors, albeit weakly. This could explain why child sex was always included in wave 1 random forest models, was of low importance, and was only included in two penalized regression models.

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Both child and mother expression during their dyadic interactions were among the most important variables in several random forest models. This suggests that child behavior and expression with their mothers is relatively consistent with their expression and behavior when alone. Further, it emphasizes the important role that maternal emotion expression when interacting with children has on children's own emotion expression. It should be noted that these are assessed using the same observational method so the results should be interpreted in light of the possibility that shared method variance may have led to these findings. Another aspect of maternal influence on children is mother's mental health. The maternal mental health variables were never among the most nor least important variables in random forest models. These variables may have a moderate and consistent effect on children's emotion expression. Finally, maternal report of children's temperament seems to be reliable in predicting child behavior. This supports the use of questionnaires, at least high-quality ones such as the CBQ, in studying child development and predicting children's future behavior.

There are also interesting findings from the random forest models based on wave 2 variable selection. In these models, importance of variables was much more similar to one another. Even when a variable was more or less important than other variables in the model the difference between variables was much smaller. The models based on these variables also fit better in the test sample, which furthers the idea that the first set of models may have been overfit. Additionally, child sex was only included in two of the models and it was by far the least important variable in both of those models. This brings up the possibility that child sex may have been such a consistently included variable in

the first set of random forests only because of the stratification strategy. Based on the results of the first wave of variable selection demographic variables were consistently among the least important variables in a model, then when a second wave of variable selection occurred only child sex was included in any model. Perhaps the variables in the demographic stratification were all not important in predicting the outcome and child sex was simply the strongest of a set of variables that are weakly related to the outcome. Further investigation of this finding is certainly warranted but perhaps there is some aspect of how child sex relates to negative emotion expression that requires further investigation.

The penalized regression models included many fewer variables compared with the random forest models, but one similar finding is the consistency of child sex. Child sex is the only variable that was found to be significant in more than 3 penalized regression models. Further, since child sex was significant in every random forest model it appears that these statistical learning models are finding that child sex is among the most consistent predictors of children's negative expression. However, many other variables that were important in the random forest models were not included in the penalized regression models. To provide a direct comparison there were a total of 20 variables that were included in the penalized regression models, when counting variables that appear multiple times more than once. In comparison there were 65 variables included in the initial random forest models excluding the variables that only appeared in one model.

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There are several possible reasons that many more variables appeared in the random forest than the penalized regression. Since random forests consider interactions among variables it is possible that some of the variables included in the random forest are only important when interactions are allowed. This could also provide an explanation for why the penalized regression models fit the data in the test sample better. It is possible that some of these interactions are unstable or artifacts of the data and are not present in the test sample. Additionally, the variable selection process in the random forest models guarantees that at least one variable from each stratification is included, while this is not the case for the penalized regression model. It is possible to include 0 variables from a stratification. This could reduce some of the overfitting and improve the model fit in the test sample for the random forests. The second wave of random forests provides some support for this perspective as many fewer variables were used and the models fit better in the test sample.

The use of both random forest and penalized regression does provide valuable insight, however. Variables such as children's negative emotion expression with their mothers, which is used and important in many random forest models but not penalized regression, may have a nuanced relationship with children's behavior when they are alone. However, the possibility remains that the random forest may have discovered an idiosyncrasy of the data and modeled this. The penalized regression model is more conservative and far less likely to make this type of error. Therefore, using these two models together to examine how children develop emotion expression and regulation skills is quite valuable. The random forest model allows the detection of non-linear or interactions among variables and the penalized regression allows for results that are more conservative and more likely to generalize. In this case further investigation of children's negative emotion with their mothers may be warranted, particularly examining non-linear relations and interactions. This can help to resolve whether the random forest model overfit child negative expression in the lab or if the lack of interactions and non-linear relationships resulted in the variable not being highly used in in the penalized regression.

A major concern with this study is the random forest model is both opportunistic and is generally quite good at finding a set of variables to predict outcomes (James et al., 2013). This means that the model may overfit or find some idiosyncrasy in the data to predict the outcome; the typical method to deal with this problem is to use cross validation with a training and test sample (James et al., 2013). This methodology can certainly help mitigate overfitting and help increase the likelihood that the model will generalize to other samples. However, there is still a concern that the random forest, particularly in smaller samples, will not generalize even with the use of a test sample. This is particularly the case when the outcome is difficult to predict and somewhat unstable, such as human behavior. There is a fair amount of random forest usage in areas with more stable outcomes, such as genetics (Chen & Ishwaran, 2012), as there is less concern about results not generalizing. The ideal test would be to attempt to replicate these results in another sample that is collected separately. If the results replicate, and the model performs well, that greatly increases the confidence in these findings.

Penalized regression generally outperformed the random forests in the test sample providing a better fit, particularly when compared with the random forests using the first wave of variable selection. This suggests that the random forest may have overfit to the data. This could be a result of the use of a stratification method to select the variables, further supported by the random forests from the second wave of variable selection. The model fit of the random forests based on the second wave of variable selection were much more similar to the model fit of the penalized regression models. It is possible that if some of the variables in the random forest were included in the same variable selection analysis at least some of the variables would be excluded. However, this could lead to a stratification being entirely excluded from the analysis. Since inclusion of at least one variable from all stratifications was considered a priority this method was not used. However, a better model fit was achieved at the cost of excluding some stratifications and using only the variables in the second save of variable selection. Which strategy is preferred is based upon the goals of the study and the researcher's goals. Studies that are focused on prediction quality or model fit may want to avoid the stratification strategy used in this study. However, if certain variables need to be included in the model or at least one of a set of variables must be included a stratification strategy as used in this study may be most appropriate. Alternatively, it is possible that the linear relations considered by the penalized regression are a better representation of the true relation between these variables and the random forest models are finding relationships in the training data that are non-existent in the test data and are not good representations of the true relation between these variables.

The methods in this study also provide an interesting opportunity for future psychological and social science work to utilize machine learning methods to analyze their data. Particularly, selecting variables using random forests can be useful and easily implemented in current studies. Even if the final model used to examine the relationship of interest is not a random forest or penalized regression model selecting variables by random forest can still be valuable. Particularly in the case when there are several candidate variables that are designed to measure the same/similar construct(s) allowing a model to decide which variables to include can be useful. The variables identified by the model can then be used in whatever analysis was originally planned. This allows for a more objective selection of variables compared with human selection of variables.

There are several limitations of this study. First, the sample size of the ACER sample is small and limits the confidence in the results from the analysis. Additionally, the model fit in the test sample is not stellar which suggests that the model has limited predictive power. However, it should be remembered that predicting behavior is quite difficult in general and often only explain a small portion of the variance in an outcome (e.g., Yap et al., 2014; Yap & Jorm, 2015). Some previous studies using this same sample have produced larger R-squared values, however, it is noteworthy that those models did not split data into training and test samples (e.g., Gerhardt et al., 2020). Hence the R-squared from those studies should be compared to the R-squared in the training models for the current study. In fact, the training models in the current study often had R-squared much higher than studies previously published on this data, often being above 0.8. Additionally, this study relied heavily on maternal report to understand child and mother

behavior and expression at home. Utilizing another reporter from the home environment, for example the father, could provide valuable insight into the home environment and reduce concerns of shared method variance. Finally, inducing negative expression in the lab was difficult and was not universally effective. Even though this study combined negative expression across several tasks, several of which were designed to induce negative emotion, there were still many children who showed zero or very little negativity. Other studies using this same sample have found a similar problem with relatively low levels of negative affect observed in the study (Gerhardt et al., 2020). It is possible that with a more effective negative emotion task a model with better fit could be found, although the current study used tasks from the widely adopted Laboratory Temperament Assessment Battery, more effective tasks at inducing negative emotion could exist (Goldsmith & Rothbart, 1996).

This study also has several strengths. The use of observational micro-coded data to measure children's negative emotion expression allowed this study to measure children's behavior away from maternal influence and without utilizing maternal report. Secondly, this study used a wide variety of variables that represent a variety of different areas of child development. Further, the use of both a random forest and penalized regression model allowed this study to both model potentially more nuanced relationships between variables and children's negative emotion expression and have a model that is more conservative in its evaluation of how variables may relate to children's negative expression. Finally, the use of three waves on longitudinal data allowed for examination of both concurrent and longitudinal relationships. Future studies can extend and improve the current study in several ways. First, the use of larger, multiple data sets that include similar assessments during the similar age range. There are also other methods such as gradient boosting machine (James et al., 2013) that could produce models with better fit, although these models typically require more hyperparameter tuning and may benefit more from a larger sample. An interesting possibility for future studies could be to develop statistical learning models with the goal of predicting which children are most in need of intervention to improve their emotion regulation skills. If future studies can develop models that are able to do this effectively it can be helpful both to practitioners who can target their efforts more effectively and children who receive support in developing necessary skills to regulate their negative emotion and expression.

In conclusion, the current study examined how children's expression and regulation of negative emotion relates to their individual characteristics, behaviors, and parenting they receive. Using statistical learning techniques, it was determined which variables were most important in predicting children's negative expression both concurrently and longitudinally. It was found that children's sex, mother's marital status, children's externalizing behavior, maternal depressive symptoms, and children's temperamental sadness were among the strongest and/or most consistent predictors of children's self-regulation of negative emotion. The models developed were then examined using another sample to test how these models performed out of sample. Results from this study are encouraging for future work that may attempt to utilize

statistical learning methods, particularly random forests and penalized regression, to study children's negative emotion expression.

Categories	Variables	Age3	Age4	Age5	Age3-4	Age4-5	Age3-5
Demographic	Child age	5351.89				1177.42	
	Child sex	934.50	2276.79	145.58	2630.45	295.79	307.38
	M education			179.85		508.29	430.12
	Marital status	1084.03		97.54			430.12
	Bio-Father			48.41			
	Child White ^a			46.01			
	Mom White ^a	311.82		51.29		127.05	
Maternal personality &	BDI	3380.60	4269.96		5700.81		668.18
psychopathology	STAI	2384.41	4592.54		6263.84	990.26	779.18
	PANAS- Pos			866.68	6608.79		842.06
	PANAS-Neg	1775.73	4204.61	326.97	4892.76		

Table 4.1: Random forest wave 1 variables

Categories	Variables	Age3	Age4	Age5	Age3-4	Age4-5	Age3-5
Maternal parenting/Mother	PDH-freq	4168.29				911.94	580.81
-child Emotion	PDH-intensity	3665.01					878.96
Expression in the	RSQ-Rum	2854.09		570.80			
Lab	RSQ-Dis						606.50
	RSQ- PbS	3301.29					712.97
	RCE- support	3741.84					
	RCE- Magn			821.63		683.75	
	M Pos -Lab		7570.46	1021.84	7554.45		
	Child Pos -Lab	3705.82		618.12			
	Child Neg -Lab	4553.15	5919.02	1647.93	6620.53	1594.21	874.73
Child characteristics	CBQ - NA		8786.44	707.45		1071.63	905.55
	CBQ - EC		5224.00	650.59			
	CBQ- surgency			627.17			
	CBCL – Ext	3318.47	5675.63	727.84	6827.16	888.42	899.54
	CBCL – Int			505.03			

Note. All values are Gini index decreases. ^a: binary, 1 is coded as yes. M:mother, C:child, Pos: positive, Neg: negative, freq: frequency, Rum: rumination, Dis: distraction, Pbs: problem solving, Magn: magnification, NA: negative affect, EC: effortful control, Ext: externalizing, Int: internalizing

Categories	Variables	Age3	Age4	Age5	Age3-	Age4-	Age3-
					4	5	5
Demographic	Child age		-0.91				
	Child sex		3.22	1.20	4.61	1.46	0.81
	M education		-1.69			0.02	-0.28
	Marital status		-0.60				-0.29
	Mom White ^a		-0.04				
Maternal	BDI						
personality &	STAI						
psychopathology	PANAS-Pos			-1.63	1.57		
	PANAS-Neg			-0.81			
Maternal	PDH-freq			1.00			
parenting/Mother	PDH-intensity			-1.23			
-child Emotion	RSQ-Rum			-1.01			
Expression in the	RCE- Magn			1.63			
Lab	Child Neg -Lab					1.49	
Child	CBQ - NA	1.43					-0.10
characteristics	CBQ - EC	-2.30					-0.28
	CBCL – Ext	0.94					0.42

Table 4.2: Penalized regression variables

Note. All values are log odds. ^a: binary, 1 is coded as yes. M:mother, C:child,

Pos: positive, Neg: negative, freq: frequency, Rum: rumination, Magn: magnification, NA: negative affect, EC: effortful control, Ext: externalizing

Categories	Variables	Age3	Age4	Age5	Age3-4	Age4-5	Age3-5
Demographic	Child sex					503.98	506.45
Maternal personality	BDI	9693.66					1371.46
& psychopathology	STAI				9304.07		
	PANAS-Pos			1375.36	8756.46		
	PANAS-Neg				7605.95		
Maternal	PDH-freq	10273.36				1384.69	
parenting/Mother	PDH-intensity	10210.42				1334.41	1544.64
-child Emotion	RSQ-Rum						
Expression in the	RSQ- PbS						1258.34
Lab	M Pos -Lab		15904.70	1573.52			
	Child Neg -Lab	10069.07	14779.26	2020.80	9010.63	1785.69	
Child characteristics	CBQ - EC			1142.82			
	CBQ- surgency			1097.23			
	CBCL – Ext		14104.04	1212.54	9227.67	1258.86	1516.91
	CBCL – Int			948.84			

Table 4.3: Random forest second variable selection variables

Note. All values are Gini index decreases. ^a: binary, 1 is coded as yes. M:mother, C:child, Pos: positive, Neg: negative, freq:

frequency, Rum: rumination, Pbs: problem solving, EC: effortful control, Ext: externalizing, Int: internalizing

Chapter 5: General Discussion

Children's development of emotion regulation is a major task in their early childhood and the skills developed during this time will be used throughout children's lives (Berk & Meyers, 2016; Kochanska et al., 2001; Montroy et al., 2016). It is well established and accepted that in children, as well as throughout the lifespan, emotion regulation is related to better academic performance, peer relations, and mental health (Berk & Meyers, 2016; Bridgett et al., 2015; Kochanska et al., 2001; Montroy et al., 2016). Research has clearly demonstrated that a wide variety of factors relate to children's emotion regulation abilities and that these relationships can be quite complicated (Miller et al., 2013; Morris et al., 2007; Sanders et al., 2015). Several of these factors relating to children's development of emotion regulation abilities were the focus on this dissertation which examined parenting behavior, mother-child interactions, child characteristics, and children's physiological regulation. These factors have a complicated, multifaceted, relationship with emotion regulation, interacting with other variables and relating non-linearly, and thus require a wide variety of studies that consider a wide variety of candidate variables (Berk & Meyers, 2016; Gerhardt et al., 2020; Kogan et al., 2013; Volling et al., 2019; Wu, Feng, et al., 2019). The current dissertation advanced our knowledge, understanding, and ability to measure children's development of emotion regulation. Further, using advanced statistical techniques, variables that may not have been previously considered were included in this dissertation. Specifically, this dissertation advanced our knowledge of how parenting, child characteristics, and children's physiological regulation relate to children's development of emotion regulation.

Integrating the Findings

This dissertation was chiefly concerned with advancing our understanding of children's development of emotion regulation. The studies reported in chapters 2 to 4 have examined several different aspects of children's development of emotion regulation. The results from the study presented in chapter 2 show that children's RSA is related to their ability to regulate their negative emotions in response to a stressful mask task. Further, the use of generalized additive models allowed for a potential non-linear relationship to be modeled. As it has been found that RSA may have a non-linear relationship with behavior this is of great importance (Miller et al., 2017). This study examined baseline RSA, change in RSA in response to a stressful situation, and the difference in RSA between the baseline and response to the stressful situation in relation to children's ability to regulate their negative emotions. Findings from this study suggested that RSA has a non-linear relationship with children's regulation of negative affect. Most of the reduction in negative affect occurred near the average levels of baseline and response to stressful situation RSA. In some cases, high RSA was related to higher levels of negative affect, which is consistent with some past findings, and suggests that increases in RSA are not monotonically good for emotion regulation (Kogan et al., 2013). Additionally, boys' and girls' RSA were modeled separately allowing for sex differences to be examined. This is important as previous studies have found that there

are differences in RSA between males and females (Snieder et al., 2007). However, findings suggest that there is no difference between boys and girls in the relationship between their RSA and regulation of negative affect. Results from this study suggest that researchers may want to examine non-linear relationships between RSA and child negative affect and generalized additive models can be a useful tool to model these relationships.

The findings from the study in the third chapter improve our understanding of a new concept in the field of parental roles in child development, challenging parenting behavior. This study examined the measurement invariance of the challenging parenting behavior questionnaire (CPBQ) and how it relates to children's anxiety. The CPBQ is a newly developed scale that has not been widely used, widely studied, nor used in the United States. This study administered the CPBQ to over 700 parents of children ages 3-4 and examined measurement invariance between mothers and fathers. This study offered several advances for the field of child development. First, development of a new scale is important as it allows for the possible range of studies and research questions to be expanded. Finding measurement invariance for this scale is of importance as it has been hypothesized that mothers and fathers differ on their challenging parenting behavior (Majdandžić et al., 2016). Further, how this challenging parenting behavior relates to children's anxiety has been hypothesized to differ between mothers and fathers; to even begin exploring these hypotheses a strong case for measurement invariance must be established as without measurement invariance any differences found between mothers and fathers could be the result of measurement error (Chan et al., 2019; Majdandžić et al., 2016; Möller et al., 2013). As the study presented in chapter 3 found full measurement invariance at the scaler level researchers can be more confident that this scale can accurately measure challenging parenting behavior across men and women. Additionally, finding scalar invariance allowed for latent means of challenging parenting behavior to be compared. It was found that fathers had higher levels of challenging parenting behavior which is consistent with previous hypotheses (Majdandžić et al., 2016). However, the factor structure found in the American sample was different from the previous factor structure found in Australian and Dutch parents (Majdandžić et al., 2018). The structure found in the American sample had only 5 factors compared with 6 in the previous work. This new factor structure needs to be replicated in future studies of American parents.

The results from chapter 3 also show that challenging parenting behavior as measured by the CPBQ is related to child anxiety. It was found that rough-and-tumble play, physically engaging and exciting play between children and their parents, was related to reduced child anxiety. Further, autonomy support by fathers but not mothers was related to reduced levels of child anxiety. However, challenging parenting behavior was not ubiquitously related to lower levels of child anxiety. Bravery support by fathers was related to higher levels of child anxiety as was teasing by both mothers and fathers. These findings suggest that parents engaging in certain types of challenging parenting behavior may enhance their children's ability to regulate their anxiety or reduce their anxiety in general. Given how widespread anxiety problems are in contemporary society, as well as the personal and societal costs associated with anxiety issues, reducing these issues are of major importance (Ghandour et al., 2019).

The fourth chapter used two statistical learning techniques, random forests and penalized regression, to consider a wide variety of variables and their relations with children's ability to regulate their negative emotions in response to a distressing task. There are two areas of interest that result from this study. First, which variables are included, and which have the strongest relationship with children's regulation of negative affect is of interest. This study was able to leverage statistical learning techniques to consider a much larger number of variables than it would have been able to otherwise. This is a major advantage as previous studies using the same dataset have only been able to consider a small number of variables in a single study (Gerhardt et al., 2020; Ku et al., 2019; Wu, Hooper, et al., 2019). Utilizing a larger number and wider variety of variables allows for the discovery of new and interesting relationships among the included variables. Interestingly the random forest and penalized regression models included different numbers of variables. The random forest models included many more variables than the penalized regression models. However, the penalized regression models did a better job at predicting the outcome suggesting that the random forest may have overfit to the data.

The second finding of interest is how the variables included in the model relate to children's regulation of negative emotion. This study differs from many psychological studies of children's regulatory abilities in that the focus is primarily on prediction quality rather than explanation (Yarkoni & Westfall, 2017). Typically, psychology studies attempt to produce models that provide an explanation of the processes, however, finding models that predict future behavior is also valuable and can help further the understanding of behavior. This is not to say that explanation is without value but there is also value in being able to accurately predict an outcome. Particularly in a field that focuses on models that produce results with strong exploratory power a different modeling goal can be valuable (Yarkoni & Westfall, 2017).

Both the random forest and penalized regression models produced interesting findings regarding how variables related to children's regulation of negative emotion. A consistent finding of the random forest models is that child sex was consistently included in models and consistently among the least important variables. Demographic variables in general were among the least important in random forests models they were included in. Interestingly, child sex was also included in most penalized regression models and had a strong relationship with the outcome. Another finding of interest from the random forest models was the importance of maternal report of child behavior, suggesting that mothers provide accurate and reliable reports of children's behavior.

When these studies are considered together, they provide new and interesting insights into children's development of emotion regulation. Chapters 2 and 3 highlight the importance of considering both children's personal characteristics and the parenting they receive. Both of these studies were able to predict children's regulatory capacity. This provides evidences that children's internal characteristics and their parent's behavior are important to their development. This also provides further support for models that include both parenting behavior and child characteristics (Morris et al., 2007). These studies also show the value of larger sample sizes as the models that were used would not have been feasible with smaller samples. The studies presented in chapter 2 and chapter 4 show that consideration of complicated relations between child characteristics and behavioral outcomes are worth examining and considering. The models in both of these chapters allow for non-linear relationships between predictor variables and the outcome variables. This results in models that are harder to interpret, particularly in the case of the random forest, but can produce strong relations between the predictor and outcome variables. Even when the model used is not as readily interpretable and is more focused on prediction this can still provide valuable insights (Yarkoni & Westfall, 2017). The modeling techniques used in these chapters allow for non-linear relationships to be considered and are more data driven than some other widely used models (James et al., 2013; Kline, 2015; Wood, 2017). This allows for new and interesting relationships to be discovered. Additionally, these newly discovered relationships, even if they are found by data driven techniques, can help produce new explanations and hypotheses (Yarkoni & Westfall, 2017).

All three of these studies together highlight the complexity in children's development of emotion regulation. There are many different ways to measure emotion regulation, including behavior, such as emotion expression and regulatory behavior, as used by the current study. Further still, there are other manifestations of emotion regulation such as physiological responses. The relations among these different manners and aspects of emotion regulation can be entangled and difficult to parse apart. This is further complicated by the possibility that these relations may be non-linear and/or may vary according to child and parental characteristics and numerous other factors such as SES, demographics, and sex. Currently, researchers have a limited ability to measure the

salient variables and a limited ability to model these variables, particularly given the wide variety of salient and potentially salient variables. The current studies have examined some of the many ways to measure emotion regulation and many different relevant variables to children's regulation of emotion. These studies show that researchers have a great deal to learn about new variables relevant to children's emotion regulation. These studies also suggest that variables that have previously been studied require further examination and a more nuanced understanding may need to be developed.

Collectively these studies have explored constructs that are not widely used in the field of child development and advanced our understanding of these aspects of child development. Further, many of the methods used in these studies are not widely used in social science. These modeling methods offer the possibility of expanding the number of possible research questions that can be addressed. Additionally, the use of MTurk to evaluate the psychometric properties of scales, particularly in the early stages, of scale development is supported by the current dissertation.

Limitations

There are also a number of limitations for each of these studies as well as the current dissertation as a whole. The study in chapter 2 evaluated measurement invariance of the challenging parenting behavior questionnaire. However, the factor structure found in a previous study was not replicated in this study. The questionnaire is newly developed and has not been widely studied so there is not a clearly established structure that has been replicated in multiple studies. Therefore, there was an exploratory aspect to this study. An issue with the current methodology used to arrive at the current factor structure

is that the same data was used to conduct the exploratory factor analysis and confirmatory factor analysis and no holdout sample was used. This makes it more likely that these results will not generalize.

The study in chapter 3 also has a limitation due to the sample. In the case of this study the sample size is relatively modest, and it is possible that the statistical learning models produced results that may not generalize well. While a training and test sample was used to help alleviate these concerns this does not entirely prevent an issue with generalizability arising. Further, only two modeling techniques were used to examine the results, there are other models that could potentially do a better job of modeling the data such as gradient boosting machine, particularly if a larger data set was collected.

The study in chapter 4 has a somewhat different limitation when compared with chapter 2 and 3. This study uses a protocol that attempts to induce stress in children using two different tasks at two different times. Both of these tasks may not induce the desired level of stress in children, empirically there were many children who were not negatively reactivity to the scary mask portion of the task. Also, many children did not have large changes in their RSA from baseline to the stressful task further supporting the argument that these tasks may have relatively small effects on children's stress and negativity. Further, the tasks used, particularly the scary mask task, are not typical of children's everyday experience. This means that the results may not be generalizable.

The dissertation has several limitations as well. First, there is no long-term study of outcomes, the longest period covered by any study is two years. As regulation is expected to contribute to functioning throughout an individual's life in a wide variety of contexts and mental health being able to examine long term outcomes is of great value. The study in chapter 4 is/has collected some longer term follow up data but this data is not yet available. Second, in all studies there are some concerns with the outcome variable. Both of the studies that attempted to induce negative emotion expression had many children that either showed zero or very low levels of negative reactivity. It is possible that because relatively limited levels of negative emotion could be induced, the results of the study could be biased in some manner. It is possible that only children higher in reactivity were highly negative in response to these tasks and the results are based on these highly reactive children. A task that can induce negative reactivity and result in a more normal distribution could be of benefit. This issue is certainly not unique to this dissertation (Gerhardt et al., 2020; Wu, Feng, et al., 2019) and inducing negative emotion in an ethical way can be difficult but results for these studies should be considered in light of this fact.

Strengths

This study also had several strengths both at the individual study level and at the dissertation level. The study in chapter 2 collected a large number of participants to examine measurement invariance. This allowed the use of diagonally weighted least squares and for many parameters to be estimated with confidence. Particularly as this study used a recently developed questionnaire that has not yet been widely used and examined, collecting a large sample is of particular value.

The study in chapter 3 used statistical learning methods that are known to be good at predicting outcomes and allow for a more objective consideration and inclusion of variables in the modeling process (James et al., 2013). This resulted in new variables of interest being discovered. Further, these models are not as widely used in the study of child emotion regulation and therefore provide different strengths and weaknesses than many other studies. By using different models with different strengths and weaknesses new perspectives and findings related to child development can be discovered. This can result in models that are more accurate in predicting which children that may have difficulties in regulating their emotions. A model that can accurately predict which children need additional support for developing self and emotion regulation skills, if such a model were developed, could be of great value in applied settings.

Chapter 4 uses generalized additive models to examine the non-linear effects of RSA on negative reactivity. This allows for a variety of different functional forms to be considered and non-linearity of the relationship to be tested. Further, the sample collected for the Family Life Project is both large, having over 1,000 participants, and contains demographic diversity (Vernon-Feagans et al., 2018). This allows further examination of polyvagal theory as, if this theory is correct, it should apply to everyone regardless of demographic factors.

This dissertation also has several strengths. First, the use of advanced statistical techniques permits nuanced understandings of the relationships between variables. Additionally, several of the models used allow for non-linearity in the relationship between predictor and outcome variables to be modeled. This allows for more accurate modeling of the data and for potentially interesting relationships to be discovered. This dissertation also examined many different aspects of how children regulate their emotions and how this regulation develops. By studying and considering these various aspects of the development and application of regulation, this dissertation was able to gain a more complete understanding of children's regulation.

Future Directions

There are a number of extensions and future directions that can be developed from this dissertation. Perhaps the clearest future direction is further examination of the challenging parenting behavior questionnaire. The data collected for this dissertation was, to the author's knowledge, the first data collected using this questionnaire in an American sample. Further, the factor structure suggested by the data in this dissertation differed from previous findings using this same scale in other countries. There are a number of possibilities that could explain this result. It is possible that the factor structure of the questionnaire differs between Americans and Dutch/Australians that were used in the original factor structure. It is also possible that there is some aspect of the MTurk data that results in this factor structure. Further work to determine the factor structure of the challenging parenting behavior questionnaire in the United States appears to be warranted based on the results of this dissertation needed.

Similarly, future work replicating the statistical learning results in a different sample would be of great value. The results presented in this dissertation are based on a sample of 126 participants. While cross validation was used to test model fit, replication of these results in another sample would provide further support for both the use of this methodology in studying children's development of regulation and the specific results from this study. A similar study is currently underway and data collection is ongoing, however, the data from this study is several years and thousands of hours of coding from being comparable to the dataset used in this study.

This dissertation also offers an interesting direction for future studies of the role of RSA in regulation. There have been suggestions and findings that the effect of RSA on behavior is non-linear for some time now (e.g., Kogan et al., 2013; Miller et al., 2017). It appears this effect is non-linear both in behavior that is observed at the same time point and behavior that is observed at a later time point. This study further finds evidence that this relation is non-linear and future studies may want to take this into consideration when developing their hypotheses and models. Another interesting future direction could be to examine the relation between RSA and behavior that happen at the same time or based on lags of only a couple of seconds. Examining if RSA related non-linearly to behavior, even concurrently or on very short time lags, could further our understanding of physiological regulation.

Another future direction could be to examine previous findings using some of the advanced modeling techniques used in this dissertation. If previous findings are explored for non-linearity it is possible that new hypotheses and understandings can be generated. With methodological and technological advances, it is becoming increasingly possible to fit more complicated models in a realistic timeframe. Future studies may want to consider using models that allow for non-linearity in their analyses and consider this possibility when developing their hypotheses.

Conclusions

In conclusion, this dissertation examined children's development of regulation and the role of parenting, as well as children's own characteristics, in children's development. It was found that parental behavior is related to children's ability to regulate their emotions. Further, findings support the relation of RSA and children's individual characteristics to their regulatory ability. This dissertation provides a useful steppingstone towards advancing our understanding of children's regulation of emotions and the adoption of modern statistical methods in pursuit of this goal.

References

- Achenbach, T. M., & Ruffle, T. M. (2000). The Child Behavior Checklist and related forms for assessing behavioral/emotional problems and competencies. *Pediatrics in Review*, 21(1). http://pedsinreview.aappublications.org/cgi/doi/10.1542/pir.21-8-265
- Achenbach, T. M., Hensley, V., Phares, V., & Grayson, D. (1990). Problems and competencies reported by parents of Australian and American children. *Journal of Child Psychology and Psychiatry*, *31*(2), 265–286. https://doi.org/10.1111/j.1469-7610.1990.tb01566.x
- Ahn, W.-Y., Hendricks, P., & Haines, N. (2017). Easyml: Easily build and evaluate machine learning models. *BioRxiv*, *October*. https://doi.org/10.1101/137240
- Baker, C. N., & Hoerger, M. (2012). Parental child-rearing strategies influence self-regulation, socio-emotional adjustment, and psychopathology in early adulthood: Evidence from a retrospective cohort study. *Personality and Individual Differences*, 52(7), 800–805. https://doi.org/10.1016/j.paid.2011.12.034

Bayley, N. (1969). Bayley scales of infant development. Psychological Corp.

- Beck, A. T., & Steer, R. A. (1996). Beck depression inventory-II. 78(2), 490-498.
- Belsky, J., & Pluess, M. (2009). Beyond diathesis stress: Differential susceptibility to environmental influences. *Psychological Bulletin*, 135(6), 885–908. https://doi.org/10.1037/a0017376
- Belsky, J., Bakermans-Kranenburg, M. J., & van IJzendoorn, M. H. (2007). For better and for worse: Differential susceptibility to environmental influences. *Current Directions in*

Psychological Science, *16*(6), 300–304. https://doi.org/10.1111/j.1467-8721.2007.00525.x

- Berk, L., & Meyers, A. (2016). *Infants and children: Prenatal through middle childhood*. Pearson.
- Blair, C., Granger, D. A., Willoughby, M., Mills-Koonce, R., Cox, M., Greenberg, M. T., Kivlighan, K. T., & Fortunato, C. K. (2011). Salivary cortisol mediates effects of poverty and parenting on executive functions in early childhood. *Child Development*, 82(6), 1970–1984. https://doi.org/10.1111/j.1467-8624.2011.01643.x
- Blandon, A. Y., Calkins, S. D., Keane, S. P., & O'Brien, M. (2008). Individual differences in trajectories of emotion regulation processes: The effects of maternal depressive symptomatology and children's physiological regulation. *Developmental Psychology*, 44(4), 1110–1123. https://doi.org/10.1037/0012-1649.44.4.1110.Individual
- Bögels, S., & Perotti, E. (2011). Does father know best? A formal model of the paternal influence on childhood social anxiety. *Journal of Child and Family Studies*, 20(2), 171– 181. https://doi.org/10.1007/s10826-010-9441-0
- Bögels, S., & Phares, V. (2008). Fathers' role in the etiology, prevention and treatment of child anxiety: A review and new model. *Clinical Psychology Review*, 28(4), 539–558. https://doi.org/10.1016/j.cpr.2007.07.011
- Breiman, L. (2001). Random forests. *Machine Learning*, 45(1), 5–32. https://doi.org/10.1023/A:1010933404324

- Bridgett, D. J., Burt, N. M., Edwards, E. S., & Deater-Deckard, K. (2015). Intergenerational transmission of self-regulation: A multidisciplinary review and integrative conceptual framework. *Psychological Bulletin*, 141(3), 602–654. https://doi.org/10.1037/a0038662
- Bronfenbrenner, U. (1977). Toward an experimental ecology of human development. *American Psychologist*, *32*(7), 513–531. https://doi.org/10.1037/0003-066X.32.7.513

Brooker, R. J., & Buss, K. A. (2010). Dynamic measures of RSA predict distress and regulation in toddlers. *Developmental Psychobiology*, 52(4), 372–382. https://doi.org/10.1002/dev.20432

- Burchinal, M., Vernon-Feagans, L., Cox, M., & Key Family Life Project Investigators. (2008). Cumulative social risk, parenting, and infant development in rural low-income communities. *Parenting*, 8(1), 41–69. https://doi.org/10.1080/15295190701830672
- Burge, D., & Hammen, C. (1991). Maternal communication: Predictors of outcome at followup in a sample of children at high and low risk for depression. *Journal of Abnormal Psychology*, *100*(2), 174–180. https://doi.org/10.1037/0021-843X.100.2.174
- Butler, E. A., Wilhelm, F. H., & Gross, J. J. (2006). Respiratory sinus arrhythmia, emotion, and emotion regulation during social interaction. *Psychophysiology*, 43(6), 612–622. https://doi.org/10.1111/j.1469-8986.2006.00467.x
- Cabrera, N., Fitzgerald, H. E., Bradley, R. H., & Roggman, L. (2014). The ecology of fatherchild relationships: An expanded model. *Journal of Family Theory & Review*, 6(March), 10–12. https://doi.org/10.1111/jftr.12054

- Cabrera, N., Karberg, E., Malin, J. L., & Aldoney, D. (2017). The magic of play: Low-income mothers' and fathers' playfulness and children's emotion regulation and vocabulary skills. *Infant Mental Health Journal*, 38(6), 757–771. https://doi.org/10.1002/imhj.21682
- Calkins, S. D. (1997). Cardiac vagal tone indices of temperamental reactivity and behavioral regulation in young children. *Developmental Psychobiology*, *31*(1990), 125–135.
- Calkins, S. D., Graziano, P. A., & Keane, S. P. (2007). Cardiac vagal regulation differentiates among children at risk for behavior problems. *Biological Psychology*, 74(2), 144–153. https://doi.org/10.1016/j.biopsycho.2006.09.005
- Cassano, M., Zeman, J., & Sanders, W. (2014). Responses to children's sadness: Mothers' and fathers' unique contributions and perceptions. *Merrill-Palmer Quarterly*, 60(1), 1. https://doi.org/10.13110/merrpalmquar1982.60.1.0001
- Chan, M. H.-M., Gerhardt, M., & Feng, X. (2019). Measurement invariance across age groups and over 20 Years' time of the negative and positive affect scale (NAPAS). *European Journal of Psychological Assessment*. https://doi.org/10.1027/1015-5759/a000529
- Chen, N., Deater-Deckard, K., & Bell, M. A. (2014). The role of temperament by family environment interactions in child maladjustment. *Journal of Abnormal Child Psychology*, 42(8), 1251–1262. https://doi.org/10.1007/s10802-014-9872-y
- Chen, X., & Ishwaran, H. (2012). Random forests for genomic data analysis. *Genomics*, 99(6), 323–329. https://doi.org/10.1016/j.ygeno.2012.04.003
- Cheung, G. W., & Rensvold, R. B. (1999). Testing factorial invariance across groups: A reconceptualization and proposed new method. *Journal of Management*, 25(1), 1–27. https://doi.org/10.1177/014920639902500101

- Chida, Y., & Steptoe, A. (2009). Cortisol awakening response and psychosocial factors: A systematic review and meta-analysis. *Biological Psychology*, 80(3), 265–278. https://doi.org/10.1016/j.biopsycho.2008.10.004
- Chiorri, C., Marsh, H. W., Ubbiali, A., & Donati, D. (2016). Testing the factor structure and measurement invariance across gender of the Big Five inventory through exploratory structural equation modeling. *Journal of Personality Assessment*, 98(1), 88–99. https://doi.org/10.1080/00223891.2015.1035381
- Coulombe, B. R., Rudd, K. L., & Yates, T. M. (2019). Children's physiological reactivity in emotion contexts and prosocial behavior. *Brain and Behavior*, 9(10), 1–16. https://doi.org/10.1002/brb3.1380
- Crnic, K. A., & Booth, C. L. (1991). Mothers' and fathers' perceptions of daily hassles of parenting across early childhood. In *Journal of Marriage and the Family* (Vol. 53, Issue 4, pp. 1042–1050). https://doi.org/10.2307/353007
- Crnic, K. A., & Greenberg, M. T. (1990). Minor parenting stresses with young children. *Child Development*, 61(5), 1628. https://doi.org/10.2307/1130770
- Crouter, A. C., Lanza, S. T., Pirretti, A., Goodman, W. B., & Neebe, E. (2006). The O*Net jobs classification system: A primer for family researchers. *Family Relations*, 55(4), 461–472. https://doi.org/10.1111/j.1741-3729.2006.00415.x
- Cumberland-Li, A., Eisenberg, N., Champion, C., Gershoff, E., & Fabes, R. A. (2003). The relation of parental emotionality and related dispositional traits to parental expression of emotion and children's social functioning. *Motivation and Emotion*, 27(1), 27–56. https://doi.org/10.1023/A:1023674308969

- de Rogalski Landrot, I., Roche, F., Pichot, V., Teyssier, G., Gaspoz, J.-M., Barthelemy, J.-C., & Patural, H. (2007). Autonomic nervous system activity in premature and full-term infants from theoretical term to 7 years. *Autonomic Neuroscience*, *136*(1–2), 105–109. https://doi.org/10.1016/j.autneu.2007.04.008
- Denham, S. A., Bassett, H. Hamada., & Wyatt, T. M. (2010). Gender differences in the socialization of preschoolers' emotional competence. *New Directions for Child and Adolescent Development*, 2010(128), 29–49. https://doi.org/10.1002/cd.267
- Drabick, D. A. G., Strassberg, Z., & Kees, M. R. (2001). Measuring qualitative aspects of preschool boys' noncompliance: The response style questionnaire (RSQ). *Journal of Abnormal Child Psychology*, 29(2), 129–139. https://doi.org/10.1023/a:1005283929585
- Dumont, C., & Paquette, D. (2013). What about the child's tie to the father? A new insight into fathering, father–child attachment, children's socio-emotional development and the activation relationship theory. *Early Child Development and Care*, *183*(3–4), 430–446. https://doi.org/10.1080/03004430.2012.711592
- Dyer, W. J. (2015). The vital role of measurement equivalence in family research. *Journal of Family Theory & Review*, 7(4), 415–431. https://doi.org/10.1111/jftr.12115
- Edwards, S. L., Rapee, R. M., Kennedy, S. J., & Spence, S. H. (2010). The assessment of anxiety symptoms in preschool-aged children: The revised preschool anxiety scale. *Journal of Clinical Child and Adolescent Psychology*, 39(3), 400–409. https://doi.org/10.1080/15374411003691701
- Eisenberg, N., Cumberland, A., & Spinrad, T. L. (1998). Parental socialization of emotion. *Psychological Inquiry*, 9(4), 241–273. https://doi.org/10.1038/nature13314.A

- Eisenberg, N., Duckworth, A. L., Spinrad, T. L., & Valiente, C. (2014). Conscientiousness: Origins in childhood? *Developmental Psychology*, 50(5), 1331–1349. https://doi.org/10.1037/a0030977
- Eisenberg, N., Gershoff, E. T., Fabes, R. A., Shepard, S. A., Cumberland, A. J., Losoya, S. H., Guthrie, I. K., & Murphy, B. C. (2001). Mother's emotional expressivity and children's behavior problems and social competence: Mediation through children's regulation. *Developmental Psychology*, 37(4), 475–490. https://doi.org/10.1037/0012-1649.37.4.475
- Eisenberg, N., Sadovsky, A., & Spinrad, T. L. (2005). Associations of emotion-related regulation with language skills, emotion knowledge, and academic outcomes. *New Directions for Child and Adolescent Development*, 109, 109–118. https://doi.org/10.2964/jsik.kuni0223
- Ellenbogen, M. A., & Hodgins, S. (2004). The impact of high neuroticism in parents on children's psychosocial functioning in a population at high risk for major affective disorder: A family–environmental pathway of intergenerational risk. *Development and Psychopathology*, *16*(01). https://doi.org/10.1017/S0954579404044438
- Feldman, R. (2006). From biological rhythms to social rhythms: Physiological precursors of mother-infant synchrony. *Developmental Psychology*, 42(1), 175–188. https://doi.org/10.1037/0012-1649.42.1.175
- Feldman, R. (2009). The development of regulatory functions from birth to 5 years: Insights from premature infants. *Child Development*, 80(2), 544–561. https://doi.org/10.1111/j.1467-8624.2009.01278.x

- Feng, X., Hooper, E. G., & Jia, R. (2017). From compliance to self-regulation: Development during early childhood. *Social Development*, 26(4), 981–995. https://doi.org/10.1111/sode.12245
- Feng, X., Keenan, K., Hipwell, A. E., Henneberger, A. K., Rischall, M. S., Butch, J., Coyne, C., Boeldt, D., Hinze, A. K., & Babinski, D. E. (2009). Longitudinal associations between emotion regulation and depression in preadolescent girls: Moderation by the caregiving environment. *Developmental Psychology*, 45(3), 798–808. https://doi.org/10.1037/a0014617.Longitudinal
- Fletcher, R., StGeorge, J. M., & Freeman, E. (2013). Rough-and-tumble play quality: theoretical foundations for a new measure of father–child interaction. *Early Child Development and Care*, 183(6), 746–759. https://doi.org/10.1080/03004430.2012.723439
- Fliek, L., Daemen, E., Roelofs, J., & Muris, P. (2015). Rough-and-tumble play and other parental factors as correlates of anxiety symptoms in preschool children. *Journal of Child* and Family Studies, 24(9), 2795–2804. https://doi.org/10.1007/s10826-014-0083-5
- Forbes, E. E., Fox, N. A., Cohn, J. F., Galles, S. F., & Kovacs, M. (2006). Children's affect regulation during a disappointment: Psychophysiological responses and relation to parent history of depression. *Biological Psychology*, 71(3), 264–277. https://doi.org/10.1016/j.biopsycho.2005.05.004
- Gangel, M. J., Shanahan, L., Kolacz, J., Janssen, J. A., Brown, A., Calkins, S. D., Keane, S. P., & Wideman, L. (2017). Vagal regulation of cardiac function in early childhood and cardiovascular risk in adolescence. *Psychosomatic Medicine*, 79(6), 614–621. https://doi.org/10.1097/PSY.000000000000458

- Gentzler, A. L., Santucci, A. K., Kovacs, M., & Fox, N. A. (2009). Respiratory sinus arrhythmia reactivity predicts emotion regulation and depressive symptoms in at-risk and control children. *Biological Psychology*, 82(2), 156–163. https://doi.org/10.1016/j.biopsycho.2009.07.002
- Genuer, R., Poggi, J., & Tuleau-malot, C. (2015). VSURF : An R package for variable selection using random forests. *The R Journal, R Foundation for Statistical Computing*, 7(2), 19–33.
- Gerhardt, M., Feng, X., Wu, Q., Hooper, E. G., Ku, S., & Chan, M. H. (2020). A naturalistic study of parental emotion socialization: Unique contributions of fathers. *Journal of Family Psychology*, 34(2), 204–214. https://doi.org/10.1037/fam0000602
- Ghandour, R. M., Sherman, L. J., Vladutiu, C. J., Ali, M. M., Lynch, S. E., Bitsko, R. H., & Blumberg, S. J. (2019). Prevalence and treatment of depression, anxiety, and conduct problems in US children. *Journal of Pediatrics*, 206, 256-267.e3. https://doi.org/10.1016/j.jpeds.2018.09.021
- Giuliano, R. J., Skowron, E. A., & Berkman, E. T. (2015). Growth models of dyadic synchrony and mother-child vagal tone in the context of parenting at-risk. *Biological Psychology*, 105, 29–36. https://doi.org/10.1016/j.biopsycho.2014.12.009
- Goldsmith, H. H., & Rothbart, M. K. (1996). *The Laboratory Temperament Assessment Battery, Locomotor version (manual).*
- Goodman, S. H., Rouse, M. H., Connell, A. M., Broth, M. R., Hall, C. M., & Heyward, D. (2011). Maternal depression and child psychopathology: A meta-analytic review. *Clinical*

Child and Family Psychology Review, *14*(1), 1–27. https://doi.org/10.1007/s10567-010-0080-1

- Gottman, J. M., & Katz, L. F. (2002). Children's emotional reactions to stressful parent-child interactions. *Marriage & Family Review*, 34(3–4), 265–283. https://doi.org/10.1300/J002v34n03_04
- Gottman, J. M., Katz, L. F., & Hooven, C. (1996). Parental meta-emotion philosophy and the emotional life of families: Theoretical models and preliminary data. *Journal of Family Psychology*, 10(3), 243–268. https://doi.org/10.1037/0893-3200.10.3.243
- Graziano, P. A., Keane, S. P., & Calkins, S. D. (2007). Cardiac vagal regulation and early peer status. *Child Development*, 78(1), 264–278. https://doi.org/10.1111/j.1467-8624.2007.00996.x
- Hampson, S. E., Edmonds, G. W., Barckley, M., Goldberg, L. R., Dubanoski, J. P., & Hillier, T. A. (2016). A Big Five approach to self-regulation: Personality traits and health trajectories in the Hawaii longitudinal study of personality and health. *Psychology, Health & Medicine*, 21(2), 152–162. https://doi.org/10.1080/13548506.2015.1061676
- Han, Z. R., Ahemaitijiang, N., Yan, J., Hu, X., Parent, J., Dale, C., DiMarzio, K., & Singh, N.
 N. (2019). Parent mindfulness, parenting, and child psychopathology in China. *Mindfulness*. https://doi.org/10.1007/s12671-019-01111-z

Harkness, S., Super, C. M., & Tijen, N. van. (2000). Individualism and the "Western mind" reconsidered: American and Dutch parents' ethnotheories of the child. *New Directions for Child and Adolescent Development*, 2000(87), 23–39. https://doi.org/10.1002/cd.23220008704

- Hastings, P. D., Nuselovici, J. N., Utendale, W. T., Coutya, J., McShane, K. E., & Sullivan, C. (2008). Applying the polyvagal theory to children's emotion regulation: Social context, socialization, and adjustment. *Biological Psychology*, *79*(3), 299–306. https://doi.org/10.1016/j.biopsycho.2008.07.005
- Hering, H. (1910). A functional test of heart vagi in man. *Menschen Munchen Medizinische Wochenschrift*, 57, 1931–1933.
- Hertz, S., Bernier, A., Cimon-Paquet, C., & Regueiro, S. (2017). Parent–child relationships and child executive functioning at school entry: The importance of fathers. *Early Child Development and Care*, 4430, 1–15. https://doi.org/10.1080/03004430.2017.1342078
- Hinnant, J. B., & El-Sheikh, M. (2009). Children's externalizing and internalizing symptoms over time: The role of individual differences in patterns of RSA responding. *Journal of Abnormal Child Psychology*, 37(8), 1049–1061. https://doi.org/10.1007/s10802-009-9341-1
- Hooper, E. G., Feng, X., Christian, L., & Slesnick, N. (2015). Emotion expression, emotionality, depressive symptoms, and stress: Maternal profiles related to child outcomes. *Journal of Abnormal Child Psychology*, *43*(7), 1319–1331. https://doi.org/10.1007/s10802-015-0019-6
- Hooper, E. G., Wu, Q., Ku, S., Gerhardt, M., & Feng, X. (2018). Maternal emotion socialization and child outcomes among African Americans and European Americans. *Journal of Child and Family Studies*, 27(6). https://doi.org/10.1007/s10826-018-1020-9

- Hooven, C., Gottman, J. M., & Katz, L. F. (1995). Parental meta-emotion structure predicts family and child outcomes. In *Cognition & Emotion* (Vol. 9, Issues 2–3). https://doi.org/10.1080/02699939508409010
- James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). An introduction to statistical *learning*. Springer.
- Jonason, P. K., Lyons, M., & Bethell, E. (2014). The making of Darth Vader: Parent-child care and the Dark Triad. *Personality and Individual Differences*, 67, 30–34. https://doi.org/10.1016/j.paid.2013.10.006
- Jönsson, P., & Sonnby-Borgström, M. (2003). The effects of pictures of emotional faces on tonic and phasic autonomic cardiac control in women and men. *Biological Psychology*, 62(2), 157–173. https://doi.org/10.1016/S0301-0511(02)00114-X
- Kendler, K. S., Kuhn, J., & Prescott, C. A. (2004). The interrelationship of neuroticism, sex, and stressful life events in the prediction of episodes of major depression. *American Journal of Psychiatry*, 161(4), 631–636. https://doi.org/10.1176/appi.ajp.161.4.631
- Kessler, R. C., Berglund, P., Demler, O., Jin, R., Merikangas, K. R., & Walters, E. E. (2005).
 Lifetime prevalence and age-of-onset distributions of DSM-IV disorders in the national comorbidity survey replication. *Archives of General Psychiatry*, *62*(6), 593.
 https://doi.org/10.1001/archpsyc.62.6.593
- Kim, S.-Y. (2009). Effects of sample size on robustness and prediction accuracy of a prognostic gene signature. *BMC Bioinformatics*, 10(1), 147.
 https://doi.org/10.1186/1471-2105-10-147

- Kline, R. (2015). *Principles and practice of structural equation modeling*. Guilford publications.
- Kochanska, G. (2001). Emotional development in children with different attachment histories:
 The first three years. *Child Development*, 72(2), 474–490. https://doi.org/10.1111/1467-8624.00291
- Kochanska, G., Coy, K. C., & Murray, K. T. (2001). The development of self-regulation in the first four years of life. *Child Development*, 72(4), 1091–1111. https://doi.org/10.1111/1467-8624.00336
- Kochanska, G., Coy, K. C., Tjebkes, T. L., & Husarek, S. J. (1998). Individual differences in emotionality in infancy. *Child Development*, 69(2), 375–390. https://doi.org/10.1111/j.1467-8624.1998.tb06196.x
- Koenig, J., Rash, J. A., Campbell, T. S., Thayer, J. F., & Kaess, M. (2017). A meta-analysis on sex differences in resting-state vagal activity in children and adolescents. *Frontiers in Physiology*, 8(AUG). https://doi.org/10.3389/fphys.2017.00582
- Kogan, A., Gruber, J., Shallcross, A. J., Ford, B. Q., & Mauss, I. B. (2013). Too much of a good thing? Cardiac vagal tone's nonlinear relationship with well-being. *Emotion*, 13(4), 599–604. https://doi.org/10.1037/a0032725
- Ku, S., Feng, X., Hooper, E. G., Wu, Q., & Gerhardt, M. (2019). Interactions between familial risk profiles and preschoolers' emotionality in predicting executive function. *Journal of Applied Developmental Psychology*, 63. https://doi.org/10.1016/j.appdev.2019.06.001
- Lafreniere, P. (2011). Evolutionary functions of social play: Life histories, sex differences, and emotion regulation. *American Journal of Play*, *3*(4), 464–488.

- Laurent, H. K., Duncan, L. G., Lightcap, A., & Khan, F. (2017). Mindful parenting predicts mothers' and infants' hypothalamic-pituitary-adrenal activity during a dyadic stressor. *Developmental Psychology*, 53(3), 417–424. https://doi.org/10.1037/dev0000258
- Lazarus, R. S., Dodd, H. F., Majdandžić, M., de Vente, W., Morris, T., Byrow, Y., Bögels, S. M., & Hudson, J. L. (2016). The relationship between challenging parenting behaviour and childhood anxiety disorders. *Journal of Affective Disorders*, *190*, 784–791. https://doi.org/10.1016/j.jad.2015.11.032
- Legge, J. (2011). The works of Mencius. Dover books.
- Leonard, B. E. (2001). Stress, norepinephrine and depression. *Journal of Psychiatry and Neuroscience*, *26*(SUPPL.), 11–16. https://doi.org/10.1034/j.1601-5215.2002.140403.x
- Liaw, A., & Wiener, M. (2002). Classification and regression by randomForest. *R News*, 2(3), 18–22.
- Loehlin, J. C., McCrae, R. R., Costa, P. T., & John, O. P. (1998). Heritabilities of common and measure-specific components of the Big Five personality factors. *Journal of Research in Personality*, 32(32), 431–453. https://doi.org/10.1006/jrpe.1998.2225
- Longin, E., Gerstner, T., Schaible, T., Lenz, T., & König, S. (2006). Maturation of the autonomic nervous system: differences in heart rate variability in premature vs. term infants. *Journal of Perinatal Medicine*, *34*(4), 303–308.

https://doi.org/10.1515/JPM.2006.058

Lonigan, C. J., Allan, D. M., & Phillips, B. M. (2017). Examining the predictive relations between two aspects of self- regulation and growth in preschool children's early literacy skills. *Developmental Psychology*, 53(1), 63–76.

- Lukianoff, G., & Haidt, J. (2019). *The coddling of the American mind: How good intentions and bad ideas are setting up a generation for failure*. Penguin Books.
- Lunkenheimer, E., Kemp, C. J., Lucas-Thompson, R. G., Cole, P. M., & Albrecht, E. C. (2017). Assessing biobehavioural self-regulation and coregulation in early childhood: The parent-child challenge task. *Infant and Child Development*, 26(1), 1–26. https://doi.org/10.1002/icd.1965
- Lunkenheimer, E., Shields, A. M., & Cortina, K. S. (2007). Parental emotion coaching and dismissing in family interaction. *Social Development*, 16(2), 232–248. https://doi.org/10.1111/j.1467-9507.2007.00382.x
- Magai, C. (1997). Emotions as a Child Self-rating Scale. In Unpublished measure.
- Majdandžić, M., de Vente, W., & Bögels, S. M. (2016). Challenging parenting behavior from infancy to toddlerhood: Etiology, measurement, and differences between fathers and mothers. *Infancy*, 21(4), 423–452. https://doi.org/10.1111/infa.12125
- Majdandžić, M., Lazarus, R. S., Oort, F. J., van der Sluis, C., Dodd, H. F., Morris, T. M., de Vente, W., Byrow, Y., Hudson, J. L., & Bögels, S. M. (2018). The structure of challenging parenting behavior and associations with anxiety in Dutch and Australian Children. *Journal of Clinical Child & Adolescent Psychology*, 47(2), 282–295. https://doi.org/10.1080/15374416.2017.1381915
- Majdandžić, M., Lazarus, R. S., Oort, F. J., van der Sluis, C., Dodd, H. F., Morris, T. M., de Vente, W., Byrow, Y., Hudson, J. L., & Bögels, S. M. (2018). The structure of challenging parenting behavior and associations with anxiety in Dutch and Australian

Children. Journal of Clinical Child & Adolescent Psychology, 47(2), 282–295. https://doi.org/10.1080/15374416.2017.1381915

- Majdandžić, M., Möller, E. L., de Vente, W., Bögels, S. M., & van den Boom, D. C. (2014). Fathers' challenging parenting behavior prevents social anxiety development in their 4year-old children: A longitudinal observational study. *Journal of Abnormal Child Psychology*, 42(2), 301–310. https://doi.org/10.1007/s10802-013-9774-4
- Marcovitch, S., Leigh, J., Calkins, S. D., Leerks, E. M., O'Brien, M., & Blankson, A. N. (2010). Moderate vagal withdrawal in 3.5-year-old children is associated with optimal performance on executive function tasks. *Developmental Psychobiology*, 52(6), 603–608. https://doi.org/10.1002/dev.20462
- McCrae, R. R., Costa, P. T., Ostendorf, F., Angleitner, A., Hrebícková, M., Avia, M. D., Sanz, J., Sánchez-Bernardos, M. L., Kusdil, M. E., Woodfield, R., Saunders, P. R., & Smith, P. B. (2000). Nature over nurture: Temperament, personality, and life span development. *Journal of Personality and Social Psychology*, 78(1), 173–186. https://doi.org/10.1037/0022-3514.78.1.173
- McLeod, B. D., Wood, J. J., & Weisz, J. R. (2007). Examining the association between parenting and childhood anxiety: A meta-analysis. *Clinical Psychology Review*, 27(2), 155–172. https://doi.org/10.1016/j.cpr.2006.09.002
- Milfont, T., & Fischer, R. (2010). Testing measurement invariance across groups: applications in cross-cultural research. *International Journal of Psychological Research*, 3(1), 111– 130. https://doi.org/10.21500/20112084.857

- Miller, J. G., Chocol, C., Nuselovici, J. N., Utendale, W. T., Simard, M., & Hastings, P. D. (2013). Children's dynamic RSA change during anger and its relations with parenting, temperament, and control of aggression. *Biological Psychology*, 92(2), 417–425. https://doi.org/10.1016/j.biopsycho.2012.12.005
- Miller, J. G., Kahle, S., & Hastings, P. D. (2017). Moderate baseline vagal tone predicts greater prosociality in children. *Developmental Psychology*, 53(2), 274–289. https://doi.org/10.1037/dev0000238
- Möller, E. L., Majdandžić, M., & Bögels, S. M. (2014). Fathers' versus mothers' social referencing signals in relation to infant anxiety and avoidance: A visual cliff experiment. *Developmental Science*, 17(6), 1012–1028. https://doi.org/10.1111/desc.12194
- Möller, E. L., Majdandžić, M., & Bögels, S. M. (2015). Parental anxiety, parenting behavior, and infant anxiety: Differential associations for fathers and mothers. *Journal of Child and Family Studies*, 24(9), 2626–2637. https://doi.org/10.1007/s10826-014-0065-7

Möller, E. L., Majdandžić, M., Vente, W., & Bögels, S. (2013). The evolutionary basis of sex differences in parenting and its relationship with child anxiety in Western societies. *Journal of Experimental Psychopathology*, 4(2), 88–117.
https://doi.org/10.5127/jep.026912

Möller, E. L., Nikolić, M., Majdandžić, M., & Bögels, S. M. (2016). Associations between maternal and paternal parenting behaviors, anxiety and its precursors in early childhood: A meta-analysis. *Clinical Psychology Review*, 45, 17–33. https://doi.org/10.1016/j.cpr.2016.03.002

- Montroy, J. J., Bowles, R. P., Skibbe, L. E., McClelland, M. M., & Morrison, F. J. (2016). The development of self-regulation across early childhood. *Developmental Psychology*, 52(11), 1744–1762. https://doi.org/10.1037/dev0000159
- Moore, G. A., & Calkins, S. D. (2004). Infants' vagal regulation in the still-face paradigm is related to dyadic coordination of mother-infant interaction. *Developmental Psychology*, 40(6), 1068–1080. https://doi.org/10.1037/0012-1649.40.6.1068
- Morales, S., Beekman, C., Blandon, A. Y., Stifter, C. A., & Buss, K. A. (2015). Longitudinal associations between temperament and socioemotional outcomes in young children: The moderating role of RSA and gender. *Developmental Psychobiology*, 57(1), 105-119. https://doi.org/10.1002/dev.21267
- Morris, A. S., Silk, J. S., Steinberg, L., Myers, S. S., & Robinson, L. R. (2007). The role of the family context in the development of emotion regulation. *Social Development*, 16(2), 361–388. https://doi.org/10.1111/j.1467-9507.2007.00389.x
- Muris, P., Meesters, C., & Blijlevens, P. (2007). Self-reported reactive and regulative temperament in early adolescence: Relations to internalizing and externalizing problem behavior and "Big Three" personality factors. *Journal of Adolescence*, *30*(6), 1035–1049. https://doi.org/10.1016/j.adolescence.2007.03.003
- Nietzsche, F. (2018). The twilight of the idols. Jovian Press.
- Oosterman, M., & Schuengel, C. (2007). Physiological effects of separation and reunion in relation to attachment and temperament in young children. *Developmental Psychobiology*, 49(2), 119–128. https://doi.org/10.1002/dev.20207

- Oppenheimer, L. (2004). Perception of individualism and collectivism in Dutch society: A developmental approach. *International Journal of Behavioral Development*, 28(4), 336–346. https://doi.org/10.1080/01650250444000009
- Panksepp, J. (1993). Rough-and-tumble play: A fundamental brain process. In K. MacDonald (Ed.), Parent-child play: Descriptions & implications (pp. 147–184). State University of New York Press.
- Paquette, D. (2004). Theorizing the father-child relationship: Mechanisms and developmental outcomes. In *Human Development*, 47, 193-219. https://doi.org/10.1159/000078723
- Paquette, D., & Bigras, M. (2010). The risky situation: A procedure for assessing the father– child activation relationship. *Early Child Development and Care*, 180(1–2), 33–50. https://doi.org/10.1080/03004430903414687
- Paquette, D., Coyl-Shepherd, D. D., & Newland, L. A. (2013). Fathers and development: New areas for exploration. *Early Child Development and Care*, 183(6), 735–745. https://doi.org/10.1080/03004430.2012.723438
- Parent, J., & Forehand, R. (2017). The Multidimensional Assessment of Parenting Scale (MAPS): Development and psychometric properties. *Journal of Child and Family Studies*, 26(8), 2136–2151. https://doi.org/10.1007/s10826-017-0741-5
- Pellegrini, A. D., & Smith, P. K. (1998). Physical activity play: The nature and function of a neglected aspect of play. *Child Development*, 69(3), 577–598. https://doi.org/10.1111/j.1467-8624.1998.tb06226.x
- Perry, N. B., Nelson, J. A., Swingler, M. M., Leerkes, E. M., Calkins, S. D., Marcovitch, S., & O'Brien, M. (2013). The relation between maternal emotional support and child

physiological regulation across the preschool years. *Developmental Psychobiology*, 55(4), 382–394. https://doi.org/10.1002/dev.21042

- Porges, S. W. (2007). The polyvagal perspective. *Biological Psychology*, 74(2), 116–143. https://doi.org/10.1016/j.biopsycho.2006.06.009
- Porges, S. W., Doussard-Roosevelt, J. A., Portales, A. L., & Greenspan, S. I. (1996). Infant regulation of the vagal "brake" predicts child behavior problems: A psychobiological model of social behavior. *Developmental Psychobiology*, 29(8), 697–712. https://doi.org/10.1002/(SICI)1098-2302(199612)29:8<697::AID-DEV5>3.0.CO;2-O
- Putnam, S. P., & Rothbart, M. K. (2006). Development of short and very short forms of the Children's Behavior Questionnaire. *Journal of Personality Assessment*, 87(1), 103–113.
- Radloff, L. S. (1977). A self-report depression scale for research in the general population. *Appl. Psychol. Meas.*, 1(3), 385–401. https://doi.org/10.1177/014662167700100306
- Reuben, J. D., Shaw, D. S., Neiderhiser, J. M., Natsuaki, M. N., Reiss, D., & Leve, L. D.
 (2016). Warm parenting and effortful control in toddlerhood: Independent and interactive predictors of school-age externalizing behavior. *Journal of Abnormal Child Psychology*, 44(6), 1083–1096. https://doi.org/10.1007/s10802-015-0096-6
- Revelle, W., & Zinbarg, R. E. (2009). Coefficients alpha, beta, omega, and the glb: Comments on Sijtsma. *Psychometrika*, 74(1), 145–154. https://doi.org/10.1007/s11336-008-9102-z
- Rodell, J. B., & Judge, T. A. (2009). Can "good" stressors spark "bad" behaviors? The mediating role of emotions in links of challenge and hindrance stressors with citizenship and counterproductive behaviors. *Journal of Applied Psychology*, 94(6), 1438. https://doi.org/10.1037/a0016752

- Ross, H., & Taylor, H. (1989). Do boys prefer daddy or his physical style of play? *Sex Roles*, 20(1–2), 23–33. https://doi.org/10.1007/BF00288024
- Rosseel, Y. (2012). lavaan: An R package for structural equation modeling and more. *Journal* of *Statistical Software*, 48(2), 1–22. https://doi.org/10.18637/jss.v048.i02
- Rothbart, M. K. (2011). *Becoming who we are: Temperament and personality in development*. Guilford Press.
- Rothbart, M. K., Ahadi, S. A., Hershey, K. L., & Fisher, P. (2001). Investigations of temperament at three to seven years: The Children's Behavior Questionnaire. *Child Development*, 72(5), 1394–1408.
- Rozin, P., Berman, L., & Royzman, E. (2010). Biases in use of positive and negative words across twenty natural languages. *Cognition & Emotion*, 24(3), 536–548. https://doi.org/10.1080/02699930902793462
- Rubin, K. H., Coplan, R. J., Fox, N. A., & Calkins, S. D. (1995). Emotionality, emotion regulation, and preschoolers' social adaptation. *Development and Psychopathology*, 7(1), 49–62. https://doi.org/10.1017/S0954579400006337
- Rudolph, K. D., Davis, M. M., Monti, J. D., Abaied, J., Agoston, M., Banagale, H., Hessel, E., Llewellyn, N., Miernicki, M., & Pauly, J. (2017). Cognition-emotion interaction as a predictor of adolescent depressive symptoms. *Developmental Psychology*, 53(12), 2377– 2383.
- Russell, A., Hart, C. H., Robinson, C. C., & Olsen, S. F. (2003). Children's sociable and aggressive behaviour with peers: A comparison of the US and Australia, and

contributions of temperament and parenting styles. *International Journal of Behavioral Development*, 27(1), 74–86. https://doi.org/10.1080/01650250244000038

- Sanders, W., Zeman, J., Poon, J., & Miller, R. (2015). Child regulation of negative emotions and depressive symptoms: The moderating role of parental emotion socialization. *Journal* of Child and Family Studies, 24(2). https://doi.org/10.1007/s10826-013-9850-y
- Schechtman, V. L., Harper, R. M., & Kluge, K. A. (1989). Development of heart rate variation over the first 6 months of life in normal infants. *Pediatric Research*, 26(4), 343–346. https://doi.org/10.1203/00006450-198910000-00011
- Schoppe-Sullivan, S. J., Kotila, L. E., Jia, R., Lang, S. N., & Bower, D. J. (2013). Comparisons of levels and predictors of mothers' and fathers' engagement with their preschool-aged children. *Early Child Development and Care*, *183*(3–4), 498–514. https://doi.org/10.1080/03004430.2012.711596
- Shadish, W., Cook, T., & Campbell, D. (2002). *Experimental and quasi-experimental designs* for generalized causal inference (2nd ed.). Wadsworth Cengage Learning.
- Shallcross, A. J., Ford, B. Q., Floerke, V. A., & Mauss, I. B. (2013). Getting better with age: The relationship between age, acceptance, and negative affect. *Journal of Personality and Social Psychology*, *104*(4), 734–749. https://doi.org/10.1037/a0031180
- Shannon, J. D., Tamis-LeMonda, C. S., London, K., & Cabrera, N. (2002). Beyond roughand-tumble: Low-income fathers' interactions and children's cognitive development at 24 months. *Parenting*, 2(2), 77–104. https://doi.org/10.1207/S15327922PAR0202
- Shiner, R. L., & DeYoung, C. G. (2013). The Structure of temperament and personality traits: A developmental perspective. In P. D. Zelazo (Ed.), *The Oxford handbook of*

developmental psychology, Vol. 2: Self and other (pp. 113–141). Oxford University Press.

- Shiner, R. L., Buss, K. A., Mcclowry, S. G., Putnam, S. P., Saudino, K. J., & Zentner, M. (2012). What is temperament now? Assessing progress temperament research on the twenty-fifth anniversary of Goldsmith et al. *Child Development Perspectives*, 6(4), 436– 444. https://doi.org/10.1111/j.1750-8606.2012.00254.x
- Silk, J. S., Morris, A. S., Kanaya, T., & Steinberg, L. (2003). Psychological control and autonomy granting: Opposite ends of a continuum or distinct constructs? *Journal of Research on Adolescence*, *13*(1), 113–128. https://doi.org/10.1111/1532-7795.1301004
- Singelis, T. M., Triandis, H. C., Bhawuk, D. P. S., & Gelfand, M. J. (1995). Horizontal and vertical dimensions of individualism and collectivism: A theoretical and measurement refinement. *Cross-Cultural Research*, 29(3), 240–275.

https://doi.org/10.1177/106939719502900302

- Skoranski, A. M., Lunkenheimer, E., & Lucas-Thompson, R. G. (2017). The effects of maternal respiratory sinus arrhythmia and behavioral engagement on mother-child physiological coregulation. *Developmental Psychobiology*, 59(7), 888–898. https://doi.org/10.1002/dev.21543
- Slonim, T. (2014). The polyvagal theory: Neuropsychological foundations of emotions, attachment, communication, & self-regulation. *International Journal of Group Psychotherapy*, 64(4), 593–600.

- Snieder, H., van Doornen, L. J. P., Boomsma, D. I., & Thayer, J. F. (2007). Sex differences and heritability of two indices of heart rate dynamics: A twin study. *Twin Research and Human Genetics*, 10(2), 364–372. https://doi.org/10.1375/twin.10.2.364
- Sokol, R. L., Qin, B., & Poti, J. M. (2017). Parenting styles and body mass index: A systematic review of prospective studies among children. *Obesity Reviews*, 18(3), 281–292. https://doi.org/10.1111/obr.12497
- Spera, C. (2005). A review of the relationship among parenting practices, parenting styles, and adolescent school achievement. *Educational Psychology Review*, 17(2), 125–146. https://doi.org/10.1007/s10648-005-3950-1
- Spielberger, C. D., Gorsuch, R. L., Lushene, R., Vagg, P. R., & Jacobs, G. A. (1983). Manual for the State-Trait Anxiety Inventory. Consulting Psychologists Press.
- Spinrad, T. L., Eisenberg, N., Gaertner, B., Popp, T., Smith, C. L., Kupfer, A., Greving, K., Liew, J., & Hofer, C. (2007). Relations of maternal socialization and toddlers' effortful control to children's adjustment and social competence. *Developmental Psychology*, 43(5), 1170–1186. https://doi.org/10.1037/0012-1649.43.5.1170
- Stekhoven, D. J., & Buhlmann, P. (2012). MissForest--non-parametric missing value imputation for mixed-type data. *Bioinformatics*, 28(1), 112–118. https://doi.org/10.1093/bioinformatics/btr597
- Stevenson, M. M., & Crnic, K. A. (2013). Activative fathering predicts later children's behaviour dysregulation and sociability. *Early Child Development and Care*, 183(6), 774–790. https://doi.org/10.1080/03004430.2012.723441

- StGeorge, J. M., & Freeman, E. (2017). Measurement of father–child rough-and-tumble play and its relations to child behavior. *Infant Mental Health Journal*, 38(6), 709–725. https://doi.org/10.1002/imhj.21676
- StGeorge, J. M., Fletcher, R., Freeman, E., Paquette, D., & Dumont, C. (2015). Father–child interactions and children's risk of injury. *Early Child Development and Care*, 185(9), 1409–1421. https://doi.org/10.1080/03004430.2014.1000888
- StGeorge, J. M., Goodwin, J. C., & Fletcher, R. J. (2018). Parents' views of father–child rough-and-tumble Play. *Journal of Child and Family Studies*. https://doi.org/10.1007/s10826-017-0993-0
- Stifter, C. A., & Braungart, J. M. (1995). The regulation of negative reactivity in infancy: Function and development. *Developmental Psychology*, *31*(3), 448–455. https://doi.org/10.1037/0012-1649.31.3.448
- Stormshak, E. A., Bierman, K. L., McMahon, R. J., & Lengua, L. J. (2000). Parenting practices and child disruptive behavior problems in early elementary school. *Journal of Clinical Child Psychology*, 29(1), 17–29. https://doi.org/10.1207/S15374424jccp2901_3
- Sulik, M. J., Eisenberg, N., Spinrad, T. L., & Silva, K. M. (2015). Associations between respiratory sinus arrhythmia (RSA) reactivity and effortful control in preschool-age children. *Developmental Psychobiology*, 57(5), 596–606. https://doi.org/10.1002/dev.21315

Taleb, N. N. (2012). Antifragile: Things that gain from disorder. Random House Incorporated.

- Tang, F., & Ishwaran, H. (2017). Random forest missing data algorithms. *Statistical Analysis and Data Mining: The ASA Data Science Journal*, *10*(6), 363–377.
 https://doi.org/10.1002/sam.11348
- Team, R. D. C. (2008). R.
- Thompson, R. A. (1994). Emotion regulation: A theme in search of definition. *Monographs of the Society for Research in Child Development*, 59(2/3), 25. https://doi.org/10.2307/1166137

Tull, M. T., & Aldao, A. (2015). Editorial overview: New directions in the science of emotion regulation. *Current Opinion in Psychology*, *3*, iv–x. https://doi.org/10.1016/j.copsyc.2015.03.009

- Urao, Y., Yoshinaga, N., Asano, K., Ishikawa, R., Tano, A., Sato, Y., & Shimizu, E. (2016).
 Effectiveness of a cognitive behavioural therapy-based anxiety prevention programme for children: a preliminary quasi-experimental study in Japan. *Child and Adolescent Psychiatry and Mental Health*, *10*(1), 4. https://doi.org/10.1186/s13034-016-0091-x
- van der Bruggen, C. O., Stams, G. J. J. M., Bögels, S. M., & Paulussen-Hoogeboom, M. C. (2010). Parenting behaviour as a mediator between young children's negative emotionality and their anxiety/depression. *Infant and Child Development*, 3(December 2007), n/a-n/a. https://doi.org/10.1002/icd.665
- van der Giessen, D., & Bögels, S. M. (2018). Father-child and mother-child interactions with children with anxiety disorders: Emotional expressivity and flexibility of dyads. *Journal of Abnormal Child Psychology*, *46*(2), 331–342. https://doi.org/10.1007/s10802-017-0271-z

Vandenberg, R. J. (2002). Toward a further understanding of and improvement in measurement invariance methods and procedures. *Organizational Research Methods*, 5(2), 139–158.

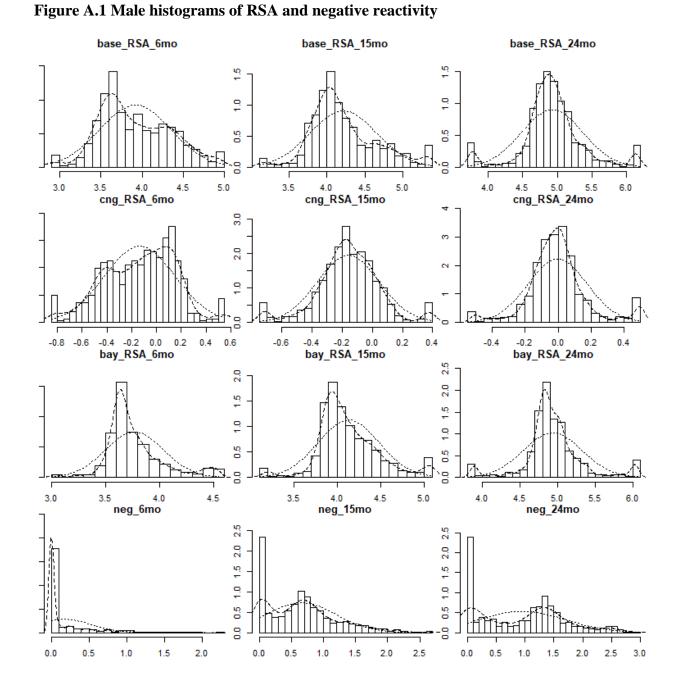
Vandenberg, R. J., & Lance, C. E. (2000). A review and synthesis of the measurement invariance literature: Suggestions, practices, and recommendations for organizational research. *Organizational Research Methods*, 3(1), 4–70. https://doi.org/10.1177/109442810031002

- Vernon-Feagans, L., Crouter, A. C., & Cox, M. J. (2018). The family life project, Phase I, United States, September 2003-January 2008. *Inter-University Consortium for Political* and Social Research [Distributor], 2018-06-27. https://doi.org/10.3886/ICPSR34602.v4
- Volling, B. L., Cabrera, N. J., Feinberg, M. E., Jones, D. E., McDaniel, B. T., Liu, S.,
 Almeida, D., Lee, J., Schoppe-Sullivan, S. J., Feng, X., Gerhardt, M. L., Dush, C. M. K.,
 Stevenson, M. M., Safyer, P., Gonzalez, R., Lee, J. Y., Piskernik, B., Ahnert, L., Karberg,
 E., ... Cookston, J. T. (2019). Advancing research and measurement on fathering and
 children's development. *Monographs of the Society for Research in Child Development*,
 84(1), 7–160. https://doi.org/10.1111/mono.12404
- Watson, D., Clark, L. A., & Carey, G. (1988). Positive and negative affectivity and their relation to anxiety and depressive disorders. *Journal of Abnormal Psychology*, 97(3), 346–353. https://doi.org/10.1037/0021-843X.97.3.346
- Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: The PANAS scales. *Journal of Personality and Social Psychology*, 54(6), 1063–1070. https://doi.org/10.1037/0022-3514.54.6.1063

- Wei, C., & Kendall, P. C. (2014). Parental involvement: Contribution to childhood anxiety and its treatment. *Clinical Child and Family Psychology Review*, 17(4), 319–339. https://doi.org/10.1007/s10567-014-0170-6
- Wolff, M. S., & van Ijzendoorn, M. H. (1997). Sensitivity and attachment: A meta-analysis on parental antecedents of infant attachment. *Child Development*, 68(4), 571–591. https://doi.org/10.1111/j.1467-8624.1997.tb04218.x
- Wood, S. (2017). *Generalized Additive Models: An Introduction with R* (2nd edition). Chapman and Hall/CRC.
- Wu, Hao., & Estabrook, Ryne. (2016). Identification of confirmatory factor analysis models of different levels of invariance for ordered categorical outcomes. *Psychometrika*, 81(4), 1014–1045. https://doi.org/10.1007/s11336-016-9506-0
- Wu, Q., Feng, X., Gerhardt, M., & Wang, L. (2019). Maternal depressive symptoms, rumination, and child emotion regulation. *European Child & Adolescent Psychiatry*. https://doi.org/10.1007/s00787-019-01430-5
- Wu, Q., Feng, X., Hooper, E. G., Gerhardt, M., Ku, S., & Chan, M. H.-M. (2019). Mother's emotion coaching and preschooler's emotionality: Moderation by maternal parenting stress. *Journal of Applied Developmental Psychology*, 65. https://doi.org/10.1016/j.appdev.2019.101066

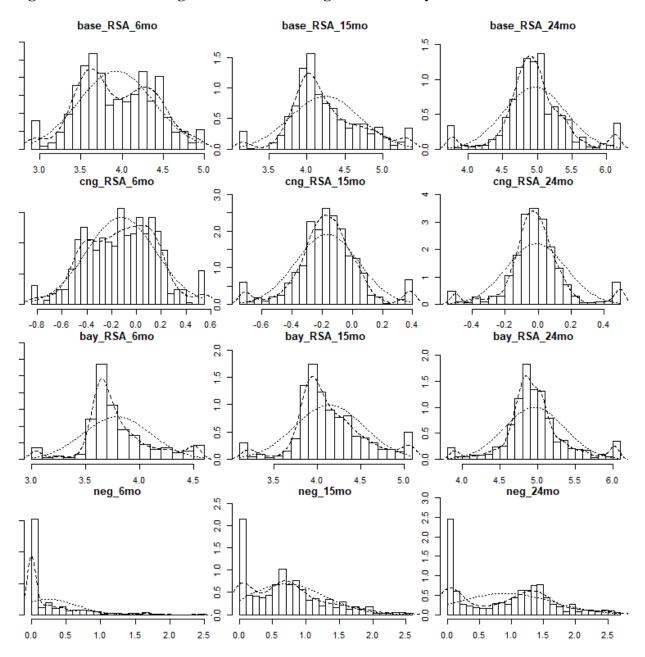
Wu, Q., Hooper, E. G., Feng, X., Gerhardt, M., & Ku, S. (2019). Mothers' depressive symptoms and responses to preschoolers' emotions: moderated by child expression. *Journal of Applied Developmental Psychology*, *60*, 134–143. https://doi.org/10.1016/j.appdev.2018.09.005

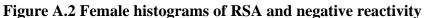
- Yap, M. B. H., & Jorm, A. F. (2015). Parental factors associated with childhood anxiety, depression, and internalizing problems: A systematic review and meta-analysis. *Journal* of Affective Disorders, 175, 424–440. https://doi.org/10.1016/j.jad.2015.01.050
- Yap, M. B. H., & Jorm, A. F. (2015). Parental factors associated with childhood anxiety, depression, and internalizing problems: A systematic review and meta-analysis. *Journal* of Affective Disorders, 175, 424–440. https://doi.org/10.1016/j.jad.2015.01.050
- Yap, M. B. H., Pilkington, P. D., Ryan, S. M., & Jorm, A. F. (2014). Parental factors associated with depression and anxiety in young people: A systematic review and metaanalysis. *Journal of Affective Disorders*, 156, 8–23. https://doi.org/10.1016/j.jad.2013.11.007
- Yarkoni, T., & Westfall, J. (2017). Choosing prediction over explanation in psychology: Lessons from machine learning. *Perspectives on Psychological Science*, *12*(6), 1100–1122. https://doi.org/10.1177/1745691617693393
- Yoo, Y.-G., Lee, D.-J., Lee, I.-S., Shin, N., Park, J.-Y., Yoon, M.-R., & Yu, B. (2016). The effects of mind subtraction meditation on depression, social anxiety, aggression, and salivary cortisol levels of elementary school children in South Korea. *Journal of Pediatric Nursing*, 31(3), e185–e197. https://doi.org/10.1016/j.pedn.2015.12.001



Appendix A. Supplementary material for Chapter 2

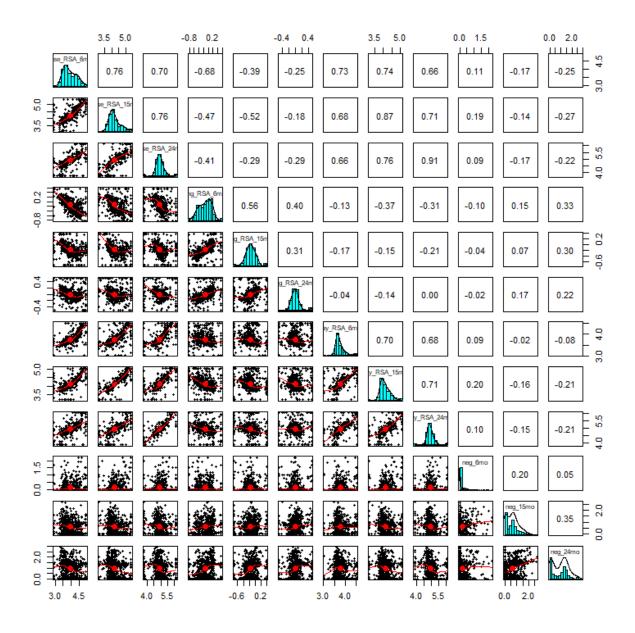
Note. base_RSA: baseline RSA, cng_RSA: change in RSA, bay_RSA: Bayley RSA, neg_6mo: negative reactivity at 6 months, neg_15mo: negative reactivity at 15 months, neg_24mo: negative reactivity at 24 months



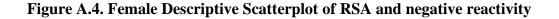


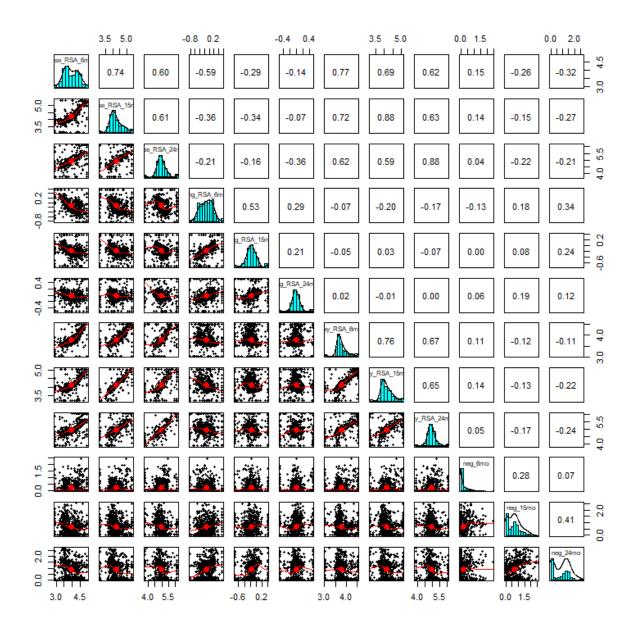
Note. base_RSA: baseline RSA, cng_RSA: change in RSA, bay_RSA: Bayley RSA, neg_6mo: negative reactivity at 6 months, neg_15mo: negative reactivity at 15 months, neg_24mo: negative reactivity at 24 months





Note. Lower half of matrix is linear relationship between variables, diagonal is distribution of variables, upper half is correlation between variables. Variables are presented in order along the diagonal and this ordering is used throughout the plot, for example the scatterplot in [2,1] is baseline RSA at 6 and 15 months





Note. Lower half of matrix is linear relationship between variables, diagonal is distribution of variables, upper half is correlation between variables. Variables are presented in order along the diagonal and this ordering is used throughout the plot, for example the scatterplot in [2,1] is baseline RSA at 6 and 15 months

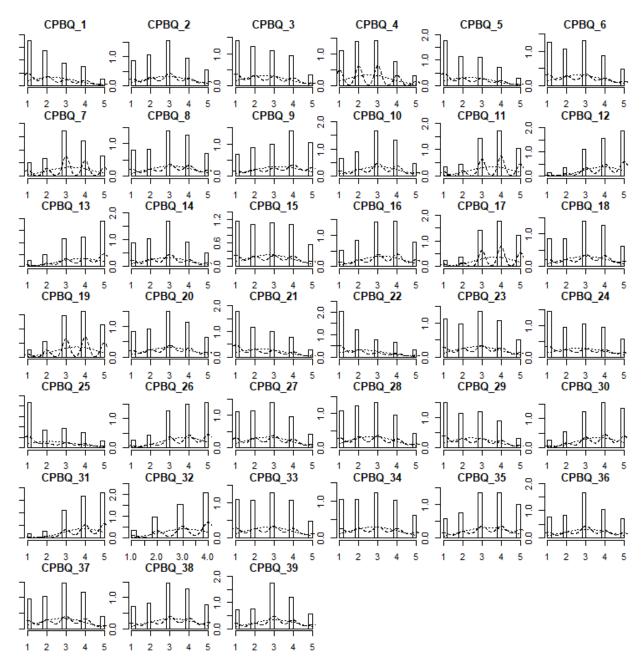


Figure: B.1 Distribution of CPBQ responses

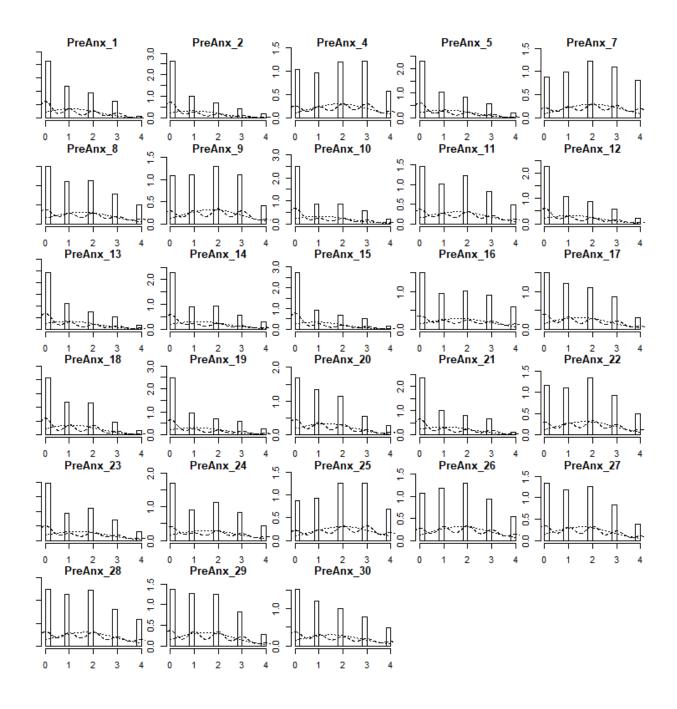


Figure B.2 Distribution of Child Anxiety Responses

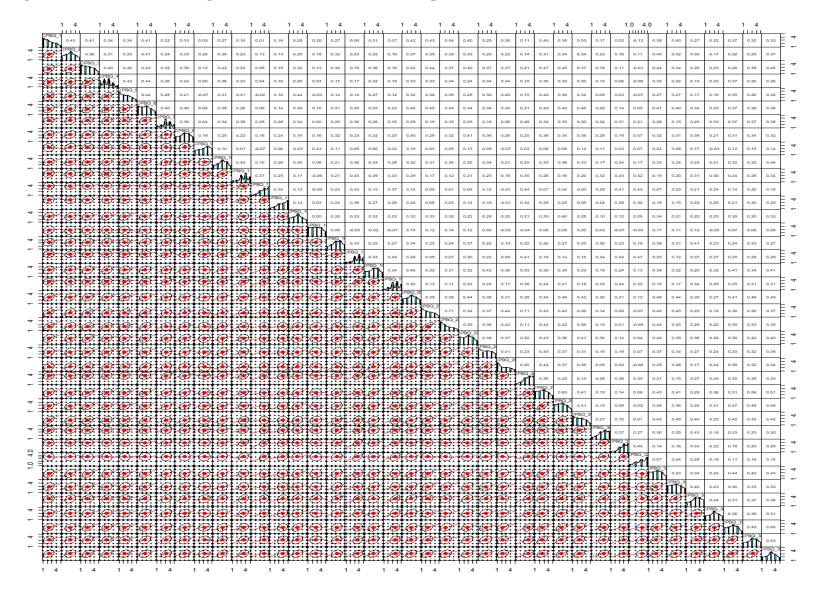


Figure B.3 Correlation, histograms, and bivariate correlation plots of CPBQ

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	0.66	0.33	0.58	0.21	0.35	0.39	0.67	0.42	0.55	0.62	0.47	0.64	0.31	0.39	0.53	0.40	0.51	0.60	0.33	0.55	0.38	0.32	0.45	0.46	0.34	0.52	0.42
	PreArix_2	0.31	0.65	0.19	0.39	0.40	0.63	0.41	0.61	0.60	0.44	0.75	0.32	0.42	0.58	0.45	0.46	0.60	0.34	0.48	0.40	0.29	0.42	0.43	0.35	0.45	0.40
	.	PreArx_4	0.39	0.32	0.39	0.42	0.35	0.42	0.36	0.34	0.34	0.32	0.35	0.37	0.36	0.30	0.35	0.26	0.36	0.34	0.38	0.33	0.38	0.28	0.39	0.41	0.34
~			PreArox_5	0.27	0.40	0.45	0.58	0.38	0.62	0.58	0.46	0.62	0.33	0.39	0.58	0.42	0.48	0.52	0.35	0.52	0.42	0.33	0.46	0.42	0.37	0.48	0.38
□ 		Ð.		ProArx_7	0.34	0.32	0.26	0.31	0.24	0.29	0.27	0.25	0.21	0.38	0.30	0.25	0.18	0.20	0.26	0.25	0.31	0.28	0.34	0.22	0.48	0.36	0.29
~					PreArix_8	0.44	0.40	0.40	0.43	0.41	0.43	0.40	0.42	0.37	0.43	0.38	0.36	0.36	0.40	0.36	0.43	0.35	0.40	0.33	0.40	0.41	0.39
		2		$\overline{\mathbf{A}}$		ProArx_9	0.40	0.32	0.47	0.44	0.37	0.45	0.34	0.43	0.50	0.31	0.34	0.36	0.32	0.44	0.41	0.58	0.57	0.33	0.36	0.43	0.34
₹		$\tilde{\boldsymbol{\omega}}$					PreArex_10	0.42	0.53	0.72	0.51	0.64	0.34	0.43	0.56	0.45	0.53	0.59	0.31	0.56	0.45	0.33	0.45	0.44	0.39	0.56	0.43
		100	6					PreArx_11	0.43	0.44	0.37	0.40	0.40	0.35	0.38	0.36	0.36	0.40	0.41	0.43	0.43	0.27	0.40	0.33	0.39	0.42	0.49
→ ↓ ↓ ↓ ↓									PreArix_12	0.57	0.46	0.64	0.41	0.47	0.62	0.42	0.45	0.52	0.37	0.51	0.43	0.41	0.53	0.40	0.37	0.48	0.40
- ₽		47 27				2		(- <u>/</u> -		PreArx_13	0.46	0.64	0.37	0.42	0.55	0.45	0.53	0.59	0.39	0.59	0.45	0.36	0.48	0.48	0.43	0.55	0.45
	¥ + + + 1	\mathcal{O}				\mathcal{O}					PreArox_14	0.50	0.33	0.42	0.50	0.50	0.41	0.41	0.33	0.43	0.50	0.32	0.40	0.35	0.38	0.46	0.45
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			****			\mathcal{O}							0.32 PreArox_16	0.46	0.58	0.48	0.48	0.63	0.35	0.55	0.41	0.35	0.47	0.45	0.38	0.52	0.44
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Figure B.4 Correlation and histogram plots of Preschool Anxiety Questionnaire

	Df	χ	$\Delta \chi$	$\Delta \mathrm{Df}$	CFI	$\Delta \mathrm{CFI}$	RMSEA	SRMR
Configural	1100	2053.0			0.902		0.067	0.083
Threshold	1170	2092.3	84.148	70	0.900	.002	0.065	0.083
Metric	1200	2172.5	40.378	30	0.903	003	0.063	0.083
Scalar	1230	2233.8	42.051	30	0.905	002	0.062	0.083

Table B.1. Male Parent by Child Sex

Note. p**<.001

Table B.2 Female Parent by Child Sex

Df	χ	Δχ	$\Delta \mathrm{Df}$	CFI	$\Delta \mathrm{CFI}$	RMSEA	SRMR
1100	2152.1			0.913		0.068	0.088
1170	2181.0	73.218	70	0.912	.001	0.067	0.088
1200	2208.0	18.833	30	0.916	004	0.064	0.088
1230	2292.9	52.428*	30	0.916	.000	0.063	0.089
	1100 1170 1200	1100 2152.1 1170 2181.0 1200 2208.0	1100 2152.1 1170 2181.0 73.218 1200 2208.0 18.833	1100 2152.1 1170 2181.0 73.218 70 1200 2208.0 18.833 30	1100 2152.1 0.913 1170 2181.0 73.218 70 0.912 1200 2208.0 18.833 30 0.916	1100 2152.1 0.913 1170 2181.0 73.218 70 0.912 .001 1200 2208.0 18.833 30 0.916 004	1100 2152.1 0.913 0.068 1170 2181.0 73.218 70 0.912 .001 0.067 1200 2208.0 18.833 30 0.916 004 0.064

Note. p*<.05

Df	χ	$\Delta \chi$	$\Delta \mathrm{Df}$	CFI	$\Delta \text{ CFI}$	RMSEA	SRMR
1100	3146.8			0.903		0.070	0.075
1170	3176.8	72.414	70	0.901	002	0.069	0.075
1200	3229.8	29.929	30	0.905	.004	0.067	0.075
1230	3304.7	52.300*	30	0.906	.001	0.066	0.075
]	1170 1200	11703176.812003229.8	11703176.872.41412003229.829.929	11703176.872.4147012003229.829.92930	11703176.872.414700.90112003229.829.929300.905	11703176.872.414700.90100212003229.829.929300.905.004	11703176.872.414700.9010020.06912003229.829.929300.905.0040.067

Table B.3 Child Sex with both parents combined

Note. p*<.05

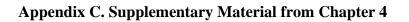
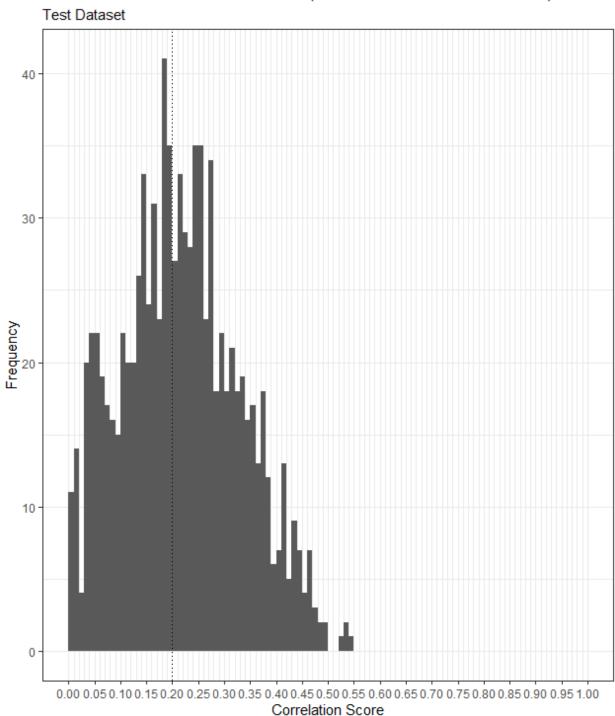
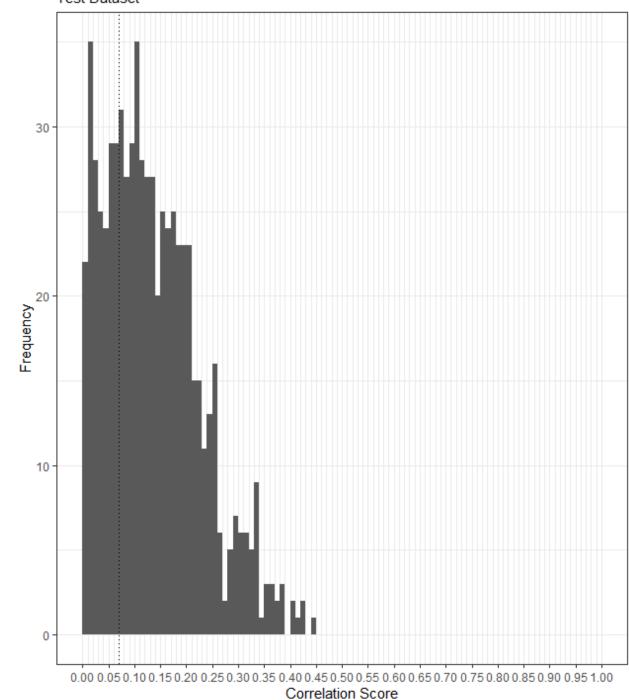


Figure C.1: Age 3 concurrent random forest fit

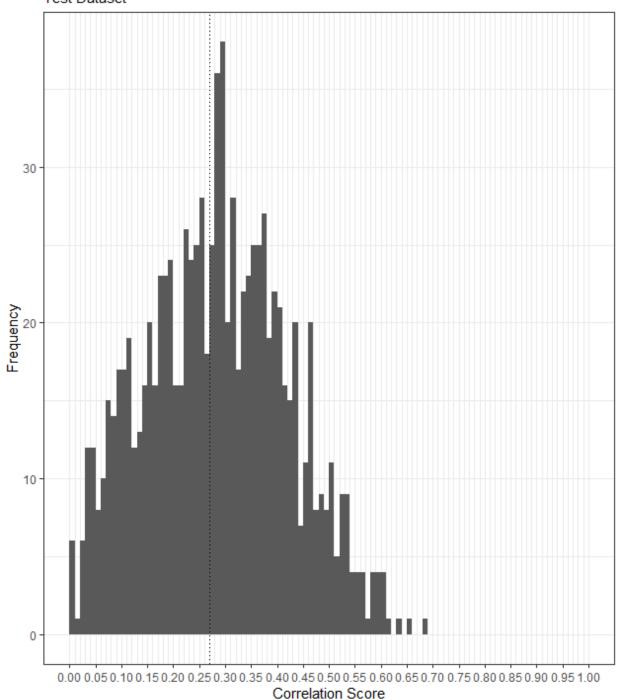


Distribution of Correlation Scores (Mean Correlation Score = 0.2) Test Dataset Figure C.2: Age 4 concurrent random forest fit

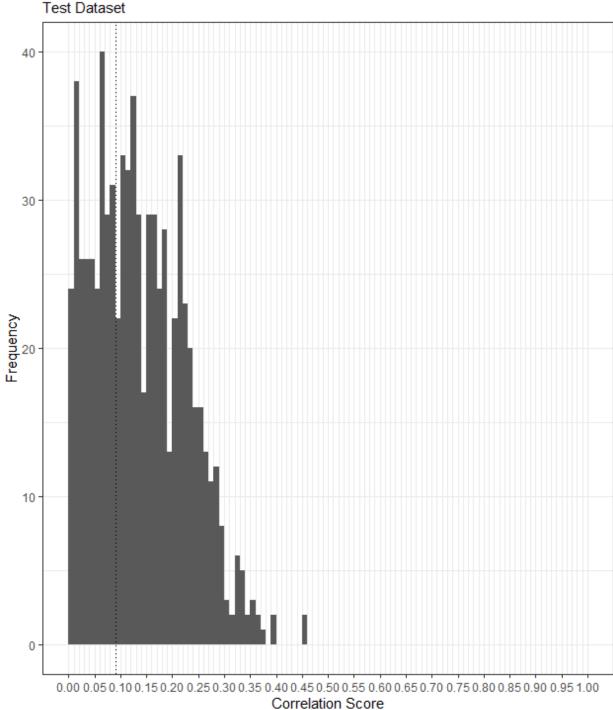


Distribution of Correlation Scores (Mean Correlation Score = 0.07) Test Dataset

Figure C.3: Age 5 concurrent random forest fit

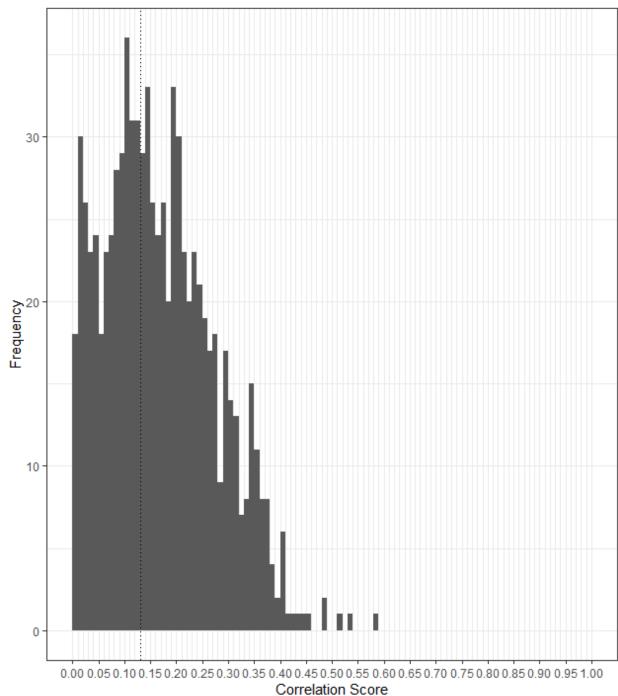


Distribution of Correlation Scores (Mean Correlation Score = 0.27) Test Dataset



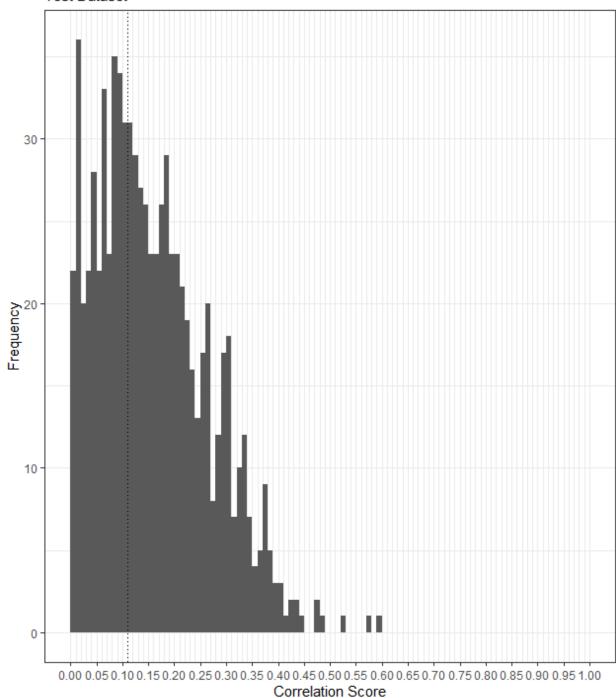
Distribution of Correlation Scores (Mean Correlation Score = 0.09) Test Dataset

Figure C.4: Age 3 predicting age 4 random forest fit



Distribution of Correlation Scores (Mean Correlation Score = 0.13) Test Dataset

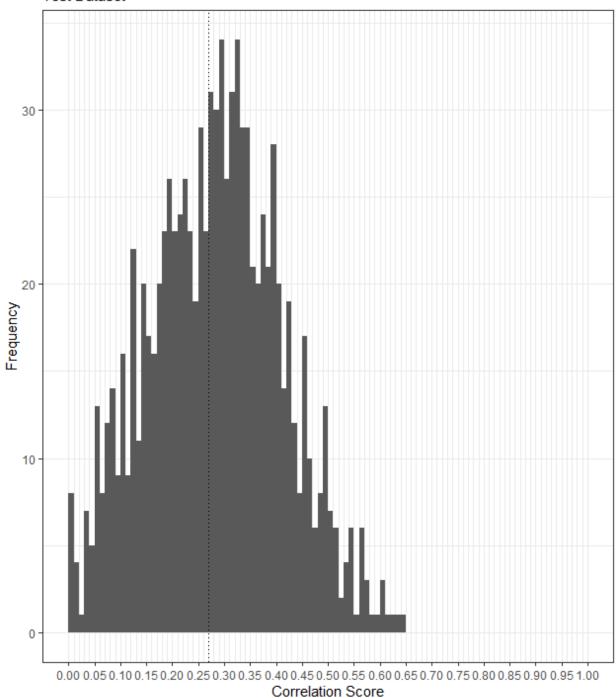
Figure C.5: Age 3 predicting age 5 random forest fit



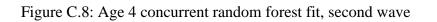
Distribution of Correlation Scores (Mean Correlation Score = 0.11) Test Dataset

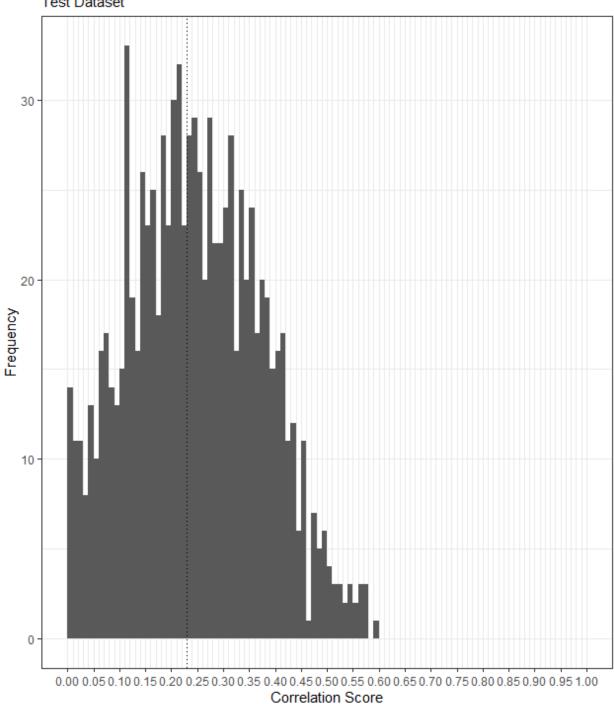
Figure C.6: Age 4 predicting age 5 random forest fit

Figure C.7: Age 3 concurrent random forest fit, second wave

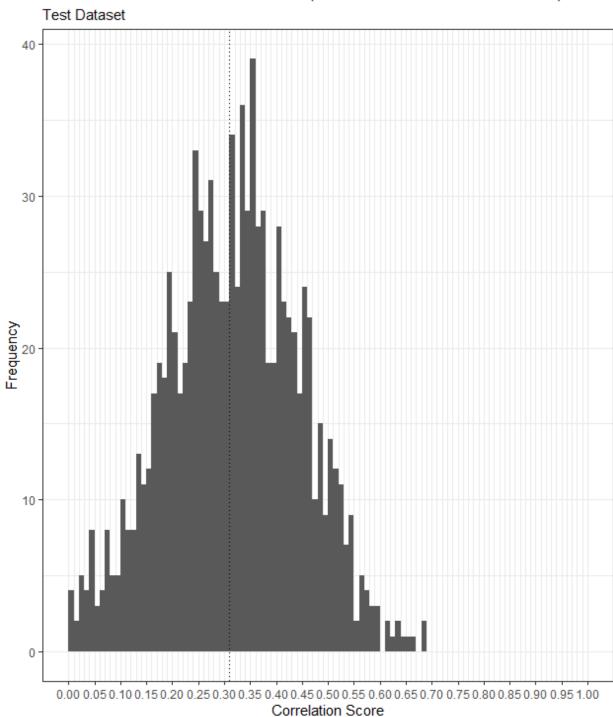


Distribution of Correlation Scores (Mean Correlation Score = 0.27) Test Dataset





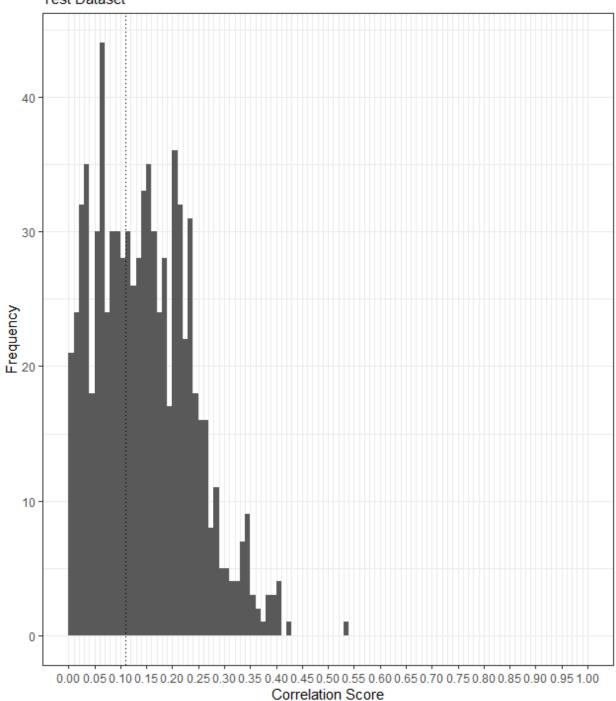
Distribution of Correlation Scores (Mean Correlation Score = 0.23) Test Dataset



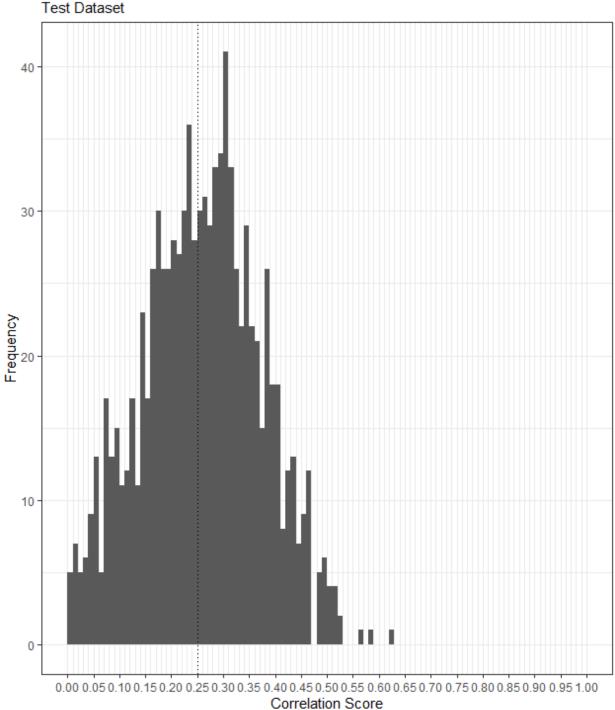
Distribution of Correlation Scores (Mean Correlation Score = 0.31)

Figure C.9: Age 5 concurrent random forest fit, second wave

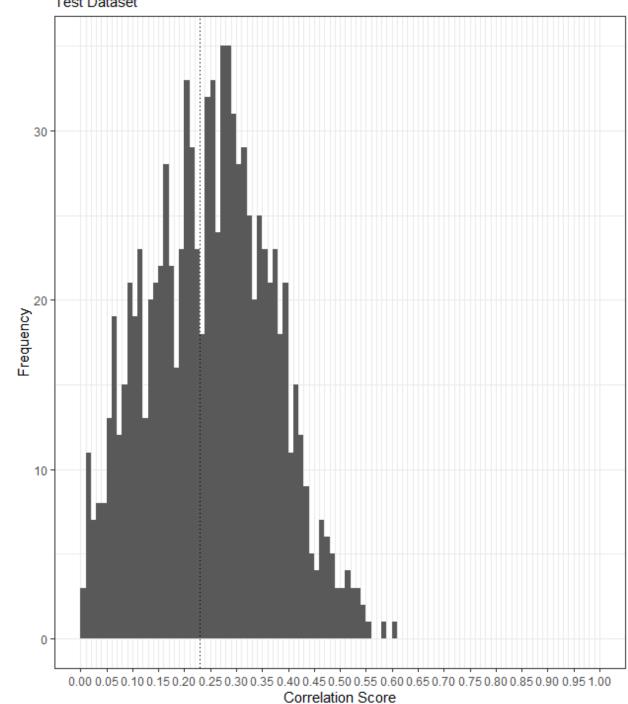
Figure C.10: Age 3 predicting age 4 random forest fit, second wave



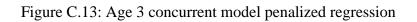
Distribution of Correlation Scores (Mean Correlation Score = 0.11) Test Dataset Figure C.11: Age 3 predicting age 5 random forest fit, second wave

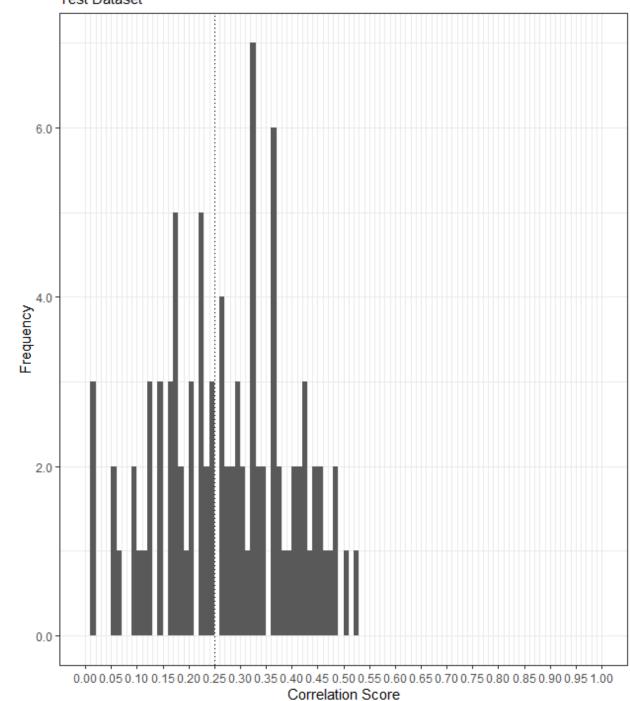


Distribution of Correlation Scores (Mean Correlation Score = 0.25) Test Dataset Figure C.12: Age 4 predicting age 5 random forest fit, second wave



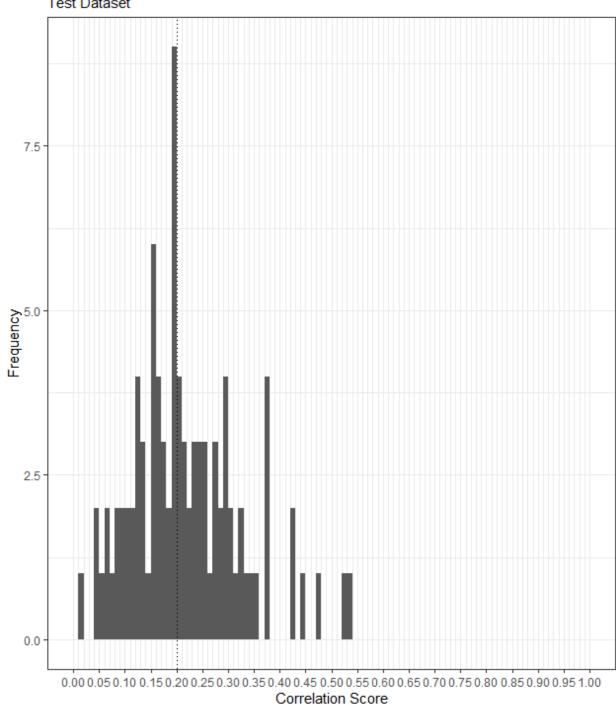
Distribution of Correlation Scores (Mean Correlation Score = 0.23) Test Dataset



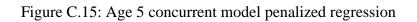


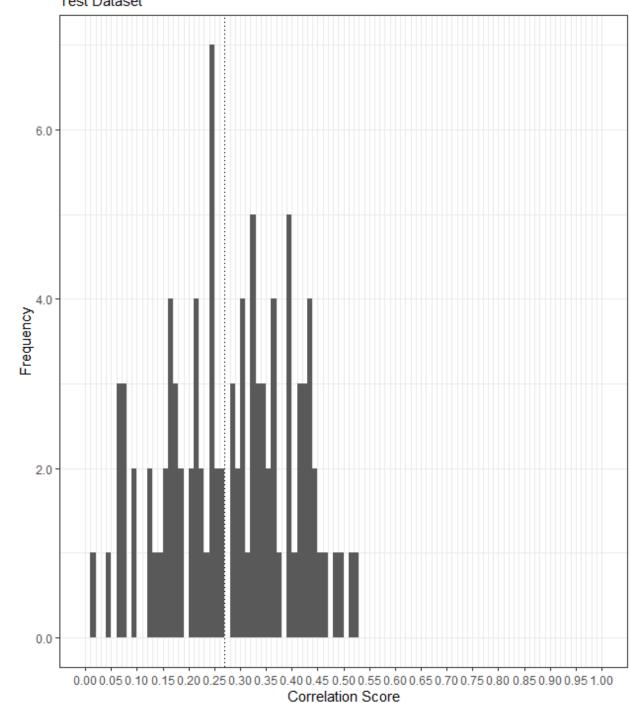
Distribution of Correlation Scores (Mean Correlation Score = 0.25) Test Dataset

Figure C.14: Age 4 concurrent model penalized regression

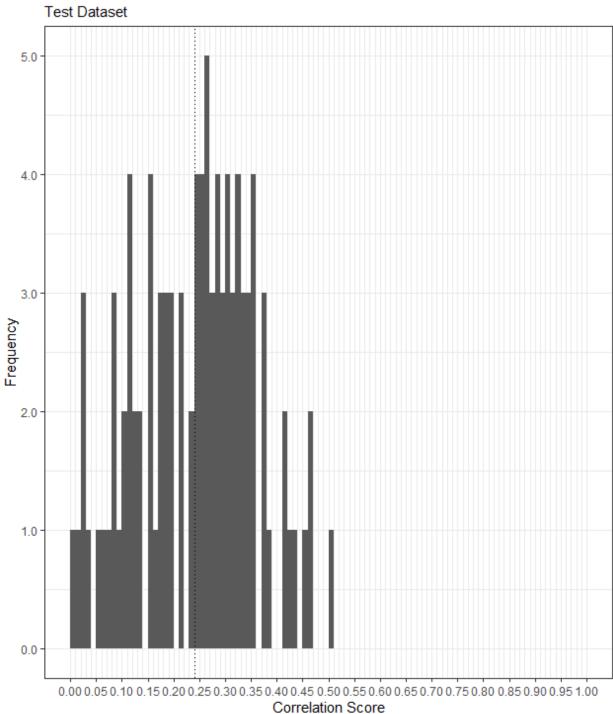


Distribution of Correlation Scores (Mean Correlation Score = 0.2) Test Dataset





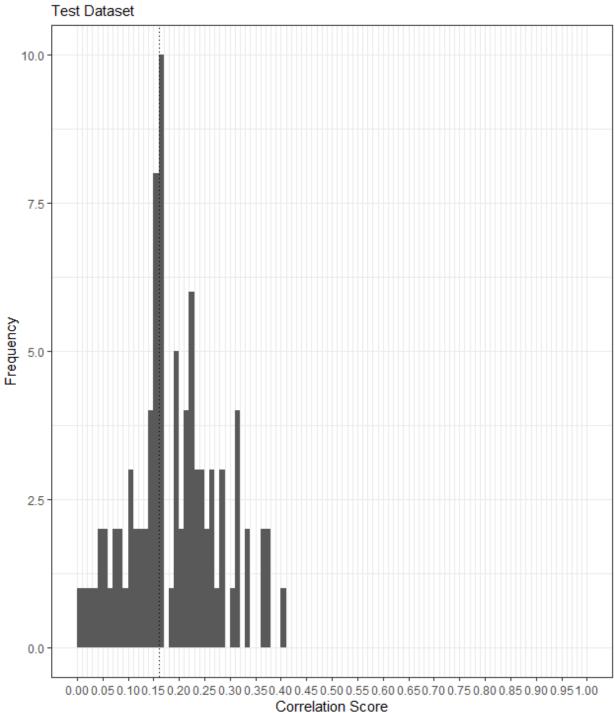
Distribution of Correlation Scores (Mean Correlation Score = 0.27) Test Dataset



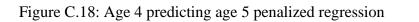
Distribution of Correlation Scores (Mean Correlation Score = 0.24)

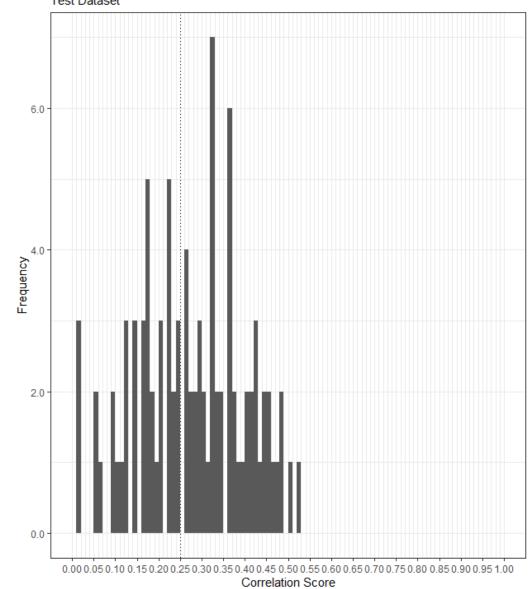
Figure C.16: Age 3 predicting age 4 model penalized regression

Figure C.17: Age 3 predicting age 5 model penalized regression



Distribution of Correlation Scores (Mean Correlation Score = 0.16) Test Dataset





Distribution of Correlation Scores (Mean Correlation Score = 0.25) Test Dataset