Emotion Regulation and Socialization in the Context of Cumulative Risk: Social-Emotional Adjustment in Children Experiencing Homelessness

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Abstract

The acquisition of emotion regulation skills is a key developmental task, largely socialized by caregivers, that lays the foundation for healthy social-emotional adjustment. Unfortunately, both parental socialization and children's self-regulation are disrupted in contexts of high cumulative risk. The current dissertation evaluated emotion regulation and socialization during observed parent-child interaction as predictors of social-emotional adjustment in young children experiencing homelessness. Study 1 used linear regression and latent profile analysis to identify links among child reactivity and regulation, parental affect profiles, and teacher-reported adjustment in the context of risk and adversity. Children's difficulty down-regulating anger during parent-child interaction was linked to more teacher-reported social-behavioral problems. Empirically-derived profiles of parent affect were related to child behavior during the interaction and in the classroom: the minority of parents showing elevated anger had children who were observed to struggle with anger down-regulation and were reported by teachers to have more social-behavioral problems at school. Sociodemographic risk additionally predicted more social-behavioral problems, controlling for child and parent anger expression. Study 2 built on these findings using dynamic structural equation modeling to investigate dyadic interplay between parent and child anger across the problem-solving discussion. Parents and children showed significant stability in anger from one interval to the next, as well as cross-lagged associations consistent with bidirectional feedback processes and significant novel anger reactivity. Individual differences in child anger stability were related to more social-behavioral problems at school. More observed anger contagion, particularly from child to parent, predicted more parent-reported externalizing problems, as did higher family adversity. Results are interpreted in light of theory and research and future directions are discussed.

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Children who grow up in severe poverty are at high risk for a wide range of adversities known to threaten healthy social-emotional development, including housing instability, food insecurity, and exposure to violence (Evans, Li, & Whipple, 2013). These risks are particularly salient for homeless families, who report lower income, higher life stress, and more recent adversity than families who are impoverished but stably housed (Masten et al., 1993; Samuels, Shinn, & Buckner, 2010). Both poverty and homelessness have been linked to impaired social, behavioral, and academic functioning, and some studies suggest worse outcomes for children experiencing homelessness as well as poverty, consistent with elevation on a continuum of cumulative risk (e.g., Cutuli et al., 2013; Masten et al., 1993; Vostanis et al., 1998). Importantly, however, many impoverished children function well despite adversity (Masten & Labella, 2016). Evidence of resilience motivates a search for malleable protective factors that can be targeted to promote healthy development in the context of poverty-related risk.

Candidate protective processes include parenting quality and children's self-regulation skills. Decades of resilience research have converged on high quality parenting as a powerful protective factor for a wide range of risks, including poverty and homelessness (Blair & Raver, 2012; Herbers et al., 2011; Masten, 2001). Unfortunately, parenting is often impaired in the context of poverty-related stress, and has been repeatedly identified as a crucial mediator of the effects of such stress on child outcomes (Conger & Donnellan, 2007; Simons et al., 2016). Similarly, effective emotion regulation (ER) – that is, the modulation of emotional arousal in the service of social interaction and goal directed behavior (Thompson, 1994) – has been shown to buffer children from a wide range of risks (Blair & Raver, 2012; Lengua, 2002). However, poverty-related stress undermines the development of regulatory skills (Blair & Raver, 2012; Evans & English, 2002), and impaired ER has been linked to a wide range of social, emotional, and behavioral problems (Cole & Deater-Dickard, 2009; Eisenberg, Spinrad, & Eggum, 2010). Maintaining adaptive ER in the face of adversity may be a crucial protective process for families facing poverty and homelessness.

Development of ER occurs in the context of the parent-child relationship (Morris, Silk, Steinberg, Myers, & Robinson, 2007; Zeman, Cassano, Perry-Parrish, & Stegall, 2006). Parents play a critical role in shaping children's ER through modeling emotion expression and regulation, explicit teaching, and responses to children's emotion displays. These emotion-related parenting behaviors – termed emotion socialization – teach children familial and cultural norms for appropriate expression and regulation of emotion (Eisenberg, Cumberland & Spinrad, 1998; Eisenberg et al, 2010; Morris et al., 2007). However, most emotion socialization research has been conducted with predominantly white middle-class samples, complicating attempts to generalize findings to other groups (Cole & Dennis, 1998; Cole & Tan, 2015).

Parental influence on ER development holds promise as a target for intervention because of its responsiveness to environmental influence and relevance for adaptive function. Prior interventions have successfully enhanced children's self-regulation by targeting child, classroom, and family processes (Bierman et al., 2008; Bodrova & Leong, 2007; Espinet, Anderson, & Zelazo, 2013; Raver et al., 2011). Research suggests that self-regulation is especially amenable to intervention during early childhood, a period of rapid brain development and heightened neural plasticity (Diamond & Lee, 2011; Zelazo & Carlson, 2012). Furthermore, past prevention programs have effectively improved children's outcomes by changing parenting behavior, confirming that parenting is both dynamic and influential. One relevant program has successfully improved social-emotional functioning in community and clinical samples of Australian preschoolers by training parents to support children's efforts to express and regulate emotion (Havighurst, Wilson, Harley, Prior, & Kehoe, 2010). Again, however, little is known about how these findings relate to ethnically diverse families under substantial sociodemographic stress.

This dissertation addressed significant gaps in existing literature by investigating associations linking emotion expression and regulation during parent-child interaction with young children's social-emotional adjustment in families experiencing homelessness. The dissertation comprises two studies that employed dynamic observational measures of emotion regulation and socialization rather than more commonly used but potentially biased self-report questionnaires. It extended research on emotion socialization to an underrepresented population of families at extreme sociodemographic risk, in hopes of better understanding and supporting adaptive social-emotional development in children and families experiencing severe poverty-related stress.

Study 1

Effective emotion regulation (ER), defined as adaptive modulation of emotional arousal in the service of social interaction and goal-directed behavior (Thompson, 1994), is a powerful predictor of adjustment across domains and throughout the lifespan. In particular, acquisition of skills to regulate negative emotions has been identified as a crucial developmental task that lays the foundation for adaptive behavior and social-emotional health (Blair & Diamond, 2008). Among children, effective ER has been linked to higher social competence, lower internalizing and externalizing behavior, and better academic achievement (Cole, Martin, and Dennis, 2004; Denham et al., 2003; Grazanio, Reavis, Keane, & Calkins, 2007; Eisenberg et al., 2010; Zeman et al., 2006). Additionally, regulatory competence has been shown to buffer effects of risk on children's psychosocial functioning. For example, in study of low-income families with preschool-aged boys, children's regulated responses to simulated adult conflict buffered the association between high interparental conflict and more behavior problems, both concurrently and 1.5 years later (Ingoldsby, Shaw, Owens, & Winslow, 2009). Similarly, in a community sample, the temperamental aspect of self-regulation (effortful control) moderated associations between multiple domains of risk and children's adjustment problems over time (Lengua, Bush, Long, Kovacs, & Trancik, 2008).

ER thus holds promise as a protective factor in the context of cumulative risk. Unfortunately, however, self-regulatory development may be undermined in the presence of stress and adversity (Raver et al., 2004; Blair & Raver, 2012). Higher cumulative risk predicts lower ER in early and middle childhood, with evidence of mediation through disrupted parenting behavior and/or stress-related alterations to neurobiological mechanisms of regulatory control (Blair & Raver, 2012; Evans & English, 2002; Lengua, 2002; Lengua, Honorado, & Bush, 2007; Zalewski et al., 2012). Additional risk factors for emotion dysregulation include interparental conflict, maternal depression, and child maltreatment (Ingoldsby et al., 1999; Feng et al., 2008; Kim & Cicchetti, 2012; Kim-Spoon, Rogosch, & Cicchetti, 2012; Maughan & Cicchetti, 2002; Maughan, Ciccheti, Toth, & Rogosch, 2009; Shields & Cicchetti, 1998, 2001).

Deficits in emotional, behavioral, and cognitive self-regulation have also been identified among young children experiencing homelessness, who are typically exposed to chronic poverty-related risk as well as the acute stressor of residential instability (Masten et al., 1993; Samuels, Shinn, & Buckner, 2010). Self-regulation skills have been consistently linked to positive school adjustment among young homeless children (Herbers et al., 2011; Masten et al., 2012; Obradović, 2010), as well as global resilience among formerly homeless school-age youth (Buckner, Mezzacappa, & Beardslee, 2003; 2009). Taken together, these studies suggest that maintaining adaptive ER development in the face of adversity may be a crucial protective process for children facing poverty and homelessness.

Parental emotion socialization and child regulation

Notably, development of ER occurs in the context of the parent-child relationship (Morris et al., 2007; Zeman et al, 2006). Infants rely almost exclusively on caregivers to externally regulate their emotions (e.g., to soothe distress and frustration by meeting the infants' basic needs). This external regulation is gradually internalized, progressing to dyadic co-regulation as infants become more active in using their caregivers to self-soothe (Eisenberg et al., 2010). Caregivers' contingent responses shape their children's emotion management skills, and over the over the course of development, children are expected to require less external support and become increasingly proficient at self-regulation of their own emotions (Yap, Allen, & Sheeber, 2007; Zeman et al., 2006). School transition is a particularly salient time for children's self-regulatory development, coinciding with brain development supporting cognitive control, increased emotional complexity, individuation from parents, and increased demands on self-regulation at school (e.g., Denham et al., 2003; Zelazo & Carlson, 2012).

The term parental emotion socialization refers to the processes by which caregivers communicate social norms for appropriate expression and regulation of emotion (Eisenberg, Cumberland & Spinrad, 1998; Eisenberg et al, 2010; Morris et al., 2007). Emotion socialization begins in infancy and encompasses many parenting behaviors, including emotion modeling and parental responses to children's emotion displays. Research suggests that social-emotional competence is optimized by predominantly positive emotion expressiveness and supportive responses to emotion displays (Eisenberg et al., 1998; Katz, Maliken & Stetler, 2012; Morris et al., 2007). In contrast, highly negative emotion expressiveness and minimizing or punitive responses to children's emotions have been linked to worse social-emotional functioning and more psychopathology, with associations extending into adulthood (Eisenberg et al., 1998; Katz et al., 2012; Krause, Mendelson, & Lynch, 2003; Morris et al., 2007; Thomas & Meyer, 2007; Ramsden & Hubbard, 2002). Mechanisms of these relations likely include children's internalization of a maladaptive model of emotion regulation, as well as heightened exposure to negative emotion (e.g., while being criticized or punished) without parental assistance to regulate it (Fosco & Grych, 2007).

Limited evidence on high-risk populations suggests that emotion socialization may be altered in contexts of stress and adversity. Low-income parents typically display less positive and more negative emotion (McLoyd, 1990), and are less supportive than middle-income parents in response to their children's emotions (Shaffer, Suveg, Thomassin, & Bradbury, 2012). Income level and poverty-related stress have been linked to negative emotional expressivity in families with preschoolers, both in community

(Zalewski, Lengua, & Fisher, 2013) and low-income samples (Raver & Spagnola, 2003). Similarly, among mother-toddler dyads involved in Early Head Start, maternal demographic risk was related to lower scores on a latent index of positive emotion socialization, including positive expressivity and maternal warmth (Brophy-Herb et al., 2012). Greater parental expression of negative emotion, including anger and fear, as well as more restrictive responses to children's negative expressions, may represent proximal adaptations to a stressful environment that may compromise children's functioning in other contexts (McCoy & Raver, 2011; McLoyd, 1990). Parents who are able to maintain supportive emotion socialization practices in the face of acute stress, such as homelessness, may buffer their children from the effects of adversity (Raver, 2004).

Methodological concerns

Research regarding parental socialization of ER is thus scientifically and clinically valuable. However, it is complicated by several methodological questions. Researchers disagree on the extent to which emotional reactivity can be disentangled from ER (e.g., Gross & Thompson, 2007; Gross & Barrett, 2011; Campos et al., 2004); for example, low affect expression may indicate low emotional reactivity, high ER, or both. On theoretical grounds, however, researchers have argued that emotion reactivity and emotion regulation are separable constructs, with self-regulation serving to modulate reactivity (e.g., Rothbart, Posner, & Kieras, 2006). Others have noted that the reactivity-regulation distinction is clinically meaningful and scientifically useful, despite the inherent difficulty of differentiating them empirically (Cole & Deater-Deckard, 2009; Gross & Barrett, 2011).

Researchers vary in their operationalization of emotional processes. Some researchers have used questionnaire measures of children's emotion regulation, typically completed by parents or teachers (e.g., Maughan, Cicchetti, Toth, & Rogosch, 2007). Others have coded emotion, either globally or dynamically, focusing on aspects of emotional experience such as latency, intensity, frequency, and duration (Calkins & Fox, 2002; Zeman et al., 2006). Dynamic codes are better suited for understanding regulatory processes as they unfold over time, and using multiple measures of ER has proven useful for more precisely delineating affective processes driving global associations. For example, Sheeber and colleagues (2009) found that emotion duration (rather than frequency or intensity) consistently distinguished healthy from depressed adolescents. Additionally, some researchers have productively leveraged person-centered approaches to characterize overall patterns of emotion and ER in both children (Maughan et al., 2007) and parents (Nelson et al., 2012). A profile-oriented approach may be particularly useful in identifying the affective context of negative emotion expression (e.g., does it occur in the context of high or low warmth?) and in distinguishing people who are low in affect overall (e.g., "very low positive" parents from Nelson et al., 2012; "over-controlled" children from Maughan et al., 2007).

Researchers also vary in their operationalization of emotion socialization. Although some researchers have used observations of parent-child interactions to evaluate socialization in real time (e.g., Baker, Fenning, & Crnic, 2010; Garner, 2006; Lunkenheimer, Albrecht, & Kemp, 2013), the field relies heavily on self-report of parenting behaviors (e.g., self-expressiveness and responses to children's emotions). This is potentially problematic, as motivation, mood, and memory-related factors may bias self-reports (DeGarmo, Knutston & Reid, 2006; Power et al., 2013; Radke-Yarrow, 1963). Indeed, in a comprehensive study of the coherence of emotion socialization, mothers' observed emotion coaching did not load with self-reported measures onto a latent factor of emotion socialization behavior (Baker et al., 2010). Existing research suggests modest overlap between self-reported and observed parenting measures, highlighting a need for more observational studies of emotion socialization.

A subset of studies using observational measures have found links between maternal emotion modeling and child outcomes. For example, among toddler-aged children with or without a history of maltreatment, parent positive affect intensity was concurrently related to higher child positive affect and lower child anger, whereas parent negative affect intensity was related to children's lower positive affect, higher anger, and lower effortful control (Robinson et al., 2009). Similarly, among families of preschool-aged children with and without developmental delay, maternal negative affective behavior during parent-child interaction was directly related to more concurrent and future child anger, as well as mother-reported behavior problems two years later (Newland & Crnic, 2011). Less is known about the role of parental emotion modeling in the context of severe poverty-related stress.

The current study

Existing literature thus underrepresents diverse families experiencing high levels of psychosocial risk and is weakened by methodological concerns, including difficulty differentiating emotion reactivity and regulation and an over-reliance on parental self-reports. The current study is designed to build on prior research by evaluating affective dynamics during observed parent-child interaction as predictors of classroom social-emotional adjustment among young children experiencing homelessness. Analyses employ data from School Success in Motion, a series of iterative data collections conducted in collaboration with local emergency shelters for families experiencing homelessness (Masten & Labella, 2016). An overarching goal of this community research partnership is to identify predictors of resilient functioning in young homeless children during school entry (aged four to six years). Thus far, findings have converged on children's cognitive self-regulation skills (i.e., executive functions) and high-quality parenting as promotive/protective factors associated with school success (Herbers et al., 2011; Herbers, Cutuli, Monn, Narayan, & Masten, 2014; Masten et al., 2012; Obradović, 2010).

Prior research by this team has also investigated affective qualities of parent-child interaction as a predictor of classroom adjustment among young children experiencing homelessness. Specifically, Labella and colleagues (2016) found that sociodemographic risk was associated with higher depression and anxiety in homeless parents, which was in turn associated with more negativity when discussing their children. The affective tone of parents' speech was associated with children's affect during a subsequent parent-child interaction, and parental negativity was further associated with less prosocial behavior at school, underscoring the salience of parents' affective expression for children's social-emotional adjustment in this very high-risk population. Contrary to hypotheses, neither parent nor child affective expression predicted teacher reports of children's peer acceptance or externalizing behavior at school (Labella et al., 2016). Limitations of this earlier study include the global nature of its affect codes, which reflected children's overall positive and negative affect over the course of the entire interaction. Global codes are not suited to answer questions about emotion regulation, which involves the dynamics of emotion unfolding over time. Additionally, parental affective expression was coded from speech *about* the child rather than interactions *with* the child, and thus did not reflect active modeling of emotion expression or dynamic responses to the child's own emotions. A relatively modest sample size (n = 138) also limited the size of effects that could be detected.

The current investigation leveraged data from two School Success in Motion studies conducted in summers 2012 and 2014. Both data collections included parent reports of family-level risk factors (sociodemographic risk, experiences of family adversity), video-recorded parent-child interaction tasks, and teacher reports of children's social-emotional adjustment. Interaction tasks were coded using a microsocial affect coding scheme, with parents and children rated by independent coders on three discrete affects (anger, internalizing distress, positive affect) in 10-second intervals across two interaction tasks (a problem-solving discussion and a teaching game). This microsocial approach allowed for fine-grained characterization of parent and child emotion expression as they relate to children's social-emotional adjustment at school. Study 1 took a monadic approach to data analysis, investigating how dimensions of child and parent affect independently and jointly relate to children's social-emotional adjustment at school. This study had three primary aims:

1. To evaluate children's affect reactivity and regulation as predictors of children's emotion regulation and social-behavioral problems at school.
2. To characterize latent profiles of parent affect expression during observed parent-child interaction, including correlations with sociodemographic covariates.

3. To evaluate latent profile membership as a predictor of concurrent child affect and children's social-emotional adjustment at school (independently and jointly with child affect).

With regard to aim 1, I hypothesized that worse regulation (defined as longer duration of anger and distress, shorter duration of positive affect) would be associated with higher sociodemographic risk and adversity, and would predict more teacher-reported social-behavioral problems and lower emotion regulation (net of covariates). Regarding aim 2, I did not have strong a priori hypotheses regarding the number and form of latent profiles, but took an exploratory approach to heterogeneity in parental affective expression. However, I anticipated that some profile(s) would be distinguished by greater preponderance of negative affect, and that these profile(s) would be associated with higher sociodemographic risk, higher family adversity, and higher children negative affect. I also expected that high-negative affect profile(s) and child negative affect expression would each predict more social-behavioral problems and poorer emotion regulation by teacher report.

Method

Participants

Participants were 214 primary caregivers and their four- to six-year old children (54.2% male, mean age 5.8 years, *SD* = .6 years; 62.6% African American, 23.8% multiracial, 5.1% American Indian, 3.7% white, 4.6% other). Participants were recruited from two urban emergency shelters housing the majority of all sheltered families in a midsized Midwestern city. Families were recruited to participate in two protocols over the course of two summers, with 107 eligible families participating each year. Families were eligible to participate if they had a child who was entering kindergarten or first grade and lived in shelter for at least three days (to allow for acute acclimation). Only one child per family participated. Exclusion criteria were insufficient English to complete tasks or severe developmental delay interfering with study completion (e.g., severe autism spectrum disorder). Families were recruited through fliers in mailboxes and informational tables set up during mealtimes.

The current study includes all dyads with affect codes from parent-child interaction (n = 203). Of the 214 participating families across both data collections, 5 did not complete interaction tasks. An additional 6 families were excluded because video-recordings were not at all codable (e.g., faces were out of the frame or backs were to the camera for both interaction tasks). When interaction data was partially complete (e.g., only one task or one dyad member had sufficient data to calculate composites), available data was used.

Procedure

The University of Minnesota institutional review board approved all study procedures. Parents provided informed consent for themselves and their children, and children provided verbal assent. Study sessions took place in dedicated research rooms located in the shelters. These rooms were private and located on a nonresidential floor. Assessors were trained graduate and undergraduate students. Children participated in an hour-long assessment of school readiness skills while parents were interviewed about demographics, child behavior, and stressful life events. Following individual sessions, parents and children participated in a structured sequence of videotaped interaction tasks developed by the Parent Management Training: Oregon Model (PMTO) research team, adapted for use with homeless and highly mobile families (Gewirtz, DeGarmo, Plowman, August, & Realmuto, 2009), abridged to decrease participant burden. In 2012, the parent-child interaction included five tasks and took about 35 minutes. In 2014, the parent-child interaction was further abridged to three tasks (about 15 minutes). Interaction tasks were video-recorded and coded for parent and child affect. Parents received an honorarium and children received a small toy for participation.

With parent permission, teachers were later contacted to report on children's social-emotional adjustment, after children had been in school for at least two months. About 80% of children were successfully located in schools (80.3% in 2012, 78.5% in 2014) and the vast majority of identified teachers completed questionnaires (96.5% in 2012, 94.0% in 2014). Overall, teacher data were available for 75.7% of the combined sample.

Measures

Parent and child affect. During videotaped interactions, dyads engaged in a series of structured tasks designed to elicit mutual enjoyment, limit setting, communication, cooperation, and competitive play (DeGarmo, Patterson, & Forgatch, 2004). Two tasks (problem-solving discussion and marble maze) were selected for the current study and coded for parent and child affective expressions. These tasks were selected because they were available across both protocols and expected to elicit a range of emotional expressions (i.e., more distress and anger during the conflict discussion, more positive affect during the marble maze).

Interaction tasks were coded using a microsocial coding system adapted from manuals used by Dr. Amanda Morris at Oklahoma State University in previously published research on parent-child interaction (Morris et al., 2011; Cui, Morris, Harrist, Larzelere, & Criss, 2015). Dr. Morris and her research team also provided consultation on training and reliability procedures. Independent coding teams were trained to rate intensity of one affect (anger, internalizing distress, positive affect) on a five-point scale (from *1 – none* to 5 – *very strong*). Different coders were responsible for rating affect in the parent and the child to minimize shared rater bias. Intensity of each affect (anger, internalizing distress, and positive affect) was coded for each dyad partner (parent and child) in ten second intervals across the two interaction tasks. Each task took approximately five to six minutes, resulting in ten to twelve minutes of codable interaction per dyad. Occasionally, tasks ended early at the participants' request or were prolonged due to examiner error (e.g., examiner returned to the room after seven minutes of problem-solving discussion rather than five minutes; examiner gave more participants more time for game play than allotted in the protocol). Individual intervals were coded as missing if there was no evidence of a given affect from a given dyad member *and* the individual was not codable for 5 or more seconds of the 10 second interval (e.g., moved off screen, turned away from the camera so their face was not visible, etc.). If a person's face was not visible but there was evidence of a given affect in body language or voice (e.g., nervous body movements, raised voice), the given affect was coded based on available information. This resulted in somewhat different numbers of missing intervals across affects.

Affect coding teams were composed of one graduate and three undergraduate coders; the distress team additionally included a B.A.-level study coordinator. The first author served as anchor coder for all affects. Inter-rater reliability was calculated using intra-class correlations (*ICC*s) with two-way random effects (appropriate when a subset of coders do reliability ratings on a subset of participant data; McGraw & Wong, 1996). Each coder achieved good reliability with the anchor coder [*Intraclass correlation* (*ICC)* ≥ .75] on practice tapes derived from a prior data collection before coding interaction tasks for the present study (Koo & Li, 2016). Twenty percent of videotapes were randomly selected for double coding. Discrepancies were discussed and resolved by consensus at weekly reliability meetings to minimize rater drift. When available, consensus codes were used for analyses. Inter-rater reliability of child affect codes ranged from moderate to good (*ICC* = .67 for anger, .77 for distress, .89 for positive affect), as did inter-rater reliability of parent affect codes (*ICC* = .70 for anger and distress, *ICC* = .86 for positive). Lower inter-rater reliability for anger and parent distress likely reflect lower variability in these affect ratings.

For dyads with any affect data, number of codable discussion intervals ranged from 1 (parent anger) to 46 (parent anger, distress, and positive); mean discussion duration ranged from 31.4-34.1 intervals (corresponding to 5.2-5.7 minutes) depending on the affect. Number of codable game intervals ranged from 3 (parent anger, child positive) to 97 (parent anger, distress, and positive); mean game duration ranged from 31.3-32.6 intervals (corresponding to 5.2-5.4 minutes) depending on the affect. Overall affect indices were calculated for a given dyad partner in a given task provided that at least 20 intervals (corresponding to 3.33 minutes) were codable, in order to ensure that composites were drawn from relative stable estimates. Number of participants meeting this threshold ranged from 184 (parent anger) to 197 (parent and child distress) for the discussion, and from 191 (child positive) to 197 (child distress) for the game.

Two distinct measures of emotion dynamics were derived for each child affect (Calkins & Fox, 2002). Maximum intensity (i.e., highest affect rating from 1 to 5) was used to capture affect reactivity, whereas affect regulation was indexed by maximum duration (i.e., the highest number of consecutive intervals with an intensity rating ≥ 3, corresponding to *clear*, *strong*, or *very strong* levels of affect, divided by the number of intervals in the interaction). Given typical regulatory goals of minimizing negative emotions and cultivating positive emotions (Rottenberg & Gross, 2007), longer duration of anger and distress is believed to reflect regulatory weakness, whereas longer duration of positive affect is interpreted as adaptive regulation. Reactivity and regulation measures were calculated for each task separately as well as the interaction overall.

Mean intensity ratings were derived for each parent affect separately by task, in order to capture differential emotion demands of a conflict discussion versus collaborative game. Mean intensity scores were selected for latent profile analysis (LPA) as normally distributed, efficient indicators of overall affective expression. Although this strategy does not differentiate between reactivity and regulation, it is appropriate for LPA because it limits the number of indicators required and avoids violations of normality.

Sociodemographic risk. In both protocols, parents reported sociodemographic information, including education, employment status, and history of homelessness. Ten binary risk factors previously identified as relevant to disadvantaged families (single parent; four or more children in the household; parent under 18 at birth of first child; primary caregiver has less than high school education; primary caregiver unemployed; family unable to afford rent; lived in substandard housing; lived in unsafe neighborhood; target child has lived at five or more addressed; primary caregiver homeless three or more times) were summed to create a cumulative sociodemographic risk score for each family (Obradović et al., 2012).

Family adversity. In both protocols, parents reported on their child's lifetime experience of stressful life events using the Lifetime Events Questionnaire (Masten et al., 1993, Cutuli et al., 2010). Consistent with previous research (Labella, Narayan, McCormick, Desjardins, & Masten, 2017), ten items were selected to reflect adverse experiences within the family unit (death of parent; death of brother or sister; inter-parental conflict; parental separation or divorce; parental substance abuse problem; parental mental illness; parental physical illness; parental incarceration; foster care; prolonged parent-child separation). Endorsed items were summed to create a cumulative family adversity score for each family.

Child social-emotional adjustment in the classroom. Teachers reported on children's social-emotional adjustment using standard questionnaires.

Emotion regulation. In both protocols, teachers completed the emotion regulation subscale of the Emotion Regulation Checklist (ERC; Shields & Cicchetti, 1997). The emotion regulation subscale consists of eight items rated on a 4-point scale reflecting the degree to which the child is able to behave appropriately in the context of strong emotion ($\alpha = .80$).

Total problems. In both protocols, teachers completed the conduct problems, emotional symptoms, hyperactivity, and peer problems subscales of the Strengths and Difficulties Questionnaire (SDQ; Goodman, 1997). Each subscale consists of five items rated on a 3-point scale from *Not true* to *Certainly true.* Using standard scoring procedures, item scores are summed to form subscale scores, which are in turn summed to form a total problems composite. The total problems score, reflecting all social-behavioral problems reported by the teacher (possible range 0-40), is the primary endpoint for this measure (α = .87), with planned follow-up testing by problem domain to clarify significant findings.

Covariates. Parents provided information on age and sex of parents and children. Protocol (2012 or 2014) and shelter type (public or private) were included as additional covariates.

Plan for analysis

All analyses were conducted in Mplus, Version 8 (Muthén & Muthén, 1998-2017). To address aim 1, social-emotional adjustment outcomes were regressed on children's reactivity and regulation, controlling for relevant covariates. Parameters were estimated using maximum likelihood with robust standard errors (MLR) to account for mild non-normality in social-behavioral problems.

To address aim 2, latent profile analysis was conducted using mixture modeling in Mplus (Muthén & Muthén, 1998-2017). Mixture modeling is a model-based clustering technique that assumes sample data was generated by a mixture of heterogeneous component distributions, or classes (Berlin, Williams & Parra, 2014; Masyn, 2013). These latent classes, whose number and size are unknown a priori, are treated as qualitatively distinct subgroups. The underlying statistical model sets mixture modeling apart from sample-specific clustering approaches, such as *k*-means cluster analysis, and facilitates evaluation of model fit and extension of parameter estimates to data from other samples. Additionally, mixture modeling allows for probabilistic classification of individual observations based on parameter estimates and observed scores (Berlin et al., 2014; Vermunt & Magidson, 2002).

Latent profile analysis (LPA) refers to a special case of mixture modeling involving a latent categorical variable (i.e., class membership) and continuous manifest variables, or indicators. As with other forms of mixture modeling (e.g., latent class analysis or LCA), model estimation for LPA is accomplished by treating class membership as missing data assuming MAR (i.e., missing at random; Dempster, Laird, & Rubin, 1977; Little & Rubin, 2002). Values for missing data (i.e., class membership) are obtained by maximizing the likelihood function (i.e., choosing the parameters whose values maximize the probability of observing what was in fact observed). This is accomplished with the expectation-maximization algorithm (EM), an iterative estimation procedure that begins with a random split and converges on ML solutions over time (Dempster et al., 1977; Masyn, 2013).

As with LCA, class enumeration for LPA involves fitting a series of *k*-class models beginning with a one-class model and increasing *k* until models are not well-identified. Poor model identification is suggested by failure to replicate best log-likelihood value across random start values, model non-convergence, and very small estimated class size (e.g., <5% of the total sample, suggesting over-extraction; Masyn, 2013). LPA enumeration differs from LCA enumeration in that continuous manifest indicators require specification of within-class variance/covariance structure. Iterative *k*-class enumeration is undertaken for each of four possible variance/covariance structure: diagonal/class invariant (i.e., classes have the same variance and do not covary; most restrictive option), diagonal/class varying, non-diagonal/class invariant, and non-diagonal/class-varying (least restrictive, often fails to converge). The best-fitting *k*-class solution is selected from each and directly compared on a range of fit measures.

There are no consensual measures of absolute fit in use for latent profile models. Instead, models are compared to an absolute fit benchmark model (i.e., fully saturated in terms of sample means and covariances but assuming all higher-order moments have values of zero). This fully-saturated model is equivalent to the 1-class solution for the class-invariant, non-diagonal specification.

Models are also evaluated on several indicators of relative fit. First, the Likelihood Ratio Test Statistic (LRTS) compares log-likelihoods (*LL*) of nested models (*k*-1-class versus *k*-class), with a significant difference favoring the more complex model. The distribution of the LRTS can be analytically derived using Lo, Mendel, and Rubin's (2001) extension of Vuong's (1989) theorem, and can be empirically derived using bootstrapping (Masyn, 2013; Muthén & Muthén, 1998-2017). Additionally, information-heuristic criteria incorporate information on model fit (i.e., maximum log-likelihood value) with a penalty for number of parameters, balancing model parsimony with complexity. Four information-heuristic criteria with slightly different complexity penalty were evaluated here (Akaike information criterion, or AIC; Bayesian information criterion, or BIC; consistent Akaike information criterion, or CAIC, and the approximate weight of evidence criterion, or AWE). In all cases, lower values indicate better relative fit. The Bayes Factor (*BF*), derived from the BIC, directly compares two models (which need not be nested) and quantifies which is more likely to be the true model, assuming one of the models is true. Specifically, the *BF* represents the ratio of Model A's probability of being true to Model B's probability of being true, with *BF* ratios of 1-3, 3-

10, and greater than 10 representing weak, moderate, and strong evidence, respectively, for a given Model A (Masyn, 2013; Nagin, 1999). Similarly, the approximate correct model probability (*cmP*) uses the BIC to approximate the probability of Model A being the correct model relative to a set of *J* models, assuming that the true model is in fact one of the models being considered (Masyn, 2013; Nagin, 1999).

After identifying a subset of well-fitting candidate models, solutions are further evaluated in terms of theoretical interpretation and classification diagnostics. Useful models are characterized by a high degree of class homogeneity (i.e., similarity of response patterns within class) and class separation (i.e., dissimilarity of response patterns across classes). Adequate homogeneity and separation are particularly important when latent class assignment is intended for use in subsequent analysis (Collins & Lanza, 2010), as in the current study. Classification diagnostics are based on posterior class probabilities, that is, individuals' model-estimated probabilities of being in each of the latent classes. Relative entropy summarizes the overall precision of classification across all latent classes and ranges from 0 (chance-level) to 1 (perfect classification; Ramasway, DeSarbo, Reibstein, & Robinson, 1993). Average posterior class probability indexes classification uncertainty for each of *k* classes among individuals modally assigned to class *k*, with *AvePP* > .70 considered indicative of adequate assignment accuracy and class separation (Masyn, 2013; Nagin, 2005). The odds of correct classification ratio (*OCC*) divides the odds of correct classification based on modal class assignment (derived from *AvePP*) by the odds of correct classification based on random assignment using model-estimated class proportions. An *OCC* of 1.0 indicates chance-level performance, and an *OCC* greater than 5.0 indicates good class separation and high classification accuracy. Finally, modal class assignment proportion (*mcaP*) indicates the proportion of individuals in the sample modally assigned to a given class, and can be compared to model-estimated class proportions as another class-specific index of classification certainty. After weighing classification diagnostics, the selection of the final unconditional measurement model is guided by theoretical considerations, notably the clarity, meaning, and interpretability of resultant classes (Bergman & Trost, 2006; Magnusson, 1998).

After a final *k*-class solution is identified, associations between the latent classes and auxiliary observed variables were explored. Historically, this has often been accomplished by treating modal class assignments as observed variables in a subsequent analysis. This post-hoc "classify-analyze" approach is problematic because it ignores measurement error in modal class assignment (Masyn, 2013; Tueller, Drotar, & Lubke, 2011). On the other hand, simultaneous estimation of the latent class measurement model and structural associations with auxiliary variables can result in undesirable shifts in classification, with putative "outcome" variables substantially altering the latent class variable in question. Multiple 3-step approaches have been proposed to remedy this problem (Bray et al., 2014; Lanza et al., 2013; Vermunt, 2010), but simulation studies indicate these methods fail to resolve shifting classes in certain situations (i.e., when predicting continuous outcomes, particularly when entropy is low and the distal outcome has unequal variance across classes; Asparouhov & Muthen, 2014, 2015). The current study uses the modified Bolck-Croon-Hagenaars (BCH) method (Bakk, Tekle, & Vermunt, 2013; Asparouhov & Muthen, 2014, 2015; Vermunt, 2010), which estimates auxiliary models using weights for each observation based on measurement error.

Provided that entropy is sufficiently high, all BCH weights will be positive and the method can be used to estimate arbitrary secondary models with any number and types variables. In the current analysis, the BCH method will be used to investigate class differences in sociodemographic variables, child affect parameters, and children's social-emotional adjustment at school.

Missing data. The proportion of missing data from the shelter session was minimal, ranging from 0% (sociodemographic risk and family adversity) to 6.5% (child affect). Teacher data were available for 75.7% of the sample (77.6% from the 2012 protocol and 73.8% from the 2014 protocol). This rate of missingness is typical for studies following highly mobile families, even with helpful information from families about best ways to stay in touch. Homeless and highly mobile families move frequently, often regionally but sometimes out of state, and often change their contact information for a variety of reasons, including safety. Missingness of teacher data is unlikely to reflect the child's social-emotional adjustment or systematically bias analyses, permitting the assumption that data are missing at random (MAR). Full information maximum likelihood (FIML) estimation was used to generate unbiased parameter estimates making full use of available data assuming the data are at least MAR (Peng et al., 2006).

Results

Aim 1: Child reactivity and regulation

Descriptive statistics and bivariate correlations are presented in Table 1. Maximum intensity of child distress ranged from 3 to 5, indicating that all children displayed *clear* to *very strong* distress at least once across the entire parent-child interaction; task-specific frequencies indicated that this was driven by normative distress during the problem-solving discussion rather than the teaching game. Maximum intensity of anger ranged from 2 to 5 and was approximately normally distributed. Maximum intensity of positive affect covered the full range (1-5) but showed evidence of a ceiling effect, with about half the sample (48.6%) receiving the highest positive rating at least once across the interaction. Maximum duration of each affect (adjusted for overall length of interaction) showed evidence of positive skew. Maximum duration of anger distress ranged from .01-.52, indicating that children's longest bouts of distress ranged from 1% to 52% of the parent-child interaction; task-specific frequencies revealed that three children showed unremitting distress for the entirety of the problem-solving discussion. Maximum duration of child anger ranged from .00-.22, and maximum duration of child positive affect ranged from .00-.45.

Reactivity and regulation measures were moderately to strongly correlated within affect (r = .43-.68, all p's < .001). Anger and distress parameters were modestly inter-correlated. Contrary to expectations, affect reactivity and regulation were not significantly related to sociodemographic risk or family adversity, nor were they linked to child sex. Anger intensity and duration were modestly higher among younger children and children staying at the public shelter. Maximum child distress was significantly related to protocol such that lower distress was observed in summer 2014.

Regarding classroom social-emotional adjustment, teacher-reported total problems were significantly related to higher anger intensity, longer anger duration, and higher sociodemographic risk. As expected, teacher reports of adaptive emotion regulation were strongly associated with lower social-behavioral problems. Emotion regulation was higher among female children and children staying at the private shelter.

Contrary to hypotheses, teacher-reported emotion regulation was not significantly related to children's affect reactivity and regulation.

Overall, findings supported further investigation of associations linking measures of child anger expression with teacher-reported social-behavioral problems, but not emotion regulation. Multiple regression models were specified using maximum likelihood estimation with robust standard errors, entering anger intensity and duration together on the first step. To ensure robustness of results, covariates and affect variables showing bivariate associations with anger expression and/or social-emotional behavior problems were entered on the second step; this included child distress intensity and duration, child age, protocol, and sociodemographic risk. Follow-up analyses were planned to probe significant findings, first by replacing total social-behavioral problems with subscale scores (emotional symptoms, conduct problems, hyperactivity problems, peer problems), and second by replacing overall anger expression parameters with task-specific parameters.

Multiple regression results predicting total social-behavioral problems are presented in Table 2. When entered together, duration of child anger, but not maximum anger intensity, significantly predicted total problems ($\beta = .31$, $p < .01$). This association was robust to covariates in Step 2 ($\beta = .34$, $p < .01$); social-behavioral problems were additionally related to higher sociodemographic risk ($\beta = .16$, $p = .05$). Planned follow up analyses revealed that, controlling for covariates, duration of child anger was positively related to each problem domain, although size and significance of the association varied ($\beta = .36$, $p < .001$ for peer problems; $\beta = .22$, $p < .05$ for hyperactivity; $\beta = .32$, $p = .06$ for emotional symptoms; $\beta = .18$, $p = .08$ for conduct problems). Follow-up testing comparing the magnitude of regression coefficients (Paternoster, Brame, Mazerolle, & Piquero, 1998) indicated that the strength of the relation with anger duration did not vary significantly by domain (maximum $z = 1.28$, $p = .20$). Overall, follow-up analyses suggested that child anger duration is a non-specific risk factor for social-behavioral problems at school.

Finally, planned follow-up analyses were conducted regressing total social-behavioral problems on two task-specific variables denoting anger duration in problem-solving discussion and game, respectively. Child anger duration during the problem-solving discussion, but not the game, was significantly and robustly related to social-behavioral problems at school.

Aim 2: Latent profile analysis of parent affective expression

Latent profile analysis was undertaken to characterize heterogeneity in parent affective expression with the goal of identifying parental profiles associated with child affect and social-emotional adjustment at school. Given documented associations between children's anger duration and teacher-reported social-behavioral problems, I was particularly interested in identifying patterns of parental affect expression associated with prolonged child anger. Descriptive statistics and bivariate correlations linking parental affect to demographic covariates and adjustment outcomes are presented in Table 3. Parent affect showed moderate inter-relations across task ($r = .26$-$.46$, $p < .01$), with scattered associations across different affect types. Child anger duration was related to higher parental anger expression, primarily during the discussion, as well as lower parental positive affect.

A series of latent profile models were fit for each of four variance-covariance structures (Table 4): diagonal/invariant (i.e., indicator covariance set to zero, indicator variance constrained to be equal across classes), diagonal/class-varying (i.e., indicator covariance set to zero, indicator variance allowed to vary across classes), non-diagonal/class-invariant (i.e., indicators allowed to covary, indicator variance constrained to be equal across classes), and non-diagonal/class-varying (i.e., indicators allowed to covary, indicator variance allowed to vary across classes). Because the log-likelihood surface for mixtures is often multimodal, multiple random sets of starting values were used to replicate the maximum log-likelihood, in order to better distinguish between a global versus local solution (Masyn, 2013). Within each variance-covariance structure, *k*-class models were compared to each other and the fully-saturated model (i.e., the non-diagonal one-class solution), which provides a benchmark of absolute fit. Models were compared on measures of relative fit and best-fitting candidate models were selected for each variance-covariance structure. No candidate model was advanced from the non-diagonal/class-invariant structure, as all *k*-class models ($k > 1$) failed to converge on a stable solution. Across variance-covariance structures, the data did not support extraction of very many classes, with many higher-order class models failing to replicate log-likelihood. Given the absence of viable higher-class solutions, it was often impossible to calculate Likelihood Ratio Test Statistic and Bayes Factor ratios comparing model *k* and k+1. Based on information criteria and Bayesian-derived comparison statistics, best-fitting candidate models represented two-class (diagonal/class-varying; non-diagonal/class-varying) and three-class solutions (diagonal-class invariant).

The three candidate models were further evaluated based on relative fit, theoretical considerations, and classification diagnostics (Table 5). The two-class non-diagonal/class-varying solution showed the poorest fit on all relative fit indicators, with the exception of AIC; AIC is susceptible to over-extraction and underperforms relative to BIC in mixture modeling contexts (Masyn, 2013). The non-diagonal/class-varying structure imposes no restrictions on indicator variances and covariances, requiring more than double the number of parameters to be estimated (*npar* = 55) compared to the other two candidate models. The two-class non-diagonal/class-varying solution was eliminated from consideration due to poor relative fit indices and lack of parsimony.

The remaining two candidate models (two-class diagonal/class-varying solution and three-class diagonal/class-invariant solution) had similar model complexity. Although the three-class solution requires an additional class to be estimated, a similar number of parameters are required (*npar* = 26 vs. 25) because only one set of indicator variances are estimated in the class-invariant structure. The diagonal/class-varying solution outperformed the diagonal/class-invariant solution in terms of relative fit, with lower information and higher Bayes Factor ratio compared to the saturated model. Classification diagnostics were generally adequate for both solutions: modal class assignment was commensurate with modal-estimated proportions and class-specific assignment accuracy was high (all *avePP* > .80, all *OCC* > 5.00). Overall entropy was higher for the diagonal/class-invariant solution (.86 versus .69), suggesting that global precision and accuracy may be better when estimating three invariant classes. Entropy is not typically heavily weighted during class enumeration, but is germane in the present instance due to planned analyses relating latent classes to auxiliary variables using the modified BCH method. This multistage classify-analyze approach requires well-separated classes, and the BCH method is sensitive to low entropy; indeed, exploratory analyses indicated that the BCH method was incompatible with the diagonal/class-varying solution because low entropy introduced negative weights.

Regarding theoretical considerations, both models yielded interpretable classes, summarized in Table 6. In the diagonal/class-varying solution, class one (69.1% estimated class proportion) was characterized by higher positive affect, lower anger, and less distress relative to class two (30.9%). Estimated variances for all four anger and distress parameters were substantially higher in class two, whereas the estimated variance of positive affect during the discussion (but not game) was higher in class one. The diagonal/class-invariant solution yielded three classes, with class two of the diagonal/class-varying solution subdividing into two smaller classes reflecting a preponderance of parental anger primarily during the discussion (class one, estimated class proportion 8.7%) versus a preponderance of parental distress across tasks (class two, estimated class proportion 10.8%). The third class (81.4%) was distinguished by -higher positive affect across tasks, similar to class one of the diagonal/class-varying solution. Comparison of class proportions indicated that some parents in class two of the diagonal/class-varying solution moved into the positive affect class (class three) of the diagonal/class-invariant solution. Variances were constrained to be equal across classes, and were higher for distress during the discussion and positive affect across both tasks.

After weighing relative fit indices, theoretical considerations, and classification diagnostics, the three-class diagonal/class-invariant solution was selected as the final model. Although relative fit indices were not as favorable as the two-class/class-varying solution, both models fit the data well. The diagonal/class-invariant solution was felt to be more interpretable, as differences in affect variances across groups were not predicted or readily explained. A three-class solution differentiating parental anger from parental distress is theoretically meaningful, given the distinct functions of discrete negative emotions. I expected that distinguishing anger propensity from distress may also be informative in predicting specific patterns of child affect (i.e., duration of child anger) found to be associated with children's social-emotional adjustment in Aim 1. Finally, higher entropy of the diagonal/class-invariant solution renders the BCH method feasible for subsequent analysis relating latent profiles to covariates and child outcomes. Thus, the three-class diagonal/class-invariant solution was advanced to the analyze-classify stage, with three profiles described in terms of predominant affect: Parental Anger, Parental Distress, and Parental Positive Affect. The three-class solution was used to generate BCH weights, which were then used in secondary models relating class membership to auxiliary variables. As described above, the BCH method incorporates class assignment error into secondary model estimation while minimizing latent class-shifting with the inclusion of auxiliary variables.

First, a series of exploratory models were estimated to identify sociodemographic predictors of latent class membership. The latent class membership variable was regressed on each of the following potential covariates: protocol, shelter, child age, child sex, parent age, parent sex, sociodemographic risk, and family adversity. For each model, a Wald statistic was computed as an omnibus test of overall association between the covariate and the latent class variable. To probe a significant effect, pairwise comparisons of class-specific means were examined. Alpha was set at .01 to adjust for multiple testing while also being conservative in identifying potential confounding variables for inclusion in subsequent tests of parent-child affect associations. Unexpectedly, latent class membership was not significantly related to any of the sociodemographic variables.

Aim 3. Relating parental affect profiles to child affect and social-emotional adjustment.

Associations between parental affect profiles and adjusted duration of child affect were tested sequentially using the BCH method and Wald test. Follow-up analyses were planned to probe task-specific affect durations for any significant results. Latent profiles did not differ significantly in terms of children's distress duration (Wald = 2.22, $p = .33$) or positive affect duration (Wald = 2.43, $p = .30$). They did differ significantly in terms of children's anger duration (Wald = 10.28, $p = .006$). Pairwise comparisons indicated that the Parental Anger profile was associated with longer maximum duration of child anger expression ($M = .07$, corresponding to 7% of the interaction), compared to both the Parental Distress profile ($M = .02$, pairwise comparison $p = .002$) and the Parental Positive profile ($M = .02$, pairwise comparison $p = .001$). Parental Distress and Positive profiles did not differ from each other. Planned follow-up analyses indicated that this finding held for child anger duration during the discussion (Wald = 12.50, $p = .002$) but not the game (Wald = 4.27, $p = .12$).

Parental affective profiles were then evaluated as predictors of children's social-emotional adjustment at school. Similar to child findings, parental profiles were significantly associated with teacher reports of classroom social-behavioral problems (Wald = 51.07, $p < .001$) but not emotion regulation (Wald = 2.83, $p = .24$). Planned follow-up analyses by problem domain indicated that parental profiles were associated significantly associated with peer problems (Wald = 7.85, p = .02) and marginally with conduct problems (Wald = 5.30, p = .07), again such that parents in the Parental Anger profile had children with higher teacher-reported problems. Parental profiles were not significantly related to children's hyperactivity (Wald = 1.70, p = .43) or emotional symptoms (Wald = 2.53, p = .28) based on teacher report.

Regression mixture modeling was used to evaluate parent and child affect as joint predictors of social-behavioral problems (Asparouhov & Muthen, 2015). Given its known associations with teacher-reported social-behavioral problems, sociodemographic risk was included as a covariate. Class membership was regressed on child anger duration during the discussion, and total social-behavioral problems was regressed on child anger duration and sociodemographic risk (depicted in Figure 1). As before, parental anger profile was significantly related to child anger duration (class 1 vs. class 2: b = 18.95, p < .01; class 1 vs. class 3: b = 17.35, p < .01). However, results indicated that neither parental profile (Wald = 1.95, p = .38) nor child discussion anger duration (b = 23.46, p = .44) significantly predicted total social-behavioral problems, suggesting that total problems were related to variance shared between child and parent anger expression. Sociodemographic risk weakly predicted total problems adjusting for parental profile and child discussion anger duration (b = .87, p = .04).

Discussion

The purpose of this study was to clarify relations among child reactivity and regulation, parental affect profiles, and children's social-emotional adjustment in a very high-risk sample. I anticipated that child and parent affective patterns would be related to higher sociodemographic risk and family adversity, the other dyad member's affect, and children's social-emotional adjustment at school. These hypotheses were partially supported. Unexpectedly, no child affect variable was related to teacher-reported emotion regulation, and neither child distress nor positive affect associated with children's social-emotional adjustment at school. However, children's difficulty downregulating anger was uniquely linked to more teacher-reported social-behavioral problems, controlling for covariates. This association was driven by child affect during the problem-solving discussion, rather than the game, highlighting the relevance of anger regulation when the dyadic system is under stress.

Planned follow-up testing revealed associations between child anger duration and higher problems across domains, although they varied in magnitude and significance. The modest and nonsignificant effect for conduct problems ($\beta = .18$) was somewhat surprising, given its theoretical relevance to anger dysregulation. However, this should be interpreted with caution, as regression coefficients for problem domains were not significantly different from each other. Overall, findings provide valuable insight into emotional processes linked with social-behavioral problems at school among young children at high psychosocial risk. Specifically, anger duration emerged as a robust predictor of social-behavioral problems in young homeless children across multiple problem domains, suggesting that difficulty downregulating anger may be an important target for intervention among young children experiencing severe poverty-related stress.

Few sociodemographic covariates were related to child affect at the bivariate level, although anger expression was modestly lower among older children, likely reflecting age-related gains in self-regulatory functioning (Zelazo & Carlson, 2012). Anger expression was also higher among children staying in the public shelter. Of note, compared to the private shelter, the public shelter enforces fewer behavioral restrictions, houses more people, has more short-term stays, and allots less space per family (i.e., family rooms versus family apartments) in order to meet substantial community need. As such, the public shelter may be experienced as more chaotic by resident children and families. Additionally, in the current study, families at the public shelter reported more experiences of family adversity in the target child's lifetime, suggesting that public shelter residence may function as an additional indicator of psychosocial risk. Regarding classroom adjustment, public shelter residence was associated with more hyperactivity and worse emotion regulation. Sociodemographic risk was linked to more social-behavioral problems.

Overall, associations with family-level risk factors illustrated links among higher family risk, child anger expression, and adjustment problems at school. Sociodemographic risk and public shelter residence were particularly relevant for children's self-regulation of emotion, behavior, and attention. Similar patterns were observed in prior research with this sample (Labella et al., 2017), which found that sociodemographic risk predicted higher child externalizing symptoms (particularly those related to hyperactivity). In this previous study, parenting interacted with risk such that higher quality parenting predicted lower externalizing behavior only when sociodemographic risk was comparatively low (i.e., more than .8 standard deviations below the mean in this uniformly high risk sample). This suggests that promotive effects of parenting on behavioral regulation may be overwhelmed at extreme levels of sociodemographic risk (Labella et al., 2017). Taken together, these findings emphasize the relevance of variations in sociodemographic risk for child adjustment, even among families who are all at very elevated risk compared to the general population.

Additional findings from the current study include the identification of three parental profiles, characterized by above-average Parent Anger (especially during the discussion), Parent Distress, and Parent Positive Affect. Importantly, the Parent Positive Affect profile was largest in size (model-estimated proportion = 79.0%) and the Parent Anger profile was smallest (8.7%). Thus, the majority of parents showed a preponderance of positive affect across interaction tasks, reflecting high levels of resilient parenting in the context of substantial psychosocial risks. Contrary to expectations, parent profiles were not associated with any covariates, including family adversity and sociodemographic risk. This suggests that there may be other important influences on parenting (e.g., parental mental health, perceived stress) that were not considered in this study.

Using a classify-analyze approach with the modified BCH method, Parent Anger profile membership was found to be related to longer child anger duration, particularly during the problem-solving discussion. Parent Anger profile membership was also associated with higher teacher-reported social-behavioral problems, robust to the inclusion of sociodemographic risk. This echoes findings from prior multimethod studies that illustrate links between parent affect, child affect, and children's social-emotional adjustment (e.g., Newland & Crnic, 2011; Robinson et al., 2009). Planned follow-up testing indicated that Parent Anger profile membership predicted significantly more peer problems and marginally more conduct problems in children. In contrast to findings for child anger duration, the Parent Anger profile was not significantly associated with children's hyperactivity problems, suggesting that pathways from family risk to hyperactivity may not be mediated through parents' affective behavior. Finally, when child anger duration and parental profile membership were tested as simultaneous predictors of child social-behavioral problems, both effects were attenuated in size and reduced to non-significance. This suggests that teacher-reported total problems are related to variance shared between child and parent anger expression, specific to one conversation partner. Sociodemographic risk continued to predict higher social-behavioral problems adjusting for parent and child affect, emphasizing its direct relevance to children's classroom adjustment.

Overall, latent profile results clarified risk processes involved in parent-child interaction. Specifically, high levels of parental anger expression during a mildly stressful task predicted concurrent child anger duration, as well as subsequent social-behavioral problems at school. Homeless parents exhibiting high levels of negative affect may benefit from parenting training focused on building problem-solving skills for family conflict and enhancing adaptive self-regulation of anger. Additionally, persistent associations between sociodemographic risk and social-behavioral problems highlights the importance of poverty reduction for resilience promotion, complementing interventions that build families' adaptive capacity. Public policies aimed at reducing families' exposure to sociodemographic risks (e.g., employment programs, affordable housing) may help to reduce children's behavioral dysregulation and initiate positive cascades toward social-emotional health (Masten & Labella, 2016).

Strengths and Limitations

The study has notable strengths and limitations. It extends research on emotion regulation and socialization to an understudied population of children at very high risk.

Research with families in emergency housing offers unique insight into risk and resilience processes in the context of acute adversity. The study was strengthened by the use of diverse measurement strategies, including parental report of risk and adversity, observations of parent and child affect, and teacher reports of classroom adjustment. Multiple dimensions of child affect were assessed in order to a) better distinguish reactivity from regulation and b) identify specific processes conferring risk, clarifying the most promising intervention targets. Additionally, latent profile analysis was leveraged to characterize heterogeneity in parental affect, and an appropriate weighting strategy was used to relate parental affect profiles to child outcomes, taking classification uncertainty into account.

In addition to several strengths, the study also has limitations. It used summary measures of parent and child affect, which are not suited for evaluating dynamic contingencies between parent and child affect over time. Recruitment was limited to homeless families staying in emergency housing, complicating efforts to generalize results to low-income but housed families or homeless families not currently in shelter. Past research suggests that homeless children are quantitatively rather than qualitatively different from low-income housed children, consistent with extreme elevation on a continuum of poverty-related risk (Masten et al., 1993; Masten, 2014). However, generalizability would be strengthened by replicating findings with families who are demographically similar but stably housed. Teacher-reported outcome data were not available for 24% of the sample, due to the substantial practical challenges of locating highly mobile children in schools; however, the response rate of teachers was extremely high (95%) for the 79% of children who were successfully located.

Finally, some unexpected null results suggested limitations in measurement. Parental profile membership was not related to risk and adversity, but may be distinguished by parental mental health, perceived stress, and/or use of maladaptive ER strategies. Measures of these constructs were not available across both data collections. Similarly, null associations between observed affect regulation and teacher-reported emotion regulation may reflect use of ERC's adaptive regulation subscale, which taps more general aspects of social-emotional competence, rather than the lability/negativity subscale, which reflects specific difficulty modulating intense emotion. The latter construct is of particular theoretical relevance but was not assessed in both data collections. Future research on emotion reactivity and regulation should include measures of emotion dysregulation as well as adaptive regulation.

Conclusions and Future Directions

The current study confirms the role of emotion regulation and socialization in predicting social-emotional adjustment among young children experiencing homelessness. In particular, dysregulated expression of child and parent anger were related to social-behavioral problems at school. Both child anger duration and Parent Anger profile membership predicted total teacher-reported social-behavioral problems, and showed similar associations across problem domains. These findings highlight the importance of parental anger modeling and child anger regulation in social competence and behavioral adjustment at school. Gatekeepers of resources for impoverished families might screen parents and children for anger dysregulation, providing emotion regulation coaching in group or individual formats as needed.

Additionally, higher sociodemographic risk was related to more social-behavioral problems, especially to hyperactivity. This corroborates previously identified associations between poverty-related risk and difficulty self-regulating (Blair & Raver, 2012; Labella et al., 2017), and illustrates a need for complementary risk-reduction interventions aimed at mitigating poverty-related stress. A multi-pronged intervention approach that combines poverty relief measures with emotion regulation training has the potential to help young children thrive in the face of homelessness.

Future research should extend these findings to larger, more diverse samples, incorporating additional adaptive outcomes (e.g., emotional lability/negativity, teacher-child relationship) and following children over time. Given research suggesting cultural variations in emotion socialization (e.g., Labella, 2017) and situating emotion socialization in a broader context of ethnic-racial socialization (Dunbar et al., 2017), further studies should incorporate measures of sociocultural influences (e.g., discrimination experiences) on emotion expression, regulation, and socialization goals. Research that incorporates physiological data would provide more comprehensive insight into self-regulation at multiple levels of analysis and may help to identify biological mechanisms linking environmental challenge and child adjustment. For example, prior research has linked anger dysregulation to lower vagal suppression to challenge (Calkins & Fox, 2002). Ongoing research clarifying associations between child and parent emotion regulation and subsequent school adjustment, as well as sociocultural context and potential biological pathways, is needed to further specify targets for intervention promoting resilience among vulnerable children and families. The current study suggests promising new avenues for research and practice, highlighting parent and child affect regulation as promising intervention targets to enhance resilience in families at very high psychosocial risk.

Study 2

Study 1 confirmed the relevance of observed affect during parent-child interaction as a robust predictor of social-emotional adjustment among young homeless children. However, Study 1 was limited by its use of summary affect codes, which obscure temporal dynamics of parent-child interaction, including contingencies in affect over time. This limits our ability to make inferences about directionality and/or assess parents' responses to children's emotions, a key aspect of emotion socialization (e.g., Eisenberg et al., 1998; Morris et al., 2007). The current study uses a dynamic analytic strategy to evaluate dyadic associations between parent and child anger during a problem-solving discussion, previously linked to children's teacher-reported social-behavioral problems (Study 1).

Micro-analytic strategies have previously been used to analyze dynamic processes linking parent-child affect, particularly during mother-infant interaction (e.g., Cohn & Tronick, 1988; Field, 1994; Malatesta & Haviland, 1982). For example, Feldman and colleagues (1999) examined mother-infant affect synchrony during three minutes of face-to-face play. Changes in affective states were coded in split-second phases and analyzed using autoregressive integrated moving averages models, a time-series technique accounting for autocorrelations in each dyad member's affective behavior. Results indicated that maternal synchrony at three months (i.e., infant-leads-mother-follows) and mutual synchrony at nine months (i.e., cross-dependence between and maternal and infant affect) predicted child self-control at age two years, particularly for children with difficult temperaments (Feldman, Greenbaum, & Yirmiya, 1999). Similarly, in a longitudinal study of mothers with and without depression, lag-sequential analyses revealed predictable contingencies in mother-toddler affect (Denham, 1993). For example, mothers and toddlers tend to match each other's happiness, mothers responded to child anger with anger, and maternal tenderness was reciprocally related to child fear. Toddlers' observed social-emotional competence was related to lower maternal sadness and more adaptive emotional responsiveness to children's fear, anger, sadness, and neutrality (Denham, 1993). Overall, research with parents of infants and toddlers illustrates the active co-regulation of affect and attention, as well as the importance of affective attunement for early social and self-regulatory development (Raver, 2004; Zeman et al., 2006).

Research on affective dynamics during parent-child interaction are less common outside of infancy, but available research confirms the ongoing relevance of mutual regulation for children's social-emotional development. A study with mother-preschooler dyads identified evidence of emotional contingencies (defined as emotional responses initiated within five seconds of an emotional communication) during a frustrating wait task (Cole, Teti, & Zahn-Waxler, 2003). Results indicated that children tended to reciprocate mothers' positive emotion and mothers tended to reciprocate both positive emotion and angry distress. Maternal emotion dynamics were related to externalizing problems two years later: more contingent angry distress and less contingent positive affect predicted more externalizing symptoms by teacher and parent report, respectively. Additionally, two-year stability in conduct problem status was related to less mutual positive emotion, more mutual anger, and more emotion mismatches (Cole et al., 2003).

In a sample of mothers with and without childhood-onset depression, Feng and colleagues (2007) used Actor-Partner Independence Modeling and concluded that mothers' contingent positive responsiveness to toddler positive emotion (i.e., initiated within three seconds of a child's positive emotion display) predicted lower child negative expressiveness three years later, controlling for stability in child expressiveness over time. Mothers' overall positive expressiveness was also found to predict growth in children's positive expressiveness over time.

Methodological concerns

Taken together, results suggest ongoing emotional co-regulation in the parent-child relationship through early childhood. Additionally, aspects of parent-child contingencies have been linked to children's social-emotional adjustment in other contexts. However, the existing literature is limited by a preponderance of small sample studies and an underrepresentation of families at high psychosocial risk. Additionally, studies are limited by available analytic techniques, many of which are computationally cumbersome and require somewhat arbitrary decisions from the researcher (e.g., what time interval to use when defining contingent responses; Cole et al., 2003; Feng et al., 2007). Some popular methodologies, including cross-lagged panel models and extensions thereof (e.g., Connell, McKillop, Patton, Klostermann, & Hughes-Scalise, 2015; Eisenberg et al., 1999; Feng et al., 2007; Mancini, Luebbe, & Bell, 2016) are not optimal for differentiating within-person from between-person effects. Although cross-lagged panel models seek to account for stability through cross-time paths, they do not differentiate within-person stability from between-person stability (i.e., trait-like differences in constructs of interest), introducing bias into estimates of the cross-lagged coefficients (Berry & Willoughby, 2017; Curran & Bauer, 2011; Hamaker, Kuiper, & Grasman, 2015). In such models, cross-lagged coefficients reflect a weighted composite of the within-person and between-person effects (i.e., a "convergence" effect; Berry & Willoughby, 2017; Bryk & Raudenbush, 1992). In some cases, cross-lagged panel models may generate similar results as statistical methods that explicitly distinguish inter-individual from intra-individual variability (Kim, Conger, Lorenz, & Elder, 2001). In other cases, however, distinguishing within-person from between-person variability may lead to dramatic changes in model results (Berry & Willoughby, 2017).

A range of contemporary statistical analytic techniques are available to assess dynamic

dyadic data, many of which are well suited to differentiate within-person from between-person variation (Gates, 2016). Novel statistical strategies include differential equation modeling of dyadic interactions (Ferrer & Helm, 2013), Hidden Markov Modeling (Lunkenheimer et al., 2017), and State Space Grids (Granic et al., 2003; Hollenstein, 2007; Hollenstein & Lewis, 2006). State Space Grids (SSGs) represent a graphical approach to analyzing behavioral sequences of dyadic states, permitting evaluation of dynamic systems parameters such as flexibility, dispersion, and attractor states (Hollenstein, 2007). SSG analyses have revealed links between dyadic flexibility in parent-child affective expression and lower teacher-reported problems in preschool-aged children (Lunkenheimer et al., 2013). In research with families experiencing homelessness, SSG analyses have been productively leveraged to show links between positive co-regulation (i.e., adaptive synchronization of parent-child affective-behavioral states) and child outcomes, including emotional-behavioral symptoms, executive function skills, and child IQ (Herbers, Cutuli, Supkoff, Narayan & Masten, 2014; Herbers, Cutuli, Monn, Narayan, & Masten, 2014).

Perhaps the most common contemporary analytic approach is multilevel modelling, which partitions variance into within-person and between-person levels (Berry & Willoughby, 2017; Bryk & Raudenbush, 1992; Curran & Bauer, 2011). Related approaches include multilevel survival analysis (e.g., Lougheed et al., 2016) and unified Structural Equation Modeling (Beltz, Beekman, Molenaar, & Buss, 2013). In monadic studies, multilevel modeling has been used to demonstrate links between depressive symptoms and emotional inertia (i.e., high autoregressive parameters), net of mean level and variability of emotions (Kuval, Sutterlin, & Kuppens, 2016; Kuppens, Allen, & Sheeber, 2012). In dyadic analyses of parents and children, multilevel modeling has illustrated longitudinal associations linking parents' physiological regulation with parenting behavior (Skowron et al., 2013) and with subsequent adolescent affect (Cui et al., 2015). In a study of preschoolers through second graders, mother-child use of adaptive emotion regulation strategies predicted lower intensity of children's sadness and anger after receiving a disappointing gift (Morris et al., 2011). Contemporary statistical models thus hold substantial promise for dyadic analysis of parent-child interactions.

Dynamic structural equation modeling

Dynamic structural equation modeling (DSEM) is another novel analytic strategy for intensive longitudinal data, newly available in Mplus version 8 (Asparouhov, Hamaker, & Muthen, 2017; Muthén & Muthén, 1998-2017). DSEM integrates techniques from several analytic traditions, including time series modeling, multi-level modeling, and a general latent variable modeling framework, in order to model different sources of covariation in intensive longitudinal data. DSEM also addresses multiple limitations of dynamic multilevel modeling with standard multilevel software, including negative bias in autoregression when centering the lagged predictor and difficulty accommodating unbalanced and missing data (Asparouhov et al., 2017; Hamaker, Asparouhov, Brose, Schmiedek, & Muthén, 2017).

The current study uses DSEM to build on findings from Study 1, investigating dynamic interplay between parent and child anger during the problem-solving discussion. I anticipated significant autoregressive and cross-lagged effects for the sample as a whole, indicating carryover in child and parent anger over time as well as spillover from person to person. Significant variances around these fixed effects were also predicted, representing dyad-level differences in strength of time-series parameters. Between-dyad differences in time-series parameters were expected to predict children's socioemotional adjustment, with higher autoregressive and cross-lagged parameters predicting more behavior problems (teacher-reported social-behavioral problems, parent-reported internalizing and externalizing behaviors) and worse emotion regulation (by teacher-report). I anticipated that affective dynamics would be related to higher sociodemographic risk and family adversity, and that predictive associations with child adjustment would be robust to sociodemographic covariates.

Method

Participants

As described in Study 1, participants were 214 primary caregivers and their four- to six-year old children (54.2% male, mean age 5.8 years, *SD* = .6 years; 62.6% African American, 23.8% multiracial, 5.1% American Indian, 3.7% white, 4.6% other). Families were recruited from two urban emergency shelters in a midsized Midwestern city to participate in two similar data collections over the course of two summers (2012 and 2014). For each protocol, families were eligible to participate if they had a child who was entering kindergarten or first grade and lived in shelter for at least three days (to allow for acute acclimation). Only one child per family participated. Exclusion criteria were insufficient English to complete tasks or severe developmental delay interfering with study completion (e.g., severe autism spectrum disorder). Families were recruited through fliers in mailboxes and informational tables set up during mealtimes.

The current study includes all dyads with useable affect data for both parents and children from the problem-solving discussion (*n* = 189). Of the 214 participating families across both data collections, 11 had no codable interaction data and 14 were missing affect codes for one or both participants during the problem-solving discussion.

Procedure

The University of Minnesota institutional review board approved all study procedures. Parents provided informed consent for themselves and their children, and children provided verbal assent. Study sessions took place in dedicated research rooms located in the shelters. These rooms were private and located on a nonresidential floor. Assessors were trained graduate and undergraduate students. Children participated in an hour-long assessment of school readiness skills while parents were interviewed about demographics, child behavior, and stressful life events. Following individual sessions, parents and children participated in a structured sequence of videotaped interaction tasks developed by the Parent Management Training: Oregon Model (PMTO) research team, adapted for use with homeless and highly mobile families (Gewirtz, DeGarmo, Plowman, August, & Realmuto, 2009), abridged to decrease participant burden. Interaction tasks were video-recorded and coded for parent and child affect. Parents received an honorarium and children received a small toy for participation.

With parent permission, teachers were later contacted to report on children's social-emotional adjustment, after children had been in school for at least two months. About 80% of children were successfully located in schools (80.3% in 2012, 78.5% in 2014) and the vast majority of identified teachers completed questionnaires (96.5% in 2012, 94.0% in 2014). Overall, teacher data were available for 75.7% of the combined sample.

Measures

Parent and child affect. During videotaped interactions, dyads engaged in a series of structured tasks designed to elicit mutual enjoyment, limit setting, communication, cooperation, and competitive play (DeGarmo, Patterson, & Forgatch, 2004). Two tasks (problem-solving discussion and marble maze) were selected for the current study and coded for parent and child affective expressions. teaching game (the marble maze) were coded for parent and child affective expressions. These tasks were selected because they were a) available across both protocols, and b) expected to elicit a range of emotional expressions (i.e., more distress and anger during the problem-solving discussion, more positive affect during the marble maze).

Interaction tasks were coded using a microsocial coding system adapted from manuals used by Dr. Amanda Morris at Oklahoma State University in previously published research on parent-child interaction (Morris et al., 2011; Cui, Morris, Harrist, Larzelere, & Criss, 2015). Dr. Morris and her research team also provided consultation on training and reliability procedures. Independent coding teams were trained to rate intensity of one affect (anger, internalizing distress, positive affect) on a five-point scale (from *1 – none* to 5 – *very strong*). Different coders were responsible for rating affect in the parent and the child to minimize shared rater bias. Intensity of each affect (anger, internalizing distress, and positive affect) was coded for each dyad partner (parent and child) in ten second intervals across the two interaction tasks. Each task took approximately five to six minutes, resulting in ten to twelve minutes of codable interaction per dyad. Affect coding teams were composed of one graduate and three undergraduate coders; the distress team additionally included a B.A.-level study coordinator. The first author served as anchor coder for all affects. Inter-rater reliability was calculated using intra-class correlations (*ICC*s) with two-way random effects (appropriate when a subset of coders do reliability ratings on a subset of participant data; McGraw & Wong, 1996). Each coder achieved good reliability with the anchor coder [*Intraclass correlation* (*ICC)* ≥ .75] on practice tapes derived from a prior data collection before coding interaction tasks for the present study (Koo & Li, 2016).

Twenty percent of videotapes were randomly selected for double coding. Discrepancies were discussed and resolved by consensus at weekly reliability meetings to minimize rater drift. When available, consensus codes were used for analyses. Inter-rater reliability of child affect codes ranged from moderate to good (*ICC* = .67 for anger, .77 for distress, .89 for positive affect), as did inter-rater reliability of parent affect codes (*ICC* = .70 for anger and distress, *ICC* = .86 for positive). Lower inter-rater reliability for anger and parent distress likely reflect lower variability in these affect ratings. The current analyses use raw anger codes for parents and children during the discussion task.

Sociodemographic risk. In both protocols, parents reported sociodemographic information, including education, employment status, and history of homelessness. Ten binary risk factors previously identified as relevant to disadvantaged families (single parent; four or more children in the household; parent under 18 at birth of first child; primary caregiver has less than high school education; primary caregiver unemployed; family unable to afford rent; lived in substandard housing; lived in unsafe neighborhood; target child has lived at five or more addressed; primary caregiver homeless three or more times) were summed to create a cumulative sociodemographic risk score for each family (Obradović et al., 2012).

Family adversity. In both protocols, parents reported on their child's lifetime experience of stressful life events using the Lifetime Events Questionnaire (Masten et al., 1993, Cutuli et al., 2010). Consistent with previous research (Labella et al., 2017), ten items were selected to reflect adverse experiences within the family unit (death of parent; death of brother or sister; inter-parental conflict; parental separation or divorce; parental substance abuse problem; parental mental illness; parental physical illness; parental incarceration; foster care; prolonged parent-child separation). Endorsed items were summed to create a cumulative family adversity score for each family.

Child social-emotional adjustment. Teachers and parents reported on children's social-emotional adjustment using standard questionnaires.

Teacher-reported emotion regulation. In both protocols, teachers completed the emotion regulation subscale of the Emotion Regulation Checklist (ERC; Shields & Cicchetti, 1997). The emotion regulation subscale consists of eight items rated on a 4-point scale reflecting the degree to which the child is able to behave appropriately in the context of strong emotion (α = .80).

Teacher-reported social-behavioral problems. In both protocols, teachers completed the emotional problems, conduct problems, hyperactivity, and peer problems subscales of the Strengths and Difficulties Questionnaire (SDQ; Goodman, 1997). Each subscale consists of five items rated on a 3-point scale from *Not true* to *Certainly true.* Using standard scoring procedures, item scores are summed to form subscale scores, which are in turn summed to form a total problems composite. The total problems score, reflecting all social-behavioral problems reported by the teacher (possible range 0-40), is the primary endpoint for this measure (α = .87), with planned follow-up testing by problem domain.

Parent-reported behavior problems. Parents reported on children's internalizing and externalizing behavior in both protocols, but specific measures differed. In 2012, parents completed the emotional symptoms and conduct problems subscales from the Strengths and Difficulties Questionnaire (SDQ; Goodman, 1997). The emotional problems subscale consists of five items reflecting internalizing symptoms (e.g., worries, sadness), each rated on a 3-point scale from *Not true* to *Certainly true*. Similarly, the conduct problems subscale consists of five items reflecting externalizing symptoms (e.g., defiance, temper outbursts) rated on the same 3-point scale.

In 2014, parents rated their children's internalizing and externalizing behavior using subscales from the HBQ (Armstrong & Goldstein, 2003). The internalizing scale consists of 19 symptoms from three subscales (depression, overanxious, and separation anxiety), all rated on a 3-point scale from *Not true* to *Very true*. The externalizing scale includes 31 items from four subscales (oppositionality, conduct problems, overt hostility, and relational aggression), rated on the same 3-point scale. Typically, items are averaged using standard scoring procedures to yield composite scores, which show adequate reliability and strong validity in discriminating clinical and community samples (Armstrong & Goldstein, 2003). In this case, however, I selected individual HBQ items matching the content of SDQ items. This strategy is facilitated by the close correspondence of many items and the similarity of the 3-point response scales.

HBQ items with overlapping content were selected for each SDQ item. When multiple HBQ items matched the content of one SDQ item, relevant HBQ items were averaged, resulting in one composite score for each SDQ item (Table 7). This strategy has been successfully used in prior research to harmonize teacher reports of internalizing and externalizing behavior on the SDQ and HBQ across data collections (Labella et al., 2017). For all participants, five internalizing scores and five externalizing scores were averaged to form internalizing and externalizing behavior composites. Composites showed weak to adequate reliability (internalizing α = .59, externalizing α = .65), likely due in part to the small number of items per scale. The low α for internalizing was driven by low internal consistency in 2012, when the full SDQ was administered (α = .54 in 2012 versus .68 in 2014). Given that the SDQ is a well-established and commonly used measured, I proceeded with analyses despite low internal consistency of internalizing symptoms in 2012; however, results related to parent-reported internalizing should be interpreted with caution. To address variation in measurement, internalizing and externalizing behavior composites were z-scored within protocol.

Covariates. Parents provided information on age and sex of parents and children. Protocol (2012 or 2014) and shelter type (public or private) were included as additional covariates.

Plan for analysis

Two-level dynamic structural equation models (DSEM; Asparouhov, Hamaker, & Muthen, 2017) were used to model dynamics of parent and child affect over time, decomposing data into within-person and between-person variation in observed parent and child anger during the problem-solving discussion. As described by Hamaker and colleagues (2017), the two-level model decomposes a given individual's affect ratings into a within-person mean and a vector of time-specific within-person deviations from one's own mean (described in detail below). Factor loadings, regression coefficients, variances, and covariances are permitted to be random, allowing for individual differences in time-series parameters (e.g., auto-regressive and cross-lagged effects). Random means and random effects from the within-person level become latent variables in the between-person level model. Individual differences in these within-person processes can then be used as between-person predictors of distal outcomes (e.g., children's social-emotional adjustment; Asparouhov et al., 2017; Hamaker et al., 2017).

DSEM is implemented in Mplus using Bayesian estimation (Muthén & Muthén, 1998-2017), which can accommodate many more random effects than are feasible in a maximum likelihood (ML) framework. ML estimation uses the joint distribution of all variables to converge on a log-likelihood maximum, which becomes prohibitively computationally intensive as the number of observations increases. In contrast, Bayesian estimation works with a series of conditional distributions based on prior distributions for unknown values to yield posterior distributions for these parameters (Asparouhov et al., 2017; Gelman, Carlin, Stern, & Rubin, 2014; Hamaker et al., 2017). As a default, Mplus uses diffuse non-informative priors, yielding estimates that are asymptotically equivalent to ML estimation.

Estimation proceeds with iterative sampling from conditional distributions based on the Markov chain Monte Carlo (MCMC) algorithm. Model convergence can be assessed using the potential scale reduction (PSR) criterion, which is computed for each model parameter as a function of the total variability across two chains of the MCMC algorithm (i.e., within-chain + between-chain variability) divided by the variability within a chain (Asparouhov & Muthén, 2010; Gelman et al., 2014; Hamaker et al., 2017). A PSR value close to one indicates that between-chain variation is small relative to within-chain variation and suggests that the MCMC algorithm has converged on stable posterior distributions. The first 100 iterations (termed the burn-in phase) are then discarded to ensure the integrity of the posterior distribution, minimizing the influence of prior specification on final estimation. Point estimates are identified by taking the mean or median for each parameter, and credible intervals (CI) are obtained directly from the posterior distribution at desired cut-off values (e.g., 95%). In contrast to confidence intervals, credible intervals do not require the assumption of a normal or symmetric parameter distribution (Asparouhov et al., 2017; Hamaker et al., 2017).

Model comparison of Bayesian models is typically conducted using the deviance information criterion (DIC), a function of the deviance and the effective number of parameters estimated (Asparouhov et al., 2017; Spiegelhalter et al., 2002). However, DIC tends to be unstable when used in the DSEM framework due to large numbers of individual effects, and is not always directly comparable across models due to differences in parameterization (e.g., whether latent variables are treated as parameters). Thus, when comparing simpler nested models with few differing parameters, DSEM authors recommend focusing model comparison efforts on evaluating significance of individual parameters, inferred from credibility intervals excluding 0 (Asparouhov et al., 2017; Hamaker et al, 2017).

In the current analyses, I began by specifying Model 1, a two-level DSEM model based on a first-order vector autoregressive (VAR(1)) model of child anger (CA) and parent anger (PA). The two-level model was used to decompose a given individual's anger ratings into a person-specific mean (expressed as $\mu_{CA,i}$ and $\mu_{PA,i}$ respectively) and time-specific deviations from one's one mean (expressed as $CA_{it}^{(W)}$ and $PA_{it}^{(W)}$, where W denotes within, t denotes time, and i indicates that individuals may differ in the magnitude of these parameters). Within a dynamic systems framework, person-specific means may be conceptualized as the attractor state to which the dynamic system returns in the absence of external influence (Hamaker et al., 2017; Thelen & Ulrich, 1998). Temporal deviations from this person-specific mean were modeled using within-person affective dynamics. At each time point, child anger (CA) and parent anger (PA) were regressed simultaneously on the lag-1 observation of the same series (i.e., autoregression, reflecting carryover in anger from interval to interval) as well as the cross-series lag-1 observation (i.e., cross-lag or spillover in anger from person to person, Figure 2). For example, current child anger was regressed on child anger in previous interval (autoregression) and parent anger in the previous interval (cross-lag). This extends the traditional cross-lagged panel model by: (1) explicitly disaggregating between-person variation from the autoregressive and cross-lag processes, and (2) allowing each of these processes to vary randomly across individuals. The model for within-person deviations is expressed as:

$$CA_{it}^{(W)} = \varphi_{CC,i}CA_{it-1}^{(W)} + \varphi_{CP,i}PA_{it-1}^{(W)} + \zeta_{CA,it}$$

$$PA_{it}^{(W)} = \varphi_{PP,i}PA_{it-1}^{(W)} + \varphi_{PC,i}CA_{it-1}^{(W)} + \zeta_{PA,it}$$

where $\varphi_{PP,i}$ and $\varphi_{CC,i}$ represent the autoregressive (carryover) parameters for CA and PA respectively, $\varphi_{CP,i}$ represents the cross-lagged (spillover) effect from PA to CA at the next occasion, $\varphi_{PC,i}$ represents the cross-lagged (spillover) effect from PA to CA, ζ_{CA} represents the within-person residual of CA, and ζ_{PA} represents the within-person residual of PA. The within-person residuals, also called innovations or disturbances, reflect time-specific deviations in the variable not accounted by autoregressive processes, cross-lagged associations, or the individual's own mean for the series. These innovations have a mean of zero by definition and are assumed to have a multivariate normal distribution. In Model 1, innovation variances and their covariance were fixed to be equal across individuals.

At the between-person level, which captures between-*dyad* effects, this model contains six random effects: two random intercepts (i.e., person-specific means; $\mu_{CA,i}$ and $\mu_{PA,i}$), two random autoregressive parameters ($\varphi_{CC,I}$ and $\varphi_{PP,i}$), and two random cross-lagged parameters ($\varphi_{CP,I}$ and $\varphi_{PC,i}$). The between-dyad equations can be expressed as follows, where the six γ's represent fixed (averaged) effects and the six u's represent the individual-specific deviations:

$$\mu_{CA,i} = \gamma_C + u_{C,i}$$

$$\mu_{PA,i} = \gamma_P + u_{P,i}$$

$$\varphi_{CC,I} = \gamma_{CC} + u_{CC,i}$$

$$\varphi_{PP,i} = \gamma_{PP} + u_{PP,i}$$

$\varphi_{CP,i} = \gamma_{CP} + u_{CP,i}$

$\varphi_{PC,i} = \gamma_{PC} + u_{PC,i}$

The individual differences are assumed to come from a multivariate normal distribution of a six by six covariance matrix, such that six variances, 15 covariances, and six fixed effects are estimated at the between-dyad level. Including the three parameters estimated at the within-dyad level, 30 total parameters are estimated for this multilevel VAR(1) model.

Model 2 is a more complex DSEM model, extending the multilevel VAR(1) model with random innovation variances and their covariance (Figure 3). In Model 1, innovation variances and their covariance were estimated at the within-person level and fixed to be equal across individuals. However, people may be expected to differ meaningfully in the magnitude of their deviations from lag-predicted values (Jongerling, Laurenceau, & Hamaker, 2015; Hamaker et al., 2017). For example, some individuals may show greater increases in anger in response to transient frustrations, and some dyads may encounter more stressful moments in the course of their problem-solving discussion. Dyads may further differ in the extent to which parent and child deviations covary, reflecting parents' and children's reactivity to the other dyad member's concurrent anger – or to a shared experience.

In order to model individual differences in variances, innovation variances were scaled to a log normal distribution. This ensures that each individual will have a positive value for the innovation variance and permits calculation of a random effect (i.e., the random log of the innovation variance). Estimating the random covariance was accomplished by modeling an additional latent variable representing what the two innovations have in common, while the unique aspects were modeled as residuals. In order to estimate this latent common factor, one must fix the factor loadings to be -1 and 1 (implying negative covariance) or 1 and 1 (implying positive covariance; Hamaker et al., 2017). In the current model specification, the covariance between parent and child anger was fixed to be positive in order to reflect theorized emotion contagion effects. Total innovation variances are modeled as the sum of the unique variances and the innovation covariance.

Model 2 does not involve parameter estimation at the within-person level. Instead, nine random effects are estimated at the between-dyad level. In addition to effects estimated in Model 1, the following between-dyad effects are estimated: two for the unique parts of the innovation variances and one for the positive covariance between innovations. Again, the three γ's represent fixed (averaged) effects and the three u's represent the individual-specific deviations from the sample means:

$$log_{(\pi CA,i)} = \gamma_{log(\pi CA)} + u_{log(\pi CA,i)}$$

$$log_{(\pi PA,i)} = \gamma_{log(\pi CA)} + u_{log(\pi CA,i)}$$

$$log_{(}\Psi_{i)} = \gamma_{log(\Psi)} + u_{log(\Psi)}$$

The nine individual deviations are again assumed to come from a multivariate normal distribution, implying nine variances and 36 covariances. When added to the nine fixed effects, this results in a total of 54 parameters estimated at the between-dyad level of Model 2.

Models 1 and 2 were estimated in Mplus, version 8, using default non-informative priors (Muthén & Muthén, 1998-2017). Trace plots were inspected to ensure adequate model convergence. The *DIC* of Model 1 and Model 2 were compared and the significance of additional parameters (i.e., random innovation variances and their random covariance) were assessed in order to evaluate the incremental utility of the more complex model. As described below, Model 2 was found to be better fitting, with significant random effects for innovation variances and their covariance.

Random effects from Model 2 were then exported as factor scores and treated as predictors in subsequent models in order to detect associations linking between-dyad differences in affective dynamics with children's social-emotional adjustment and covariates. This two-stage analytic strategy has been used in other research within the multilevel modeling framework (e.g., Merz & Roesch, 2011). Associations with affective dynamics were tested for four distal outcomes (teacher-reported social-behavioral problems, teacher-reported emotion regulation, parent-reported internalizing behavior, and parent-reported externalizing behavior) and six covariates (substantive covariates: sociodemographic risk, family adversity; control covariates: child age, child sex, shelter, and protocol). Parent reports were included to evaluate the possibility that affective patterns during parent-child interaction may relate differentially to parent versus teacher reports of child adjustment.

To test links between affective dynamics and social-emotional adjustment, I regressed the distal outcomes on the model-implied factor scores representing individual differences in autoregressive (carry-over), cross-lag (spill-over), and innovations (i.e., deviations from model-predicted paths) for parents and children. All models were fitted using robust maximum likelihood estimation. Of note, this two-stage strategy is not optimal, as treating random effects as observed rather than estimated introduces bias in standard errors (Hamaker et al., 2017). DSEM is theoretically capable of simultaneous estimation of time-series dynamics and their associations with distal parameters. However, due to the newness of the method and the complexity of the model, model parameters did not converge.

Missing data. For Bayesian estimation of DSEM models, missing data is sampled from their conditional posterior at each iteration of the MCMC algorithm. The conditional posterior of the missing value will reflect the individual's autocorrelation structure. Thus, for a given interval with missing affect data, the conditional posterior depends on neighboring affect ratings, the individual's autoregressive parameter in the current MCMC iteration, and the residual variance (Hamaker et al., 2017). This method generates consistent estimation provided that data is at least missing at random (MAR). Most missing affect data was a consequence of examiner error (i.e., video cameras set up without a clear view of both participants' faces). Remaining missing data is likely conditioned on variables included in the model (e.g., a child turns fully away from the interaction out of anger). Thus, affect data is assumed to be at least MAR.

In subsequent models relating time-series random effects to covariates and distal outcomes, full information maximum likelihood (FIML) was used to generate unbiased parameter estimates making full use of available data. As noted in Study 1, there was minimal missing data from the shelter session, including parent reports of child adjustment (1.6% missing). Teacher data were available for 75.7% of the sample, comparable to prior studies with homeless and highly mobile families (e.g., Herbers et al., 2011; Narayan et al., 2015). Missingness of teacher data is unlikely to reflect the child's social-emotional adjustment or systematically bias analyses, permitting the assumption that data are MAR and thus appropriate for FIML (Peng et al., 2006).

Results

Preliminary analyses

To estimate the within- and between-person variability in parent and child anger (respectively), I fitted two random intercepts models. Intraclass correlations (ICCs; computed as the ratio of between-person variance to total variance) were .27 for child anger and .23 for parent anger, indicating that the majority of the variance is within-person. Correlations between child anger and parent anger were significant at both the between-person level and the within-person level, but the magnitude of the correlation was substantially larger on the between-person level (between-level $r = .45$, *CI* [.31, .57]; within-level $r = .16$, *CI* [.13, .18]). Thus, trait-like aspects of child and parent anger are moderately to strongly related and within-dyad fluctuations are modestly related, suggesting a mild tendency for parents and children to show similar levels of anger in the same 10-second interval.

Time-series analyses of parent and child anger

Next, I specified two DSEM models as described in the data analytic plan. Bayesian estimation proceeded with 50,000 iterations, and adequate convergence was verified through PSR close to one and absence of significant trends, spikes, or other irregularities in trace plots. Results of Model 1 revealed significant fixed and random effects for person-specific means, autoregressive parameters, and cross-lagged parameters (Table 8). In Model 2, I additionally estimated fixed and random effects for the unique innovation variances of child anger and parent anger and their shared innovation covariance, both scaled with a log-normal distribution. All three new parameters had significant fixed and random effects based on 95% credible intervals, and previously estimated parameters were similar to results obtained in Model 1 (Table 8). The DIC was lower for Model 2 (20461.26 vs. 23466.60 for Model 1), indicating better fit. Given lower DIC and statistical significance of novel parameters, Model 2 was selected as the better fitting model.

Results from Model 2 indicated that participants tended to show low levels of anger across the problem-solving discussion, as indicated by person-specific means (μ_{CA} = 1.49, *CI* [1.45, 1.54], μ_{PA} = 1.37, *CI* [1.34, 1.41]; scale = 1-5). Across the sample as a whole, there was statistically significant temporal stability in child and parent anger across the problem-solving task, as evidenced by significant autoregressive paths for child anger (b = .21, *CI* [.17, .25]) and parent anger (b =.19, *CI* [.15, .23]). Consistent with the idea of bidirectional feedback processes, the cross-lagged parameters were positive and statistically significant in both directions (parent to child anger b = .03, *CI* [<.01, .06]; child to parent anger b = .05, *CI* [.01, .08]). Estimates for cross-lagged paths were comparable when scaled on within-person variances (parent to child anger b = .04; child to parent anger b = .04; Hamaker et al., 2017).

Results further indicated that parents and children deviated from their model-predicted paths (i.e., showed significant innovation variances), reflecting anger reactivity that does not correspond to prior anger from either conversation partner or person-specific means. Log innovation variances were -1.44 (*CI* [-1.56, -1.33]) and -1.52, *CI* [-.1.65, -1.39] for child and parent anger, respectively. When exponeniated, this translates to unique innovation variances of .24 for child anger and .22 for parent anger. Additionally, novel anger reactivity tended to co-vary within dyad, reflecting residual associations in parent-child anger within the 10-second coding interval (log innovation covariance = -3.79, CI = [-3.98, -3.42], exponentiated to an innovation covariance of .03).

All parameter variances (i.e., random effects) were significant, indicating individual differences in the magnitude of all estimated effects. Parents and children each differed in terms of person-specific means, autoregressive paths, and cross-lagged paths. Thus, individuals differed in their overall level of anger across a mildly stressful discussion, as well as in the degree of affective stability and affective responsiveness they showed. Cross-lag variances were quite small for both parents and children (lower bound of *CI* close to 0), suggesting limited variation in magnitude of anger spillover from one conversation partner to the other. Parents and children also differed in degree of novel anger reactivity and the extent to which novel anger reactivity covaried within coding intervals. In all cases, higher between-person effects reflect greater anger expression.

Between-person correlations revealed significant associations among random effects (Table 9). There were consistent moderate-to-large associations linking person-specific means and innovation-related random effects, as well as scattered small-to-moderate associations among autoregressive and cross-lagged parameters.

Overall, Model 2 accounted for 20.2% of the variance in child anger (averaged within-person $R^2 = .20$, *CI* [.17, .23]) and 21.4% of the variance in parent anger ($R^2 = .21$, *CI* [.19, .24]). In comparison, models estimating only autoregressive parameters and person-specific innovation variances accounted for 8.4% of the variance in child anger ($R^2 = .08$, *CI* [.07, .10]) and 8.9% of the variance in parent anger ($R^2 = .09$, *CI* [.07, .10]), suggesting prediction is improved by including dyadic parameters (cross-lagged paths and innovation covariance).

Association of time-series parameters with covariates and child adjustment

Between-person effects from Model 2 were exported as factor scores and treated as predictors in subsequent models assessing associations of dyad-level differences in affective dynamics with children's social-emotional adjustment and covariates. Bivariate correlations linking novel variables (between-dyad effects and parent-reported behavior problems) with teacher-reported social-emotional adjustment and sociodemographic covariates are presented in Table 10. I hypothesized that higher sociodemographic risk and family adversity would be associated with greater carryover and more spillover in anger. This hypothesis was partially supported: parents exposed to more family adversity had higher autoregressive parameters, indicating more stability in anger from one interval to the next. Unexpectedly, cross-lagged parameters were not related to risk or adversity, and children's novel reactivity (i.e., innovation variance) was lower among children at higher sociodemographic risk.

Bivariate associations between affective dynamics and adjustment outcomes indicated that children with higher autoregressive parameters (i.e., more carryover in anger) had more teacher-reported social behavioral problems. No affective parameter predicted teacher-reported emotion regulation or parent-reported internalizing problems. However, higher parent-reported externalizing behavior was related to several aspects of parent-child anger dynamics: larger cross-lag from child to parent anger (suggesting parental angry responses to child anger expression), higher parent innovation variance (reflecting novel anger reactivity), and higher innovation covariance (indicating parent-child covariation in novel anger reactivity).

Regression models predicting children's social-emotional adjustment

Covariates were selected for inclusion in regression models based on zero-order associations with focal predictors and/or outcomes. Sociodemographic risk was included in models predicting teacher-reported social-behavioral problems due to prior evidence that higher risk was related to more problems at school (Study 1). Child age, sociodemographic risk, and family adversity were included in models predicting parent-reported externalizing behavior, which showed bivariate associations with lower age, higher risk, and higher adversity (Table 11). Protocol was additionally included as a covariate when testing parent innovation variance, given evidence that lower novel anger reactivity was observed in the 2014 data collection (Table 11).

Teacher-reported social-behavioral problems. In the first step, I regressed teacher-reported social-behavioral problems on the child anger autoregressive parameter controlling for sociodemographic risk (Table 11). Stability in child anger robustly predicted social-behavioral problems (b = 11.18, p = .01, β = .21).

In the second step, model-estimated mean child anger was entered to test the unique role of child anger stability. The inclusion of mean child anger attenuated the effect of child anger stability (b = 7.56, p = .19, β = .14), and no predictors were statistically significant. This likely reflects collinearity, given high covariation between the person-specific mean and autoregressive component of child anger (between-person correlation = .57, *CI* [.38, .73]). Results suggest that the link between child anger and social-behavioral problems reflects variance shared between mean anger levels and anger persistence.

Parent-reported externalizing problems. I then fit a series of models regressing parent-reported externalizing behavior on affective parameters and relevant covariates

(Table 12). Three separate models were fitted for each between-dyad effect significantly correlated with parent-reported externalizing (i.e., child to parent cross-lag, parent innovation variance, and parent-child innovation covariance), controlling for relevant covariates (sociodemographic risk, family adversity, and child age in all three models, as well as protocol in the parent innovation variance model).

Controlling for covariates, higher child to parent cross-lag (reflecting more spillover in anger from children to parents) predicted more parent-reported externalizing behavior ($b = 5.12$, $p = .001$, $\beta = .22$). Younger child age and more family adversity uniquely predicted parent-reported externalizing. In a separate model, the magnitude of the link between externalizing behavior and parent innovation variance (i.e., novel anger reactivity) was attenuated in size and reduced to marginal significance ($b = .15$, $p = .07$, $\beta = .11$). Finally, parent-reported externalizing behavior was robustly predicted by higher innovation covariance (i.e., parent-child covariation in anger reactivity; $b = .17$, $p < .01$, $\beta = .20$), as well as more family adversity. Externalizing behavior was not significantly predicted by sociodemographic risk.

Significant associations were further challenged by including all three time-series parameters in a single model (Table 13). When the child-to-parent cross-lag, parent innovation variance, and innovation covariance were entered as simultaneous predictors, only the cross-lagged parameter continued to predict externalizing behavior ($b = 4.22$, $p < .05$, $\beta = .18$). This is likely due in part to collinearity between innovation variance and covariance (between-person correlation = .56, *CI* [.32, .75]. The unique predictive association of the cross-lag parameter was robust to the inclusion of demographic covariates as well as mean parent anger (Table 13). In the most complex models, family adversity also continued to significantly predict parent-reported externalizing behavior.

Discussion

The current study uses a novel analytic strategy to evaluate the dynamic interplay between parent and child affect in families experiencing homelessness. Specifically, I evaluated the affective dynamics of parent and child anger during a problem-solving discussion as potential predictors of children's social-emotional adjustment in the context of higher cumulative risk. Two DSEM models were tested and compared. The more complex model showed better fit to the data, underscoring the importance of modeling residual processes (i.e., innovations) that may reflect individual differences in emotion reactivity. The final model estimated within-person means for child and parent anger, as well as autoregressive parameters (i.e., stability in anger from one interval to the next), cross-lag parameters (i.e., spillover from one conversation partner to the other), log innovation variances (i.e., novel anger reactivity) and log innovation covariance (i.e., parent-child covariation in anger reactivity). As hypothesized, all fixed and random effects were significant, together accounting for 20.2% of the variance in child anger and 21.4% of the variance in parent anger.

In the sample as a whole, child and parent anger tended to persist from one interval to the next, and parents and children reciprocated each other's expressions of anger. This provides novel evidence of within-dyad transactions of parent-child anger in a diverse sample of families at high psychosocial risk. Furthermore, significant random effects indicated that parents and children varied in the magnitude of autoregressive and cross-lag parameters. Individuals who show higher stability in anger may have particular difficulty regulating mood and behavior, corresponding to evidence of 'emotional inertia' as a risk factor for depression (Kuppens et al., 2012; Kuval et al., 2016). Of note, parents reporting more family adversity showed more stability in anger expression, suggesting that affective dynamics may be one mechanism by which effects of adversity are carried forward. Regarding cross-lag parameters, individuals who respond more angrily to others' angry expressions may also be at risk for mood or behavior dysfunction. In particular, parents' angry responses to children's anger expressions may reflect a punitive style of emotion socialization linked to social-emotional maladjustment across the lifespan (e.g., Katz et al., 2012; Krause et al., 2013).

Parents and children also showed novel anger reactivity that was not explained by prior anger from either conversation partner or by person-specific means. These deviations from the expected anger trajectory, termed innovations, may reflect internal processes (e.g., sudden bursts of frustration) and/or evolving challenges in the problem-solving discussion (e.g., perceived rudeness from the conversation partner, difficulty sustaining focus on the task). Importantly, individuals showed significant variability in the size of deviations from their own lagged trajectories. Children and parents with higher innovation variances may be more reactive to external influences and/or encounter more challenges during the problem-solving process. To the extent that high innovations reflect lability and negative emotionality, this may also index risk for emotional maladjustment (Shields & Cicchetti, 1997).

Finally, parents and children showed modest innovation covariance, reflecting associations in child and parent anger reactivity *within* the 10-second intervals used for affect coding. Innovation covariance may reflect very rapid affect contagion and/or covarying responses to a shared experience. Again, dyads differed in their propensity toward anger reactivity co-variation. Parents and children with higher innovation co-variances may be more prone to anger escalation, as in a coercive cycle (e.g., Patterson, DeBaryshe, & Ramsey, 1990).

Of note, younger child age was related to higher child and parent innovation variance, as well as higher innovation covariance, suggesting higher anger reactivity at the individual and dyadic level. Young children and their parents may be more reactive to external influences, more likely to encounter challenges during the discussion, and/or more prone to anger reciprocation. Less-developed self-regulatory skills of younger children may contribute to greater anger reactivity in parents *and* children (Zelazo & Carlson, 2012). Parents of young children may need particular support to maintain healthy affective dynamics, particularly in the context of high poverty-related stress.

Between-dyad parameters capturing affective dynamics were exported as factor scores and evaluated as predictors of children's social-emotional adjustment, as reported by parents as well as teachers. The autoregressive component of child anger (i.e., stability) was robustly related to higher teacher-reported social-behavioral problems, but not worse emotion regulation, echoing findings from Study 1. This enhances confidence that the association between difficulty downregulating anger and teacher-reported problems is robust to different parameterizations and statistical tests.

With regard to family-based outcomes, affective dynamics were significantly related to parent-reported externalizing behavior, but not internalizing behavior. The latter finding may reflect functional differences in discrete emotions: internalizing symptoms are typically associated with expressions of sadness and fear, rather than anger. In contrast, higher parent-reported externalizing behavior was related to multiple aspects of parent-child anger dynamics. Specifically, parent-reported externalizing was related to more parental anger following children's anger (child to parent cross-lag), higher parent anger reactivity (innovation variance), and greater parent-child covariation in anger reactivity (innovation covariance). Measures of anger contagion (i.e., child to parent cross-lag and innovation covariance) continued to predict more parent-reported externalizing controlling for sociodemographic risk, family adversity, and child age. Additionally, when entered all three between-dyad effects were entered simultaneously, higher child to parent cross-lag continued to predict more parent-reported externalizing problems, and this association was robust to covariates and within-person mean anger. Although findings for innovation variance and covariance may have been suppressed by collinearity, results of follow-up testing demonstrate unique and persistent predictive associations between parents' contingent anger and children's externalizing behavior.

Consistent links between anger contagion and parent-reported behavior problems may reflect involvement in mutual escalation of coercive cycles (Patterson et al., 1990), implicated in the development and maintenance of conduct problems. Additionally, punitive responding to children's anger may elicit growth in anger over time, as children experience escalating negative emotion without parental support to regulate it (Eisenberg et al., 1998; Fosco & Grych, 2007; Morris et al., 2007; Thompson & Meyer, 2007). Teachers' reports of social-behavioral problems were not related to anger contagion between parents and children, perhaps because parent-child anger transactions are particularly related to children's behavior in the family context. However, given that parents reported on externalizing behavior, this finding may in part reflect reporter characteristics: parents who respond more angrily to their children's anger expressions may be more likely to interpret child behavior as problematic. Further research with collateral reporters (e.g., shelter staff, study staff, additional caregivers) would be helpful in clarifying interpretation of this result.

With regard to family-level risk factors, parent-reported externalizing behavior showed bivariate associations with more sociodemographic risk and family adversity. Associations with family adversity persisted after controlling for the role of affective dynamics. As noted in Study 1, sociodemographic risk was related to more social-behavioral problems at school. These findings underscore the relevance of variation in risk and adversity for social-emotional adjustment among young homeless children, despite generally high level of cumulative risk.

Strengths and Limitations

The study has notable strengths and limitations. It builds on prior research to incorporate rigorous assessment of the dynamic interplay between parent and child anger over time, providing novel insight into parent-child affect co-regulation. Like Study 1, it extends research on emotion regulation and socialization to a diverse sample of families experiencing high levels of chronic risk and acute adversity. The study was strengthened by the use of diverse measurement strategies, including parental report of risk and adversity, microsocial coding of parent-child anger, and parent and teacher reports of children's social-emotional adjustment. Multimethod assessment of children's behavior problems generated new insights and hypotheses regarding context- versus reporter-specific associations with parent- and teacher-reported functioning.

The study has limitations as well as strengths. Recruitment was limited to homeless families staying in emergency housing, complicating efforts to generalize results to low-income but housed families or homeless families not currently in shelter. Generalizability would be strengthened by replicating findings with families who are demographically similar but stably housed. Teacher-reported outcome data were not available for 24% of the sample, due to the substantial practical challenges of locating highly mobile children in schools; however, the response rate of teachers was extremely high (95%) for the 79% of children who were successfully located in schools. Finally, I was not able to analyze associations linking between-dyad effects with distal outcomes in a single DSEM model due to issues with model convergence, perhaps related to treating ordinal anger variables as continuous. Personal communication with the DSEM team indicated that new capabilities for ordinal variables will be included in the next update of MPlus, and focal analyses will be rerun as soon as they are available. In the meantime, the current two-stage strategy has precedent in the literature and, within the limits of current statistical functionality, provides a reasonable estimate of associations among affective dynamics and adjustment outcomes.

Conclusions and future directions

The current study confirms the role of parent-child affect co-regulation in predicting social-emotional adjustment among young children experiencing homelessness. In particular, stability in child anger was related to social-behavioral problems at school, whereas measures of anger contagion (child-to-parent cross-lag and innovation covariance) were related to higher parent-reported externalizing problems. Further research is needed to extend these findings to larger, more diverse samples, incorporating additional adaptive outcomes (e.g., emotional lability/negativity, teacher-child relationship) and following children over time. Research that incorporates sociocultural contextual variables (Dunbar et al., 2017) and physiological data would provide more comprehensive insight into dyadic co-regulation at multiple levels of analysis (e.g., Cui et al., 2015).

The current study builds on past findings and suggests promising new avenues for research and practice. Parent-child anger co-regulation has emerged as a promising intervention target. In particular, working with parents to minimize angry responses to children's anger may enhance social-emotional adjustment among young children experiencing homelessness. This may be targeted in parenting groups, individual therapy focused on parents' self-regulation of anger, and/or dyadic therapy techniques, depending on level of need. For children with severe behavior dysregulation, Parent-Child Interaction Therapy (Zisser & Eyberg, 2003) may be helpful for enhancing positive parent-child interaction, effective limit-setting, and children's behavioral regulation, promoting resilience in families at very high psychosocial risk. Similar to Study 1, direct associations between sociodemographic risk, family adversity, and aspects of child adjustment illustrate the need for complementary risk-reduction interventions aimed at mitigating poverty-related stress. A multi-pronged intervention approach combining poverty relief measures with support for emotion co-regulation may prove most effective at supporting child and family resilience in the context of severe psychosocial risk.

General conclusions

The current dissertation investigated emotion regulation and co-regulation during observed parent-child interaction as predictors of social-emotional adjustment in families experiencing homelessness. This program of research aims to better understand risk and protective processes in families at high psychosocial risk in order to inform targeted interventions to mitigate social-emotional risks associated with poverty and homelessness. Emotion regulation skills and parental emotion socialization represent plausible targets for intervention, as they are amenable to environmental influence and implicated in resilience across a variety of risks. However, nuanced multimethod research on emotion regulation and socialization is limited, particularly among families experiencing high risk and adversity.

The current dissertation addressed gaps in current literature by using observational measures of emotion reactivity and regulation in families with young children experiencing homelessness. The two studies employed complementary analytic strategies, first using a monadic approach to identify aspects of child and parent affect expression relevant to social-emotional adjustment. Results indicated children's difficulty down-regulating anger and parental membership in the Parent Anger profile each predicted more social-behavioral problems at school, as did higher sociodemographic risk. Dyads in the Parental Anger profile had children with more difficulty downregulating anger, corroborating theorized links between emotion regulation in parents and children.

Study 2 built on Study 1 by incorporating fine-grained analyses of affective dynamics over time. Dynamic structural equation modeling was used to differentiate within-person and between-person variation in anger expression over the course of the problem-solving interaction. Individuals showed significant temporal stability in anger expression, as well as significant cross-lagged paths from one person's anger to the other, consistent with bidirectional feedback processes. Individuals also showed novel anger reactivity (i.e., deviations from their predicted trajectory), which covaried modestly between parents and children. Importantly, participants showed individual differences in all estimated parameters, indicating that parents and children vary in anger dynamics.

Between-dyad differences in anger dynamics showed limited associations with cumulative risk variables, although parents exposed to more family adversity showed more stability in anger over time. Individual differences in child anger stability were linked to more social-behavioral problems at school. Meanwhile, more parent-reported externalizing problems were robustly associated with measures of anger contagion (higher child-to-parent cross-lag, higher innovation covariance) as well as more family adversity. Overall, findings support hypothesized bidirectional associations in parent and child anger, as well as their relevance for social-emotional adjustment in multiple domains.

Across both studies, findings highlight the importance of parent-child co-regulation for young children developing in contexts of risk and adversity. Intervention efforts targeted at enhancing anger regulation and co-regulation may help to promote resilient functioning in families at high cumulative risk, including those affected by homelessness. Furthermore, persistent links among sociodemographic risk, family adversity, and children's social-emotional adjustment underscore the value of complementary efforts to promote resilience by reducing poverty-related risk.

This dissertation builds on prior theory and research to enhance our understanding of emotion regulation and co-regulation in contexts of poverty-related stress. Results provide a more dynamic and nuanced understanding of affective dynamics among parents and children affected by homelessness, with implications for research and practice dedicated to promoting resilience among children and families experiencing high cumulative risk.

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Table 1. *Descriptive statistics and bivariate associations among child affect intensity and duration, social-emotional adjustment, and sociodemographic covariates.*

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Child distress intensity	--													
2. Child distress duration	.43***	--												
3. Child anger intensity	.19*	.16*	--											
4. Child anger duration	.30***	.24**	.68***	--										
5. Child positive intensity	.04	.03	.14†	.03	--									
6. Child positive duration	.09	.06	-.00	-.11	.50***	--								
7. Social-behavioral problems	-.03	.02	.19*	.31***	.11	-.10	--							
8. Emotion regulation	-.03	.02	-.14†	-.11	-.06	.06	-.56***	--						
9. Child sex (Male)	-.02	.02	.14†	.02	-.00	.07	.12	-.20*	--					
10. Child age	-.10	.03	-.13†	-.25**	.01	.07	-.12	.04	-.00	--				
11. Sociodemographic risk	.01	.07	.09	-.03	-.08	-.04	.17*	-.08	.15*	-.04	--			
12. Family adversity	.14†	.06	.03	.12	.05	-.01	.09	-.11	.04	-.00	.22**	--		
13. Shelter (Public)	.06	.06	.22**	.13†	.12	.06	.14†	-.18*	.05	.04	.06	.18*	--	
14. Protocol (2014)	-.16*	-.12	.06	.00	-.01	.03	-.01	.10	-.03	-.12†	-.11	.15*	.13†	--
Mean (% if binary)	3.62	.16	2.78	.02	3.11	.09	10.88	22.67	56%	5.79	4.12	2.10	68%	51%
Standard Deviation	.62	.11	.74	.03	1.10	.07	7.81	3.99	--	.62	1.55	1.70	--	--
Minimum to Maximum	3-5	.01-.52	2-5	0-.22	1-5	0-.45	0-31	0-13	--	4.2-7	1-9	0-7	--	--

N = 203. † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$.

Table 2. *Child anger intensity and duration as predictors of total teacher-reported social-behavioral problems, adjusting for covariates.*

	SDQ Total Problems		
	β	95% CI (β)	R^2
1. Child anger intensity	-.03	[-.23, .18]	.10
Child anger duration	.31**	[.09, .53]	
2. Child anger intensity	-.04	[-.25, .17]	.16*
Child anger duration	.34**	[.12, .56]	
Child distress intensity	-.12	[-29, .06]	
Child distress duration	-.00	[-.17, .17]	
Child age	-.04	[-.20, .12]	
Shelter (Public)	.08	[-.06, .23]	
Sociodemographic risk	.17*	[.00, .33]	

† $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$

Table 3. *Descriptive statistics and bivariate associations linking parent affect with child affect, social-emotional adjustment, and covariates.*

	1	2	3	4	5	6
1. Mean parent distress: discussion	--					
2. Mean parent distress: game	.46***	--				
3. Mean parent anger: discussion	-.13†	-.05	--			
4. Mean parent anger: game	.03	.18*	.26**	--		
5. Mean parent positive: discussion	-.12*	.04	-.18**	-.08	--	
6. Mean parent positive: game	-.11†	-.14**	-.09	-.02	.43***	--
7. Child distress duration	.03	.06	.13	.04	-.08	-.02
8. Child anger duration	-.06	.02	.45**	.16†	-.13*	-.21**
9. Child positive duration	-.01	-.01	.02	.00	.13	.33***
10. Social-behavioral problems	-.18**	.06	-.04	.00	.00	-.14
11. Emotion regulation	-.01	-.01	-.14	-.04	.02	-.16†
12. Child sex (Male)	.02	-.02	.08	.08	.03	-.02
13. Child age	.04	.11†	-.25***	-.14*	-.14*	.07
14. Sociodemographic risk	.10	-.04	-.07	.03	.00	.04
15. Family adversity	-.12**	-.06	-.02	.04	-.04	-.03
16. Shelter (Public)	-.06	.03	-.01	.18**	.03	-.12
17. Protocol (2014)	-.21***	.03	-.11	-.24**	-.02	.11
Mean (% if binary)	1.91	1.50	1.39	1.26	1.82	2.21
Standard Deviation	.42	.29	.74	.32	.20	.51
Minimum-Maximum	1.08-3.93	1.03-2.97	1.00-3.26	1.00-1.95	1.00-3.66	1.00-3.91

N=203. † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$. See Table 1 for descriptive statistics and correlations of child affect and covariates.

Table 4. *Fit indices for latent profile analyses of parent affective expression.*

Model	*LL*	*npar*	*AIC*	*BIC*	*CAIC*	*AWE*	*LRTS χ^2 (k, k+1)*	*LMR-LRT p-value*	*Bootstrap p-value*	*BF(K, K+1)*	*cmP(K)*	*BF(K, M0)*
Diagonal class-invariant												
1-class solution	-466.8	12	957.5	997.3	1009.3	**1097.2**	69.1	.40	<.001	.00	.00	.00
2-class solution	-432.2	19	902.5	965.5	984.5	1123.5	48.4	.16	<.001	.00	.00	.00
3-class solution	**-393.0**	26	**838.0**	**924.3**	**950.3**	1140.6	--	--	--	--	**1.0**	**4230.4**
Saturated model	-398.7	27	851.4	941.0	968.0	1165.6	--	--	--	--	--	--
Diagonal class-varying												
1-class solution	-.466.8	12	957.5	997.3	1009.3	1097.2	183.8	<.001	<.001	.00	0.0	0.0
2-class solution	-374.8	25	799.7	**882.6**	**907.6**	**1090.6**	--	--	--	--	1.0	**$4.7*10^{12}$**
3-class solution	--	--	--	--	--	--	--	--	--	--	--	--
4-class solution	**-316.2**	51	**734.1**	903.4	954.4	1327.6	--	--	--	--	0.0	**$1.5*10^{8}$**
Saturated model	-398.7	27	851.4	941.0	968.0	1165.6	--	--	--	--	--	**--**
Non-diagonal class-invariant												
1-class solution/ Saturated	-398.7	27	851.4	941.0	968.0	1165.6	--	--	--	--	--	**--**
Non-diagonal class-varying												
1-class solution/ Saturated	-.398.7	27	851.4	941.0	**968.0**	**1165.6**	156.1	.0012	<.001	.03	.03	1.0
2-class solution	**-320.7**	55	**751.3**	**933.8**	988.8	1391.3	--	--	--	--	**.97**	**36.2**

LL = loglikelihood; n = number of parameters; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; CAIC = Consistent Akaike Information Criterion; AWE = Approximate Weight of Evidence Criterion; LRTS = Likelihood Ratio Test Statistic; LMR-LRT p-value = adjusted Lo-Mendell-Rubin Likelihood Ratio Test (H_0 comparing K classes vs. K + 1 classes); BF(K, K+1) = Bayes Factor ratio of Models K and K+1; cmP(K) = correct model probability; BF(K, M0) = Bayes Factor ratio of Model K and the Mean-Variance Saturated Model. Bolded values correspond to the best fit indicator for a given variance/covariance structure. Columns with no bolded values indicate that index was not reached prior to the maximum class extraction supported by the data.

Table 5. *Classification diagnostics for three candidate models*.

Solution	*Class*	*Estimated k-class proportion*	$mcaP_k$	$AvePP_k$	OCC_k	*Entropy*
Diagonal, class-invariant	Profile 1	.087	.078	.908	103.57	.856
3-class	Profile 2	.123	.108	.883	53.81	
	Profile 3	.790	.814	.950	5.05	
Diagonal, class-varying	Profile 1	.691	.716	.922	5.29	.693
2-class	Profile 2	.309	.284	.890	18.09	
Non-diagonal, class-varying	Profile 1	.773	.784	.954	6.09	.796
2-class	Profile 2	.227	.216	.886	26.47	

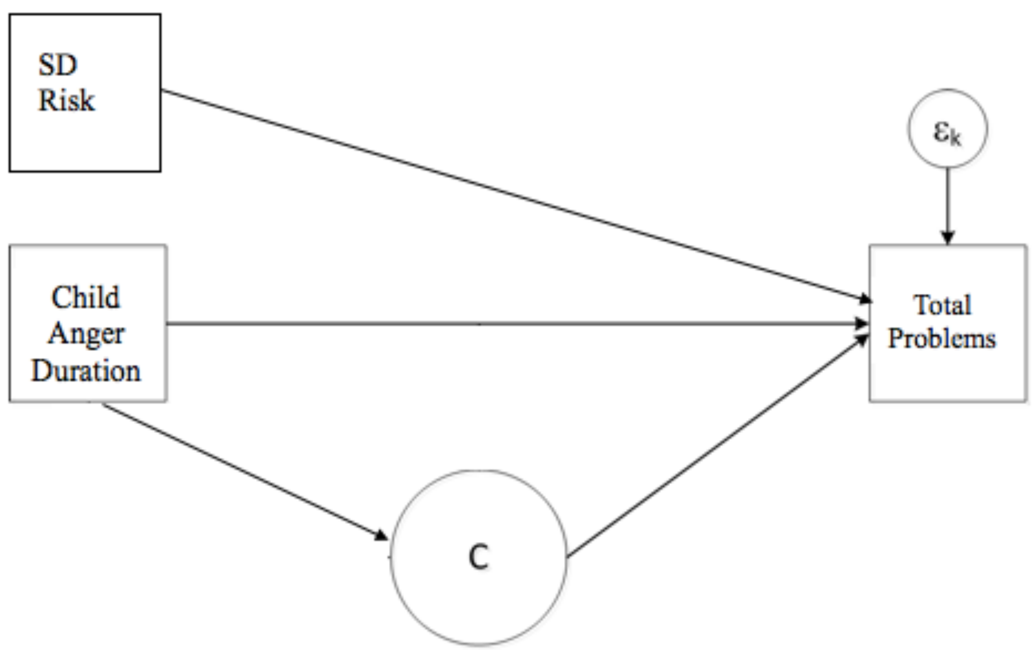
$mcaP_k$ *= modal class assignment proportion for class k.* $AvePP_k$ *= Average posterior class probability.* OCC_k *= odds of correct classification ratio for class k.*

Table 6. *Mean levels of parent affect by profile in the final two candidate models.*

Solution	*Profile*	*Parent Distress Discussion*	*Parent Distress Game*	*Parent Anger Discussion*	*Parent Anger Game*	*Parent Positive Discussion*	*Parent Positive Game*
Diagonal, class-invariant	Profile 1	1.82 (*SD* .11)	1.49 (*SD* .07)	2.11 (*SD* .05)	1.34 (*SD* .04)	1.41 (*SD* .22)	1.70 (*SD* .26)
3-class	Profile 2	2.58 (*SD* .11)	1.88 (*SD* .07)	1.36 (*SD* .05)	1.30 (*SD* .04)	1.44 (*SD* .22)	1.73 (*SD* .26)
	Profile 3	1.82 (*SD* .11)	1.45 (*SD* .07)	1.32 (*SD* .05)	1.25 (*SD* .04)	1.91 (*SD* .22)	2.34 (*SD* .26)
Diagonal, class-varying	Profile 1	1.81 (*SD* .10)	1.44 (*SD* .05)	1.30 (*SD* .04)	1.22 (*SD* .03)	1.97 (*SD* .25)	2.38 (*SD* .23)
2-class	Profile 2	2.14 (*SD* .28)	1.65 (*SD* .13)	1.60 (*SD* .18)	1.37 (*SD* .07)	1.45 (*SD* .09)	1.83 (*SD* .22)

SD = Standard deviation

Figure 1. *Model depicting latent class regression of social-behavioral problems on parental profiles, child anger duration during the discussion, and sociodemographic risk.*

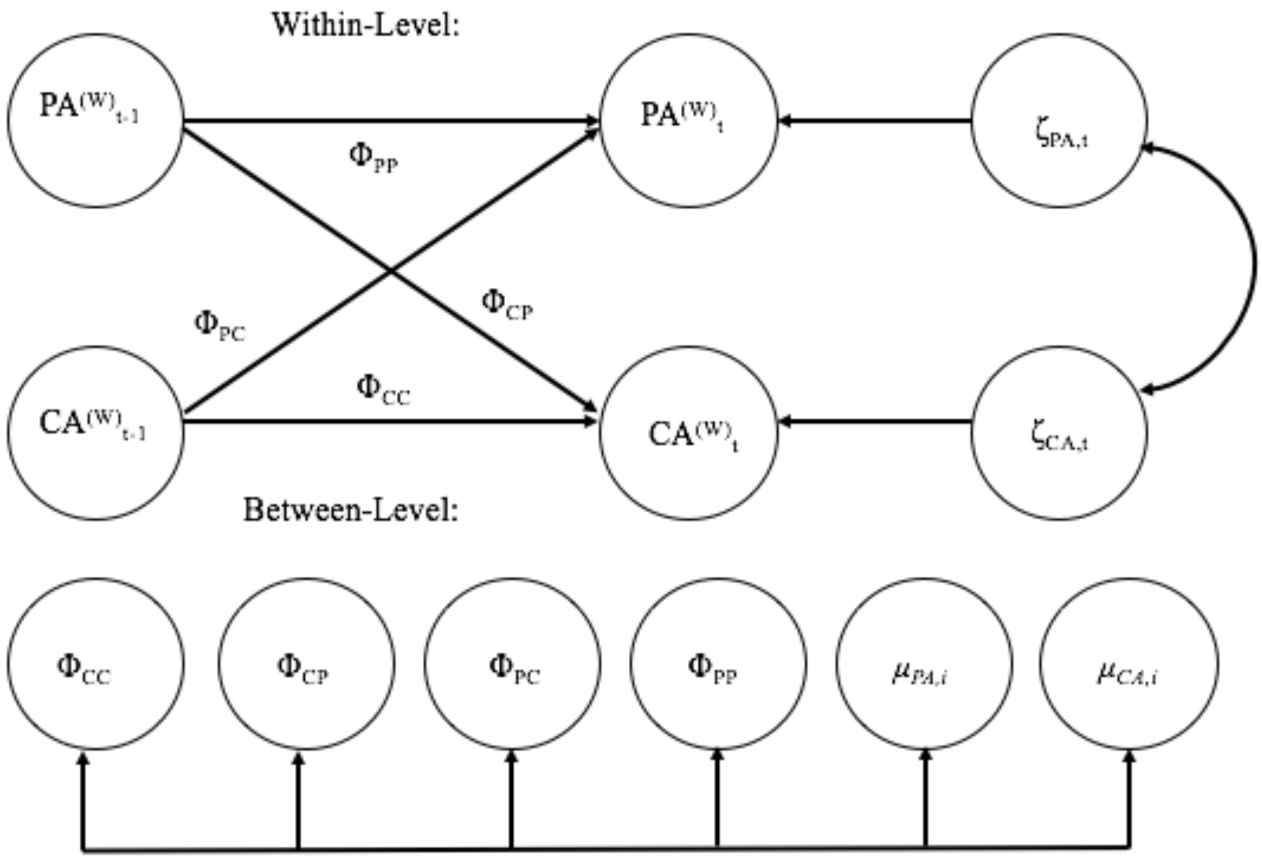


SD Risk = Sociodemographic risk. C = Class membership. Total Problems = Total teacher-reported social behavioral problems on the Strength and Difficulties Questionnaires.

Table 7. *Child behavior items by protocol.*

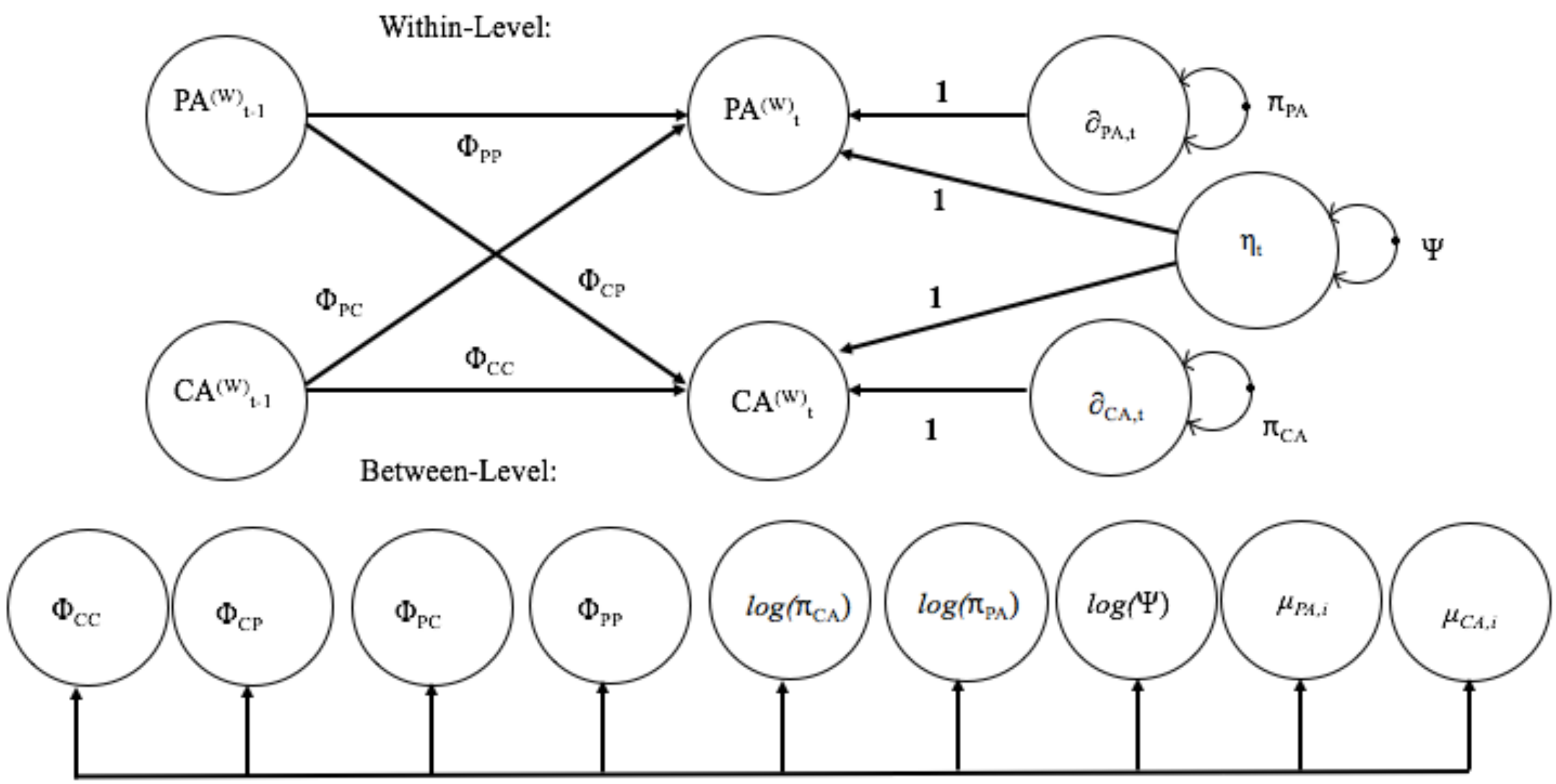
Scale/Symptom	**SDQ item (2012 protocol)**	**HBQ item(s) (2014 protocol)**
Externalizing		
Loses temper	5. Often loses temper	69. Has temper tantrums or hot temper
Disobedience/ defiance	7. Generally well behaved, usually does what adults request (reversed)	77. Argues a lot with adults 87. Defiant, talks back to adults 132. Disobedient at school
Fights with peers	12. Often fights with other children or bullies them	78. Argues a lot with peers 135. Kicks, bites or hits other children 138. Cruel, bullies, or mean to others 143. Gets in many fights
Lies/cheats	18. Often lies or cheats	80. Lies or cheats
Steals	22. Steals from home, school, or elsewhere	72. Steals, takes things that don't belong to him/her
Internalizing		
Somatic complaints	3. Often complains of headaches, stomachaches, or sickness	95. Physical problems without known medical cause: 95a. Aches and pains 95b. Headaches 95c. Nausea, feels sick 95d. Stomachaches or cramps
Frequent worries	8. Many worries or often seems worried	68. Worries about things in the future 75. Worries about past behavior 86. Worries about doing better at things
Sad mood	13. Often unhappy, depressed, or tearful	123. Unhappy, sad, or depressed 137. Cries a lot
Self-consciousness/ Need for reassurance	16. Nervous or clingy in new situations, easily loses confidence	102. Self-conscious or easily embarrassed 109. Needs to be told over and over that things are okay
Fearfulness/vigilance	24. Many fears, easily scared	115. Nervous, high strung, or tense

Figure 2. *Diagram of within- and between-levels of DSEM Model 1.*



$PA_{it}^{(W)}$ and $CA_{it}^{(W)}$ reflect temporal deviations from person-specific means of Parent Anger and Child Anger, respectively. $\Phi_{PP,i}$ and $\Phi_{CC,i}$ denote stability (i.e., autoregression) in parent and child anger. $\Phi_{PC,i}$ and $\Phi_{CC,I}$ denote spillover (i.e., cross-lags) from child to parent anger and vice versa. ζ_{PA} and ζ_{CA} reflect residuals (i.e., innovations) in parent and child anger. In Model 1, innovation variance and covariance are fixed to be equal across individuals.

Figure 3. *Diagram of within- and between-levels of DSEM Model 2.*



$PA_{it}^{(W)}$ and $CA_{it}^{(W)}$ reflect temporal deviations from person-specific means of Parent Anger and Child Anger, respectively. $\Phi_{PP,i}$ and $\Phi_{CC,i}$ denote stability (i.e., autoregression) in parent and child anger. $\Phi_{PC,i}$ and $\Phi_{CC,I}$ denote spillover (i.e., cross-lags) from child to parent anger and vice versa. η_t is common factor of shared residual (i.e., innovation) variance, whereas $\partial_{CA,t}$ and $\partial_{PA,t}$ denote unique variances of child and parent residuals. Shared and unique variances are summed to obtain total innovation variances π_{PA} and $\pi_{CA,}$ whose covariation is denoted Ψ. Innovation variances and covariances are scaled on log-normal distributions.

Table 8. *Point estimates (posterior means) and 95% credible intervals for fixed and random effects in DSEM Models 1 and 2.*

	Model 1		***Model 2***	
Variable	***Fixed effects (means)***	***Random effects (variances)***	***Fixed effects (means)***	***Random effects (variances)***
Person-specific mean: CA	1.52 [1.47, 1.58]	.12 [.09, .16]	1.49 [1.45, 1.54]	.08 [.06, .11]
Person-specific mean: PA	1.41 [1.37, 1.46]	.08 [.06, .11]	1.37 [1.34, 1.41]	.04 [.03, .05]
AR parameter: CA	.21 [.17, .25]	.03 [.02, .05]	.21 [.17, .25]	.04 [.03, .06]
CL parameter: PA to CA	.03 [<.01, .07]	.01 [<.01, .02]	.03 [<.01, .06]	.01 [<.01, .01]
CL parameter: CA to PA	.05 [.01, .23]	.02 [.01, .03]	.05 [.02, .23]	.01 [<.01, .02]
AR parameter: PA	.19 [.15, .23]	.03 [.02, .05]	.19 [.15, .23]	.05 [.04, .07]
Log innovation variance CA	--	--	-1.44 [-1.56, -1.33]	.51 [.39, .66]
Log innovation variance PA	--	--	-1.52 [-1.65, -1.39]	.67 [.52, .87]
Log innovation covariance	--	--	-3.69 [-3.98, -3.42]	1.39 [.97, 1.92]

CA = Child Anger, PA = Parent Anger. AR = Autoregressive. CL = Cross-lagged. Person-specific mean refers to a given individual's mean, equilibrium, or attractor state across the interaction. Autoregressive parameters reflect carryover in an individual's anger from one interval to the next. Cross-lagged parameters reflect spillover from one conversation partner to the other. Innovation variance refers to anger reactivity not accounted for by prior anger and innovation covariance reflects concurrent covariation in parent-child anger reactivity. Innovation variance and covariances are scaled on log-normal distributions.

Table 9. *Between-person correlations among random effects in DSEM Model 2: point estimates and 95% credible intervals*

	1	2	3	4	5	6	7	8
1. AR parameter: CA	--							
2. CL parameter: PA to CA	-.15 [-.54, .27]	--						
3. CL parameter: CA to PA	.04 [-.30, .38]	.39 [-.14, .76]	--					
4. AR parameter: PA	.17 [-.09, .41]	.22 [-.17, .57]	.12 [-.23, .49]	--				
5. Log innovation variance CA	.37* [.15, .56]	.20 [-.16, .51]	-.04 [-.38, .30]	.23* [.02, .41]	--			
6. Log innovation variance PA	.12 [-.10, .33]	.14 [-.27, .54]	.24 [-.04, .50]	.19 [-.02, .39]	.19* [.01, .36]	--		
7. Log innovation covariance	.33* [.02, .58]	.30 [-.15, .68]	.30 [-.12, .66]	.20 [-.08, .45]	.56* [.32, .75]	.55* [.34, .74]	--	
8. Person-specific mean CA	.57* [.38, .73]	.26 [-.12, .58]	.07 [-.24, .38]	.17 [-.04, .37]	.89* [.82, .94]	.27* [.09, .43]	.71* [.52, .85]	--
9. Person-specific mean: PA	.17 [-.06, .38]	.26 [-.13, .61]	.33* [.01, .63]	.49* [.30, .65]	.35* [.17, .50]	.91* [.84, .95]	.68* [.48, .75]	.40* [.23, .55]

N= 189. CA = Child Anger, PA = Parent Anger. AR = Autoregressive. CL = Cross-lagged. * denotes statistical significance (i.e., 95% credible interval not including 0).

Table 10. *Descriptive statistics and bivariate correlations of between-dyad effects and parent-reported behavior problems with covariates and teacher-reported adjustment.*

	AR path: CA	CL path: PA to CA	CL path: CA to PA	AR path: PA	Log Inn. Var. CA	Log Inn. Var. PA	Log Inn. Cov.	Person Mean CA	Person Mean PA	Int. (P)	Ext. (P)
Internalizing (P)	.05	-.07	.02	.03	-.03	.05	-.01	-.02	.03	--	
Externalizing (P)	.12†	.13	.26***	.16†	.08	.16**	.24***	.15†	.19**	.25**	--
Social-behavioral problems (T)	.21*	.06	.06	.13	.15	.08	.11	.18†	.11	-.01	.27**
Emotion regulation (T)	-.03	-.01	.02	-.06	-.10	-.13†	-.08	-.09	-.13†	-.08	-.23**
Child sex	.04	.05	-.02	.09	.10	.04	.02	.08	.07	.01	-.02
Child age	-.11	-.13†	-.18*	-.14†	-.14*	-.25**	-.21**	-.18**	-.23**	-.06	-.19*
Sociodemo-graphic Risk	.07	-.04	.08	-.09	-.14*	.07	-.06	-.09	.00	.12	.17*
Family Adversity	.12†	.00	.11	.16*	.10	.03	.14†	.12	.08	.32***	.22**
Shelter (Public)	.13†	.06	-.06	.13†	.23**	-.03	.06	.19*	.03	-.01	.10
Protocol (2014)	.06	.16*	-.06	.02	.18**	-.21**	.09	.18*	-.13†	.04	.02

N= 189. CA = Child Anger, PA = Parent Anger. AR = Autoregressive. CL = Cross-lagged. Inn. = Innovation. Var. = Variance. Cov. = Covariance. T = teacher-report. P = Parent-report. Int. = Internalizing. Ext = Externalizing. † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$. For descriptive statistics and correlations among covariates and teacher outcomes, see Table 1. Person mean refers to a given individual's mean, equilibrium, or attractor state across the interaction. Autoregressive parameters reflect carryover in an individual's anger from one interval to the next. Cross-lagged parameters reflect spillover from one conversation partner to the other. Innovation variance refers to anger reactivity not accounted for by prior anger and innovation covariance reflects concurrent covariation in parent-child anger reactivity. Innovation variance and covariances are scaled on log-normal distributions.

Table 11. *Predicting total social-behavioral problems from the autoregressive component of child anger and covariates.*

	SDQ Total Problems			
	b	*β*	95% *CI (β)*	R^2
1. AR parameter: CA	11.18*	.21*	[.05, .37]	.06
Sociodemographic risk	.60	.12	[-.04, .28]	
2. AR parameter: CA	7.56	.14	[-.07, .35]	.07
Sociodemographic risk	.68	.14	[-.03.30]	
Child mean anger	2.95	.10	[-.12, .33]	

N = 189. AR = Autoregressive. Autoregressive parameters reflect carryover in an individual's anger from one interval to the next. * $p < .05$.

Table 12. *Predicting parent-reported externalizing problems from between-dyad effects and covariates.*

	CL parameter: Child to parent anger			*Log innovation Parent anger*			*Log innovation covariance*		
	b	*β*	R^2	*b*	*β*	R^2	*b*	*β*	R^2
Between-dyad effect	5.12**	.22**	.14**	.15†	.11†	.10*	.17**	.20**	.13**
Child age	-.27*	-.16*		-.27*	-.16*		-.23†	-.14†	
Sociodemographic risk	.07	.10		.07	.10		.09†	.13†	
Family adversity	.09*	.16*		.11**	.18**		.09*	.15*	
Protocol	--	--		.00	.00		--	--	

N = 189. CL = Cross-lagged. Cross-lagged parameters reflect spillover from one conversation partner to the other. Innovation variance refers to anger reactivity not accounted for by prior anger and innovation covariance reflects concurrent covariation in parent-child anger reactivity. Innovation variance and covariances are scaled on log-normal distributions. † $p < .10$, * $p < .05$, ** $p < .01$

Table 13. *Predicting parent-reported externalizing problems from multiple time-series parameters and covariates.*

	SDQ Total Problems			
	b	*β*	95% *CI (β)*	R^2
1. CL parameter CA to PA	4.22*	.18*	[.03, .34]	.08*
Log innovation PA	.01	.01	[-.13 .14]	
Log innovation covariance	.11	.13	[-.04, .31]	
2. CL parameter CA to PA	3.84*	.17*	[.02, .31]	.15**
Log innovation PA	-.01	-.01	[-.14, .12]	
Log innovation covariance	.09	.11	[-.07, .28]	
Child age	-.24†	-.14†	[-.30, .01]	
Sociodemographic risk	.08†	.12†	[-.02, .26]	
Family adversity	.09*	.15*	[.01, .28]	
3. CL parameter CA to PA	4.22*	.18*	[.03, .33]	.15**
Log innovation PA	.11	.08	[-.43, .60]	
Log innovation covariance	.11	.13	[-.08, .33]	
Child age	-.24†	-.15†	[-.30, .00]	
Sociodemographic risk	.07	.11	[-.03, .25]	
Family adversity	.09*	.15*	[.01, .29]	
Parent mean anger	-.64	-.12	[-.74, .51]	

N = 189. CA = Child Anger. PA = Parent Anger. CL = Cross-lagged.
† $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$.