INTRODUCTION

From the micro-level, moment-to-moment interactions between parents and children, to the schemas developed about childhood, the parent-child relationship provides critical scaffolding over child development. Decades of research on child development in mammals converge on the finding that parents, even when passive, are major orchestrators of offspring emotional, physiological, and neural reactivity. For example, in rats, proximity to the mother regulates the pup's heart rate (Hofer, 1973), alters their neural oscillations (Sarro et al., 2014), and reduces their behavioral reactivity to painful events (Richardson et al., 1989). In humans, parental presence/support can decrease cortisol levels in response to a socioemotional stressor (Hostinar et al., 2015a), engage unique patterns of neural activity in children (Gee et al., 2014), and can alter behavioral reactivity to scary situations (van Rooij et al., 2017). Together these studies demonstrate that across numerous different species and neurobiological systems, parents play an important and powerful role in the biological and associated emotional reactivity of their child.

Numerous theories have been developed to describe how parents exert such a strong influence over their children's emotion-associated systems, with many arguing that parental effects over...
child neurobiology are essential for the emergence of subsequent emotional self-regulation in the child (Callaghan & Tottenham, 2016; Feldman, 2007; Hofer, 1994; Welch, 2016). For example, in one theory, an optimal level of parent-child dependence (when the child can explore the environment, but looks to the parent for support) coincides with the opening of a sensitive period where subsequent parental inputs can shape child neurobiology in ways that promote eventual emotion self-regulation (Callaghan & Tottenham, 2016).

A consequence of this hypothesis is, of course, that a lack of parental input or poor-quality parent-child interactions are predicted to increase risk for emotional dysregulation in children. In other words, if parental regulation over child neurobiology is important for the emergence of emotional self-regulation and thus, emotional health, then the absence of parents might have an outsized impact on the maturation of children’s emotion-associated neurobiology, which could increase risk for later mental health problems. Indeed, poor early caregiving is consistently associated with elevated psychiatric symptoms (e.g., anxiety and depression; Bos et al., 2011; Green et al., 2010), as well as alterations in the development of emotion circuitry, for example, interactions between amygdala and prefrontal cortex (Gee et al., 2013; Herringa et al., 2016; Marusak et al., 2016; Thijssen et al., 2017). Moreover children exposed to disrupted/absent caregiving in the form of relinquishment into institutional care have been shown to exhibit hormonal and neural reactivity profiles that are less responsive to parental presence and absence. For example, children who were exposed to institutional care prior to adoption did not show the same (putatively adaptive) reductions in cortisol levels to stress in the context of parental presence, as did their peers who had not experienced prior institutionalization (Callaghan, et al., 2019; Hostinar et al., 2015b). In another study, children exposed to disrupted/absent caregiving did not engage the same unique neural reactivity patterns to parental input as did their never-institutionalized peers (Callaghan et al., 2019). Specifically, whereas never institutionalized children showed lower amygdala reactivity when viewing pictures of the parent’s face, relative to pictures of a stranger’s face (interpreted as greater parental “buffering”), the group of children who were exposed to disrupted/absent caregiving showed no amygdala differentiation between pictures of parents and strangers. Interestingly, in that study, the neural profile characteristic of the group exposed to disrupted/absent caregiving (no amygdala differentiation to parents and strangers) was associated with sustained elevations in anxiety 2 years later. Hence, consistent with past theories (Callaghan & Tottenham, 2016) these data suggest that parental effects over child neurobiology are altered in phasic macro-level ways following exposure to disrupted/absent caregiving, and that such changes are associated with increased risk for mental illness.

The studies discussed above suggest that children’s phasic interactions with their parents (as they vacillate between periods of parental presence and absence at a macro-level) help to sculpt their emotional and neurobiological development. Specifically, it has been suggested that during phases of parental presence or support, children’s neurobiological systems are engaged in mature regulatory patterns, which gradually facilitates subsequent self-regulation when parents are absent (Callaghan & Tottenham, 2016). In other words, according to this theory, it is the transition between phases of parental presence and then absence that gradually tones the neural network into a regulatory system.

Even within periods of parental presence, evidence suggests that there are dynamic transactional exchanges between parent and child behavior and biology, which may further shape child emotional development, as shown in the examples below. In humans, it has been shown that parent-child interactions can shape child biology in a moment-to-moment fashion (e.g., Leong et al., 2017). Much (but not all) of this work has relied on physiological measures, such as heart rate, because of the temporal resolution (which enables investigation of parent-child interactions in increments less than a second), and because of the strong positive association between certain heart rate metrics, such as heart rate variability, and emotional health across the lifespan (Beauchaine & Thayer, 2015; Rukmani et al., 2016; Sharma et al., 2011). For example, during periods of face-to-face interaction, mothers and infants will synchronize their heart rates with lags of less than one second (Feldman et al., 2011). In that study, cardiac synchronization was further promoted during periods of affective and vocal synchrony between mother and infant (i.e., during periods of time when mother and infant matched their positive affect or positive vocalizations). In other words, positive emotions fortified moment-to-moment biological synchronization in humans, a finding which has recently been supported in neuroimaging studies of brain activity synchrony in adult dyads (Smirnov et al., 2019). In other human studies, biological synchronization in mother-infant dyads has been observed between physiological systems. For example, during periods of skin-to-skin contact, parental cardiac rhythms influenced infant respiratory stability (Bloch-Salisbury et al., 2014). Together these studies reveal a complex picture in which multiple levels of parent-child biology and behavior can become more or less synchronized on a moment-to-moment basis as a function of the dynamics of the interaction, with (at least positive) emotion playing a particularly important role. Given this importance of in-the-moment emotion influencing physiological synchrony, it is not surprising that such synchrony has itself been connected to the long-term emotional health of the child. Periods of biobehavioral synchrony in infancy have been suggested to form the basis of attachment (Fleming et al., 1999), and studies have also shown that synchrony provides a scaffold for the infant’s future emotional development, even into adolescence (Feldman, 2010; Feldman et al., 1996, 1999). Importantly, it has been suggested that synchronous parent-child interactions create a biological framework within which the infants themselves will later parent, influencing the next generation (Feldman et al., 2010).

The importance of moment-to-moment parent-child interactions for the child’s long-term emotional health suggests that groups at risk for emotional dysregulation, e.g., those exposed to caregiving adversity, may be less responsive during moment-to-moment interactions with the caregiver. That is, that the opportunities for shaping child emotional health through biobehavioral synchrony are lessened or missed in adversity exposed youth. Although the
literature examining how early experiences alter micro-dynamics in parent-child biological and behavioral regulation is sparse, there is some evidence that caregiving adversity (in the form of maternal depression) is associated with less synchronous parent-infant interactions. Specifically, studies have shown lower levels of synchronous gaze and touch in depressed mother-infant dyads (Granat et al., 2017), which is also true of synchronous cardiac activity in depressed mother-child/adolescent dyads (Amole et al., 2017; McKillop & Connell, 2018; Suveg et al., 2019; Woody et al., 2016). Parent-adolescent cardiac synchrony was also reported to be lower in dyads where adolescent emotional instability was high (Li et al., 2020), and both maternal aggression and child internalizing symptoms were associated with weaker parent-child cardiac synchrony in young children (Lunkenheimer et al., 2018). Thus, cardiac synchrony is associated with both adult and child/adolescent emotional health. Together, these studies clearly demonstrate that micro-level, moment-to-moment dynamics can be disrupted in conditions of parental depression, and are associated with mental health outcomes in youth. However, it remains unknown if caregiving adversities beyond maternal depression, for example, disrupted/absent caregiving due to institutional care, would alter such micro-level synchronization. This is an important gap in the literature as disrupted/absent caregiving is not only strongly associated with emotional dysregulation across the lifespan (McLaughlin et al., 2010), but numerous within-individual physiological measures, such as heart rate variability, have been shown to be disrupted in youth who were adopted from institutional care (Esposito et al., 2016; McLaughlin et al., 2015). To address this gap in the literature, in the current study we examined the effects of caregiving adversity on moment-to-moment heart rate physiology in parent-child/adolescent dyads where the child/adolescent had experienced disrupted/absent caregiving prior to adoption and in a comparison group of children who were never chronically separated from their caregivers.

One question to emerge from studies of physiological synchrony between parent and child, is what these events represent. Synchrony is a measure of temporal concordance between two signals, and as such, measures of synchrony are limited by a lack of information on directional relationships in the signal. Such associations might be important, providing information on which signal conveys vs. receives information. This is particularly interesting for parent-child dyads where a hierarchical relationship naturally exists, and because of data showing associations between child emotional health and parents who are more responsive to their child (i.e., follow the child’s lead; Blair et al., 2015; Stacks et al., 2014). An alternative approach to computing synchrony is to instead examine Transfer Entropy (TE). TE tracks information flow between two signals, enhancing quantification of directional coupling, allowing for the examination of parent-child and child-parent influences (Lucchini et al., 2017; Schreiber, 2000). Moreover TE measures both linear and non-linear contributions to coupling, allowing for the capture of more complex dynamics. In specific terms, TE measures how much unique variance in signal A can be predicted from past instances of signal B, and vice versa, with higher TE values indicating a greater level of predictability (which we label ‘transference’). Past studies have used TE to understand within-person transference, for example, the direction of influence within an active brain circuit (Vicente et al., 2011; Wibral et al., 2011), information transfer between cardiac and respiratory signals (Faes et al., 2014), or the development of rhythmic motor movements (Trendafilov et al., 2020). Similarly, TE has been used to examine between-person transference, e.g., transfer of information between parent gaze and child hand movements (Nagai et al., 2012), parent and infant sensorimotor activity (Choi et al., 2011), as well as heart rate variability (HRV) between mother and infant (Lucchini et al., 2017; Marzbanrad et al., 2015). Thus, TE is a powerful causal measure which can provide additional information beyond synchrony-based approaches. We refer readers to the following reviews on the benefits of TE as compared to other causal modelling approaches (Barnett et al., 2009; Faes et al., 2011; Friston et al., 2013; Schulz et al., 2013).

Notably, TE has not been used previously to examine cardiac coupling beyond the infancy/early childhood stage of development, nor how such coupling is associated with emotional outcomes in youth, and may be altered in those who have experienced early life caregiving adversity. Thus, the aim of the present study was to use TE to understand moment-to-moment physiological information transfer in cardiac signals between parents and their children/adolescents, whether such information transfer was altered in youth who had experienced disrupted/absent caregiving (prior institutionalization or maltreatment, resulting in adoption), and finally, whether information transfer was related to emotional health in those youth. Although most past studies of moment-to-moment parent-child synchrony have focused on interaction tasks (e.g., positive and negative discussions; Suveg et al., 2019; Woody et al., 2016), there are no studies which have used TE on dyadic cardiac data during periods of interaction. As this is the first known test of cardiac transference in parent-youth dyads, we therefore decided to focus on TE at rest. As such, we ask the important question of whether TE occurs during the ubiquitous passive interactions that parents and their children are so frequently engaged in (e.g., as they travel, work, and eat as a family).

2 | METHODS

2.1 | Participants

Participants were N = 118 individuals, aged between 4 and 18 years old, and who had either been raised with their birth families (Comparison, N = 74), or had experience disrupted/absent caregiving (Disrupted/Absent Care, N = 44; see Table 1 for age, sex, and racial/ethnic distributions across the two groups). The Disrupted/Absent Care group consisted of youth who had been separated from their birth parents due to institutional or foster care abroad before international adoption (N = 41) or domestic foster care followed by adoption within the United States (N = 3; see Table 1 for youth region of origin). While qualitatively different experiences, both forms of disrupted/absent caregiving (institutional and foster care) represent significant deviations in species
TABLE 1 Age, sex, race/ethnicity, region of origin distributions in the two study groups, and caregiving variables in the Disrupted/Absent Care group

<table>
<thead>
<tr>
<th></th>
<th>Comparison (N = 74)</th>
<th>Disrupted/absent care (N = 44)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean age (range)</td>
<td>10.3 years (4.4–17.3 years)</td>
<td>12.3 years (5.4–17.7 years)</td>
</tr>
<tr>
<td>Sex</td>
<td>Female = 38, Male = 36</td>
<td>Female = 30, Male = 14</td>
</tr>
<tr>
<td>Race/ethnicity N(%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>African American</td>
<td>16 (22%)</td>
<td>5 (11%)</td>
</tr>
<tr>
<td>Asian American</td>
<td>5 (7%)</td>
<td>18 (41%)</td>
</tr>
<tr>
<td>European American</td>
<td>18 (24%)</td>
<td>6 (14%)</td>
</tr>
<tr>
<td>Hispanic</td>
<td>12 (16%)</td>
<td>4 (9%)</td>
</tr>
<tr>
<td>Multiple race</td>
<td>12 (16%)</td>
<td>2 (5%)</td>
</tr>
<tr>
<td>Other or not disclosed</td>
<td>11 (15%)</td>
<td>9 (20%)</td>
</tr>
<tr>
<td>Region of origin, N(%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>East Asia</td>
<td>NA</td>
<td>21 (48%)</td>
</tr>
<tr>
<td>South Asia</td>
<td>NA</td>
<td>1 (2%)</td>
</tr>
<tr>
<td>North America</td>
<td>NA</td>
<td>3 (7%)</td>
</tr>
<tr>
<td>Central America</td>
<td>NA</td>
<td>2 (5%)</td>
</tr>
<tr>
<td>South America</td>
<td>NA</td>
<td>1 (2%)</td>
</tr>
<tr>
<td>Central Africa</td>
<td>NA</td>
<td>1 (2%)</td>
</tr>
<tr>
<td>East Africa</td>
<td>NA</td>
<td>4 (9%)</td>
</tr>
<tr>
<td>Eastern Europe</td>
<td>NA</td>
<td>4 (9%)</td>
</tr>
<tr>
<td>No response</td>
<td>NA</td>
<td>7 (15%)</td>
</tr>
<tr>
<td>Median age of adoption (range) in months</td>
<td>NA</td>
<td>11 months (0.5–90 months)</td>
</tr>
<tr>
<td>Median time with adoptive family by study participation (range) in months</td>
<td>NA</td>
<td>139.55 months (43.16–199.16 months)</td>
</tr>
<tr>
<td>Other children in the adoptive home N(%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>NA</td>
<td>11 (25%)</td>
</tr>
<tr>
<td>Yes</td>
<td>NA</td>
<td>27 (61%)</td>
</tr>
</tbody>
</table>

*Data were missing for N = 6 children on this measure.

expectations for caregiving, and are both associated with elevations in emotional difficulties in exposed youth (Brand & Brinich, 1999; Ellis et al., 2011; Gunnar et al., 2000; Van Den Dries et al., 2012). As such, we considered it appropriate for the purposes of the analyses in this paper to group together all of the youths exposed to disrupted/absent caregiving into one Disrupted/Absent Care group. The experience of parental separation followed by institutionalization and/or switches in caregiving homes are themselves significant stressors to a developing infant (Dozier et al., 2012, 2014; Jiménez-Morago et al., 2015), in addition to a range of other possible adversities (e.g., abuse, neglect, abandonment).

At entry to the study, mean levels of total problem scores on the Child Behavior Checklist (CBCL; Achenbach, 1991, available in N = 84) were significantly higher in children from the Disrupted/Absent Care group than those from the Comparison group, t(82) = 3.90, p < .0002 (Comparison M = 42.2, range = 26–65; Disrupted/Absent Care M = 51.29, range = 30–80; clinically elevated range T-score > 70). We saw no group differences in mean child-reported feelings of security in the attachment relationship as measured by the Security Scale (Kerns, Klepac, & Cole, 1996; available on N = 109), t(107) = 0.13, p = .893 (Comparison M = 3.21, range = 1.93–4; Disrupted/Absent Care M = 3.19, range = 2.2–4). There were also no differences between the Comparison and Disrupted/Absent Care groups in stressful life events experienced over the past 12 months before participation in the study (summed score of the Life Events Questionnaire, Berden, Althaus, & Verhulst, 1990, available in N = 84), t(82) = −1.68, p = .097 (Comparison M = 3.58, range = 0–15; Disrupted/Absent Care M = 5, range = 0–18). The Wechsler Abbreviated Scale of Intelligence (WASI-II; McCrimmon & Smith, 2013; Wechsler, 1999) provided estimated IQ for a subset of participants over 6 years of age (data available on N = 68). Mean levels of measured intelligence were in the high average range for both groups (Comparison: mean ± SD = 117.14 ± 12.56; Disrupted/Absent Care: mean ± SD = 113.75 ± 7.89) and were not significantly different between groups, t(66) = 0.53, p = .599. Modal household yearly income (N = 88) was between $125,000–$190,000 for Comparison families, and was between $185,000–$250,000 for prior Disrupted/Absent Care families, which is consistent with prior data on a similar sample (Callaghan, et al., 2019) and is above the national median for family households with related children under 18 years of age $72,535 (Fontenot et al., 2018). Parental education (N = 109) was calculated for each caregiver (primary, and secondary if applicable). For the Comparison group, modal education level for the primary caregiver was a master’s degree, and for the secondary caregiver was a 4-year college degree. For the Disrupted/Absent Care group, the modal education level for the primary and secondary caregivers was some graduate school.

Recruitment of participants occurred through local birth records, local classifieds, international adoption agencies, family networks, posted flyers, and friend referral. The Institutional Review Board at Columbia University approved the protocol. Parents provided written consent for their children, children 7+ years old provided written assent, and children under 7 provided verbal assent.

2.2 | Procedures

Participants and their parent/s came to the laboratory for an in-person data collection session which involved a range of computer tasks that the parent and child/adolescent completed (not assessed or described in this paper) as well as questionnaire completion (described below), cognitive tasks (Wechsler Abbreviated Scales of Intelligence; WASI-II (Wechsler, 1999)—Vocabulary and Matrix Reasoning subscales to derive a full-scale IQ estimate reported descriptively in the participants section of this paper), as well as
a dyadic electrocardiogram collected at rest (described below). Parents were asked to attend the session if they were the child’s “primary caregiver,” which was the child’s mother in 91% of cases.

2.3 | Measures

2.3.1 | Child behavior checklist (CBCL) - parent report

To assess child mental health, we administered the Child Behavior Checklist (CBCL) 4–18 years, parent report version (Achenbach, 1991) to parents. The CBCL is a 118-item questionnaire that uses a 3-point scale (0 = not true, 1 = somewhat true, 2 = very true) on which parents rate child behaviors for the preceding 6 months. The measure was normed on a U.S. nationally representative sample of 2368 children between the ages of 4 and 18 years. The measure contains three broadband scales of internalizing, externalizing, and total problems and T-scores of 70 or greater on those scales indicate clinical significance of that symptom category. For the current analyses, we used the broadband internalizing scale, which consists of withdrawn/depressed, somatic complaints and anxious/depressed subscales, as well as the broadband externalizing scale, which consists of rule breaking and aggressive behaviors. These broadband scale scores were available on $N = 83$ children/adolescents.

2.3.2 | Electrocardiogram (ECG)

The electrocardiogram was collected in a small electrically shielded and soundproof room with no windows within the laboratory. The room contained a desk, holding a computer and the physiology equipment, and three chairs. The parent and child sat side-by-side on two chairs (with the parent always on the child’s left), and the other chair was left unoccupied. Dyads were told that their heart rate was being collected at rest and were given a children’s magazine to read if they wished. ECG was acquired continuously while parents and children were at rest, for approximately 5 minutes. Participants were asked to refrain from eating immediately before the session.

A three-lead ECG (right and left clavicle and lower left rib) was collected using pre-gelled disposable sticker electrodes (BIOPAC - EL503). A BIOPAC Amplifier-System (MP100) was used to amplify and filter the signals before digitization at 1000 Hz. R-peaks were detected on the ECG with a proprietary software (Gmark, Ledano Solutions) based on the Pan–Tompkins algorithm and subsequently checked by visual inspection.

ECG data cleaning

Depending on the considered measure (described below) ECG recordings were subdivided in epochs of duration equal to either 30-s, or 3-min. Segments with excessive movement artifacts (determined visually) were discarded from subsequent analysis. RR intervals (i.e., the time elapsed between two successive R waves in the ECG) associated with a heart rate <40 bpm or >180 bpm were removed and substituted by means of linear interpolation. Segments with more than 10 consecutive removed RR intervals or more than 5% of discarded beats were not included in the present analysis.

2.4 | Signal processing

2.4.1 | Entropy domain

Transfer entropy

Parent and child RR series were resampled at 5 Hz. Transfer entropy (calculated in 3-min epochs) was the primary heart rate variable used in this study and was available on $N = 114$ of the original $N = 118$ participants. Data were lost on $N = 4$ participants due to insufficient confidence on the estimations of either parent, child, or joint parent-child HRV density functions (Montalto et al., 2014). For each available 3-min epoch, two TE estimates were computed for both directions: parent-to-child and child-to-parent. For a given directionality (e.g., from child-to-parent), TE quantifies the information content shared between the source (child) and the target (parent) systems. In other words, TE quantifies the contribution of the source in predicting the evolution of the target, in contrast to solely using the past behavior of the target. In this study, we employed a non-uniform embedding k nearest neighbor (knn)-based schema. The statistical significance of computed TE was assessed using surrogate data implemented by a time shift procedure. In this analysis, the number of employed surrogate series was equal to 100, with a maximum allowed time shift of 20 samples. The significance threshold was set above the 95th percentile of the surrogate series distribution.

Quadratic sample entropy

Quadratic sample entropy (QSE), a univariate measure of complexity (Richman & Moorman, 2000), was calculated on $N = 108$ of the original $N = 118$ participants considering the same 3-min epochs utilized for the computation of TE. Data were lost on $N = 10$ participants due to lack of convergence for the methodology (Delgado-Bonal & Marshak, 2019). Quadratic sample entropy measures the regularity and complexity of a time series. This measure was specifically designed to overcome the limitations of traditional entropy estimators in the context of noisy and short duration time series (Beckers et al., 2001). Additionally, the methods make no assumptions regarding underlying system dynamics, e.g., linearity (Richman & Moorman, 2000). Applied to HRV data, large QSE values indicate low predictability of fluctuations in successive RR intervals. In contrast, lower QSE estimates reflect a more regular and predictable HRV signal.

2.4.2 | Traditional ECG metrics

In addition to transfer entropy, we also calculated a set of more traditional time and frequency domain HRV metrics for exploratory group comparisons, described below.
Frequency domain

Low power frequency/high power frequency (LF/HF). LF/HF ratio is a frequency domain metric, calculated from the power spectral density (PSD) of heart rate variability signal. LF/HF ratio was calculated on N = 115 of the original N = 118 participants. Data were lost on N = 3 participants due inconsistencies in the derived HRV PSD, e.g., abnormal LF/HF ratio. Frequency indices were computed for 30-s epochs given the 5 Hz resampled HRV signal. We employed a non-parametric Welch approach using windows of 30-s with a 50% overlap. The low frequency band was defined in the interval [0.04 0.15] Hz, and the high frequency band in the interval [0.15 0.6] Hz. The rationale behind a wider high frequency range compared to traditional approaches, is to account for the variation in breathing rate in relationship to age (Shaffer & Ginsberg, 2017).

The power associated with the LF band is thought to mainly reflect baroreceptor activity during resting conditions (McCraty & Shaffer, 2015). LF power may be produced by both the sympathetic and parasympathetic branches of the autonomic nervous system (Grossman & Taylor, 2007). The HF band reflects mainly parasympathetic activity and it is also known as the respiratory band as it corresponds to HR variations modulated by breathing. These phasic HR changes are known as respiratory sinus arrhythmia (RSA). Lower HF power has been previously correlated with stress, panic, anxiety, or worry (Thayer et al., 2010). While studies have reported both linear and non-linear increases in LF/HF ratio with child age (Bobkowski et al., 2017; Yeragani et al., 1997), in this study, visual inspection of these data (which are provided primarily for descriptive purposes) supported a linear modeling approach.

2.4.3 | Time domain

This set of parameters was computed for each 30 s epoch. After computation of the parameters by epoch, the values across all epochs were averaged to obtain a single value for each of the time domain parameters. This resulted in a slightly higher sample size than the frequency domain, as the shorter epoch meant that more participants had at least one usable segment of data.

**Mean heart rate (HR)**
Data were available on N = 118 participants (i.e., the full sample).

**RMSSD**
Data were available on N = 118 participants (i.e., the full sample). Root Mean Square of the Successive Differences (RMSSD) reflects the beat-to-beat variance in HR and is the primary time-domain measure used to estimate the vagally mediated changes reflected in HRV. While the RMSSD is correlated with HF power (Kleiger et al., 2005), the influence of respiration rate on this index is still debated (Schipke et al., 1999).

**SDNN**
Data were available on N = 118 participants (i.e., the full sample). Both the sympathetic and parasympathetic branches of the autonomic nervous system contribute to Standard Deviation of the RR intervals (SDNN). This measure is often highly correlated with LF band power (McCraty & Shaffer, 2015).

2.5 | Statistical tests

All regressions and group comparisons were analyzed using R (R Core Team, 2013). The PROCESS macro (Hayes, 2017) within SPSS Statistics 26 was used to test a cross-sectional mediation. Our research questions were first tested with a series of linear regressions, with an alpha set at 0.05.

2.5.1 | Associations of disrupted/absent care and TE

We examined whether disrupted/absent care was associated with transfer entropy in the direction of child-to-parent as well as in the direction of parent-to-child, controlling for child sex, child age (mean centered), and the interaction between child age and group (effect coded; Disrupted/Absent Care or Comparison). The sample size for that analysis was N = 114. We also confirmed those associations in two separate analyses controlling for child body mass index (BMI: (Lbs/in²) * 703)), as well as parental trait anxiety on the State Trait Anxiety Inventory (Spielberger, 1983). We performed these analyses separately as data from each of these covariates were only available on a subset of the participants (BMI: N = 88; STAI: N = 83). Moreover while BMI has been shown to influence within-person time and frequency domain ECG indices (Cho et al., 2018; Gutin et al., 2000), it has not been shown to be associated with dyadic indices such as transfer entropy. As an additional exploratory analysis, we looked to see whether age of adoption was associated with either of our transfer entropy indices (child-to-parent, and parent-to-child) within the Disrupted/Absent Care group.

2.5.2 | Associations between TE and child internalizing/externalizing symptoms

We examined whether transfer entropy from child-to-parent, or the interaction of transfer entropy from child-to-parent and early caregiving experiences, was associated with child internalizing or externalizing symptom T-scores on the CBCL, controlling for group, child sex, and child age (mean centered). As we did not see associations between child BMI or parent anxiety and transfer entropy, we did not control for child BMI or parent anxiety in these analyses.

2.5.3 | Cross-sectional mediation model

As transfer entropy from child-to-parent was associated with both caregiving group and child internalizing symptoms, we also tested
a cross sectional mediation model using the PROCESS macro in SPSS (model 4) with caregiving group as the independent variable (X), internalizing symptom T-scores on the CBCL as the outcome variable (Y), and transfer entropy from child-to-parent as the mediator (M); controlling for effects of child sex, and age (mean centered). Bias corrected 95% confidence intervals (CI) using 5000 bootstrapped samples are reported for the cross-sectional mediation model. Bootstrapped confidence intervals that did not include zero were considered to be statistically significant. As we only had cross sectional data in this study, we used the mediation model to explain variance, rather than as a tool to infer causal processes (Hayes, 2017). It is also worth noting that the ‘causal steps’ logic popularized by earlier mediation theories (Baron & Kenny, 1986) does not apply to contemporary approaches to mediation, such as that used in this paper. As such, the importance of total effects (c’ + a * b) and the direct effect of X on Y, are not necessary for a significant and meaningful mediation. The sample size for the mediation analysis was N = 83.

2.5.4 Exploratory associations between caregiving group and child heart rate in the time and frequency domain

In addition to our primary analyses which were focused on transfer entropy, we also performed a series of supplemental exploratory linear regression analyses, examining differences in traditional ECG time and frequency domain metrics (i.e., LF/HF ratio, intraindividual entropy, RR interval, RMSSD, and SDNN) as a function of caregiving experience, age (mean centered), and the interaction between childhood adversity and age, controlling for child sex and BMI (we did not control for parent anxiety as these measures were only analyzed in the child). As with the primary analyses, significance was evaluated at an alpha level of .05.

3 RESULTS

3.1 Association of disrupted/absent care and transfer entropy from child-to-parent

We first examined transfer entropy in the direction of child-to-parent through multiple linear regression, as a function of group (Disrupted/Absent Care vs. Comparison), age, and the interaction between Group and Age, controlling for sex. The effect of group was significant, \( \beta = -.004, t(109) = -2.37, p = .020 \), indicating that transfer entropy, or the amount of unique variance in a parent’s heart rate that could be predicted from the child’s past heart rate, was lower in youth from the Disrupted/Absent Care group than in youth from the Comparison group (see Figure 1). The effect of age was also significant, \( \beta = .001, t(109) = 4.46, p < .0001 \), suggesting that transfer entropy increased with the age of the child. However, the interaction between Group and Age was not significant, \( \beta = -.00, t(30) = -.13, p = .900 \).

FIGURE 1 Box and whisker plots of residual values from the linear regression associating transfer entropy in the direction of child-to-parent with group, controlling for age, sex, and the Age by Group interaction for youth in the Disrupted/Absent Care group (red) and the Comparison group (blue). Individual participant data are overlaid on the boxplot in semi-transparent black circles (jittered around the midline to allow viewing of overlapping individual subject data). The midline of the box plots represents the median of the data for each group. The upper and lower limits of the box are the 75th and 25th percentiles for that group, respectively. The whiskers extending beyond the box are 1.5 times the interquartile range.
3.2 | Association of disrupted/absent care and transfer entropy from parent-to-child

We next examined transfer entropy in the direction of parent-to-child through multiple linear regression, as a function of group (Disrupted/Absent Care vs. Comparison), age, and the interaction between Group and Age, controlling for sex. There was no effect of group, $\beta = .001, t(109) = .73, p = .469$ (see Figure 2), sex, $\beta = -.001, t(109) = -.45, p = .650$, and no interaction between Group and Age, $\beta = .00, t(109) = .13, p = .894$, on transfer entropy from parent-to-child. However, there was a significant positive association between child age and transfer entropy from parent-to-child, $\beta = .001, t(109) = 2.46, p = .015$, indicating that transfer entropy, or the amount of unique variance in a child’s heart rate that could be predicted from the parent’s past heart rate, increased with child age.

When we controlled for child BMI, we again saw that BMI was not associated with transfer entropy, $\beta = -.00, t(82) = -1.86, p = .066$. There was also no effect of group, $\beta = -.001, t(82) = -.45, p = .657$, sex, $\beta = .001, t(82) = .66, p = .514$, or Group by Age interaction, $\beta = .00, t(82) = .00, p = .999$, on transfer entropy in the direction of parent-to-child. However, the effect of age on transfer entropy from parent-to-child remained significant, $\beta = .001, t(82) = 3.16, p = .002$. When we controlled for parent anxiety, we again saw that parent anxiety was not associated with transfer entropy, $\beta = -.00, t(77) = .520, p = .604$. There was also no effect of group, $\beta = -.00, t(77) = -.201, p = .841$, sex, $\beta = .002, t(77) = 1.00, p = .321$, or Group by Age interaction, $\beta = .00, t(77) = .16, p = .874$, on transfer entropy from parent-to-child. However, the effect of age on transfer entropy from parent-to-child dropped to borderline significance, $\beta = .00, t(77) = 1.67, p = .099$, when controlling for parent anxiety.

We also ran an analysis within only the Disrupted/Absent Care group to explore whether age of adoption was associated with transfer entropy in the direction of parent-to-child, controlling for child age and sex. There was no association between transfer entropy and age of adoption, $\beta = .00, t(30) = -.74, p = .468$.

3.3 | Association of transfer entropy and child internalizing/externalizing symptoms

We next examined whether the metric of transfer entropy was associated with child internalizing and externalizing symptoms using two separate multiple linear regressions, first, looking at transfer entropy in the direction of child-to-parent. As shown in Figure 3, there was a significant association between transfer entropy and child internalizing symptoms, $\beta = -3.37, t(77) = -2.36, p = .021$. However there was no association between age, $\beta = .07, t(77) = .21, p = .836$, sex, $\beta = .57, t(77) = .23, p = .816$, or group, $\beta = 14.44, t(77) = 1.29, p = .21$, and transfer entropy from child-to-parent. The association between transfer entropy and externalizing symptoms was also not significant, $\beta = .07, t(77) = .66, p = .514$; $\beta = .00, t(77) = .45, p = .650$; $\beta = .00, t(77) = .13, p = .894$, respectively. When we controlled for child BMI, the association with transfer entropy from child-to-parent remained significant, $\beta = .001, t(82) = 2.46, p = .015$, but there was no effect of group, $\beta = -.001, t(82) = -.45, p = .650$, sex, $\beta = .001, t(82) = .66, p = .514$, or Group by Age interaction, $\beta = .00, t(82) = .00, p = .999$, on transfer entropy from child-to-parent. However, the effect of age on transfer entropy from child-to-parent remained significant, $\beta = .001, t(82) = 3.16, p = .002$. When we controlled for parent anxiety, we again saw that parent anxiety was not associated with transfer entropy, $\beta = -.00, t(77) = .520, p = .604$. There was also no effect of group, $\beta = -.00, t(77) = -.201, p = .841$, sex, $\beta = .002, t(77) = 1.00, p = .321$, or Group by Age interaction, $\beta = .00, t(77) = .16, p = .874$, on transfer entropy from child-to-parent. However, the effect of age on transfer entropy from child-to-parent dropped to borderline significance, $\beta = .00, t(77) = 1.67, p = .099$, when controlling for parent anxiety.

FIGURE 2 Box and whisker plots of residual values from the linear regression associating transfer entropy in the direction of parent-to-child with group, controlling for age, sex, and the Age by Group interaction for youth in the Disrupted/Absent Care group (Adversity; red) and the comparison group (Comp; blue). Individual participant data are overlaid on the boxplot in semi-transparent black circles (jittered around the midline to allow viewing of overlapping individual subject data). The midline of the box plots represents the median of the data for each group. The upper and lower limits of the box are the 75th and 25th percentiles for that group, respectively. The whiskers extending beyond the box are 1.5 times the interquartile range.

FIGURE 3 Scatter plot of the residual values of youth internalizing problems from the linear regression associating child internalizing symptoms on the CBCL with transfer entropy (TE) in the direction of child-to-parent. Although there was no interaction between TE and group, the data are stratified by group for illustration purposes. Individual participant data are represented by open circles with the Disrupted/Absent Care group represented in red and the Comparison group represented in blue. Regression lines for each group are overlaid on the individual subjects’ data (in matching colors) with a surrounding confidence interval in semi-transparent overlay. Note that the confidence intervals get wider at the extreme ends of the distribution for each group because of the sparsity of data at those ends.
However, there was a significant effect of age on externalizing symptoms, $\beta = -2.40$, $t(77) = -1.04$, $p = .303$, or group, $\beta = .96$, $t(77) = .81$, $p = .423$, on child externalizing symptoms, and no Group by Transfer Entropy interaction for child externalizing symptoms, $\beta = .89$, $t(77) = .01$, $p = .995$. However, there was a significant effect of age on externalizing symptoms, $\beta = -.70$, $t(77) = 2.20$, $p = .031$.

For the direction of parent-to-child, there was no association between internalizing symptoms and transfer entropy, $\beta = .82$, $t(77) = 0.58$, $p = 0.567$, group, $\beta = 8.20$, $t(77) = .70$, $p = .489$, age, $\beta = -.18$, $t(77) = -.55$, $p = .582$, or sex, $\beta = -.22$, $t(77) = -.09$, $p = .932$, and no Group by Transfer Entropy interaction, $\beta = -.34$, $t(77) = -.23$, $p = .822$. There was also no association between externalizing symptoms and transfer entropy, $\beta = -.73$, $t(77) = 2.37$, $p = .020$.

### 3.4 | Mediation of disrupted/absent care on child internalizing symptoms via transfer entropy

As we saw a significant association between transfer entropy in the direction of child-to-parent and child internalizing disorders, we next tested a full cross-sectional mediation model with caregiving group as the independent variable (Disrupted/Absent Care vs. Comparison), child internalizing symptoms as the dependent variable, and transfer entropy from child-to-parent as the mediator (controlling for participant age and sex). Results are displayed in Figure 4. The path between caregiving group and transfer entropy was significant (path a), $\beta = -.004$, $SE = .002$, $t(78) = -2.40$, $p = .019$, 95% CI [−0.008, −0.001], as was the path between transfer entropy and child internalizing symptoms, controlling for group (path b), $\beta = -.35$, $SE = .15$, $t(79) = -2.33$, $p = .023$, 95% CI [−.52, 0.87]. However, the path between group and child internalizing symptoms, controlling for transfer entropy (path c’ - the direct effect) was not significant, $\beta = 4.13$, $SE = 2.52$, $t(79) = 1.64$, $p = .105$, 95% CI [−0.89, 9.14]. The bootstrapped confidence interval for the indirect or mediation effect (path c = a x b), did not overlap with zero, 95% CI [0.09, 1.68], suggesting that there was an indirect mediation of group on child internalizing symptoms through child-to-parent transfer entropy.

![Graphical representation of the cross-sectional mediation model](image-url)
3.5 | Exploratory analyses between time and frequency domain metrics, child age, and group

Although the current analyses were focused on the metric of transfer entropy, which is dyadic, we also wanted to analyze the association between age, caregiving group (Disrupted/Absent Care vs. Comparison) and more traditional within-individual heart rate metrics from the time and frequency domain using multiple regression analyses. Importantly, as these analyses are exploratory, no corrections for multiple comparisons are made; p-values are merely for descriptive purposes. Importantly, as BMI is known to influence within-person heart rate metrics in the time and frequency domain, we controlled for BMI in the following multiple linear regressions resulting in a smaller sample size (N = 88) for these analyses. The results are summarized in Table 2. As seen in Table 2, we saw significant effects of group on LF/HF ratio (higher in the Comparison group than the Disrupted/Absent Care group), as well as RMSSD, RR, and SDNN (all higher in the Disrupted/Absent Care group than in the Comparison group). However, there was no effect of group on within-subject entropy. We also saw a positive association between age and LF/HF ratio, as well as RR interval, and a negative association between age and RMSSD.

4 | DISCUSSION

Here we report on the metric of transfer entropy in cardiac data for parent-child/adolescent dyads in which the children/adolescents were exposed to disrupted/absent caregiving (followed by adoption), or had been raised by their birth/first/biological parents (comparison group). Our findings showed that information transfer differed as a function of early caregiving experiences, but only in one direction (child-to-parent). In the direction of child-to-parent, we saw that cardiac transference was lower in the group exposed to disrupted/absent caregiving, meaning that there was less information transfer from the child’s cardiac signal to the parent’s cardiac signal between youth and their adoptive parents, than between youth and their birth/first/biological parents. However, in the direction of parent-to-child, we did not observe an effect of disrupted/absent caregiving on cardiac transference. In other words, for cardiac signals, information flow between child-to-parent differed as a function of disrupted/absent caregiving, whereas information flow between parent-to-child did not, remaining intact in the group exposed to disrupted/absent caregiving. For both directions of information flow, we saw a significant positive effect of age, demonstrating that cardiac transference from child-to-parent and parent-to-child was higher in dyads that included an adolescent, than in those that included a child for both groups. We also observed that cardiac transference from child-to-parent was negatively associated with internalizing symptoms in youth, and acted as a mediator of the relationship between disrupted/absent caregiving and elevated internalizing symptoms in that group. As such, these data demonstrate that disrupted/absent caregiving is associated with disruptions in specific pathways of cardiac information flow within parent-child/adolescent dyads, and that those changes in information flow are associated with mental health symptoms in youth.

Considering the association between transfer entropy and caregiving experiences, as well as between transfer entropy and internalizing symptoms, one question to emerge from this study is what exactly transfer entropy is measuring within the dyadic relationship. To answer that question, it is important to consider past work using transfer entropy in parent-child dyads. While not many such studies exist, one in particular seems to be informative for the current study...

### Table 2: Exploratory analyses examining the association of within-individual cardiac metrics: entropy, LF/HF ratio, RMSSD, RR, and SDNN, with child age, and caregiving group, controlling for child BMI and sex

<table>
<thead>
<tr>
<th>Metric</th>
<th>β</th>
<th>SE</th>
<th>t</th>
<th>p</th>
</tr>
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<td>.138</td>
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<td>.04</td>
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<td>-.23</td>
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<td>.239</td>
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<td>.02</td>
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<td>.412</td>
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<td>Group X age</td>
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<td>.03</td>
<td>-0.60</td>
<td>.553</td>
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<td>RMSSD</td>
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<td></td>
</tr>
<tr>
<td>Group</td>
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<td>3.34</td>
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<tr>
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<td>2.63</td>
<td>-1.04</td>
<td>.300</td>
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</table>

Abbreviations: LF/HF, low frequency/high frequency; RMSSD, root mean squares of the successive differences; RR, intervals of time elapsed between two successive R waves; SDNN, standard deviation of the RR intervals. *p<.05, **p<.01, ***p<.001.
findings. In that study, TE was used to examine coordination of body movements and social contingencies between toddlers (6–8 months and 11–13 months old) and their caregivers (Nagai et al., 2012). Results indicated that TE in the direction of toddlers-to-parents increased with age in the domains of body coordination and social contingency. This was interpreted to represent a form of ‘co-development’ in parents and toddlers, whereby caregivers gradually increased the complexity of their body movements and their socially contingent interactions as toddlers developed. In other words, parents increasingly used the behaviors of their toddler to guide their own actions, resulting in higher toddler-to-parent information transfer with age. We recently theorized a similar process of parent-child co-development in the domain of emotion regulation (Callaghan & Tottenham, 2016). In that model, gradual increases in child independence from the parent were proposed to trigger decreases in parental regulation, allowing for the slow emergence of child self-regulation over developmental time. The findings we report here in the domain of cardiac signals fit well with the mechanisms proposed by Nagai and colleagues, as well as our past theory on the development of emotion regulation. Specifically, we see here that information transfer from child-to-parent increases across age. As such, it is possible that adolescents may have emitted more reliable or readily-available socioemotional signals than children, which were then perceived by parents, allowing the parents heart rate to better adjust to the adolescent. Of course, given that TE was measured at rest, any display of socioemotional signals from children and adolescents were likely subtle. Alternatively, parents may gain more skill in recognizing or perceiving their children’s socioemotional signals as their child age. Yet, another possibility is that age-related increases in both parent-to-child and child-to-parent cardiac transference may simply be related to differences in child physiology becoming more adult-like with age. That interpretation aside, taken together with the past literature, the results of the current study suggest the possible existence of a feedback loop between the parent and child, whereby the parent becomes more attuned to the child as the child ages, engaging in increasingly nuanced or responsive interactions (e.g., at the level of brain, behavior, or cardiac regulation).

Any parent-child feedback interaction of the kind described above would presumably be associated with the interactional quality of the relationship. That is, all else being equal, especially attentive and engaged caregivers would be hypothesized to be more influenced by the information coming from their child. Likewise, it could also be hypothesized that children/adolescents who engage in less self-regulatory behaviors (e.g., who are more distressed) could emit less reliable signals to be read by a caregiver. If this is true, the fact that we see lower child-to-parent TE values in dyads where the child/adolescent had been exposed to past disrupted/absent caregiving suggests that experiences of significant adversity may make it harder to establish physiological transference. It is also possible that children/adolescents exposed to adversity provide less reliable behavioral, emotional, and as a result cardiac cues, for the parent to respond to. Moreover, the biological relation between the parent-child dyads in the comparison group, and the in-utero experience, may also facilitate such cardiac concordance, giving the comparison dyads a ‘head-start’ in their physiological transference as compared to the adversity-exposed youth. However, the fact that we did not see a group difference between genetically-related (Comparison) and genetically-unrelated (adopted group) on transfer entropy in the direction of parent-to-child argues against that interpretation. Indeed, it is worth noting that despite significant adversity, some parent-youth dyads did display similar levels of transfer entropy to the comparison group, suggesting some level of resiliency in this population, and the potential role of post-adoption environments in mediating these effects. While these links are currently speculative, future work could attempt to shed light on those associations by recording dyadic heart rate under conditions of challenge, or expressed emotion, where the behavioral markers of cardiac output are more obvious. Similarly, future work could record parental sensitivity in caregiving to determine if that also moderates the group effect observed here.

Beyond the association with caregiving groups, it is also interesting to note that cardiac transference from child-to-parent was a mediator of the association between disrupted/absent caregiving and child internalizing symptoms in the current study. Although the mediation was cross-sectional, preventing causal conclusions from being drawn, it nonetheless highlights an intimate relationship between early care, cardiac transference, and internalizing symptomatology that requires further explanation. In past work, parent cues (photos of the parent, or actual parental presence) were also shown to be less effective at modulating child hormonal and neural activity following early life caregiving adversities (Callaghan, et al., 2019; Hostinar et al., 2015b). Those data have been interpreted under the framework of parental regulation, which is hypothesized to scaffold the development of child neurobiology, and precede the emergence of emotional health (Callaghan et al., 2019; Callaghan & Tottenham, 2016; Hostinar et al., 2014). Consistent with that hypothesis, in the Callaghan et al. (2019) study it was shown that the parental regulation over child amygdala reactivity was negatively associated with child anxiety levels 2 years later in adversity exposed youth. Those findings suggest that the tendency of the youth’s amygdala to be responsive to parental modulatory input was an important factor associated with emotional health in children at risk for emotional dysregulation. In the present study, children’s anxiety levels were associated with cardiac transference in parent-youth dyads, and cardiac transference was shown to explain some of the variance between adversity exposure and higher internalizing symptom levels. However, in this instance, as we were able to record both parent and child heart rate, and employ a computation that revealed directionality, we found that only the child’s influence over the parent’s heart rate was associated with child anxiety levels. Hence, unlike prior work on parental regulation, the current data reveal a new dimension to the parent-child relationship which is less commonly explored in connection to child emotional functioning: the effect of the child on the parent. Given the past literature on parental regulation, it would be interesting to examine both child-to-parent cardiac transference as well as parental regulation of child amygdala and cortisol in youth who have experienced disrupted/absent caregiving. We hypothesize
that dyads with high child-to-parent transference, where the parent's cardiac signal is responsive to the child's, would also display higher parental regulation over amygdala and cortisol, helping to explain how cardiac transference is related to child emotional health.

A final interesting point regarding cardiac transference in the group exposed to disrupted/absent caregiving is that neither child-to-parent nor parent-to-child information transfer were associated with age of adoption. As we had a wide range of ages at which people were adopted in this study (0.5 months–7.5 years), the lack of adoption timing effects suggests a range of possible interpretations. For example, it is possible that early pre-adoption factors (i.e., prior to 0.5 months of age), or genetic factors are involved in these effects. Another possibility is that only a low threshold of caregiving disruption/absence needed to be met before the effects were observed, or that the relationship between time of adoption and cardiac transference is non-linear. A final possibility (that also has support in some prior literature (Anthony et al., 2019; Callaghan et al., 2019; Garvin et al., 2012; Koss et al., 2020) is that post adoption factors, for example, relationship with the adoptive parent, might be more important for cardiac transference within parent-child dyads than pre-adoption factors. Each of these possibilities should be considered as potential mechanisms for cardiac transference group differences in future work.

Most past work on cardiac function in early adversity has focused on within-person metrics in the time and frequency domain of heart rate variability (McLaughlin et al., 2015; Reid et al., 2018). While we did not assess the same variables as in the McLaughlin et al., (2015) study, we did replicate the findings of Reid et al., (2018)—a lower mean LF/HF ratio at rest in the Disrupted/Absent Caregiving group compared to the Comparison group. However, we also reported here that youth exposed to disrupted/absent caregiving had higher RMSSD and SDNN values on average than the comparison group. To our knowledge, RMSSD and SDNN has not yet been examined in youth exposed to disrupted/absent caregiving, but the finding that these values are higher following exposure to disrupted/absent caregiving runs counter to expectations based on past work in youth with anxiety disorders, who show lower values on these metrics (Nikolić et al., 2018; Sharma et al., 2011). Such discrepancies may be related to the fact that we collected HRV at rest, or genuine differences between disrupted/absent caregiving exposed and anxious groups of youth. Both of these possibilities will need to be examined in future studies.

4.1 Limitations

As mentioned earlier, one of the strengths of this study is the use of an innovative computational approach to understand cardiac transference in parent-child dyads. While the findings revealed from the implementation of that approach are significant and novel, there are several limitations in this dataset that need to be acknowledged. First is that dyads assessed here were at rest, rather than engaging in an emotional reactivity/stressful task, or in some form of supportive talk interaction. However, the fact that we see such dynamics emerging at rest attests their ubiquity in the lives of children and adolescents, mimicking interactions that occur dynamically in the everyday lives of individuals, for example, as they passively travel, work, and eat as a family. Nonetheless, as mentioned earlier, it would be informative to perform these same analyses in parent-child/adolescent dyads under conditions that might evoke emotion and comforting/regulation responses to know whether age and group effects on TE in parent-child dyads change under challenge vs. rest conditions. Another limitation in the current study is that TE does not contain temporal information on lag dynamics (Faes et al., 2014), preventing us from knowing with what resolution information is transferred between parent and child cardiac signals. Also, we did not have movement data, but movement has been shown to not affect TE between fetuses and mothers (Avci et al., 2018) and so is unlikely to have had an impact here. There were also several technical limitations, e.g., although TE can pick up on non-linear dynamics, it may still miss some of the complexity in the dyadic system (James et al., 2016), which should be acknowledged.

Due to the wide age range of youth in our sample (4–17 years), we used a parent proxy-report measure of child internalizing symptoms (CBCL), and our findings will need to be replicated when a youth self-report questionnaire is used. Also, due to experimenter error, we were missing CBCL data on 30% of the sample. As such the analyses which use this measure should be interpreted with caution. We did not have any assessments of early trauma exposure in the comparison group and it is unclear whether the effects of disrupted/absent caregiving on transference entropy that we report here would extend to other categories of early adversity exposure. Finally, although adopted individuals had severe disruptions in care (the correlates of which were examined in this paper) it is possible that nuances in the pre-adoption environment (not measured here, such as the number of youths in the institution) may also influence cardiac transference entropy in the parent-youth dyads.

4.2 Conclusion

In conclusion, the data reported here contribute to a wide and growing body of literature that implicates the parent-child relationship as a critical player in the emotional health and development of the child. While prior work had shown that a parent’s presence can be a powerful regulator of children’s neurobehavioral and physiological function (Callaghan et al., 2019; Gee et al., 2014; Hostinar et al., 2015a; van Rooij et al., 2017), and that moment-to-moment synchronous biobehavioral interactions between parents and children are related to child emotional health (Feldman et al., 1999, 2011; Granat et al., 2017), here we show that children and parents are also regulators of one another’s physiology. Moreover we show that the degree to which the parent’s physiology changes in response to the child’s physiology relates to the child’s mental health, and may even be a pathway for mental health risk in adversity exposed youth (see putative theoretical model in Figure 5). Future work should continue to investigate how directional dynamics playing out on a
moment-to-moment basis in parent-child dyads (at the level of physiology, behavior, and neural functioning) together contribute to the emergence of emotional health across development.

CONFLICTS OF INTEREST
No authors have a conflict of interest to declare.

AUTHOR CONTRIBUTIONS
BC, NT, NP, and WF conceptualized the paper. BC, JAS, MVT, TC, and KO collected the data. NP and BC analyzed the data. BC drafted the paper, and all authors made critical comments on the paper draft.

DATA AVAILABILITY STATEMENT
Research data are not shared.

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FIGURE 5 Putative theoretical model for the macro-level (parental presence and absence, top) and micro-level (e.g., child-to-parent cardiac transference, bottom) shaping effects of parent child interactions on child mental health. In the top panel it can be seen that emotional, amygdala, and cortisol reactivity of the child increase during phases of parental absence (in red: ‘Alone’), before becoming dampened during periods of parental presence (green: ‘With Caregiver’). Earlier theoretical models have suggested that such phasic (i.e., macro-level) interaction with the caregiving entrains mature regulatory patterns of neural connectivity, leading to the eventual emergence of self-regulation, reducing child anxiety and distress across development (Callaghan & Tottenham, 2016), which is depicted on the right side of the figure. On the bottom panel, the results from the current paper are depicted as fitting in with this wider theoretical model by demonstrating the effects of parent-child moment-to-moment interaction (i.e., micro-level, during periods of parental presence) on child and parent heart rate physiology. Specifically, the more information transfer from child-to-parent (cardiac transference), the greater the eventual self-regulation capacities of the child (reflected by lower internalizing symptoms in the current paper)

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anywhere from 15% to 23% of anxious youth meet criteria for attention-deficit hyperactivity disorder (ADHD) comorbidity (Stieben et al., 2007), we predicted that youth with co-occurring anxiety symptoms and externalizing behaviors would exhibit more negative ERN amplitudes.


**How to cite this article:** Callaghan B, Pini N, Silvers JA, et al. Child-parent cardiac transference is decreased following disrupted/absent early care. *Dev Psychobiol. 2021;63:1279–1294. https://doi.org/10.1002/dev.22102*