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Dynamic Infant-Parent Affect Coupling during the Face-to-Face and Still-Face Paradigm: Inter- and Intra-Dyad Differences

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Abstract

We examined dynamic infant-parent affect coupling using the Face-to-Face/Still-Face (FFSF) paradigm. The sample included 20 infants whose older siblings had been diagnosed with Autism Spectrum Disorders (ASD-sibs), and 18 infants with comparison siblings (COMP-sibs). A series of extended autoregressive models was used to represent the self-regulation and interactive dynamics of infants and parents during FFSF. Significant bidirectional affective coupling was found between infants and parents, with the former serving as the "leading members" of the dyads. Further analysis of within-dyad dynamics revealed ongoing changes in concurrent infant-parent linkages both within and across different FFSF episodes. The importance of considering both inter- and intra-dyad differences is discussed.

The study of dyadic interaction can be construed in dynamic terms. Members of a dyad are intertwined: they act and react to each other's behaviors and emotions much in manner of a *coupled* dynamic system (Boker & Laurenceau, 2006; Newtson, 1993). The cascading effects of such interactions can often lead to highly unpredictable outcomes, triggered both by the dynamics inherent to each dyadic member, as well as the interdependencies between the *past histories* and the *future responses* of the two dyad members. Likewise, subtle between-dyad differences can manifest themselves in whether and how dyad members are "coupled" to one another over time. Such differences may be obscured if static mean differences are examined alone (Smith & Thelen, 1993; West, 1985).

Indeed, dynamic systems-based concepts have played a prominent role in contemporary studies of dyadic relationships (e.g., Boker & Laurenceau, 2006; Felmlee & Greenberg, 1999; Gottman, Murray, Swanson, Tyson & Swanson, 2002; Levenson & Gottman, 1983) and the study of affect (Bisconti, Bergeman, & Boker, 2004; Chow, Nesselroade, Shifren, & McArdle, 2004; Fredrickson & Losada, 2005). Larsen's (2000) homeostatic model of mood regulation, for instance, conceptualizes mood regulation as an ongoing *process* during which an individual attempts to minimize the discrepancies between his/her current mood states and an individualized set point. Chow, Ram, Boker, Fujita and Clore (2005) formulated this theoretical model of a "mood thermostat" as a differential equation whose dynamics are governed by two key parameters: a frequency parameter that dictates how rapidly the system shows cyclic fluctuations (i.e., *affect lability*), and a damping parameter that governs how promptly the system returns to (or diverges from) its set point (i.e., *affect adaptivity*) following a perturbation.

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The damped thermostat model provides one possible way of testing dynamic notions of mood regulation within the context of a differential equation model. With appropriate parameter constraints, a discrete-time counterpart of this model can be formulated as an autoregressive (AR) model with two lags (see Harvey, 1993; Harvey & Souza, 1987). The AR model is a well known model in the time series literature and it includes an alternative set of parameters indicative of the nature and dynamics of the process of interest (Hamilton, 1994; Shumway & Stoffer, 2000; Wei, 1990). However, the damping and frequency parameters inherent in the model in Chow et al. (2005) can only be obtained from the AR model through added parameterization constraints (see Harvey, 1993; Hamilton, 1994).

The AR formulation has some other critical advantages, however. For one, the AR model is generally more familiar to the broader social sciences community compared with the damped thermostat model in differential equation form; it is also relatively easy to implement using standard software packages such as SAS and SPSS. For another, compared to a strictly cyclic model that is characterized by one fixed frequency, the AR model with two lags is flexible enough to capture less structured, quasi-cyclic dynamics (Wei, 1990). This is an important characteristic of parent-infant interaction data because nonperiodic cycles, as opposed to periodic cycles, are much more prevalent in the behaviors of parents and infants at early ages (e.g., among infants at 3, 6 and 9 months of age; Cohn & Tronick, 1988). Still, the theoretical meanings of AR parameters and their linkages to affect regulatory mechanisms are not always clear. We provide some guidelines along this line using data collected from parent-infant dyads during the Face-to-Face/Still-Face (FFSF) paradigm.

Bivariate Damped Cyclic Model for Studying Parent-Infant Interactive Dynamics during FFSF

Under the FFSF protocol, each infant-parent dyad undergoes a *Face-to-Face (FF)* episode during which the parent engages in active interactions with the infant, a *Still-Face (SF)* episode during which the parent ceases play and holds a still face (Tronick, Adamson, Wise, & Brazelton, 1978) and a *Reunion (RE)* episode during which the parent is instructed to resume playing with the infant. The decline in positive affect and increase in negative affect during the SF episode—often known as the still-face effect—have been replicated across several studies (Adamson & Frick, 2003; Tronick & Cohn, 1989; Weinberg & Tronick, 1996; Tronick, Messinger et al., 2005; Yale, Messinger, & Cobo-Lewis, 2003). In particular, the distress caused by the SF manipulation and the reconciliations during the reunion episode provide a direct opportunity for assessing between- and within-dyad changes in affect regulatory dynamics.

In instances involving dyadic data, further complication arises because the affective equilibrium of the dyad is now defined jointly by the emotional ebbs and flows of the two dyad members. A bivariate model is thus needed to accommodate both the self-regulation as well as the interactive dynamics of the dyad members. We use the analogy of two “coupled thermostats” to describe the bivariate modeling framework undertaken in this article to represent parent-infant affective dynamics. To provide a more concrete analogy of how parents and infants might act and react to one another during active interaction in manner of two coupled thermostats, we ask the reader to consider the scenario of a three-legged race, with the two dyad members acting as “partners” on a three-legged race. If one party is making rapid strides (e.g., manifesting rapid emotional fluctuations), the other party may have to adapt accordingly and adopt a faster pace, or force the partner to slow down his/her pace. Whether one dyad member adapts to, or actively alters the pace of the other dyad member depends on who is leading the race. Alternatively, if the two dyad members are in fact two independent thermostats, they will just fluctuate around their respective equilibrium points irrespective of the dynamics of one another.

In studies of parent-child interaction, researchers have been concerned with interactive influence and with synchrony (Brazelton, Kozlowski, & Main, 1974). Interactive influence involves the impact of infant-on-parent (parental responsivity) and parent-on-infant (infant responsivity). Higher levels of parental responsivity are associated with a wide variety of developmental outcomes, including the development of secure infant attachment to the parent (Isabella & Belsky, 1991, conscience-based rule-following in the child (Kochanska, Forman, & Coy, 1999), the infant's understanding of their developing emotional expressions (Stern, 1985; Tronick, 1989), as well as linguistic and cognitive development (Feldman & Greenbaum, 1997; Feldman, Greenbaum, Yirmiya, & Mayes, 1996; Landry, Smith, Miller-Loncar, & Swank, 1997). Infant-on-parent influences can exist simultaneously with parent-on-infant influences, producing bi-directional interactions. Bi-directional influence is thought to be the basis of fundamental social competencies such as turn-taking (Cohn & Tronick, 1988; Kaye & Fogel, 1980). It has also been implicated, at both high and mid-range levels, in the development of secure attachments (Jaffe, Beebe, Feldstein, Crown, & Jasnow, 2001)

Despite empirical evidence for the impact of interactive influence on later developmental outcomes, we know little about the relative importance of each partner in creating these processes. Even research which has addressed the relative importance of parent and infant in interaction has typically done so by categorizing individual dyads as to the presence or predominance of infant-on-parent and parent-on-infant influence (Cohn & Tronick, 1988; Feldman, et al., 1996; Yirmiya et al., 1996). The FFSF procedure and the modeling framework undertaken in the present article provide a platform for evaluating the presence of parent-infant bi-directional influence, as well as the relative predominance of parental responsivity and infant responsivity.

The advent of more sophisticated modeling techniques in the last two decades has led to timely solutions for assessing the relative dominance of parental responsivity and infant responsivity. The approach undertaken in the present article incorporates features of random effects models (Beebe et al., 2007; Campbell & Kashy, 2002; Kashy & Kenny, 2000; Newsom, 2002; Raudenbush, Brennan & Barnett, 1995) into a difference equation model, the bivariate AR model (for other examples see e.g., Ferrer & Nesselroade, 2003). Parallel to their continuous-time differential equation counterparts (Boker & Laurenceau, 2006; Felmlee & Greenberg, 1999; Gottman et al., 2002), difference equations are particularly suited for evaluating the directionality of infant-parent synchrony because the issue of time precedence is explicitly addressed through the incorporation of lagged (i.e., previous) influences between dyadic members. The random effects addition allows us to examine between-dyad differences in parent-infant coupling based on the infants' gender and risks for Autism Spectrum Disorders.

Between-Dyad Differences in Affective Dynamics

Autism Spectrum Disorders (ASDs) are genetically linked neurodevelopmental disorders characterized by a spectrum of impairments in social functioning and communication (Landa, Holman, & Garret-Mayer, 2007; Mundy & Hogan, 1994). ASDs are highly heritable and may mark the diagnosable end of a genetically-linked spectrum of difficulties (Szatmari et al., 2000). Compared to infant siblings of typically developing controls, infant siblings (as well as other first-degree relatives) of individuals with an ASD are at increased risk for milder deficits in one or more of the three areas that are impaired in autism: social responsiveness, communication, and limited interests/stereotyped behavior (Yirmiya et al., 2006; Merin, Young, Ozonoff, & Rogers, 2007; Cassel et al., 2007; Pickles et al., 2000).

In a study involving 12-month-old ASD-sibs who later showed autistic symptomatology, ASD-sibs were characterized by deficits in social smiling and decreased manifestations of positive emotions (Zwaigenbaum et al., 2005). Infant ASD-sibs smiled for a smaller proportion of the FFSF than COMP-sibs (Cassel et al., 2007), showed an increased tendency for neutral affect than comparison siblings and were less upset by the still-face manipulation (Yirmiya et al., 2006). Merin et al. (2007), however, did not find differences in emotional expressivity between ASD-sibs and COMP-sibs during a FFSF study with a brief still-face episode. We seek to further clarify the differences between ASD-sibs and COMP-sibs (and lack thereof) in establishing and maintaining interactive synchrony with their parents from a dynamic standpoint. In addition, gender will be included as another predictor of between-dyad differences in affect coupling due to the higher prevalence of ASDs in males than in females (Fombonne, 1999; Honda, Shimizu, Imai, & Nitto, 2005; Lingam et al., 2003; Yeargin-Allsopp et al., 2003).

Within-Dyad Changes in Parent-Infant Synchrony

Several studies in the past decade have established meaningful within-person variability in constructs that were traditionally construed as relatively stable or “static”, including world views and perceived control (Eizenman, Nesselroade, Featherman, & Rowe, 1997; Kim, Nesselroade, & Featherman, 1996). In the study of affect, within–person day-to-day variations in emotions have been reported to constitute stable between–person differences that are different from interindividual differences in affect intensity (Chow et al., 2005; Eid & Diener, 1999; Larsen, 1987; Ong & Allaire, 2005; Zautra, Reich, Davis, Nicolson, & Potter, 2000). Given that infant and mother interactive behaviors are not deterministic but rather, encapsulate the stochastic influence of the two dyad members (Cohn and Tronick 1988; Fogel 1988), within-dyad variability in synchrony constitutes an important aspect of individual differences in regulatory mechanisms.

At a broader level, parent-infant interaction can essentially be construed as a process of matches and mismatches in affective engagement. This process is made particularly salient by the FFSF protocol, which may propel infant-parent coupling to fluctuate, rather than remaining constant over relatively brief intervals—specifically, within each FFSF episode. In previous studies involving the FFSF protocol, researchers were often interested in capturing a summary measure of infant-parent dynamics. In doing so, these dynamics were assumed to be stable over the course of an interaction. In empirical data that span longer time scales, the assumption of stationarity[1] is often violated (see e.g. Lavie, 1977;Tarvainen, Georgiadis, Ranta-aho & Karjalainen, 2006;Weber, Molenaar & Van der Molen, 1992). Studies of dyadic interaction in the past have already suggested that interpersonal dynamics can change in critical ways even during a brief episode of interaction (e.g., due to turn-taking behavior; Boker, Xu, Rotondo & King, 2002; Newtson, 1993). We pursue evidence for time-varying changes in interactive associations during the FFSF by combining a univariate AR model and a stochastic regression model (see Shumway & Stoffer, 2000). The regression model is “stochastic” because it has a time-varying regression coefficient that is used to capture whether and in what ways parent-infant synchrony changes *within dyads* over the course of each FFSF episode.

Objectives of the Present Article

The objectives of the present article are two-fold. First, we seek to examine between-dyad differences in the interactive dynamics of parents and infants during the FFSF procedure by fitting a series of random effects AR models. By representing parent-infant dyads as

[1]Statistically, strict stationarity refers to the invariance of all statistical properties of a system over time. A weaker form of nonstationarity is covariance stationaritiy, which is used to describe systems that have finite second moments and show invariance in their mean and covariance functions over time (for more precise mathematical definitions see Hamilton, 1994; Shumway & Stoffer, 2000).

"coupled thermostats", our goal is to identify the relative dominance of parents and infants in leading the dynamics of the interaction and inter-dyad differences therein. Second, we seek to evaluate within-dyad variability in parent-infant synchrony and address whether and in what ways the associations between parents and infants change over time within each of the FFSF episodes. A stochastic regression model will be combined with an AR model for this modeling purpose.

Method

Participants

Infant-parent dyads in this study were part of a longitudinal study investigating the social, emotional, and cognitive development of ASD-sibs and COMP-sibs in the first three years of life. Cassel et al. (2007) examined mean levels of smiles and cry-faces in a sample that included 82% (31 out of 38) of the infants who are part of the current mean-free analysis of rated emotional valence. Outcome data is not yet available for these infants. Infants were included in this sample if they participated in a six month assessment, were at least 36 weeks gestation at birth, and had a birthweight above 2500g. The COMP-sibs were infants whose older sibling(s) had not been diagnosed with an ASD and showed no evidence of heightened ASD symptomatology. In contrast, ASD-sibs had at least one sibling who was diagnosed with Autism, Asperger's Disorder, or Pervasive Developmental Disorder – Not Otherwise Specified (PDD-NOS). Due to persistent distress, data collection was terminated for one of the ASD-sibs (male) during the FFSF. Excluding the data from this dyad yielded a final sample of $N = 38$ dyads, with 18 COMP-sibs and 20 ASD-sibs.

Descriptive data on the sample are presented in Table 1. The mean age of the 38 infants at the six month assessment was 6.1 months ($SD = .3$; range 5.1 to 6.9 months) and did not differ by group ($p > .71$). Mean parent age in years at the six-month FFSF assessment was 36.7 ($SD= 4.8$). A total of 57.9% of the mothers and 42.1% of the fathers reported earning an advanced or professional degree and another 21.1% of mothers and 31.6% of fathers reported completed a 4-year college degree. There were no group differences with regard to parent age, education or family income between the ASD-sibs and the COMP-sibs samples.

Measures

We used Continuous Measurement Software[2] (CMS) to obtain continuous ratings for every frame of the video upon playback of the video file. The CMS was developed to enable the presentation of video files to human raters in randomized sequence and simultaneous recording of viewers' ratings of the video files (Messinger, Cassel, Acosta, Ambadar, & Cohn, 2008). While watching the video clips, raters were asked to use a joystick to move the cursor up or down along a graduated color bar adjoining the right margin of the picture frame where the video was shown.[3] A screenshot of the user interface to which the raters were exposed is shown in Figure 1. The raw ratings generated by the CMS ranged from −400 (i.e., most negative) to +400 (most positive). We defined emotional valence as a continuous, unidimensional construct with positive and negative as anchors. This relatively simple measurement scale was used to facilitate continuous measurements of emotional valence with minimal rater delays[4].

[2]The CMS is available for download at http://www.psy.miami.edu/faculty/dmessinger/dv/index.html.

[3]Raters rated the videos without access to audio. This is because the parent and infant videos contained the same audio track and we wanted to obtain valence ratings for each infant or parent independent of the influences imposed by the presence of the other dyadic member.

[4]The use of a unidimensional valence rating scale was reasonable within our modeling context given the apparently bivalent nature of infant affective valence (Messinger, 2002) and the need to include both infant and parental affective valence in our bivariate model.

Procedure

In the FFSF protocol (Tronick et al., 1978; Tronick & Cohn, 1989), parents were asked to play with their baby without toys for three minutes (Face-to-Face episode, FF), stop playing and maintain a still face with no emotional expression for two minutes (Still-Face, SF), and resume play for another three minutes (Reunion episode, RE). During all three episodes, infants were placed in an elevated car seat and their parents were positioned on a small chair directly opposed to them. Separate video cameras were used to record the face and upper body of the infant and their parent. The video signals were synchronized with respect to a common time code and exported to separate digital video files for rating.

Descriptions of Raters

Ratings of the 38 dyads were completed by 160 non-expert student raters at a large urban university in the Southeast in fulfillment of the research component of an introductory psychology course. The raters were non-experts in that they had no specialized training in coding emotion. A given rater rated either infants or parents (not both). Ninety-nine students rated the infants and 96 rated their parents. The mean age of the 26 male and 66 female students who rated infants was 19.4 (*SD* = 1.8). These raters identified themselves as White/Caucasian (51%). Hispanic (27%), Asian (7%), and Black/Other (15%). The mean age of the 28 male and 68 female students who rated parents was 19.7 (*SD* = 3.0). Among students who rated the parents, 56% identified themselves as White/Caucasian, 20% as Hispanic, 7% as Asian, and 16% as Black/Other.

Each rater rated a batch group of 6 to 7 infants (or parents) containing separate video clips for each episode of the FFSF (i.e., FF, SF, & RE). Thus, a batch group of 7 infants (or parents) contained 21 separate video clips (i.e., 7 persons x 3 episodes). Clips were rated in a randomized order and raters proceeded from one video clip to the next at their own pace. Previous Generalizability Theory (GT) analyses reported indicated strong consistency in the non-expert ratings provided by the student raters. For cross-validation purposes, a randomly selected subset of the dyads was subjected to further ratings by parents who also participated in the FFSF. Parent raters are, arguably, more experienced in coding infants' emotions than the student raters. Parent ratings were available for 7 of the 33 (i.e., 35%) dyads. The correlations between these ratings were .76 (FF), .91 (SF) and .91 (RE) for the infants, and .83 (FF), .84 (SF) and .92 (RE) for the parents. The high correlations between student and parent ratings provided further support for the use of these non-expert ratings in our subsequent analyses.

Data Preprocessing

We took several data processing steps prior to model fitting to minimize preexisting between-rater differences in ratings. First, we discarded the first 10 seconds of ratings from all raters to minimize the initial delays manifested by some raters as they were "warming up" to the rating protocol. Second, we removed spurious trends—including linear and quadratic trends, as well as other gradual (e.g., exponential) upward/downward shifts in ratings—by first applying a Loess smoother and then retaining the residuals for further analyses.

Third, for each parent/infant, we derived a time series of mean ratings by first standardizing each rater's ratings for that participant (over time) separately and then averaging these standardized ratings across all raters. The time series of mean ratings for each infant (and parent) was then restandardized over time. Thus, all dyads and all episodes were characterized by the same magnitude of within-person standard deviation over time. This means that any between-dyad or between-episode differences associated with our subsequent analyses are not due to differences in affective levels or affective variability across dyads or episodes. Plots of the detrended, standardized mean ratings for each dyad in Figure 2 confirmed that there was no systematic difference between dyads in the levels or variability of ratings over time after the preliminary data treatment.

Model Fitting

Between-dyad differences in interactive dynamics—We used a set of random effects bivariate AR models to extract *between-dyad differences* in interactive dynamics. We examined the existence of reciprocal influences between parents and infants in a bivariate extension of the AR model expressed as

$$\begin{aligned}
Infant_{ikt} &= \varphi_{1,infant} Infant_{ik,t-1} + \varphi_{2,infant} Infant_{ik,t-2} + \varphi_{parent->infant,i} Parent_{ik,t-1} + e_{infant,ikt}\\
Parent_{ikt} &= \varphi_{1,parent} Parent_{ik,t-1} + \varphi_{2,parent} Parent_{ik,t-2} + \varphi_{infant->parent,i} Infant_{ik,t-1} + e_{parent,ikt}\\
\varphi_{parent->infant,ik} &= b_0 + b_1 Status_i + b_2 Gender_i + b_3 SFvsFF/RE_{ik} + b_4 FTFvsRE_{ik} + b_5 Gender_i * Status_i + b_6 Gender_i * SFvsFF/RE_{ik} + b_7 Status_i * SFvsFF/RE_{ik} + u_{\varphi_{parent->infant_{ik}}}\\
\varphi_{infant->parent,ik} &= c_0 + c_1 Status_i + c_2 Gender_i + c_3 SFvsFF/RE_{ik} + c_4 FTFvsRE_{ik} + c_5 Gender_i * Status_i + c_6 Gender_i * SFvsFF/RE_{ik} + c_7 Status_i * SFvsFF/RE_{ik} + u_{\varphi_{infant->parent_{ik}}},
\end{aligned} \tag{1}$$

$$\begin{aligned}
\left[\begin{array}{cc} u_{\varphi_{parent->infant_{ik}}} & u_{\varphi_{infant->parent_{ik}}} \end{array}\right] &\sim N\left(\left[\begin{array}{c} 0\\ 0 \end{array}\right], \left[\begin{array}{cc} \sigma^2_{u_{parent->infant}} & \\ 0 & \sigma^2_{u_{infant->parent}} \end{array}\right]\right),\\
\left[\begin{array}{cc} e_{infant,ikt} & e_{parent,ikt} \end{array}\right] &\sim N\left(\left[\begin{array}{c} 0\\ 0 \end{array}\right], \left[\begin{array}{cc} \sigma^2_{e_{infant}} & \\ 0 & \sigma^2_{e_{parent}} \end{array}\right]\right)
\end{aligned} \tag{2}$$

where $Infant_{ikt}$ represents the emotional valence of the infant in dyad i in FFSF episode k at time t, *Status* is a dummy-coded indicator with 0 = COMP-sib and 1 = ASD-sib, *Gender* indicates the gender of the infant (−1 = Male, 1 = Female), *SFvsFF/RE* and *FFvsRE* are a set of contrast codes used to indicate the different FFSF episodes. *SFvsFF/RE* was constructed to compare the SF to the FF and RE conditions combined (*SFvsFF/RE* = 1 for SF, −1/2 for FF and −1/2 for RE) and *FFvsRE* was used to compare the FF to the RE condition (*FFvsRE* = 0 for SF, 1 for FF and −1 for RE). The parameters $\varphi_{1,infant}$ and $\varphi_{1,\ parent}$ represent the group-based AR(1) parameter for infants and parents, respectively whereas $\varphi_{2,infant}$ and $\varphi_{2,\ parent}$ denote the group-based AR(2) parameter for infants and parents, respectively. The AR parameters capture the lagged effects of a dyad member's emotional valence from $t-1$ and $t-2$ on the dyad member's current emotional valence. $\varphi_{parent\text{–}>infant,ik}$ and $\varphi_{infant\text{–}>parent,ik}$ are lag-1 cross-regression parameters that capture the lagged interactive influences between the dyad members. Specifically, the former represents the influence of parent *i*'s emotional valence at the previous time point on infant *i*'s emotional valence at the current time point whereas the latter represents the lagged influence of infant *i*'s emotional valence at time $t-1$ on parent *i*'s current emotional valence.

We allowed for random effects in the cross-regression but not the autoregressive parameters.[5] The parameters $b_1 - b_7$ and $c_1 - c_7$ are fixed effects parameters used to explain dyad-specific variability in the parent→infant and infant→parent cross regression parameters, respectively. These parameters helped reveal the impact of developmental status, episode, gender and their potential interaction effects on the cross-regression parameters. The terms$u_{\varphi_{parent\text{–}>infant_{ik}}}$ and $u_{\varphi_{infant\text{–}>parent_{ik}}}$ capture dyad-specific deviations in cross-regression parameters that could not be accounted for using the covariates in the model, with variances, $\sigma^2_{u_{parent->infant}}$ and $\sigma^2_{u_{infant->parent}}$, respectively. A path diagram representation of the bivariate model is plotted in Figure 3. This model was fit using the PROC NLMIXED option in SAS using the approach described in MacCallum, Kim, Malarkey, and Kiecolt-Glaser (1997). The corresponding −2 log-likelihood values were used to construct likelihood ratio tests in a series of nested models.

Within-dyad changes in synchrony—The models in this section were developed with the aim to examine the *nonstationarities* in *within-dyad dynamics*. In particular, we sought to explore whether the concurrent associations between parents and infants changed dynamically within and between different FFSP episodes, as opposed to remaining constant. Such time-varying changes in correlation patterns but one example of the many ways in which individuals can manifest nonstationarities in the context of dyadic interaction. To capture potential changes in parent-infant synchrony, we added a stochastic regression component to a univariate AR model and examined the question of whether and how the *concurrent linkages* between parents and infants changed over time within each dyad.

The key model used to accomplish the goal of examining time-varying interaction patterns is expressed as

$$Infant_{ikt}=\begin{bmatrix} 1 & 0 & Parent_{ikt} \end{bmatrix}\begin{bmatrix} \alpha_{ikt} \\ \alpha_{ik,t-1} \\ B_{ikt} \end{bmatrix}, \tag{3}$$

$$\begin{bmatrix} \alpha_{ikt} \\ \alpha_{ik,t-1} \\ B_{ikt} \end{bmatrix}=\begin{bmatrix} \varphi_{1k} & \varphi_{2k} & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}\begin{bmatrix} \alpha_{ik,t-1} \\ \alpha_{ik,t-2} \\ B_{ik,t-1} \end{bmatrix}+\begin{bmatrix} \zeta_{\alpha,ikt} \\ 0 \\ \zeta_{B,ikt} \end{bmatrix}, \tag{4}$$

where we used the state-space formulation (Hamilton, 1994; Shumway & Stoffer, 2000) to structure our model. Equation (3) is typically denoted as the measurement equation and it serves to link the manifest indicator, infant *i*'s valence rating in episode *k* at time *t* (i.e., $Infant_{ikt}$) to a vector of latent variables. Equation (4) is the dynamic equation and it is used to express the lagged relationships among the latent variables. Within the linear state-space framework, the dynamic equation is typically written in a one-step-ahead or difference equation form. $Parent_{ikt}$ is the measured rating of parent *i*'s emotional rating in episode *k* at time *t*, α_{ikt} is a latent variable that represents the latent AR component associated with infant *i*'s affective dynamics in episode *k* at time *t*, $\alpha_{ik,t-1}$ is its lag-1 counterpart needed to define the model as an AR(2) model. φ_{1k} and φ_{2k} are AR(1) and AR(2) parameters associated with episode *k* and B_{ikt} is a time-varying regression parameter that captures the possibly time-varying association between the two dyad members. We included the residual for the AR component, $\zeta_{\alpha,ikt}$, in the dynamic, as opposed to the measurement equation, to allow the impact of external perturbations to persist over time, rather than affecting the measurement only at one point in time. $\zeta_{B,ikt}$ is a residual or process noise component associated with B_{ikt}. When the variance of this process noise component is significantly different from zero, B_{ikt} is projected to vary over time following a random walk model—a relatively simple but well-

[5]We acknowledge that failure to include random effects for the autoregressive parameters can potentially inflate the random effects estimates attributed to the cross-regression parameters. However, a model that included the four random effects components (random effects for the two autoregressive parameters and two cross-regression parameters) were computationally intensive and did not converge. Ultimately, the model in Equations 1—2 was chosen to strike a balance between modeling parsimony and theoretical relevance.

known model that has been used in the past to represent, for instance, the path of a molecule as it travels in a liquid or gas, the price of a fluctuating stock, the path of a drunkard and the financial status of a gambler (Révész, 1990).

The vector of residuals is constrained to conform to a covariance structure of

$$\begin{bmatrix} \zeta_{\alpha,ikt} \\ 0 \\ \zeta_{B,ikt} \end{bmatrix} \sim N\begin{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma^2_{\alpha_{0k}} + d_{1k} * Status_i & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & \sigma^2_{B_{0k}} + d_{2k} * Status_i \end{bmatrix} \end{bmatrix}, \tag{5}$$

where the residual terms were constrained to be uncorrelated. $\sigma^2_{\alpha_{0k}}$ is the variance of the AR residual term for COMP-sibs in episode k and d_{1k} captures the deviation in variance for ASD-sibs relative to the variance of COMP-sibs during episode k. That was to allow the residual variance of the AR component to differ between the ASD-sibs and COMP-sibs. By the same token, $\sigma^2_{B_{0k}}$ represents the process noise variance of the regression parameter for COMP-sibs over time in episode k and d_{2k} captures the deviation in variance for ASD-sibs relative to the variance of COMP-sibs during that episode. Including the terms d_{1k} and d_{2k} allowed us to pose the questions of whether there were statistically reliable deviations between the COMP-sibs and the ASD-sibs in their magnitudes of emotional fluctuations and time variations in infant-parent concurrent associations. The model shown in Equations 3—4 was fit separately to data from each episode. A path diagram representation of the model is shown in Figure 4.

To summarize, the univariate AR model with stochastic regression expresses that an infant's emotional valence at time t can be decomposed into two main components: an AR component, α_{ikt}, and a time-varying regression component, $B_{ikt} * Parent_{it}$. The former, represented as a whole as an unobserved latent component (see Figure 4), captures the ways in which a typical infant's emotion fluctuates around a baseline. The baseline, rather than being defined by the absicca at $Infant_{it} = 0$ as in other earlier models, now varies over time contingent on the concurrent emotional valence of $Parent_{it}$. Furthermore, the extent to which the value of $Parent_{it}$ may shift the baseline of any particular infant's emotional valence is allowed to differ over time as well as over infants.

Two features of this model are worth noting. First, the way the parent-infant regression component is specified in Equations 3—4 differs from other typical linear regression models seen in the literature in that the regression parameter is allowed to vary, rather than remaining invariant over time and individuals. Thus, it is typically termed the *stochastic regression model* (e.g., Shumway & Stoffer, 2000). To formulate the stochastic regression model as part of a state-space model, the manifest indicator is included in the "factor loading matrix" in Equation 3 whereas the regression parameter is expressed as part of the vector of latent variables. This is also reflected in the path diagram in Figure 4 in which B_{ikt} is represented as a time-varying latent variable and the path linking this "latent parameter" to infant's manifest emotional valence is fixed at the value of the manifest parental emotional valence at the same time point. In the special case in which the variance of $\zeta_{B,ikt}$ is equal to zero, the time-varying regression parameter reduces to a time-invariant regression parameter and the regression component reduces to a standard linear regression model. The usual Wald test, when applied to this specific variance term, provides one possible way of testing whether the regression parameter is time invariant. In the present context, it allowed us to evaluate whether the infant-parent association showed substantial changes within each of the three episodes.

Second, infants' (as opposed to parents') emotional valence was used as the dependent variable in this model but this choice is, to some extent, arbitrary. Rather than working directly with the bivariate AR model in Equations 1—2, we chose to fit a univariate AR model in the form of Equations 3—4 to retain the linearity of the model. That is, specifying the cross-regression parameters in the bivariate AR model (see Equations 1—2) to be time-varying introduces nonlinearity in the model and added modeling complexities that cannot be handled by standard linear state-space modeling techniques. In the present context, we made infants the "dependent variable" of interest because parents, by their assertion of the SF procedure, can be conceived as an external source of perturbations to the infants. The ways in which the infants reacted to these external inputs (i.e., parents' changes in responsiveness) constitute a central question of interest. Making parent, as opposed to infant, as the dependent variable does not provide any unique information compared to the model expressed in Equations 3—5 and was thus not considered separately.

The dynamics associated with B_{ikt} were estimated over time using the Kalman smoother, specifically, the Fixed Interval smoother (Chow, Ho, Hamaker & Dolan, in press; Dolan, & Molenaar, 1991, Otter, 1986). The Fixed Interval Smoother is a factor score estimation procedure that can be used to estimate the values of the latent variables at each time point, such as the values of the (possibly) time-varying regression parameter, B_{ikt}, over time. In addition to using the Kalman smoother to estimate the values of all the latent variables (e.g., including the time-varying regression parameter), we used a maximum likelihood procedure known in the state-space modeling literature as the prediction error decomposition function (Schweppe,1965; Shumway & Stoffer, 2000) to estimate all the time-invariant parameters. These time-invariant parameters include the AR parameters, the residual variances and the deviation parameters, d_1 and d_2. All estimation procedures associated with the stochastic regression model were implemented using the SsfPack library in the OxMetrics program (Koopman, Shephard, & Doornik, 1999).

Results

We organized the results from model fitting into two sections to first summarize between-dyad differences in affect coupling and second, to address within-dyad variability in concurrent parent-infant synchrony. Correspondence between the results obtained from the two models will be discussed where appropriate.

Random Effects Bivariate AR(2) Model

Results from fitting the bivariate model indicate that all the infant and parent autoregressive parameters (including $\varphi_{1,infant}$, $\varphi_{1,\ parent}$, $\varphi_{2,infant}$ and $\varphi_{2,\ parent}$) were significantly different from zero at both lag 1 and lag 2. The baseline infant→parent and parent→infant cross-regression parameters, b_0 and c_0 (see Equation 1) were also significantly different from zero. The covariate *SFvsFF/RE* was found to have a significant main effect and an interaction effect with infant gender on the lag-1 infant→parent cross-regression parameter. A significant main effect of *SFvsFF/RE* was also found on the lag-1 parent→infant cross regression parameter, but no interaction effect with infant gender was found. Other covariates did not help account for substantial between-dyad differences in the cross-regression parameters. Parameter estimates obtained from fitting the final bivariate model in which only the statistically significant parameters were retained are summarized in Table 2.

Overall, we found a significant bidirectional cross-regression relationship from parents to infants, as well as from infants to parents. During the FF or the RE condition, the parent → infant and infant → parent cross-regression effects led to increased emotional fluctuations for both parents and infants. The significant regression effects of *SFvsFF/RE* on the cross-regression parameters, in contrast, indicated that the significant parent → infant and infant

→ parent coupling relations diminished almost completely during the SF condition. The *SFvsFF/RE* x *Gender* interaction effect revealed that compared with the male infants, female infants continued to have slight positive lagged effect on their parents during the SF manipulation. In contrast, increased emotional fluctuations in male infants actually drove their parents to restrain their emotional valence further during the SF condition. In addition, significant between-dyad differences still existed in the coupling parameters after accounting for the fixed effects of *SFvsFF/RE* on the cross-regression parameters (i.e., $\sigma^2_{u_{infant->parent}}$ and $\sigma^2_{u_{parent->infant}}$ were significantly different from zero). This suggests that even though overall parent-infant coupling diminished almost completely during the SF manipulation, some dyads continued to maintain some degree of coupling.

It is generally not meaningful to interpret the auto- and cross-regression parameter values in isolation from one another because the collective dynamics of the system are determined jointly by both of these parameters. Instead, to aid interpretation, we derived the model-implied dynamics at the group level by generating eight hypothetical model-implied trajectories for parents and infants using the fixed effects parameter estimates from the final bivariate AR models. We assumed that all of these hypothetical time series were corrupted by a common time series of process noise with a particularly notable perturbation at $t = 1$, which caused a pronounced drop in the participant's emotional valence at that time point to −3.0. The trajectories thus represent the predicted "recovery trajectories" of hypothetical parents or infants in different FFSF scenarios (see Figures 5a–b). Of course, the error variance estimates associated with the four empirical scenarios were all different so a direct comparison of the recovery trajectories by varying the auto- and cross-regression parameters alone is arbitrary. Nevertheless, the predicted trajectories help provide a general idea of the ways in which parents and infants "self-regulate" their emotional valence toward their respective means—or "baseline"—in different FFSF scenarios if all other components in the model are held equal.

Examination of Figures 5a–b reveals that across all episodes, the emotional perturbations experienced by parents and infants were projected to show sinusoidal decay over time toward an overall baseline (marked by the horizontal dotted line at $y = 0$ in Figures 5a–b). In the current context, this baseline corresponded to each individual's respective mean in each FFSF condition. The oscillatory nature of the recovery processes reflects a unique feature of systems that conform to auto- and cross-regression parameters in this range (namely, the associated eigenvalues of the matrix of auto- and cross-regression parameters contain complex numbers; for details see chapter 1 of Hamilton, 1994; Wei, 1990). The decay was found to unfold at an especially rapid rate in both parents and infants during the SF. That is, as expected, the lack of active "input" or emotional perturbations from each dyad member during the SF condition propelled both parents and infants to show more controlled regulatory dynamics. In particular, female infants continued to have a positive but attenuated lagged influence on parents during the SF. Increased emotional fluctuations in male infants, in contrast, actually expedited the damping in parents' emotional valence during SF even though the extent of lagged infant→parent influence was greater in these dyads during FF and RE. No difference was found in the how parents influenced infants' recovery trajectories as a function of infant gender.

To assess whether the parent-infant interactions were dominated more by one dyad member than the other, we constrained each of the two cross-regression parameters to be zero sequentially and compared the relative reduction in fit. We began by first constraining the effects of all remaining predictors in the final model to be zero. That is, we first constrained the effects of *SFvsFF/RE*, gender and their interaction (i.e., b_3, c_2, c_3 and c_6 in Table 2) to be zero. This led to a substantial reduction in model fit compared with the final model (Δ-2*LL* = 40 on 4 *df*, $p < .002$; -2*LL* of final model = 47932). Constraining the average infant →

parent cross-regression parameter, c_0, to be zero also led to a substantial reduction in model fit (Δ-2*LL* = 48 on 1 *df*, *p* < .001). In contrast, when b_0, the average cross-regression parameter from parent → infant was constrained to be zero, the reduction in model fit was still statistically significant, but at a much reduced magnitude (Δ-2*LL* = 25 on 1 *df*, *p* < .001). This reveals the role of the infant as the "dominating member" in an average parent-infant dyad. The lack of significant main effect of *Status* or any interaction effects thereof on the cross-regression parameters suggests that dyads with ASD-sibs did not show differential coupling patterns compared with dyads composed of COMP-sibs.

In sum, we fit a series of bivariate AR models with random effects to examine the lagged mutual influence between parents and infants with the goal to identify whether parents or infants were more likely to "dictate" the dynamics of the dyads as a whole. Infants, as opposed to parents, were found to play a leading role in determining the dynamics of the systems. In addition, we also confirmed that more subtle interactive differences between the FF/RE and the SF conditions were embedded in the dynamics of the data and such differences could still be extracted even after mean and variability differences between episodes had been accounted for. In addition, no effects of status were found on lagged parent-child coupling.

Nonstationarities in Infant-Parent Associations within Episodes

Parameter estimates obtained from fitting the state-space model expressed in Equations (3)–(4) to data from each of the three episodes are shown in Table 3. During the FF episode, all parameter estimates, except the deviation terms, d_1 and d_2, were statistically different from zero. The group-based AR estimates were in the same range as the group-based AR estimates obtained earlier from fitting the random effects AR models. The residual variance associated with the AR component, $\sigma^2_{\alpha 0}$, was significantly different from zero, indicating that the infants' emotional valence continued to show fluctuations around an infant-specific, parent-dependent (and thus, time-varying) baseline. Whenever discrepancies arise between an infant's current emotional valence value and this baseline, all infants were predicted, by nature of the AR parameter estimates, to return to their respective time-varying baseline valence in a damped oscillatory fashion. The residual variance for the time-varying regression parameter was also estimated to be significantly different from zero, thus suggesting that the infant-parent associations tended to fluctuate within dyads during the FF episode. Estimates of the dyad-specific, time-varying regression weights derived using the Kalman smoother are plotted in Figure 6a. Because d_1 and d_2 were not significantly different from zero, the ASD-sibs did not exhibit substantially different amounts of average variability in either the AR component or the regression parameter compared with the COMP-sibs.

During the SF episode, all parameter estimates except for $\sigma^2_{B_0}$ and d_2 were found to be significantly different from zero (see Table 3). Thus, unlike the FF episode, the regression parameters for the dyads were found to be invariant over time. Inspection of the dyad-specific, smoothed regression estimates for this episode (see Figure 6b) revealed that consistent with the experimental manipulation, the regression parameters mainly clustered around zero during the SF episode. The AR dynamics manifested by the infants as a group were similar to those predicted from the group-based AR parameters in the random effects model. That is, infants tended to show quicker return to their baseline affective level during SF than in the FF episode. In addition, the d_1 estimate indicates that compared with COMP-sibs, ASD-sibs tended to show slightly less variability in their AR component over time during the SF condition. In other words, ASD-sibs were less inclined, on average, to show emotional perturbations during the SF.

During the RE episode, the AR parameters for the infants were similar to the AR parameters obtained from the FF episode. The infants' regression estimates, which were statistically validated as showing substantial time-based variability (i.e., $\sigma^2_{B_0}$ was estimated to be significantly different from zero), were found to conform to very different change dynamics compared with those observed during the FF episode (see Figures 6a and 6c, respectively). That is, the infant-parent associations were much more volatile and showed greater fluctuations over the course of the RE episode. As was the case during the SF condition, ASD-sibs continued to show lower emotional fluctuations around their baseline during the RE episode than COMP-sibs (i.e., d_1 was negative and significantly different from zero).

Overall, we "decomposed" the variability in infants' emotional valence into two major components: a stochastic regression model that defines a time-varying baseline for each infant, and an AR component that describes how the infants showed fluctuations around their respective baseline levels as a group. The time-varying baseline, in turn, reflects the (possibly) time-varying nature of parent-infant synchrony. Compared with COMP-sibs, we found that ASD sibs, on average, showed less emotional perturbations (i.e., less movement away from the baseline) during the SF as well as the RE. We also found that the concurrent synchrony (or asynchrony) between parents and infants did vary substantially over time in some episodes (e.g., FF and RE) but not others (e.g., SF). In addition, by examining the dyad-specific changes in regression parameter over time, we found that the synchronization patterns between parents and infants were very different during the FF and the RE conditions. This suggests that the negative impact of the SF manipulation continued to affect subsequent infant-parent interactions in more subtle ways than differences suggested by changes in means alone.

Discussion

In the present article, we first addressed between-dyad differences in affective dynamics basedon results from fitting a series of random effects autoregressive models. We then evaluated within-dyad constancy in parent-infant synchrony over time using a stochastic regression model. We found evidence for between-dyad differences as well as within-dyad variability in affective changes from a dynamic perspective. Overall, the estimated AR parameters for the parents and infants were found to be similar in values across all models tested in the present study (bivariate AR and AR model with stochastic regression for infants only). The models indicated that the emotional valence of infants and parents was projected to return to some baseline values in an oscillatory fashion after being pushed away from them, as opposed to "wandering" away from them (i.e., showing explosive dynamics). Stated differently, both infants and parents manifested controlled affect regulation in the form of damped oscillatory return to their baseline values, as opposed to manifesting explosive fluctuations (e.g., unstable emotional tantrums) over time. We note, however, that the predicted trajectories described in the Results section pertain only to the trajectories of the "average dyad" across the three conditions. Substantial between-dyad differences still existed in the cross-regression parameters for parents and infants, as revealed by the statistically significant random effects variances.

Several previous studies contrasting ASD and comparison siblings have suggested that ASD siblings show unique affective characteristics relative to comparison siblings during the FFSF protocol (Cassel et al., 2007; Yirmiya et al., 2006). Results across the two models tested in the present article suggest that ASD-sibs and COMP-sibs did not differ per se in *how* they regulated their emotion (i.e., no substantial differences in the cross-regression parameters or the range of time-varying regression parameter, B_{it}, in the stochastic regression model). Rather, according to results from the stochastic regression model with

AR(2) component, COMP-sibs tended to show greater emotional fluctuations during the SF that persisted into the RE episode. Thus, the residual variance of the AR component was found to be significantly higher for the COMP-sibs than for the ASD-sibs during the SF and RE episodes. This finding is consistent with previous evidence suggesting that ASD-sibs tend to show more neutral affect relative to other COMP-sibs during the FFSF procedure (e.g., Yirmiya et al., 2006). Here, we provided support for this conjecture from a dynamic regulatory perspective. It is perhaps even more encouraging that we were able to extract such subtle differences after information due to mean and variability differences had already been removed prior to model fitting (via within-person standardization).

Recently, Beebe et al. (2007) used a set of univariate mixed effects AR models to demonstrate the presence of both parent → infant and infant → parent influence in the interactions of four-month-olds and their mothers. Here, we incorporated both AR(1) and AR(2) parameters to capture damped oscillatory dynamics in the participants' emotion regulation trajectories (Hamilton, 1994; Harvey, 1993). The modeling work undertaken in the current study extended the approach adopted by Beebe et al.'s (2007) by allowing for simultaneous examination of infant-to-parent and parent-to-infant lagged influences (or interactive contingencies) within one bivariate random effects AR model. Consistent with findings that infant-parent attachment emerges through ongoing, reciprocal but infant-dominated exchanges between infants and parents (Feldman, 2006; Jaffe et al., 2001; Stern, 1985), we found a significant bidirectional coupling between the affective dynamics of parents and infants. Phrased in the context of a three-legged race, the bidirectional ties between parents and infants helped deter both parties from settling into a stagnant state too quickly.

Developmental theorists have long postulated that infants show an ongoing tendency to adapt to changes in their parents' behavioral and emotional patterns (Ainsworth, Blehar, Waters, & Walls, 1978; Brazelton et al., 1974; Tronick & Gianino, 1986). Findings in the developmental literature have further suggested that infant-to-parent interactive influence is an earlier developmental achievement than parent-to-infant influence (Feldman, 2006; Moore, Cohn & Campbell, 1997). A difficulty with this literature, however, is a dependence on categorizing individual dyads according to the direction of influence shown in their interactions. Using a series of nested models, we verified that this reciprocal coupling relation was dominated more by the infants than the parents. That is, we sequentially omitted the parent-to-infant and infant-to-parent cross-regression paths and subsequently used the resultant changes in model fit to deduce the relative dominance of the role of each dyad member. Changes in chi-square values serve as a more objective, quantifiable basis for testing the lead-lag relationships between infants and parents and can supplement information from indices such as cross-correlations and time lags in the cross-correlations (as used in e.g., Yirmiya et al., 2006). Using this approach, we confirmed the predominant role of infant-to-parent influence, as opposed to parent-to-infant influence, in short-term infant-parent interaction. Contrary to results reported by Yirmiya at al. based on individual classification of dyads, our group-based approach indicated no evidence for deficits in parental responsivity to changes in infant emotional engagement among ASD-sib dyads.

One cautionary note pertaining to the interpretation of the auto- and cross-regression parameters is in order. Higher self-contingencies (i.e., higher AR(1) coefficients) in mother's behaviors during face-to-face play with infants have conventionally been regarded as reflecting greater predictability and a more adaptive interaction style (e.g., Beebe et al., 2007). Whereas this interpretation may be meaningful in the range of low to moderate AR(1) values (specifically, values that are positive but substantially less than 1.0 such as the .5-.7 range in Beebe et al.'s study), the same interpretation may not apply in cases involving AR(1) values that are close to or above 1.0 (e.g., the ones observed in the present study). In the latter cases, increasing "self-contingencies" even further may lead to increasing emotional fluctuations and consequently, a highly unstable system that shows explosive affective dynamics. In contrast, comparing a system that shows no continuity over time (i.e., the associated AR(1) parameter is equal to zero) with a system that shows some regularity it its dynamics (e.g., AR(1) parameter that is greater than 0 but less than 1.0) may lead to conclusions that favor the high self-contingency systems as more adaptive systems.

The inclusion of the cross-regression parameters—or interactive contingencies—can further alter the dynamics of the system. Thus, the proposition put forth by Jaffe et al. (2001), that midrange interactive contingencies between mothers and infants lead to more secure attachment than low or high contingencies, may be particularly pertinent in the interpretation of AR-based models. From a modeling standpoint, mid-range interactive contingencies may help strengthen the regularity in both parties' affect without pushing a dyad into an unstable state. Regardless, the substantive meanings of the AR parameters have to be considered carefully in regard to the dynamics generated by the modeling parameters as a whole, and the context within which the notion of "baseline" is defined. In some instances, it may not be desirable for an individual to show a quick return to baseline. In other instances, an individual who shows no predictability in his/her emotion may well evidence an adaptive regulatory style if the individual's emotion simply shows random fluctuations around a highly desirable baseline.

Research on infants' interactive dynamics in the past few decades have been dominated largely by a "static" notion of development. Recently, there has been a growing consensus that change, as opposed to stability, captures a fundamentally different facet of children's socioemotional development (e.g., Moore et al., 1997). For instance, De Weerth & van Geert (2002) reported that emotional behaviors in mother-infant dyads showed substantial variability during the first year of life, both between dyads and between behaviors. The stochastic regression used in the present study is a formalization of observations of apparent non-stationarities made with reference to a pair of case studies of dyadic interaction that relied on automated, computer vision measurements of facial expression (Messinger, Mahoor, Chow, & Cohn., 2008). Using the stochastic regression model, we found that parent-infant synchrony could change substantially even within a relatively brief interaction episode as well as across different FFSF episodes. In particular, the SF procedure did not eliminate some of the more subtle interactive dynamics between parents and infants, and it also led to distinctly different interactive dynamics during the RE than in the FF (see Figures 6a–c). During the FF, the parent-child associations (i.e., the time-varying regression weights) were observed to unfold more gradually following relatively smooth trajectories. In contrast, the parent-child associations during the RE were characterized by more divergent differences across dyads and relatively unstructured fluctuations at a more rapid rate. This finding highlights the ambiguity experienced by the infants in response to the parents' sudden change in affect in the RE. The rich dynamics embedded in such within-dyad fluctuations can be easily bypassed, however, if sufficient time-based information has not been available from each individual dyad.

The current procedures used to identify intra-dyad variability in parent-infant coupling can be readily utilized to study other dynamic phenomena in psychology. We used a simple random walk model in the present study because of its flexibility in approximating very diverse patterns of change with very little modeling constraints. Other, more theoretically driven models, can be used to test specific notions of how these associations vary over time (e.g., fluctuations around a stable set point, linear or exponential declines). Approaches such as regime switching models (Kim & Nelson, 1999), change point detection models (Carlin, Gelfand & Smith, 1992) and nonlinear state--space models with time-varying parameters

(Chow, Ferrer & Nesselroade, 2007; Molenaar & Newell, 2003) are all examples of other alternatives for representing more complex changes in dyadic linkages.

Given that our modeling results were based on reports provided by non-expert raters, there may be delays and imprecision in the raters' assessments. However, because the ratings used for model fitting were aggregated and standardized across multiple raters, these ratings could still serve as a helpful proxy to validate the directionality of parent-infant coupling provided that no differential rating delays were present (e.g., systematic delays existed in rating of infants but not ratings of parents). In the present context, we still found support for the much corroborated view of mutual infant-parent reciprocity despite the possible existence of rating delays. Other measurement techniques with higher time precision can be used to better determine the nature and directionality of infant-parent coupling in other contexts (Messinger, Mahoor et al., 2008; Messinger, Cassel et al., 2008)

Admittedly, the sample size in the current study (in terms of the number of dyads) was small relative to the complexity of some of the models considered herein, particularly the random effects models. Standard error estimates turned out to be reasonable, although other more subtle between-dyad differences could probably be identified with greater accuracy if data were available from more dyads. Viewed from a different angle, the availability of intensive repeated measurements data does help provide additional information concerning patterns of intraindividual changes, and such data, as we have shown here, help open up new possibilities for exploring more subtle changes and potential nonstationaries within dyads.

Conclusion

Intra-individual changes and inter-individual differences have been described metaphorically by Nesselroade (1991) as the warp and woof—threads that run lengthwise and crosswise, respectively—of the developmental fabric. Studying aspects pertaining to the warp (intra-dyad dynamics) and woof (inter-dyad differences) of dyadic interactions are equally critical to our understanding of what distinguishes a dyad from two individuals who act in isolation. The overarching goal in the present article was to present possible ways of conceiving and describing dyads as intertwined dynamic systems. The different dynamic models used in this study are but one of the many ways of representing patterns of dyadic interactions. We hope that the potential promises of these methods can help researchers envision a more enriched notion of the processes that govern dyadic interactions, and possibly inspiring them to design studies that not only capture the constancy, but also the variability in dyadic interaction.

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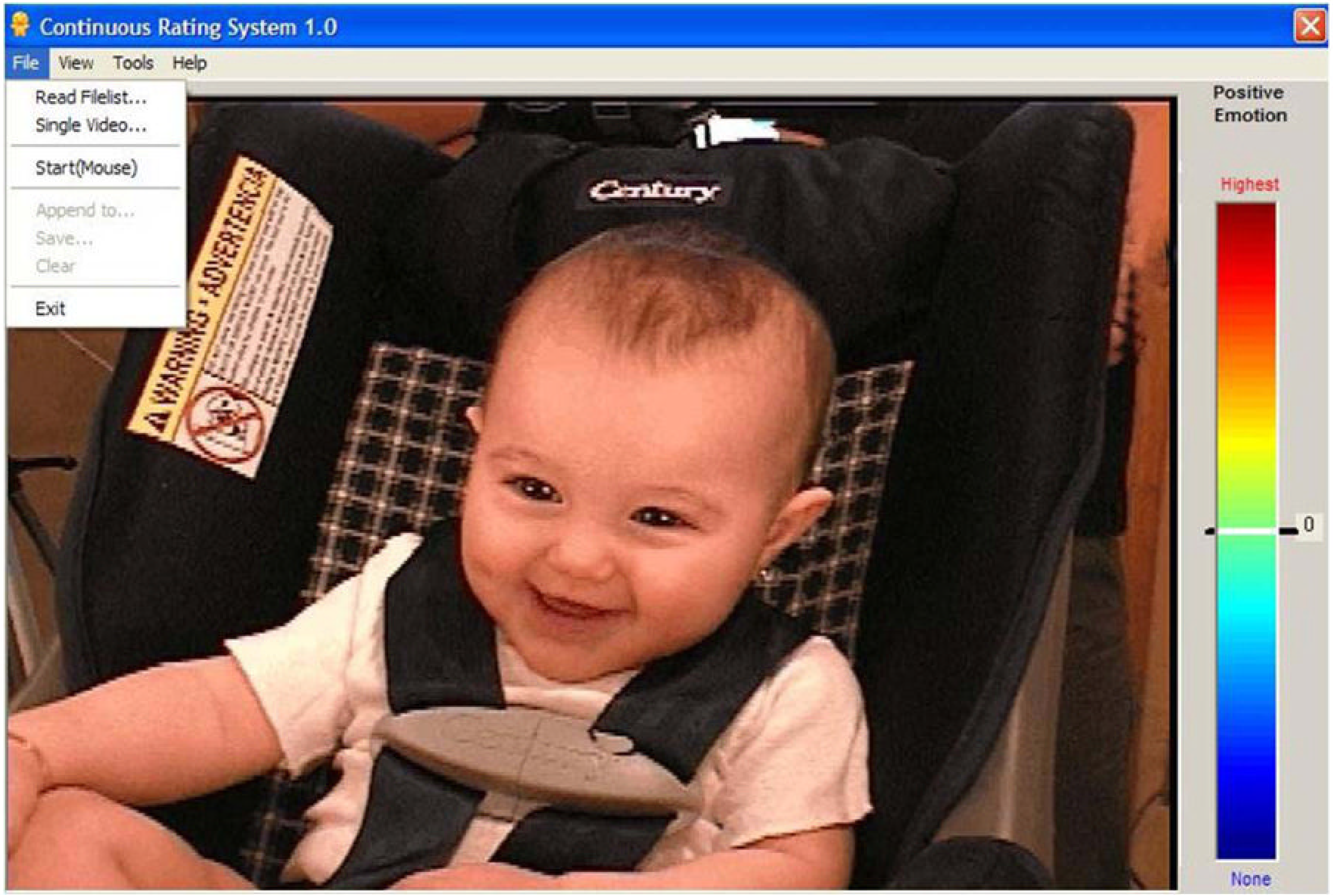

Figure 1.
Screenshot of the Continuous Measurement System (CMS).

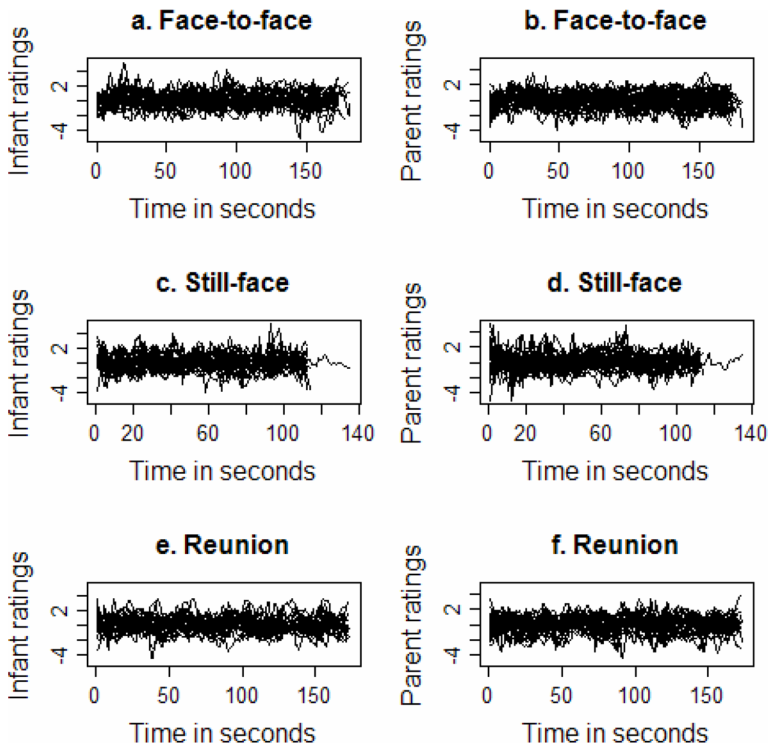

Figure 2.

(a), (c) & (d): Plots of each infant’s mean ratings during the FF, SF and RE, respectively; (b), (d) & (e): plots of each parent’s mean ratings during FF, SF and RE.

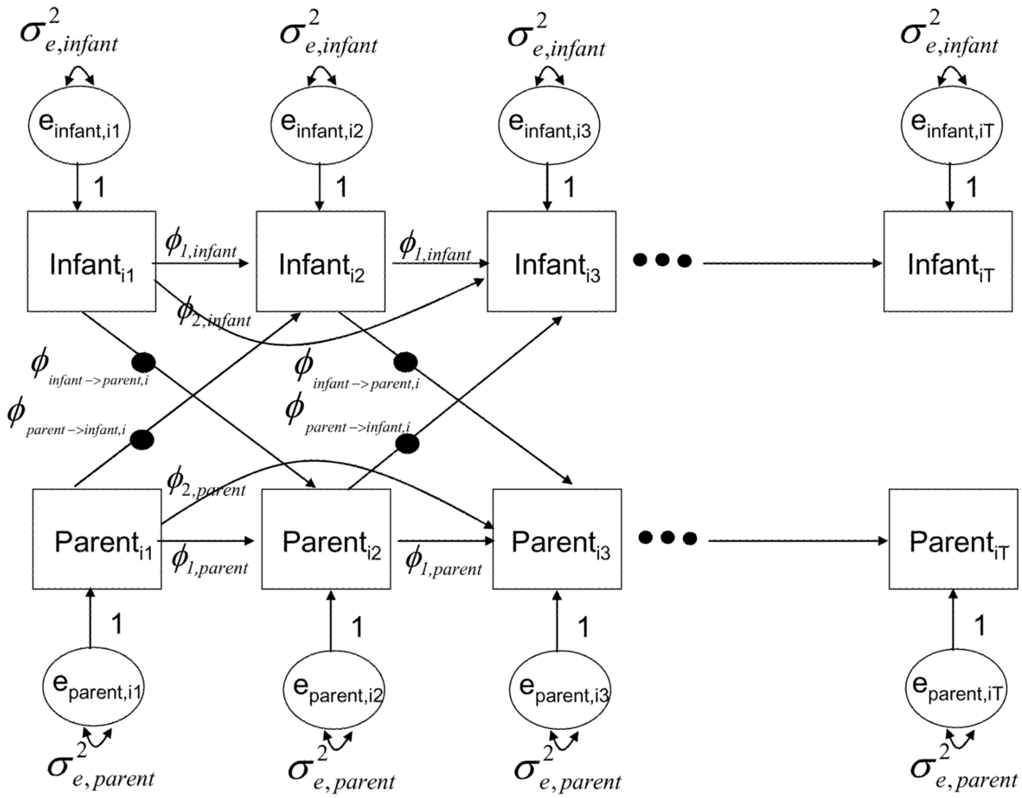

Figure 3.

Path diagram of the bivariate AR(2) model. The dark filled circles attached to the lag-1 cross-regression paths, $\varphi_{infant\text{–}>parent,i}$ and $\varphi_{parent\text{–}>infant,i}$ indicate that individual differences are included in the P→I and I→P cross-regression parameters. The index for episode (k) is omitted from the path diagram to simplify the notations. $Infant_{it}$ = manifest measurement of infant (in dyad) i's emotional valence at time t; $Parent_{it}$ = manifest measurement of parent (in dyad) i's emotional valence at time t $e_{infant,it}$ = measurement error for infant; $e_{parent,it}$ = measurement error for parent; $\sigma^2_{e,infant}$ = measurement error variance for infant; $\sigma^2_{e,parent}$ = measurement error variance for parent; $\varphi_{1,infant}$, $\varphi_{1,\ parent}$, $\varphi_{2,infant}$, $\varphi_{2,\ parent}$ = AR(1) parameter for infant, AR(1) parameter for parent, AR(2) parameter for infant and AR(2) parameter for parent; $\varphi_{infant\text{–}>parent}$ = cross-regression from infant's emotion at time t−1 to parent's emotion at time t; $\varphi_{parent\text{–}>infant}$ = cross-regression from parent's emotion at time t −1 to infant's emotion at time t.

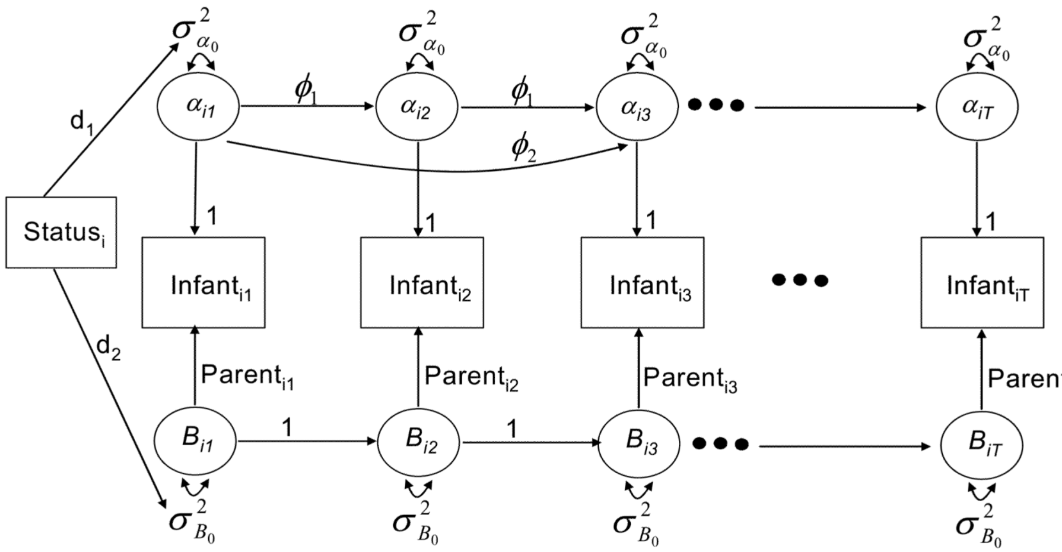

Figure 4.

Path diagram of the stochastic regression model with AR(2) component used to represent time-varying concurrent synchrony between parents and infants. The index for episode (k) is omitted from the path diagram to simplify the notations. $Infant_{it}$ = manifest measurement of infant (in dyad) i's emotional valence at time t; $Parent_{it}$ = manifest measurement of parent (in dyad) i's emotional valence at time t; $Status_i$ = ASD status for infant i (0 for COMP-sibs, 1 for ASD-sibs); α_{it} = AR component; φ_1 =AR(1) parameter; φ_2 =AR(2) parameter; B_{it} = regression parameter at time t; $\sigma^2_{\alpha_0}$ = variance for AR component; $\sigma^2_{B_0}$ = variance for time-varying regression parameter; d_1 = deviation in AR variance associated with ASD-sibs compared with COMP-sibs; d_2 = deviation in variance for the regression parameter associated with ASD-sibs compared with COMP-sibs.

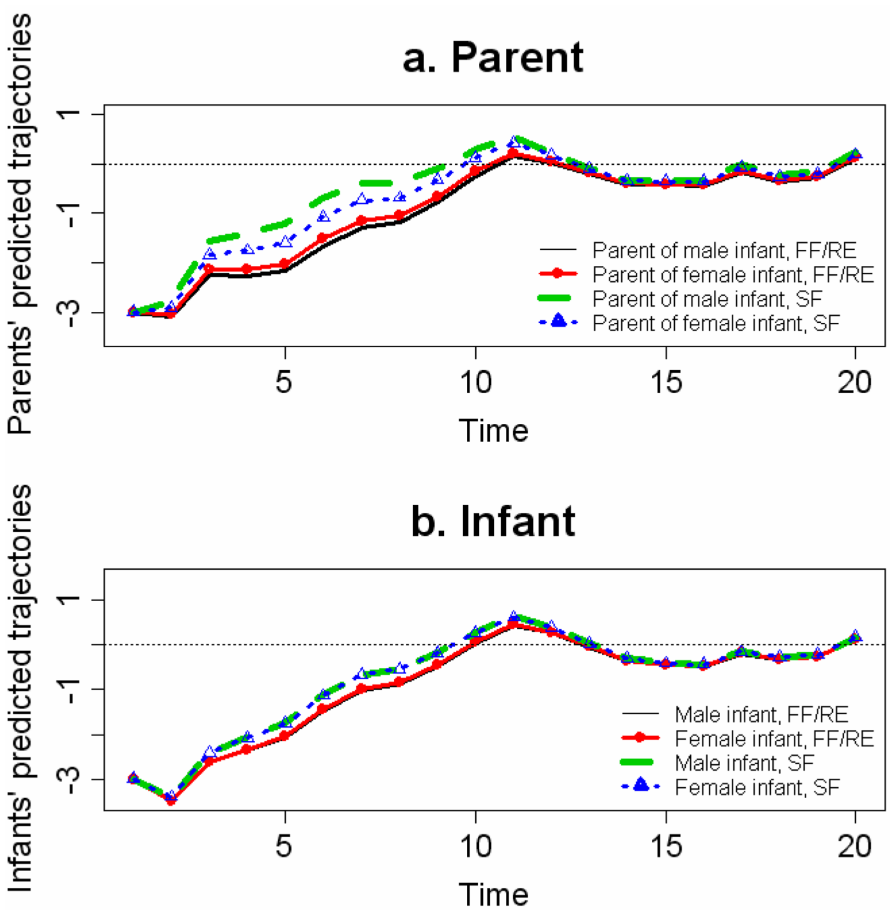

Figure 5.

(a) Predicted trajectories of parents of male vs. female infants in the SF vs. FF/RE condition; (b) Predicted trajectories of male and female infants in the SF vs. FF/RE condition. The horizontal dotted lines in (a) and (b) represent the baseline affective level toward which each participant's recovery trajectory converges. One time series of residual errors, e_t, is used in all simulations to generate the same magnitudes of perturbations in all conditions. For infants, the predicted trajectories are generated by iterating through the equation

$$Infant_{ikt}=1.16Infant_{ik,t-1}-.36Infant_{ik,t-2}+(.03-.02SFvsFF/RE_{ik})Parent_{ik,t-1}+e_t,$$

whereas the predicted trajectories for parents are generated using the same initial condition and time series of residual errors, but with

$$\begin{aligned}Parent_{ikt} =&.98Parent_{ik,t-1}\\&-.20Parent_{ik,t-2}\\&+[.05+.002Gender_i\\&-.05SFvsFF\\&/RE_{ik}]\\&+.02(Gender_i\times SFvsFF/RE_{ik})]Infant_{ik,t-1}+e_t.\end{aligned}$$

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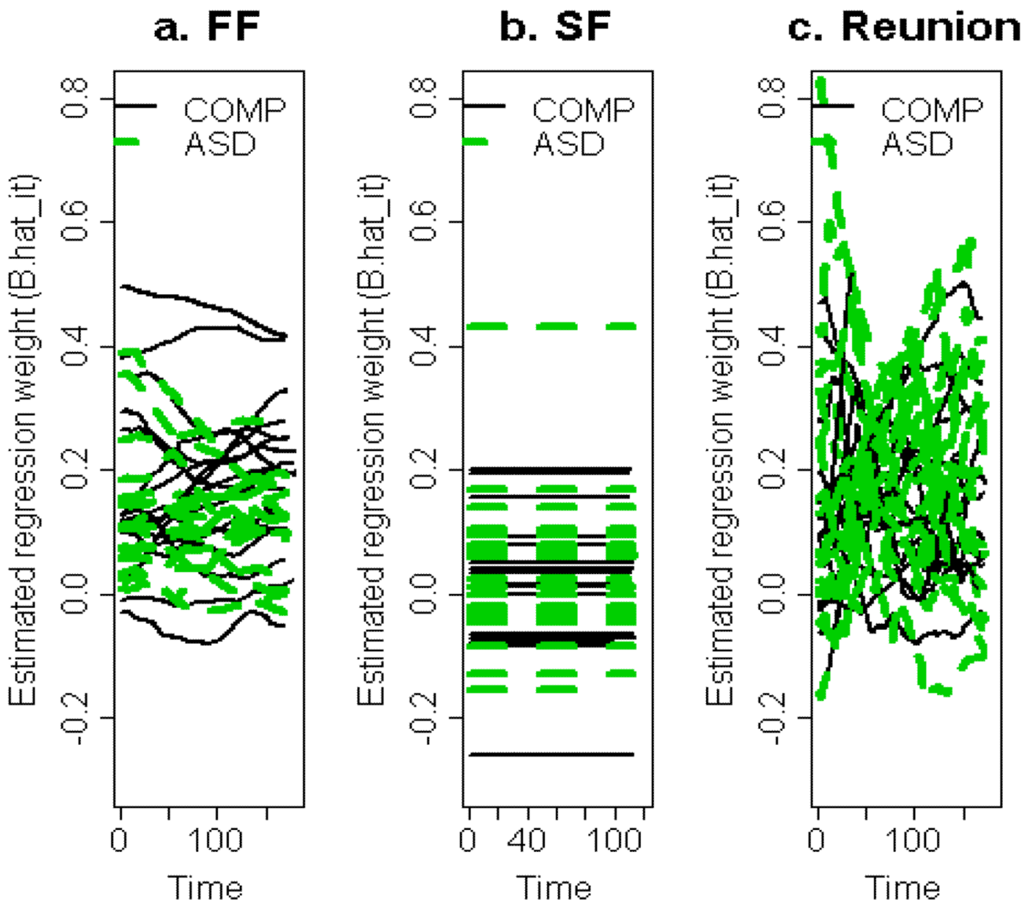

Figure 6.

Estimated regression weights for each dyad based on parameter estimates from the final AR with stochastic regression model. The regression weights were estimated by means of the Kalman smoother for (a) the FF episode, (b) the SF episode and (c) the RE episode.

Table 1

Infant Ethnicity, Gender, and Risk Status

	Infant Risk Status			
	Comparison-sibs		**ASD-sibs**	
Infant Ethnicity	**Male**	**Female**	**Male**	**Female**
White	3	5	4	3
Hispanic	4	2	7	2
Black/Other	2	2	2	2
Total	9	9	13	7

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Table 2

Parameter Estimates Obtained from Fitting the Final Bivariate VAR(2) Models.

Parameters	Estimates (SE)	Parameters	Estimates (SE)
Infant AR(1) parameter ($\varphi_{1,infant}$)	1.16 (.01)	Gender on I → P cross-regression (c_2)	.002 (.01)
Infant AR(2) parameter ($\varphi_{2,infant}$)	−.36 (.01)	SFvsFF/RE on I → P cross-regression (c_3)	−.05 (.01)
Parent AR(1) parameter ($\varphi_{1,parent}$)	.98 (.01)	SFvsFF/RE x *Gender* on I → P cross-regression (c_6)	.02 (.009)
Parent AR(2) parameter ($\varphi_{2,parent}$)	−.20 (.01)	Between-dyad variance in P → I cross-regression ($\sigma^2_{u_{parent->infant}}$)	.002 (.001)
Baseline P → I cross-regression (b_0)	.03 (.01)	Between-dyad variance in I → P cross-regression ($\sigma^2_{u_{infant->parent}}$)	.002 (.001)
SFvsFF/RE on P → I cross-regression (b_3)	−.02 (.01)	Error variance for parent ($\sigma^2_{e_{parent}}$)	.28 (.003)
Baseline I → P cross-regression (c_0)	.05 (.01)	Error variance for infant ($\sigma^2_{e_{infant}}$)	.21 (.002)

Note: All parameter estimates except for c_2 were statistically different from zero at the .05 level. P → I = parent to infant; I → P = infant to parent.

Table 3

Time-Invariant Parameter Estimates Obtained from Fitting the AR Model with Stochastic Regression Component to Data from Each of the Three Episodes.

Parameters	Estimates (SE) for FF	Estimates (SE) for SF	Estimates (SE) for RE
Group-based AR(1) parameter (φ_1)	1.24 (.01)*	1.02 (.02)*	1.25 (.01)*
Group-based AR(2) parameter (φ_2)	−.40 (.01)*	−.27 (.02)*	−.42 (.01)*
Group-based variance for AR(1) component ($\sigma^2_{\alpha_0}$)	.39 (.01)*	.59 (.01)*	.45 (.01)*
Group-based variance for time-varying regression coefficient ($\sigma^2_{B_0}$)	.012 (.005)*	.01 (.02)	.04 (.01)*
AR variance difference (ASD-sibs - COMP-sibs; d_1)	.003 (.006)	−.05(.02)*	−.08 (.01)*
Regression variance difference (ASD-sibs - COMP-sibs; d_2)	.00 (.00)	−.00 (.00)	.00 (.00)

* $p < .05$