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Estimating time-varying RSA to examine psychophysiological linkage of marital dyads

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Abstract

One of the primary tenets of polyvagal theory dictates that parasympathetic influence on heart rate, often estimated by respiratory sinus arrhythmia (RSA), shifts rapidly in response to changing environmental demands. The current standard analytic approach of aggregating RSA estimates across time to arrive at one value fails to capture this dynamic property within individuals. By utilizing recent methodological developments that enable precise RSA estimates at smaller time intervals, we demonstrate the utility of computing time-varying RSA for assessing psychophysiological linkage (or synchrony) in husband-wife dyads using time-locked data collected in a naturalistic setting.

Descriptors: Respiratory sinus arrhythmia, Time-varying RSA estimates, RSA linkage, Psychophysiological linkage

Respiratory sinus arrhythmia (RSA), a measure of parasympathetic influence on heart rate, has been widely accepted as an indicator of socially facilitative physiological regulation that responds quickly to changing environmental demands (Porges, 1995; Porges, 2007). Investigations into both intra-and interindividual differences in RSA have been predominantly conducted with block designs that extract an average RSA level across several minutes, or even hours. However, averaging across time fails to capture the very aspect of RSA proposed to facilitate social regulation; namely, that RSA reflects the ability to rapidly modulate levels of physiological arousal through direct neural control over cardiac chronotropy. Physiologically, this enables changes in heart rate on the individuals' beat-to-beat time scale, indicating a need for estimating RSA dynamics at a more comparable temporal resolution. Assessing RSA at a finer temporal resolution would provide researchers with the ability to better align RSA measurement with a wider range of dynamic stimuli or behavioral responses. We provide a demonstration of the added utility of assessing time-varying RSA, in which RSA estimates are produced in a second-by-second time series, and compare this to the traditional, aggregated estimates by exploring the relation between reported marital conflict and RSA linkage (i.e., synchrony in RSA changes across time) for married partners in a naturalistic setting.

RSA refers to the variation in cardiac rhythms across the respiratory cycle. Current standards for obtaining RSA estimates involve the discrete Fourier transform (DFT) to compute the power of heart rate in the respiratory frequency. Specifically, heart rate data are quantified as a point process of interbeat intervals (IBI) that indicate the time between each R peak in the electrocardiogram. The IBI series is then interpolated to provide values that are equidistant in time. Power in the context of RSA is the variance in the interpolated IBI series attributable to the frequency range of respiration (Porges, 2007). Estimates are typically computed across 60- to 120-s epochs in order to ensure a sufficient number of IBI data points to accurately quantify the power in all frequency ranges (Task Force, 1996). While perhaps necessary to maximize reliability of power estimation across all frequencies, this epoch length may not be required for obtaining precise power estimates in the frequency band associated with respiration (Hansson & Jönsson, 2006). Longer epoch lengths obscure the dynamic processes of interest for researchers interested in how RSA changes across time. Thus, for research questions focused on the relation between physiology and dynamic processes, such as interpersonal dynamics, there is a clear benefit to shortening the epoch length.

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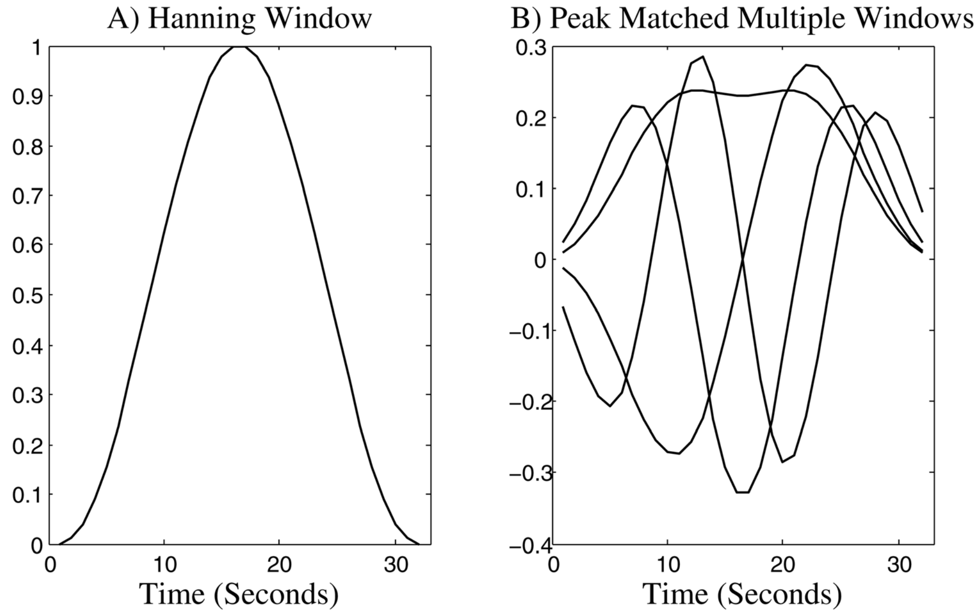

Figure 1. Depiction of two tapering techniques for 32-s windows for data sampled at 250 Hz. The Hanning window (A) is one of the current standards used in RSA estimation; the peak matched multiple window (PM MW) plotted in (B) contains multiple windows with values depicted here.

Mathematically, precision in power estimates from analysis in the frequency domain can be improved upon with tapering. Tapering involves the weighting of each epoch of data using a predefined shape that typically peaks at the center of the epoch and tapers toward zero on either side, thus maximally weighting the range of data with the most observable information. As the window reaches the epoch boundary, the tapering function discounts the information available because the arbitrary boundary obscures the ability to discriminate between frequencies when only partial waveform information is observable. In this way, optimal tapers achieve more reliable estimates of a specific frequency band of interest that avoid contamination by other frequencies (Shumway & Stoffer, 2006). A commonly applied taper in RSA analysis is the Hanning window (e.g., Martinmäki, Rusko, Saalasti, & Kettunen, 2006; see Figure 1a). However, additional taper options exist, and the selection of which should follow from the qualities of the waveforms to be differentiated as tapering techniques differ in terms of their ability to isolate specific frequencies.

In recent years, the technique of using multitaper or multiple window spectral estimation has become more popular. Multitapers imply an efficient use of finite data length with respect to bias and variance. A multitapering algorithm called peak matched multiple windows (PM MW) has been proposed to be optimal for random processes such as heart rate that exhibit large dynamics in their spectra (Hansson & Salomonsson, 1997). The PM MW algorithm applies a series of overlapping tapers that effectively accommodate the jagged (nonnormal) power spectra typical of cardiac data where power is high in certain frequencies and low in others. The sum of the weighted power estimates from the IBI series that has been modified by these multiple windows can be summed to provide one value for the frequency band of interest. For RSA estimates, this is often a frequency band of .12 to .40 Hz for adults. Hansson and Jönsson (2006) conducted a comparison of various multiple windowing techniques and found that PM MW outperformed the Hanning window, among others, for returning unbiased and low-variance RSA estimates. These researchers further demonstrated that for PM MW the use of 32-s epochs did not introduce substantial error compared to the traditional 64-s epochs. It is therefore appropriate for estimating RSA in shorter intervals.

Halving the epoch size offers substantial gains in the efforts to investigate RSA changes in individuals. Epoch sizes of approximately 30 s have been used for the purpose of identifying individual-level variability and changes in RSA (e.g., Fisher & Woodward, 2014). However, the dynamic changes in behavioral regulation that the parasympathetic system is thought to support occur at even smaller temporal resolutions. Additional techniques can complement the precision provided by PM MW to further improve the temporal resolution of time-varying estimates of RSA. Specifically, power estimates based on the short time Fourier transform (STFT), a popular approach for extracting RSA estimates that vary across time (e.g., Blain, Meste, & Bermon, 2005; Hansson-Sandsten & Jönsson, 2007; Pichon, De Bisschop, Roulaud, Denjean, & Papelier, 2004) could be used in tandem with PM MW. Obtaining power estimates via STFT has been validated in a study that used it to (a) find expected changes in RSA concomitant with postural changes, and (b) demonstrate that these changes were mitigated by the vagal blockade atropine sulfate, indicating that the extracted power estimates were reliably associated with changes in parasympathetic function (Martinmäki et al., 2006). STFT conducts sliding DFTs on epochs of data that overlap, moving across the entire time series of cardiac data. The sum of the squared STFTs (i.e., power) in the frequency range of respiration provides a series of time-varying RSA estimates. These time-varying RSA estimates enable researchers to look at RSA dynamics within a condition rather than as a single value for the condition.

Most approaches for analyzing time series data such as heart rate data assume that the data are weakly stationary, meaning that the data within a given epoch have a constant mean and the autocovariance function depends only on the lag. For instance, lag zero provides the variance using the autocovariance function, and this must remain constant across time in addition to the mean to satisfy weak stationarity. The same holds across all possible lags (Chatfield, 2004). As with most psychophysiological data, heart rate data are known to violate this assumption when looking across large windows of time (Task Force, 1996). Inherent in the use of time-frequency analysis, such as those based in STFT, is the accommodation of nonstationarity of the time series data by providing estimates that vary across time. Arriving at RSA estimates using power analysis within an STFT framework has previously been shown to perform as well as wavelet analysis, a method often used to circumvent problems caused by nonstationarity, at typical respiratory rates seen in awake adults (Cnockaert et al., 2008; Houtveen & Molenaar, 2001). Obtaining power in the respiration frequency from STFT estimates is thus sufficiently robust with regard to the nonstationarity of cardiac data. By using epochs of 32 s rather than the current standard of 60 to 120 s, the approach described herein further attends to the nonstationary quality of the data. To date, these two approaches for RSA measurement, PM MW and power estimates based on STFT, have not been used in conjunction with one another in an empirical study.

In this study, we utilize power estimates obtained from STFT in combination with PM MW to extract time-varying estimates of RSA for husband and wife dyads during a family interaction. Quantifying second-by-second RSA for each individual in a dyadic interaction enables the evaluation of physiological linkage between individuals during social interactions closer to the time scale that parasympathetic control is proposed to act to facilitate social dynamics. Conceptually, physiological linkage within dyads assesses the degree to which moment-to-moment changes in arousal for one individual are matched by their partner. Aggregate measures of RSA obtained by using nonoverlapping epochs are usually not capable of providing sufficient data points for linkage to be adequately assessed in a dyad. Psychophysiological linkage has traditionally been arrived at by computing a correlation coefficient between two streams of time-locked psychophysiological data (i.e., husband-wife); we follow this approach here but, for the first time, with RSA data. Previous research used a range of autonomic and somatic physiological measures (heart rate, skin conductance, pulse transmission time, and somatic activity) and found that 60% of the variance in marital satisfaction was explained by the extent of "linkage" in physiological arousal. Marital satisfaction was reported to be lower among couples with higher physiological linkage, but only when linkage was measured during discussion of a high-conflict problem and not when discussing mundane topics (Levenson & Gottman, 1983). A later study focusing on empathy reported physiological linkage was positively associated with correct identification of negative emotional states in their partner during a task where the spouse was asked to watch a videotaped discussion and rate how they thought the other spouse was feeling (Levenson & Ruef, 1992). Thus, linkage can be maladaptive in facilitating arousal matching, or adaptive in allowing for empathic connectivity, depending on the context.

Research on psychophysiological linkage of marriage partners has been largely dormant until fairly recently (e.g., Ferrer & Helm, 2013; Liu, Rovine, Klein, & Almeida, 2013; McAssey, Helm, Hsieh, Sbarra, & Ferrer, 2013; Reed, Randall, Post, & Butler, 2013). The relative lack of research on linkage may be due in part to the fact that some of the physiological indices used in these early studies were not well theoretically validated as indices of psychophysiology (e.g., pulse amplitude, pulse transmission time) but fulfilled the need for moment-to-moment measurement. RSA, by contrast, has not traditionally been available at such a fine temporal resolution. The interest in capturing dynamic changes in RSA in interpersonal interactions has led to an increase in studies assessing RSA in dyadic contexts, although these studies have not typically examined RSA changes in relation to a partner in a given dyadic interaction. Rather, the vast majority (e.g., Butler, Wilhelm, & Gross, 2013; Connell, Hughes-Scalise, Klostermann, & Azem, 2011) continue to arrive at averaged RSA estimates obtained in approximately 60-s intervals, which are often then averaged to obtain one value per person per condition. These aggregate estimates within conditions are then compared to assess how RSA relates to social demands or time-invariant constructs. In a more recent development, RSA estimates were obtained in smaller epochs (30 s) and submitted to a cross-lagged panel model to explore RSA relations between and within dyads across time (Helm, Sbarra, & Ferrer, 2014). This approach provides insight into coregulation by directly assessing how a typical couples' RSA relates to each other but does not capture dyad-level psychophysiological linkage at the time scale used by Levenson and colleagues (Levenson & Gottman, 1983; Levenson & Ruef, 1992).

In this paper, we report on a method for extracting RSA on a second-by-second time scale and correlate these estimates to compute RSA linkage. As the approach provided here is a natural extension of methods that have been found to be reliable and accurate (Hansson and Jönsson, 2006; Houtveen & Molenaar, 2001; Jönsson & Hansson-Sandsten, 2008), we seek primarily to demonstrate its utility with empirical data. Specifically, we examine if RSA linkage between married partners is associated with measures of marital function as reported previously for other nonparasympathetic psychophysiological indices. We hypothesize that greater linkage in RSA will be associated with greater reported conflict, in line with the proposed role of the parasympathetic system in regulating arousal for socially affiliative purposes and evidence that marital distress may be related to greater psychophysiological linkage. We further hypothesize that linkage measured during an interaction will be a better predictor of marital conflict than RSA aggregated across blocks for each individual, thus demonstrating that this technique can offer a methodological and theoretical advancement over current approaches.

Method

Participants

Families were recruited through newspaper birth announcements, flyers posted at day cares, and a database of local families interested in participating in research. To participate, families had to be married or cohabitating and have two biological children between the ages of 2 and 5 years. A total of 70 families were recruited for the larger study; for reasons described below, only 49 couples provided usable data for the present study. Wives in the present study were, on average, 33 years old ($SD = 4.07$ years) and 49% were employed. Husbands were, on average, 35 years old ($SD = 4.78$ years) and 94% were employed. The median family income was \$70,000 (range = \$10,000 to \$250,000). The sample was predominantly White (wives: 89%; 8% Hispanic/Latino, and 2% Other; husbands: 92% White; 6% Hispanic/Latino, 2% Other). Couples were married for an average of 9 years ($SD = 2.59$ years).

Procedures

Families participated in a 2 1/2 hr laboratory visit, including procedures not described here, as part of a larger study. After obtaining informed consent, electrodes for recording cardiac data were attached to each family member. Families then participated in several interaction tasks. For the current study, cardiac data were collected during a tetradic family free-play (10-min) session where parents were instructed to play with their children as they would at home.

Parents' were asked to complete a series of questionnaires. The present study utilizes wife and husband responses on the conflict subscale of the Intimate Relations Questionnaire, which is comprised of five questions concerning argument frequency, desire to change spouse, anger/resentment, problem severity, and negativity (Braiker & Kelley, 1979). Items were rated on a 9-point Likert scale (1 = *not at all* to 9 = *very much or very frequently*). Items were averaged to create a composite score. Higher values indicate higher levels of conflict. Wives' scores ranged from 1.20 to 7.80 ($M = 4.13$, $SD = 1.38$). Husbands' scores ranged from 1.80 to 7.80 ($M = 3.96$, $SD = 1.46$). Husbands and wives did not differ in level of reported conflict (paired $t = .97$, $p = .33$). Reliability for the present sample was good: Cronbach's alpha was .74 for wives and .77 for husbands.

Physiological Assessment

Cardiac data were assessed via three electrodes placed on the torso of the husband and wife in a Lead II configuration. An additional four electrodes were used to assess impedance, which was not examined in the current study. Ambulatory electrocardiographs (ECGs) (MindWare Ambulatory Impedance Cardiograph Model 1000a) using the Mindware WiFi ACQ software, Version 3.0.1 (Mindware Technologies, Ltd., Westerville, OH) were used to collect the data. The ECG signal was sampled at a rate of 500 Hz and band-pass filtered at 40 to 200 Hz. Data from both participants were recorded simultaneously and time-locked to one another. RSA analyses were performed offline. The MindWare editing program (HRV v. 3.0.17) was used to identify interbeat intervals (IBIs) and detect physiologically improbable intervals based on the overall distribution using a validated algorithm (Berntson, Quigley, Jang, & Boysen, 1990). Trained research assistants manually edited the data as appropriate, or determined it to be of insufficient quality.

Of the 70 couples who participated, 21 dyads were removed from the present analysis because equipment failure occurred for one ($n = 11$) or both ($n = 10$) of the individuals, resulting in no, or insufficient (i.e., < 60 s), paired data for the dyad. No differences were observed in reported marital conflict between participants who did and did not have cardiac data for wives ($t = -.09$, $p = .95$) or husbands ($t = -.02$, $p = .94$). The data are thus taken as missing at random. The couples' time-varying RSA estimates (explained below) were time-locked to each other, with any missing data segments for one individual also being removed for their partner. The length in time of available, artifact-free, heart rate data across individuals ranged from 209 to 600 s ($M = 513.5$; $SD = 140.9$).

Computation of RSA

Standard computation of RSA. We computed RSA for each participant across the 10-min task for comparison to existing studies. First, the point-process IBI series was interpolated at 4 Hz using a cubic spline to arrive at equidistant data points (De Boor, 1978). Nonoverlapping IBI epochs of 60 s in length, with a Hanning window as a tapering mechanism (see Figure 1a), were subjected to a DFT:

$$\hat{d}(\omega_k) = N^{-1/2} \sum_{n=0}^{N-1} h(n)x(n)e^{-2\pi j\omega_k n}, \quad (1)$$

where $h(n)$ represents the values of the tapering mechanism (here, the Hanning window) applied to the interpolated IBI signal x at time n, N the total number of observations per estimate (60 s × 4 samples per second for $N = 240$), ω_k a given frequency, and j an imaginary number. The squared absolute values of the DFT in the frequency band of .12 to .40 Hz are summed to provide the power in the IBI series associated with respiration frequency. The average of the natural log-transformed power estimates across the nonoverlapping 60-s epochs provides a value of RSA for each person. For the present paper, the traditional RSA estimates were acquired from the proprietary MindWare HRV software (Mindware Technologies).

Time-varying computation of RSA. Each individual's entire stream of IBI observations was interpolated as described above. We replaced the typical Hanning window with the PM MW and following previous research, utilized a 32-s epoch (Hansson & Jönsson, 2006). Figure 1b depicts the PM MW applied to each epoch. Briefly, the values for the multiple windows are the eigenvectors that correspond to the four largest eigenvalues following eigendecomposition of a Toeplitz covariance matrix derived as a function of the desired peak spectrum process. Technical details regarding generation of the windows used here are provided in Hansson and Jönsson (2006).

The weighted sum of the squared windowed STFT estimates provides the power spectral density estimates for each epoch m:

$$\hat{S}(m, \omega_k) = N^{-1} \sum_{i=1}^{4} a_i \left| \sum_{n=0}^{N-1} h_i(n)\, x(n+mL) e^{-2\pi j\omega_k n} \right|^2 \quad (2)$$

where parameters from Equation (1) are the same here with $N = 128$ for each epoch as a result of the shortened length from 60 to 32 s. L is the step size from a given epoch to the next, such that $N-L$ indicates the amount of overlap between two successive epochs. Unlike the current standard, in this approach each epoch shifts by 1 s and overlaps the previous epoch by 31 s. The unique weights for each of the 4 tapers $i = 1\ldots4$ in $h_i(n)$ are provided by a_i. These weights sum to one. As with the traditional approach, the sum of the values (i.e., the squared sum of STFT estimates) in the frequency band of .12 to .40 Hz provides the power in the IBI series associated with respiration frequency for each epoch m. Specifically, epoch $m = 0$ contains seconds 1 to 32, whereas epoch $m = 1$ contains seconds 2 to 33, and so forth until the last epoch. In this manner, second-by-second changes in RSA are computed. The epochs are ordered in time yet are not "real-time" valued. For instance, $m = 0$ does not provide the value for the first second, but rather the first 32 s, with $m = 1$ providing the change reflected in the next window. Thus, any given point estimate of RSA is influenced by physiological processes surrounding the focal point. Because of this, RSA estimates cannot be generated that "center" on the first or final 15 s of the interaction task. As with the traditional aggregate RSA values described in the previous subsection, estimates at each epoch were natural log transformed. The code to arrive at time-varying RSA estimates for individuals is freely available as a MATLAB toolbox at https://gateslab.web.unc.edu/programs/rsaseconds/.

Assessment of Linkage and Relation to Marital Conflict

The RSA series is first-differenced before correlation analysis, meaning that each time point is subtracted from the next one to remove linear trends in the data that may impact correlations (Shumway & Stofer, 2006). We estimated the cross-correlation (at

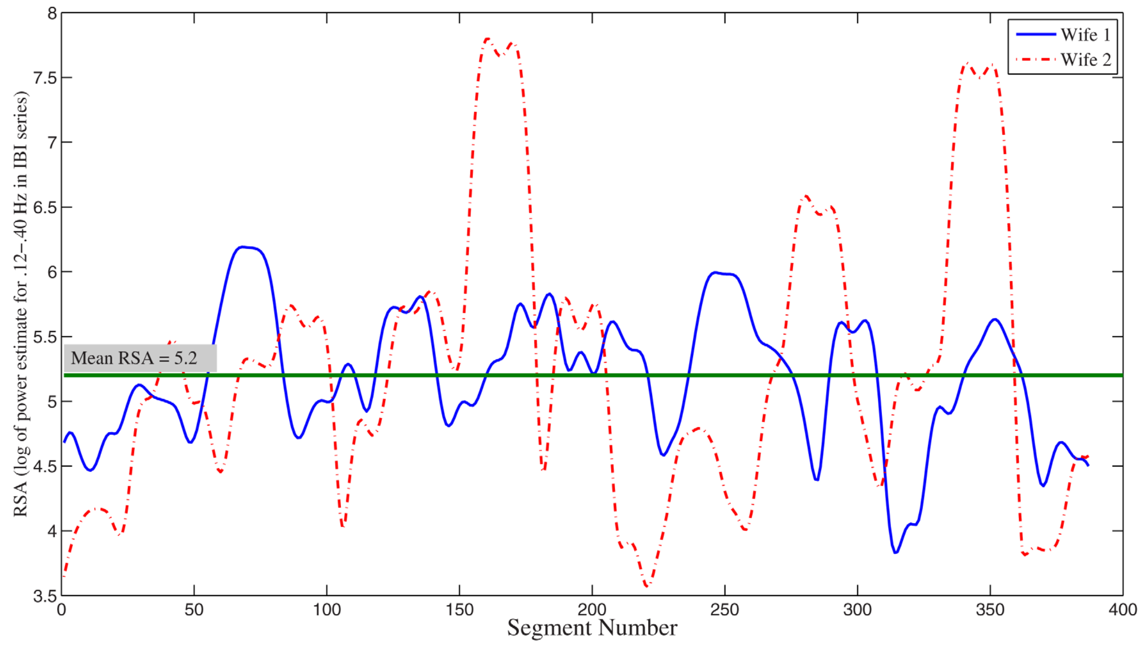

Figure 2. Two individuals with identical average RSA values can differ markedly in RSA dynamics across time.

a lag of 0) of wives' RSA estimates with their husbands' RSA estimates to arrive at an index of RSA linkage for each dyad. Since the individual RSA estimate streams were first-differenced prior to arriving at a correlation coefficient, the resulting coefficients can be interpreted as the degree to which an increase in RSA from the previous time point for one individual corresponds to an increase in the other individual at the same time. Thus, in addition to removing linear trends, the first differencing step establishes an interpretive framework for the correlation coefficient as reactive changes in RSA, directly in line with the hypotheses researchers often wish to test. The resulting correlation coefficients were then Fisher transformed, which stabilizes the variance across all values of the Pearson correlation coefficient at the population level, thus making the linkage estimates (z) appropriate for statistical comparison with the conflict measure.

Results

As expected, individuals' average RSA levels computed by estimating power using the standard DFT and the STFT approach presented here were highly correlated ($r = .94$, $p < .001$), indicating that the STFT approach produces a comparably valid estimate of RSA. However, the STFT approach produces additional, more nuanced, information regarding the pattern of RSA across time than the more coarsely measured DFT estimates. Figure 2 illustrates this distinction by displaying the STFT-extracted patterns of RSA across the task for two individuals with identical values of DFT-extracted average RSA levels. As illustrated in the figure, these individuals differ considerably in the moment-to-moment lability in RSA despite both having an average RSA of 5.2 across the task.

The mean linkage score across dyads computed from their time-varying RSA series was .044 ($SD = .183$). Individual couples' linkage scores ranged from $z = -.199$ to $z = .749$, indicating that RSA linkage varies substantially in this sample. This range indicates that some couples show high levels of arousal-matching linkage (i.e., a positive correlation indicating that when RSA is increasing in one partner it is simultaneously increasing in the other) and other couples show high levels of arousal-compensating linkage (i.e., a negative correlation indicating that when RSA is decreasing in one partner it is increasing in the other).

Individual average RSA estimates arrived at using the standard DFT approach were not associated with self-reports of marital conflict for wives ($r = .013$, $p = .930$) or husbands ($r = -.010$, $p = .946$). In contrast, estimates of dyadic RSA linkage were significantly positively correlated with reports of marital conflict for both wives ($r = .473$, $p < .001$) and husbands ($r = .453$, $p < .001$). The positive correlations indicate that greater degrees of arousal-matching linkage were associated with higher levels of self-reported marital conflict, whereas greater levels of arousal-compensating linkage were associated with lower levels of reported conflict. Scatter plots of these relations are depicted in Figure 3. After removing the outlier dyad that evidenced linkage three standard deviations above the mean (circled in the plot), the association between RSA linkage and reports of conflict remained significant for wives ($r = .347$, $p = .022$) and husbands ($r = .308$, $p = .035$). Given the moderate correlation coefficients despite the relatively small sample size, linkage in RSA arousal appears to relate to levels of marital conflict.

Discussion

The present work adds to the literature on psychophysiological linkage between individuals and extends findings to the assessment of RSA. Despite RSA's prominent use in psychophysiological research and its ability to change rapidly with changing environment demands, little work has attempted to examine RSA dynamics on a time scale comparable to social interactions. Through the application of specific statistical techniques, we were able to generate time series of second-by-second RSA data for married partners during an interaction. The time-varying RSA algorithm described here produced a nearly identical estimate of average RSA as the typical nontime-varying approach. As illustrated in Figure 2, individual differences in the magnitude of dynamic changes in RSA

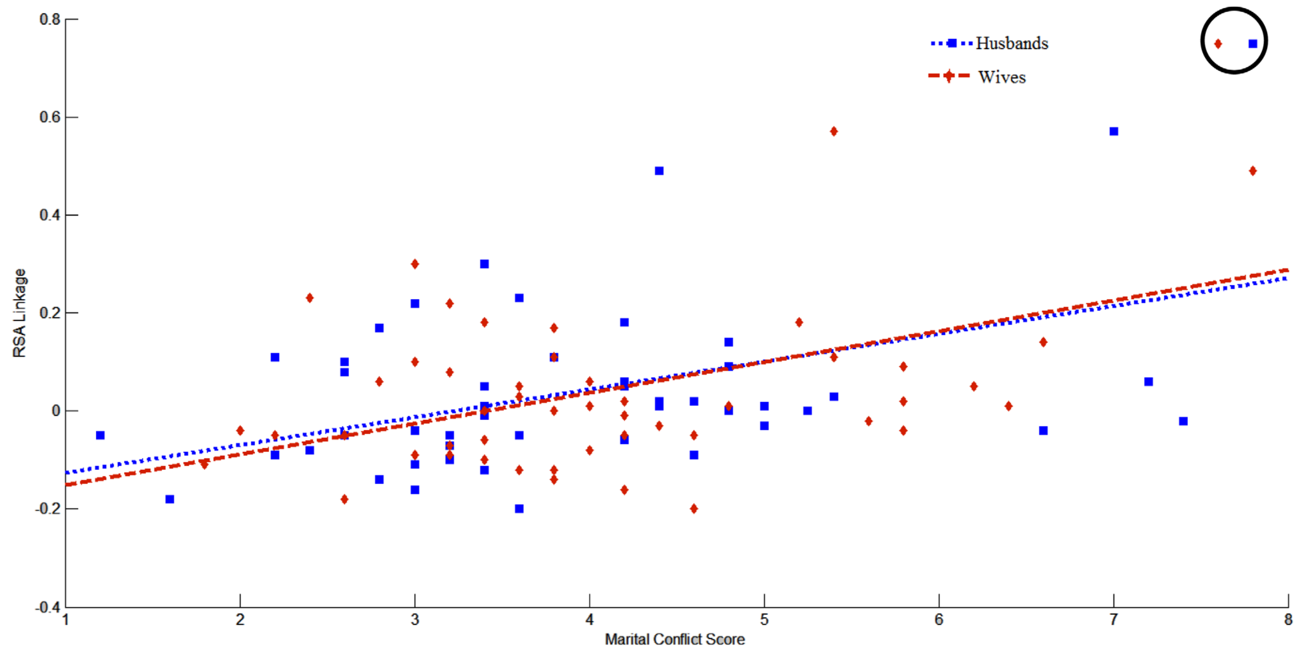

Figure 3. Scatter plot of the relations between RSA linkage in marital dyads with wives' and husbands' reports of marital conflict. Outlier greater than 3 standard deviations above the average RSA linkage score circled with dotted line.

clearly exist and can be extracted through the technique presented here. Taken together, our method provides the same information that traditional measures produce but also provides insight into RSA changes across the task. RSA linkage between partners generated on this time scale was associated with reports of martial conflict, providing validation for the hypothesis that dynamics in RSA during social interactions relate to the quality of the social relationship. In contrast, partners' average levels of RSA were not associated with measures of marital conflict for either partner. These results indicate that the generation of RSA on a second-by-second time scale provides valid data above and beyond the standard technique.

Within this sample, patterns of psychophysiological linkage were highly heterogeneous across couples. Although the average correlation across the sample neared 0, suggesting little RSA linkage between partners, individual correlation values spanned from moderate negative levels ($r = -.432$) to high positive levels ($r = .741$) prior to Fisher transformation. These data suggest that the magnitude of linkage is high for many couples, but that linkage can occur in two patterns. Couples with positive RSA linkage scores have a greater tendency to match their partner's level of physiological arousal (termed *in-phase* by Reed et al., 2013), whereas those with negative linkage scores are more likely to show opposing, or compensatory, levels of arousal (*anti-phase*; Reed et al., 2013). Higher matched RSA across time (i.e., in-phase) was associated with greater levels of reported marital conflict for both husbands and wives. In contrast, compensatory linkage patterns (anti-phase) were associated with less marital conflict, suggesting this type of physiological linkage is reflective of adaptive interaction patterns. The ability of one individual to reduce arousal at a time when the other increases arousal may serve to maintain a level of homeostasis within the dyad, even while the individuals themselves are reactive. Thus, couples with compensatory-linkage patterns may be achieving a level of linkage that facilitates better cooperative and contingent interaction. These results are consistent with other studies of psychophysiological linkage between partners that have reported associations between linkage and negative aspects of marital quality (Levenson & Gottman, 1983) as well as positive indices of marital quality (Levenson & Ruef, 1992). The degree of linkage between partners appears to reflect a degree of attunement to the other. The nature of this linkage, however, is predictive of the relatively adaptive or maladaptive interaction patterns that affect marital quality over time.

Methodologically, the work presented here represents a demonstration of the added utility of obtaining time-varying RSA estimates. More work is needed to fully exploit the information available in these measurements. Specifically, dyadic coordination could be examined at different degrees of lag. For instance, couples that experience better marital satisfaction may show correlated patterns of physiology when not estimated contemporaneously. Perhaps an increase in RSA in one spouse is followed at some interval by an increase in the other spouse, suggestive of calming. Such patterns could also be examined in parent-child dyads, and used to examine which member of the dyad leads the dynamic physiological exchange. Furthermore, this approach could be used to generate more nuanced physiological time series to pair with second-to-second changes in behavior or affect in observation or experimental designs.

Examinations of lead/lag correlations require much more investigation to guide the selection of appropriate lag windows. How dynamics in RSA relate to time series of other types of data streams is likely to differ depending on the data. For instance, correspondence between RSA and other physiological or behavioral measures within the same person (e.g., facial affective expression) may be more likely to occur contemporaneously than correspondence with external events (e.g., experimental stimuli) or to the physiological response of a partner. The methods presented here can contribute to future research in which controlled validation studies can be used to examine the temporal relationship between RSA changes and external stimuli or other time-varying constructs. This technique can be further extended to the study of time-varying linkage in contexts in which linkage itself is hypothesized to change in response to experimental or contextual demands. In the present study, results indicate that contemporaneous linkage is associated with marital conflict. However, it does not clarify why such a relation exists. While it is possible that this reflects attunement to the partner's physiological state, it could also be a function of simultaneous reactions to the context. Importantly, we demonstrate here that RSA variation as assessed using power estimates obtained by STFT with PM MW is indeed systematic and not noise, and can offer insights that are not attainable through traditional approaches for quantifying RSA.

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