Physiological Coregulation during Social Support Discussions

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Abstract

Close relationships are proposed to function as dynamic regulatory systems, whereby partners jointly regulate each other's emotions and physiology to maintain an equilibrium level of responding—a process known as coregulation. Little is known, however, regarding *when* coregulation emerges. We hypothesized that because social support interactions involve explicit interpersonal emotion regulation attempts, they might be especially likely to engender stabilizing patterns of coregulation that entrain partners' responses towards an equilibrium level. We conducted a dyadic laboratory experiment in which romantic couples engaged in social support and control discussions as cardiovascular responses were measured. To assess dyadic coregulation, we used dynamical systems modeling with Bayesian estimation to capture the frequency of oscillations around an equilibrium level and changes in amplitudes over time. Results indicated there was coregulation across discussions as a whole, as well as differences in coregulation by discussion type and gender. Stabilizing coregulatory dynamics—indicated by patterns of oscillations around an equilibrium level and decreases in amplitudes as the discussions progressed—were more pronounced during social support (vs. control) discussions, especially when the male partner received support. There was also substantial between-dyad heterogeneity in couples' coregulation trajectories, whereby some couples showed pronounced coregulatory dynamics whereas other did not. Overall, this work suggests that social support interactions may be a key context when coregulation emerges and thereby offers novel insights into how relationships might contribute to well-being.

Keywords: coregulation, dynamical systems modeling, coupled oscillator, social support, couples

Physiological Coregulation during Social Support Discussions

Social relationships are vital to health and well-being across the lifespan. Being socially integrated and involved in close relationships is linked to better physical health, mental health, and longevity, and the absence of such relationships poses significant threats to well-being (Holt-Lunstad, 2018; Holt-Lunstad, Smith, & Layton, 2010; House, Landis, & Umberson, 1988). A key open question concerns *how* and *why* relationships confer these benefits. One possibility is that relationships can be beneficial because they function as dynamic regulatory systems, whereby partners' emotional and physiological responses become linked and exert bidirectional influence on each other (Butler, 2011). This intermingling of emotions and physiology—known as *coregulation*—is believed to enable individuals to draw on their partner's state to maintain or restore an equilibrium level of responding (e.g., a baseline resting level), thereby increasing their own regulatory efficiency and effectiveness (Butler, 2011; Butler & Randall, 2013; Sbarra & Hazan, 2008).

Despite the proposed importance of coregulation as a possible mechanism underlying the benefits of close relationships, important questions have yet to be answered. As prior work has generally concluded that coregulation is a highly context-sensitive process (Mayo & Gordon, 2020; Palumbo et al., 2017; Timmons, Margolin, & Saxbe, 2015), one of the most pressing of such questions concerns *when* coregulation emerges.

To address this question, this paper investigates coregulation of couples' physiological responses during different types of dyadic interaction. We examine whether social support interactions might engender stabilizing patterns of coregulation (defined by patterns of oscillations around a baseline level of physiology and decreasing amplitudes over time). We considered social support as a candidate process because it typically occurs when people are dealing with challenges and is characterized by partners' explicit attempts to temper each other's responding. We further explore possible gender differences in coregulation, given that

men and women in heterosexual relationships tend to differ in the effectiveness of the support they provide to their partners (Bodenmann et al., 2015; Neff & Karney, 2005; Neff, Nguyen, & Williamson, 2020) and in their responsiveness to others' emotional states (Doherty, Orimoto, Singelis, Hatfield, & Hebb, 1995; Scarpa et al., 2018). Finally, we examine and quantify between-dyad heterogeneity, that is, how couples differ in their patterns of coregulation. This can better capture real-world variation in interpersonal dynamics and provide a foundation for investigating moderating processes in future research. Overall, this research reveals the role of social support in engendering coregulation and offers new insights into potential mechanisms underlying the benefits of close relationships.

Physiological Linkage in Close Relationships

For decades, interdependence has been considered a defining feature of close relationships, in which partners come to share and mutually influence each other's cognitions, behaviors, emotions, and goals (Fitzsimons, Finkel, & VanDellen, 2015; Kelley & Thibaut, 1978; Van Lange & Rusbult, 2012). Dating back to at least the 1950s (e.g., DiMascio, Boyd, & Greenblatt, 1957), it has been shown that interdependence between relationship partners can even be observed at the physiological level, as manifested through associations in partners' responses over time (Butler, 2011; Levenson & Gottman, 1983, 1985; Palumbo et al., 2017). Broadly, this phenomenon is known as *physiological linkage* (Thorson, West, & Mendes, 2017; Timmons et al., 2015). Although physiological linkage has sometimes been documented in strangers, it is proposed to be most prevalent and consequential in the context of attachment relationships, such as parent-child relationships and adult romantic relationships, which are typically characterized by an emotionally meaningful bond and the expectation of care, comfort, and security (Sbarra & Hazan, 2008).

To date, physiological linkage has been examined in a variety of interpersonal contexts using a diverse range of physiological measures (for reviews, see Timmons et al. 2015 and

Palumbo et al. 2017). This has led to the conclusion that physiological linkage can take many forms, which in turn reflect distinct types of psychosocial processes and interpersonal influence (Butler, 2011). For example, linkage may occur when physiological responses triggered as one individual experiences a stressor are then transmitted to a partner who did not experience the stressor directly (sometimes known as *stress contagion*; Peters & Jamieson, 2016; Thompson & Bolger, 1999; Waters, West, & Mendes, 2014). Linkage may also involve concurrent associations in partners' responses to a common stimulus even when they are not presently interacting with each other (Parkinson, Kleinbaum, & Wheatley, 2018), which can be considered a manifestation of *physiological synchrony*.

Coregulation

Coregulation is a particular form of physiological linkage. Coregulation has been defined as “bidirectional linkage of oscillating emotional channels between partners, which contributes to the emotional and physiological stability for both partners in a close relationship” (Butler & Randall, 2013). As this definition suggests, coregulation can be distinguished from other forms of emotional or physiological linkage in several respects.

First, coregulation arises from a combination of intra- and interpersonal influences. Intrapersonal influence comes from the effect of one person's current responding on their future responding. This can be thought of as a self-regulation effect—that is, how individuals modulate their *own* responses. Interpersonal influence reflects how one person's current responding relates to *their partner's* future responding, often referred to as partner effects. Because coregulation arises from *both* self and partner influence (Butler & Barnard, 2019; Mayo & Gordon, 2020), it can be distinguished from types of interpersonal linkage that capture how two individuals self-regulate concurrently in time but that do not involve direct cross-partner modulation. Recalling the example above, coregulation differs from processes

such as stress contagion, in that it allows for the possibility of bidirectional¹, as opposed to unidirectional, influence: Partner A may exert an influence on Partner B's responses, and Partner B may also exert an influence on Partner A's responses.

Second, coregulation is also proposed to be a stationary ("morphostatic") process, meaning that responses fluctuate around a stable equilibrium level or set point, such as a baseline resting level. Coregulation therefore differs from other types of physiological linkage or reactivity processes that involve linear increases or decreases in the level of responding over time (e.g., reciprocal and increasing levels of blood pressure in both partners during a heated argument; for details, see Supplemental Materials).

Finally, coregulation is thought to entail moment-to-moment patterns of damped oscillations over time, as emotional and physiological channels fluctuate around and converge towards an equilibrium level. This involves a pattern of negative feedback loops: Increases in a person's responses are inhibited by both self-regulatory effort and, potentially, by regulation by a partner that pull them towards equilibrium (Butler & Randall, 2013). As such, it can serve a homeostasis-maintaining function that supports the emotional stability of the dyad. This is contrasted with other forms of linkage characterized by linear associations between dyad members' responses, whose meaning and implications for dyadic functioning can typically only be inferred based on the context being studied. For example, positive, linear associations in partners' heart rate are likely to reflect reciprocal increases in negativity when observed during a conflict discussion, but are likely to reflect positive emotional connectedness when observed during an eye-gazing task.

Examples of coregulation trajectories can be seen in Figure 1. The left-hand panel shows an example of stabilizing coregulation, in which partners' responses show concurrent coordination and damping towards an equilibrium level (indicated by decreasing amplitudes).

¹We note that bidirectional influence is a feature of many, although not all, forms of physiological linkage and is not exclusive to coregulation.

The right-hand panel shows an example of de-stabilizing coregulation, or *codysregulation*: Here, partners responses show greater displacement from equilibrium over time (indicated by feedback loops that *increase*, rather than decrease, amplitudes). As we discuss in greater detail shortly, specific coregulation patterns are determined by a combination of model parameter values and specific starting values (Butler & Barnard, 2019), meaning that a large number of coregulation patterns are possible, only two of which are illustrated here. It is also worth noting that the exact nature of coregulation vs. codysregulation trajectories likely depend in part on the type of emotional or physiological measure being examined. A regulation process also serves to stabilize responses around an equilibrium level on a moment-to-moment basis, which makes it fundamentally different from processes like escalation or reactivity that involve sustained increases or decreases in levels of physiology over longer time windows (e.g., over the course of a laboratory task). For more on how coregulation and reactivity differ, see the Supplemental Materials.

Figure 1. Examples of possible coregulation (left-hand panel) and codysregulation (right-hand panel), given equivalent initial conditions.

Why focus on coregulation as a form of physiological linkage?.

Coregulation as a specific form of physiological linkage merits further study for several

reasons. First, it is believed to be a uniquely defining feature of close attachment relationships, such as romantic relationships (Sbarra & Hazan, 2008). In contrast to other forms of physiological linkage that are applicable to a wider range of interpersonal interactions, including interactions among strangers, coregulation may be especially relevant to close relationships in particular. It may therefore reveal specific ways in which partners modulate each other's emotional and physiological responses: As coregulation can help prevent escalation of responding and help keep individuals within an equilibrium range, it could be one route through which close relationships ultimately benefit well-being.

Second, there is a dearth of research on coregulation specifically. This may be because analyses of coregulation processes typically require many repeated-measures observations and the use of advanced modeling approaches to capture its hallmark pattern of oscillations and varying amplitudes over time, a point we return to shortly. As coregulation is characterized by patterns of damped oscillations, it is also necessary for the variable of interest to fluctuate. This often requires measuring physiological or emotional variables in small enough temporal units to capture these patterns; averaging over measurements spanning larger units of time (e.g., 60-seconds) could wash over these oscillations, so more intensively sampled data may be necessary. Furthermore, although a number of prior papers used the term *coregulation*, the processes described in many of these papers did not examine bidirectional damped oscillations and thus did not meet all the criteria for coregulation (Butler & Randall, 2013). Thus, more work is needed with the present definition in mind.

However, research investigating coregulation according to the current definition (Butler & Randall, 2013) has suggested its potential importance for dyadic functioning. One study examined coregulation of heart rate and respiration in heterosexual couples as they engaged in a series of laboratory tasks, including an eye-gazing task, in which couples looked into each other's eyes, and an imitation task, in which couples tried to "mirror each other's physiology" (Helm, Sbarra, & Ferrer, 2012). Generally, results indicated clear patterns of

oscillations in both couple members that were influenced by partner responding (e.g., when the typical woman's heart rate increased, the typical man's heart rate sped up).

Another investigation assessed coregulation of self-reported emotion as heterosexual couples discussed how they affected each other's health behaviors (Reed, Barnard, & Butler, 2015). The male and female partners showed a pattern of coupled oscillations over time, but such patterns of coregulation depended on couples' weight status (i.e., whether both partners were normal weight or overweight, vs. whether one partner was normal weight and the other was overweight). Collectively, these studies, and others, demonstrate the oscillatory nature of couples' emotional and physiological responses across a range of tasks and reveal the potential for cross-partner influence on regulatory dynamics.

When does coregulation emerge?. Physiological linkage is known to be context-dependent (Palumbo et al., 2017; Timmons et al., 2015), and both theory and empirical evidence speak to the context-dependent nature of coregulation as well. Theories of emotions in close relationships have posited that coregulation processes are functional: They help individuals regulate themselves more efficiently and effectively (Butler & Randall, 2013; Coan & Maresh, 2014; Sbarra & Hazan, 2008). Therefore, coregulation processes should be relatively more apparent when regulation needs are heightened, such as one partner has been perturbed away from an equilibrium level of responding (Boker & Nesselroade, 2002; Butler, 2011; Butler & Barnard, 2019; Butler & Randall, 2013).

This theoretical proposition is also echoed in work on dynamical systems, a theoretical and modeling framework that is sometimes used to quantify coregulation processes (Butler, 2011; Palumbo et al., 2017). Broadly, dynamical systems models use a combination of a variable's level and its derivatives to capture nonlinear change on a moment-to-moment basis and can be specified to examine coupled systems involving two interdependent temporal trajectories (Boker, 2012; Boker & Laurenceau, 2006; Helm, Miller, Kahle, Troxel, & Hastings, 2018). Parameters of these models index change processes such as the rate of

change (velocity) and speed of change (acceleration/deceleration).

Dynamical systems approaches are useful because they are statistical translations of physical change processes, such as the damped oscillations involved in self- and coregulation of biological systems (Boker, 2012). Importantly, these dynamics are known to be most apparent following a displacement from equilibrium, as responses attempt to stabilize towards an equilibrium attractor point (Boker & Laurenceau, 2006). Given this feature of dynamical systems, regulation processes among partners within a dyad should be more likely to emerge when one or both have been displaced from equilibrium, such as when experiencing an upsetting event. Dynamical systems should also show responsiveness and flexibility to situational demands (Mayo & Gordon, 2020), further suggesting that displacements from equilibrium might engender coregulated responding.

This notion that coregulation may be most pronounced following a disruption to equilibrium may also help explain inconsistencies regarding physiological linkage and affective interdependence. For example, a recent paper examining the concordance of couples' emotional fluctuations did not find evidence for coregulation (Sels et al., 2019). However, this paper examined coregulation during relatively routine interactions (e.g., in discussions of health behaviors and in everyday life), which presumably did not involve disruptions that would necessitate a coregulation process; if partners were already at their equilibrium levels, there would be no need for such a process to occur to restore equilibrium. Coregulation may instead be more readily apparent when there is a need for it to occur.

Role of Social Support Discussions. Coregulation is likely driven by behaviors enacted during dyadic interaction that play a role in transferring emotional and physiological states between partners. Partners may emit cues, such as expressed emotion or verbal remarks, that are then picked up by the other partner and translate into altered physiological responses (Thorson et al., 2017). Thus, it is important to consider what kinds of interpersonal processes partners are likely to engage in that would involve attunement to

each other's inner states and would help to maintain an emotional equilibrium.

Social support discussions may be one such process. Social support discussions involve the exchange of emotional (e.g., reassurance) or practical (e.g., advice) help in response to a particular problem or situation². Social support interactions frequently occur when there has been a disruption to a person's equilibrium, triggered by events like recalling an upsetting memory or experiencing a stressor. In addition, social support discussions are frequently characterized by active interpersonal regulation attempts, whereby the support provider might assist in emotion regulation strategies like helping the recipient engage in cognitive appraisal or offering validation and care, often with the explicit goal of helping the support recipient return to a calmer state (Maisel, Gable, & Strachman, 2008; Reeck, Ames, & Ochsner, 2016; Rimé, 2009; Zee, Bolger, & Higgins, 2020).

Despite the relevance of social support discussions to coregulation, to our knowledge, they have not been an explicit focus of prior work on coregulation specifically or physiological linkage more generally. Among studies of physiological linkage, most involved conflict discussions or problem-solving tasks (Timmons et al., 2015). Although some work assessed coregulation during discussions that may have included some support behaviors (e.g., discussions of how partners influence each others' health behaviors; Reed et al. (2015)), these discussions also involved other topics and behaviors and therefore did not permit a targeted examination of coregulation in the context of social support.

Nevertheless, social support interactions might contribute to the emergence of coregulation (Butler & Randall, 2013). Processes often implicated in support interactions, such as perspective taking (Nelson, Laurent, Bernstein, & Laurent, 2016), were linked to stronger physiological linkage in couples. Other work has identified social support variables,

²Note that actual support behaviors in response to a situation are known as *enacted* social support, which is distinct from another construct known as *perceived* support, which instead refers to individuals' perceptions of generally having supportive relationships (Uchino, 2009). In this paper, we discuss enacted support exclusively.

such as quantity of support, frequency of support, and support seeking, as predictors of changes in widows' emotional trajectories following spousal loss (Bisconti, Bergeman, & Boker, 2006). Although this study did not examine dyadic support behaviors, it illustrated the role of social support variables in shaping emotional self-regulation dynamics following an upsetting event. Collectively, such findings invite the possibility that dyadic social support discussions might be a context that engenders stabilizing self-regulatory and coregulatory dynamics between partners.

Moreover, research on coregulation between children and caregivers suggests the potential importance of social support for coregulation among partners in adulthood. Interpersonal factors such as maternal teaching and sensitivity have been linked to stronger parent-child coregulatory patterns and better child self-regulation over time (Calkins, 2011; Propper et al., 2008; Skoranski, Lunkenheimer, & Lucas-Thompson, 2017). Like parent-child relationships, adult romantic relationships are also characterized by strong attachment bonds. Thus, similar processes may occur in adulthood, and caregiving-related interactions, like support, may be important for engendering coregulation.

Research Aims and Overview

The present work is the first, to our knowledge, to directly examine coregulation during couples' social support discussions. By comparing physiological processes between couples' discussions that differed in supportiveness, we were able to trace the emergence of physiological self-regulation and coregulation over time. We investigated three aims:

Aim 1: Coregulation across discussions

Our first aim was to assess coregulation across couples' discussions as a whole. As we discuss in greater detail shortly, our modeling approach allowed us to capture self- and

partner influence in both cycling (the frequency of oscillations in partners' physiological responses) and damping (changes in amplitudes over time). Collectively, all of these effects give rise to overall coregulation trajectories. We hypothesized that there would be evidence in favor of coregulation across discussions.

Aim 2: Coregulation during social support discussions

Our second aim was to further examine differences discussions and test whether stabilizing patterns of coregulation would be more likely to emerge during couples' social support (vs. control) discussions. We hypothesized that there would be differences in coregulation effects across discussions, such that support (vs. control) discussions would be more likely to engender equilibrating patterns of coregulation.

We also explored potential gender differences in self- and coregulation trajectories during social support discussions. Prior work on social support among heterosexual couples has suggested that men and women differ in the support they provide to their partners, with women tending to be more effective at providing support to their partners than men (Bodenmann et al., 2015; Neff & Karney, 2005). Other work has indicated that women are more responsive to others' emotions and physiology (Doherty et al., 1995; Scarpa et al., 2018). Thus, we speculated that patterns of coregulation might differ according to whether the male or female partner was receiving vs. providing support.

Aim 3: Between-Dyad Heterogeneity

Our third aim was to assess between-dyad heterogeneity in coregulation effects. Although there is growing recognition that dyads likely differ in the direction, magnitude, and nature of the linkage they exhibit (Butler & Barnard, 2019; Palumbo et al., 2017; Sels et al., 2019), this variability has not traditionally been a primary focus of prior research.

Showing the extent of heterogeneity can explain why there have sometimes been inconclusive or null results regarding coregulation and physiological linkage: There may have been meaningful patterns of coregulation that were present among a subset of dyads but were not reflected in the average dyad. Thus, documenting and probing the extent of heterogeneity in coregulation processes stands to play an important role understanding of this process and guiding future work. This can be important for establishing the generalizability of coregulation patterns and appropriately reflecting the real-world variability of dyadic interaction. Demonstrating that a process is heterogeneous is especially useful because it can signaling the presence of important moderators to be examined in future research, even if those moderators are unknown or were not measured (Bolger & Zee, 2019; Bolger, Zee, Rossignac-Milon, & Hassin, 2019).

Physiological Coregulation of Inter-beat Interval

This research focused on a measure of autonomic physiology called inter-beat interval (IBI). IBI is a time-based measure that refers to the average number of milliseconds between heartbeats during a period of time (10 seconds in this study) and captures both sympathetic and parasympathetic activation (Mauss & Robinson, 2009). IBI is inversely related to heart rate: Higher values indicate a longer interval (i.e., slower heart rate), and lower values indicate a shorter interval (i.e., faster heart rate). Higher resting IBI values (slower resting heart rate) have been prospectively linked to better health outcomes, including lower risk of cardiovascular disease and mortality (Saxena et al., 2013).

Physiologically, IBI values are known to show an oscillatory cycling pattern, which makes IBI a suitable candidate for physiological coregulation (Boker, 2012; Butler & Barnard, 2019). IBI can also be measured intensively over time and collected in a relatively unobtrusive manner that allows for dyadic interactions to unfold naturally. This measure been used in prior examinations of coregulation (e.g., Helm et al., 2012) and physiological

linkage more broadly (Mayo & Gordon, 2020; Palumbo et al., 2017; Timmons et al., 2015); thus, focusing on IBI allowed us to better situate our investigation in the existing literature. Regulation of autonomic physiology is also believed to be a foundation for the development of emotional and behavioral regulation (Calkins, 2011), suggesting that coregulation of autonomic channels might also support coregulation of other emotional and behavioral dimensions (although see Palumbo et al. (2017)). However, it is worth noting that

IBI considered general measure of physiology and does not have direct relationship to specific psychological states (Cacioppo, Berntson, Larsen, Poehlmann, & Ito, 2000; Mauss & Robinson, 2009). IBI values are faster (shorter) during demanding situations, including both “good” and “bad” stress contexts. As such, coregulation of IBI involving decreasing amplitudes could reflect lessening volatility over time and deployment of self-regulatory effort. The notion that damped oscillations reflect a regulation process in this context is conceptually consistent with past work indicating that phasic decreases in heart rate variability³ (indexed by respiratory sinus arrhythmia; RSA) have been associated with better adaptation to demanding situations (Muhtadie, Koslov, & Mendes, 2015; Porges, 1995).

Dynamical Systems Modeling

Investigation of these aims was accomplished through the use of dynamical systems modeling with Bayesian estimation. Dynamical systems modeling is a class of analytic techniques that describes how variables change over time. These techniques, which typically involve the use of differential equation models, have shown promise for describing nonlinear within-dyad change over time (Boker & Laurenceau, 2006; Butler & Barnard, 2019; Helm et al., 2012). In particular, coupled damped oscillator models are especially useful because they feature parameters that can more directly index self-regulatory and coregulatory change

³We are not aware of any work linking damping parameters from a damped oscillator model to established measures of heart rate variability (e.g., respiratory sinus arrhythmia; RSA), so caution in this interpretation is warranted.

processes. They quantify the frequency of oscillations around an equilibrium level (*cycling*) as well as changes in amplitudes and stabilization of amplitudes toward an equilibrium level over time (*damping*), both of which are considered hallmarks of dynamic regulation processes (Butler & Barnard, 2019; Butler & Randall, 2013). In addition, they can also model cross-partner influence—the extent to which partners influence *each other's* patterns of cycling and damping to capture coregulation. We provide a more detailed discussion of this model and use of Bayesian estimation in a later section.

Methods

We used an experimental design in which romantic couples completed a series of support discussions in a laboratory setting. Methods and procedures were approved by the Columbia University Institutional Review Board (IRB-AAAQ8800). Data from this study were previously used in work by Zee and colleagues (2020; 2020)⁴. Hypotheses investigated in this paper were not preregistered. Statistical code and deidentified data are available via Github (<https://github.com/kzee/zee-bolger-coreg>).

Participants and Sample Size

Couples were recruited for a laboratory study about “couples’ communication” via campus flyers, a university paid participant pool, and online advertisements (e.g., websites of campus organizations). Couples were prescreened according to relationship criteria (currently cohabiting and in a romantic relationship for at least one year) and English language proficiency. Participants were paid \$25 each (\$50 per couple) in exchange for completing a laboratory visit together.

⁴A subset of the analyses presented in this paper was presented at the 2019 annual meeting of the Society of Multivariate Experimental Psychology and was subsequently published as a peer-reviewed, extended abstract in the Society’s journal (Zee & Bolger, 2020). The current paper presents a more elaborated discussion of the theoretical background, methods, and results presented in the earlier paper, and also presents additional research aims and analyses that have not been discussed in any prior publications.

There were 104 couples who completed the study. However, there was one participant who participated twice, with a different partner each time, and one dyad that withdrew from the study. These three dyads were excluded prior to analysis, resulting in a sample of 101 dyads ($N = 202$ individuals). There were 90 opposite-sex (heterosexual) couples, eight same-sex couples (two male-male, six female-female), and three couples in which one member did not identify as male or female. On average, participants were 27 years old ($SD = 5.80$) and had been in a relationship with their partner for about 4 years ($SD = 3.20$).

Sample size determinations were made in regards to separate hypotheses, and we note that this study was not powered *a priori* in regards to the research question discussed in this paper. Statistical power in studies of physiological linkage is a function of both the number of time points per dyad (Level 1 units) and number of dyads (Level 2 units). A large number of repeated-measures are typically needed in order to examine within-dyad physiological linkage effects (Butler & Barnard, 2019; Thorson et al., 2017). However, when there is between-dyad heterogeneity in the process under study, increasing the number of dyads is more effective at boosting power than increasing the number of time points (Bolger & Laurenceau, 2013).

Reviews of research on linkage of autonomic nervous system variables in couples found that sample sizes typically ranged from four to 49 dyads (Palumbo et al., 2017). In papers examining physiological linkage in couples, 71% of studies included 50 or fewer couples (Timmons et al., 2015). Our sample of 101 dyads is substantially larger than these samples and is 2-3 times larger than samples used in prior work using similar paradigms (Helm et al., 2012; Helm, Sbarra, & Ferrer, 2014; Reed et al., 2015; Reed, Randall, Post, & Butler, 2013).

Procedure

Participants were instructed to refrain from caffeine consumption and strenuous exercise for at least two hours prior to their session due to the collection of physiological

measures, following standard guidelines used in the second author's lab and in other psychophysiology labs we consulted. Upon arrival, partners were taken to separate rooms. After giving consent, participants completed measures of health, individual difference, and relationship variables⁵. As these variables were not analyzed in regards to the present research questions, they will not be discussed further. Participants were then fitted with sensors to measure cardiovascular responses and rested quietly for a 5-minute baseline.

Next, couple members were reunited and engaged in a series of discussions. First, they completed a 5-minute discussion of a shared goal that they were currently pursuing as a couple. They were asked to select a goal that involved each partner taking on various activities (i.e., it could not be about a goal held by just one partner or a joint goal that only involved tasks completed by one partner). Examples of shared goals that couples discussed included planning a vacation, buying a home, or saving money. Although this discussion was originally designed to probe a separate hypothesis about goal pursuit in couples, it served as a useful control condition for the present research question, as it had several features in common with support discussions (e.g., it was a goal-directed, affiliative discussion) but did not involve clear role differences (provider vs. recipient) or help for one person's stressful issue. Furthermore, this discussion was not intended to have a disequilibrating effect on participants. The control discussion always took place first in order to prevent any negative affect generated during the support discussions from carrying over or contaminating the control discussion; similar ordering of discussions has been used in prior work on physiological linkage in couples (Helm et al., 2014).

Next, participants were asked to individually select an ongoing stressful issue. Participants could select any issue they were currently dealing with and found stressful, as

⁵As part of the health questions, 11 participants indicated that they had a cardiovascular condition (e.g., high blood pressure, heart murmur, arrhythmia, mitral valve prolapse, or family history of such conditions). Because our analyses involve repeated-measures observations and within-subject comparisons, we retained these participants in our analyses. We also ran a version of our main analysis excluding participants with a cardiovascular condition, but this did not change our conclusions.

long as it did not involve their relationship with their romantic partner. Examples of the issues participants discussed included looking for a job and losing weight. After writing a brief description of and answering some questions about their issue, participants were randomly assigned to role—provider or recipient—by card draw. During a 5-minute support discussion, recipients were instructed to share the issue they had identified in the previous questionnaire with their partner and to talk about their thoughts and feelings regarding this issue. Providers were instructed to respond or help in any way that seemed appropriate.

After the discussion, participants responded to follow-up questions and then switched roles and repeated this procedure. With the exception of positive and negative affect, self-report measures were not analyzed in regards to the present research questions and will therefore not be discussed further. Thus, couples completed three discussions in all: a control discussion and two support discussions. As a feature of our random assignment procedures, the gender order of the two support discussions was counterbalanced, such that for some couples the female partner received support during the first support discussion ($n = 62$), whereas for others the male partner received support during the first support discussion ($n = 39$). All dyads completed at least one support discussion, but three dyads were unable to complete the second support discussion due to time constraints.

Physiological Assessments

During baseline and each discussion, participants' cardiovascular responses were measured continuously. We collected heart rate data using Biopac's MP150 and ECG module. Heart rate waveforms were sampled at 1000 Hz, and IBI data were scored in 10 second intervals using Mindware software (HRV 3.0.25)⁶. This yielded 30 observations per person for each of the three discussion phases—control discussion, female recipient support

⁶We selected 10 seconds as the interval length to help reduce the influence of measurement error and noise, while still retaining some temporal sensitivity. Other papers examining emotional coregulation in couples have also used similar interval lengths (e.g., Reed et al., 2015).

discussion (F Receives), and male recipient support discussion (M Receives)—for a total of up to 90 observations per participant (180 per dyad) during the discussion phases.

We defined equilibrium as each partners' average level of IBI during a 5-minute baseline resting period. This operationalization offered important advantages for reasons of theory and interpretation, as the 0 point in the data corresponded to a real and meaningful equilibrium. In the context of the present study, it was sensible to examine oscillations around true baseline level of responding, and using a common equilibrium level helped facilitate comparison across experimental phases. This is in line with recommendations from experts on dynamical systems and theory, who propose selecting a theoretically meaningful equilibrium level where possible [e.g., Boker (2012); p. 326]. We note that other equilibria could be considered, a point we raise in the General Discussion.

Emotional Context

Following in the tradition of Lazarus and colleagues (1991), we designed our study with the intent that the support discussions would be more emotionally disequilibrating for participants, as these discussions prompted them to talk about an ongoing issue. We conducted preliminary analyses using initial IBI values and coder-rated expressions of positive and negative affect to verify differences in the emotional context of the support vs. control discussions. In brief, participants' average IBI was lower (indicating a faster heart rate) at the start of the support discussion when they received support relative to the control discussion. We also found that both the typical male and typical female partner expressed less positive emotion during the first 30-seconds of the support discussions. Collectively, these results suggested that sharing an ongoing difficulty as part of the social support discussions was more physiologically and emotionally disequilibrating compared to engaging in the control discussion. For details, see Supplemental Materials.

Analysis Strategy

Coupled Damped Oscillator Model

We modeled physiological changes within in each experimental phase using a coupled damped oscillator model, which, as noted earlier, is ideally suited to examining self- and coregulation because it quantifies changes in the frequency and amplitude of participants' physiological responses around an equilibrium level as a function of their own responses and their partner's responses (Butler & Barnard, 2019). Our model involves two second-order differential equations (Boker & Laurenceau, 2006), one for each dyad partner, and the parameters of the model are allowed to vary randomly from dyad to dyad (to be detailed below). Each equation specifies how the acceleration/deceleration of one partner's IBI scores is a linear function of their own current level and rate of change in IBI and of the other partner's current level and rate of change in IBI.

The basic equations for each dyad partner are:

$$\ddot{x}_t = \eta_{ax}x_t + \zeta_{ax}\dot{x}_t + \eta_{px}y_t + \zeta_{px}\dot{y}_t + e_{xt}$$

$$\ddot{y}_t = \eta_{ay}y_t + \zeta_{ay}\dot{y}_t + \eta_{py}x_t + \zeta_{py}\dot{x}_t + e_{yt}$$

Here, x_t is the IBI level of the female partner, and y_t is the IBI level of the male partner at time t . x_t and y_t are weighted averages of 10 seconds of observations, and $\dot{x}_t$ and $\dot{y}_t$ are the first derivatives of x_t and y_t and index their instantaneous rate of change of IBI. The outcomes are the second derivatives, $\ddot{x}_t$ and $\ddot{y}_t$, which index the instantaneous acceleration/deceleration of IBI.

Given these predictors and outcomes, η_{ax} indicates the coefficient for cycling (frequency of oscillations) for the female partner; η_{ay} is the equivalent coefficient for the male partner. η values must be negative, and larger negative coefficients indicate faster cycling. ζ_{ax} indicates the coefficient for changes in amplitudes over time for the female partner; ζ_{ay} is the equivalent coefficient for the male partner. ζ is positive when amplitudes increase (indicating dysregulation, with larger displacements from equilibrium over time), and is negative when amplitudes decrease (indicating damping, which results in convergence and stabilization of amplitudes towards equilibrium over time). These parameters are intrinsic self-regulation effects (i.e., the model's predicted trajectory for a person's own cycling and damping, over and above any influence from the partner) and are equivalent to *actor effects* in dyadic data analysis terminology (Kenny, Kashy, & Cook, 2006), hence the use of the subscript a .

Cross-partner effects capture coregulation and are indicated by subscript p . η_{px} and ζ_{px} indicate the effect of the male partner's IBI position and first derivative on the female partner's second derivative of IBI—i.e., the influence of the male partner on the female partner's cycling and damping. η_{py} and ζ_{py} are the equivalent parameters indicating the influence of the female partner on the male partner's cycling and damping. This specification allows for asymmetric coupling, meaning the effects of the female partner on the male partner can differ from the effects of the male partner on the female partner (Boker, 2012). The model also allowed for correlated residuals across partners (Kenny et al., 2006).

Observations were centered on each person's average baseline IBI⁷. IBI observations from the baseline period were then removed prior to computation of derivatives and analysis. Derivatives were estimated using Generalized Local Linear Approximation (Boker, Deboeck, Edler, & Keel, 2010). GLLA entails creating a moving window of 3 or more observations

⁷An assumption of coupled oscillator models is that the underlying time series is stationary and does not involve linear increases or decreases in level over time. We found only extremely small changes in IBI from the start to the end of the discussion for the average female and male partners across discussions, corresponding to a 1% change in IBI for each partner during the entire discussion period, or a difference of 1 beat per minute when converted into a heart rate metric. This led us to baseline centered IBI values in our analysis, which was allowed us to assess deviations from a meaningful equilibrium (Boker, 2012).

(known as the embed dimension), which is then multiplied by a loading matrix to compute derivatives. We selected an embed dimension of 5 *a priori* following current recommendations (Boker, 2012), to balance issues of measurement error and precision while also ensuring a large enough number of observations per phase per dyad⁸. Because cardiovascular physiology responds relatively rapidly (Berntson, Quigley, & Lozano, 2007), we set $\tau = 1$ (within each phase), where τ indicates the number of time points between successive observations to be used in the computation of derivatives. Smaller τ values are needed to capture more rapid oscillations. For more on using coupled oscillators to assess coregulation in couples, see work by Boker and Laurenceau (2006), Helm et al. (2012), and Butler et al. (2019).

Bayesian Multilevel Approach

The differential equations presented above can be thought of as Level 1 of a multilevel model (Maxwell & Boker, 2007). At Level 2, the parameters of the Level-1 equations are specified to have a multivariate normal distribution, with the mean vector being the parameter values for the typical couple (fixed effects) and a covariance matrix with variances and covariances of between-couple differences (random effects).

We estimated this multilevel differential equation model using Bayesian methods. Bayesian estimation offers several advantages over conventional maximum likelihood (ML) estimation for fitting multilevel models of dyadic change processes. Most notably, Bayesian estimation has greater facility in handling multiple random effects and is typically able to obtain estimates for these parameters in cases where models using ML fail to converge.

Furthermore, because Bayesian estimation leads to posterior probability distributions for the locations of all model parameters, it permits the analyst to draw novel

⁸We note that some perspectives have recommended selecting embed and τ dimensions that maximize variance explained on a dyad-by-dyad basis (e.g., Butler & Barnard, 2019). However, our multilevel modeling approach required that there be commonality across dyads in the procedures used to compute derivatives. For this reason, we used a common embed dimension and τ for all dyads in the sample.

probability-based inferences on these parameters that cannot be obtained using classical Frequentist approaches. In particular, we were able to use its capabilities to draw inferences about complex patterns of cross-partner influence that would not have been possible using ML estimation (more details will be provided below).

We fit our model using the *brms* package for R (Burkner, 2017). *brms* is a flexible multilevel modeling program that uses Markov-chain Monte Carlo algorithms to arrive at Bayesian posterior distributions of model parameters. For each set of model parameters, we ran four Markov chains for 8000 iterations each with the first 4000 treated as warm-up and discarded. This resulted in posterior distributions of parameters each based on a total of 16000 sample values. We set a weakly informative prior for all fixed effects, namely a uniform distribution in the interval $[-2, 2]$. For random-effect variances and covariances, we used the default priors provided by *brms*.

The estimates we report correspond to mean values for each parameter's posterior distribution. As Bayesian estimation does not involve p-values or null hypothesis significance testing, we provide 95% credibility intervals where appropriate to reflect uncertainty in our estimates; for each parameter, these credibility intervals specify the effect-size range in which 95% of posterior sample values fall.

As described above, the model included self- and partner-influenced cycling and damping parameters. It also allowed for within-couple variation in these parameters as a function of the three discussion phases. These phases were represented by dummy variables, which were coded such that the support discussion in which the female partner received support (F Receives) was compared to (a) the support discussion in which the male partner received support (M Receives) and (b) the control discussion. The model included all two-way interaction terms between each dummy variable and the parameters described above. Each of these effects was treated as random across couples, thus allowing dyads to vary in their self-regulatory and coregulatory patterns and in differences across each of the

discussions. In addition to being a key aim, examining between-dyad heterogeneity in this context was also necessary given that social support effects are heterogeneous (Gleason, Iida, Shrout, & Bolger, 2008; Shrout et al., 2010).

As nearly all partners within couples were distinguishable by gender, we estimated separate effects for female partners and male partners (Bolger & Laurenceau, 2013). This approach was also practically and theoretically advantageous in that it allowed us to examine the directionality of cross-partner effects and to explore gender differences in coregulation. However, we note that there are important conceptual and statistical shortcomings of this approach that we hope will be resolved with future developments in dyadic data analysis⁹.

Results

Results are based on a final sample of 13,884 observations from 92 dyads. Five of the original 101 dyads could not be included because of equipment failure; five dyads did not have baseline data available for at least one partner; two dyads had no data available from the discussion phases for at least one partner; and two additional dyads had no physiological data collected from the female partner due to pregnancy.

⁹Following standard practice in dyadic analysis (Bolger & Laurenceau, 2013; Kenny et al., 2006), dyads were treated as distinguishable by gender because couples in this sample were predominantly heterosexual. At present, clear guidelines for analyzing dyadic data involving a mix of distinguishable and nondistinguishable dyads have yet to be developed. Commonly used approaches are to either (a) retain all available data and arbitrarily code one partner as male and one partner as female, or (b) exclude data from non-heterosexual couples. After careful consideration, we retained all available couples for the analysis presented in the main text, as we felt it was important for data from non-heterosexual dyads to be included. For non-heterosexual dyads, our approach was to code one partner as “A” and the other as “B” based on the rooms partners were taken to at random at the start of the study. We later coded all Partner As as female and Partner Bs as male to distinguish partners by gender in our analysis. Although this is in keeping with current practices in the field, we acknowledge it is far from an ideal approach. Unfortunately, we did not have enough non-heterosexual couples to meaningfully examine differences in coregulation as a function of couples’ gender composition and hope this will be addressed in a future investigation. As described in a subsequent footnote and in the Supplemental Materials, we conducted a version of our analysis that only included data from heterosexual couples, but results did not appreciably differ from those obtained with the full sample and did not change our conclusions.

Overview of Results

Individual parameters from coupled damped oscillator models are not readily interpretable because overall trajectories depend on combining all parameters and assigning start values (Butler & Barnard, 2019). We therefore discuss results in terms of model-predicted trajectories for the typical couple. For more details regarding the model output, including estimates for fixed and random effects, see the Supplemental Materials.

Figures 2 and 3 illustrate the model-predicted trajectories for the typical couple during each discussion, using the means of participants' observed initial IBI as start values. Figure 2 presents model trajectories within the allotted time for each discussion (5 minutes), and Figure 3 shows projections across a larger time span—i.e., what the model predicted for the typical couple if their discussions had continued for 15 minutes instead of 5 minutes. This extrapolation provides more “room” in which to see how the coregulation process unfolds. This extrapolation was used solely for visualization purposes, and none of the analyses performed in this paper relied on extrapolated data (i.e., all analyses were performed only on observed data within a 5-minute time period for each discussion).

As can be seen in these figures, the typical male and female partners showed clear patterns of cycling across all discussions, with oscillations around each person's baseline level of IBI and damping (decreasing amplitudes) over time. Also evident are differences by discussion and gender. First, damping was more apparent during the support discussions, especially when the male partner received support. This can be seen in Figure 2: Assuming the discussions had continued for an additional 10 minutes, the male partner's responses converge towards equilibrium fastest when receiving support. Figure 3 further suggests that this damping process was not observed for the typical female partner, who showed a less regular and less stable pattern of oscillations, larger amplitudes, and a smaller damping effect when she received support compared to the control discussion. These

damping amplitudes towards equilibrium could reflect greater deployment of self- and coregulatory resources by both partners to reduce volatility in responding.

These figures also show that the typical male partner generally had more volatile physiological responding, indicated by larger amplitudes at the start of all three discussions. In contrast, the typical female partner had smaller amplitudes of IBI across discussions, but especially during the control discussion and the support discussion when she provided help to her partner. This could be an indication that the typical female partner was less volatile in her responses and experienced better physiological composure on the whole.

The model-predicted trajectories also illustrate the role of partner effects. The right-hand panel of Figure 3, the discussion in which the male partner received support, shows partner attunement and convergence of their oscillations over time. In contrast, the trajectories for the control discussion and female recipient support discussion do not show this kind of partner attunement over time. This is further reflected in the trajectories of the female partner during both support discussions. Rather than showing an uninterrupted pattern of cycling and damping, which would indicate no cross-partner influence, the typical female partner was sensitive to changes the male partner's dynamics, as can be seen from the alternating patterns of higher and lower amplitudes (around minute 2 of the far right panel) and irregularities in oscillations and amplitudes (around minute 5 of the middle panel). Such patterns arise from the inclusion of partner effects and indicate a coregulatory process. In this case, the female partner's IBI changed in response to changes in the male partner's IBI.

Overall, these trajectories reveal differences in couples' physiological dynamics during the support and control discussions. Generally, coregulatory trajectories differed such that stabilizing patterns appeared most pronounced when the male partner received support¹⁰.

¹⁰As mentioned in an earlier footnote, we ran a version of this analysis omitting the non-heterosexual couples ($n = 81$ couples, vs. $n = 92$ couples for the full analytic sample). Doing so produced results that were extremely similar to those found with our original analysis and did not change our conclusions. More details are provided in the Supplemental Materials.

Figure 2. Results for the typical couple (fixed effects) during each 5-minute discussion. Results for the typical female partner are displayed in red (lighter lines), and results for the typical male partner are displayed in blue (darker lines). The horizontal line at IBI = 0 indicates baseline IBI for each partner. F Receives Support = support discussion in which female partner received support. M Receives Support = support discussion in which male partner received support.

Figure 3. Results for the typical couple (fixed effects) during each discussion. Results for the typical female partner are displayed in red (lighter lines), and results for the typical male partner are displayed in blue (darker lines). The horizontal line at IBI = 0 indicates baseline IBI for each partner. F Receives Support = support discussion in which female partner received support. M Receives Support = support discussion in which male partner received support. Heavier lines up to the 5-minute mark show model predicted results during the actual discussion period, and fainter lines after the 5-minute mark show projections for the typical couple had their discussion lasted for up to 15 minutes.

Aim 1: Is there evidence of coregulation generally?

We next conducted a series of follow-up analyses to more directly investigate our aims and to probe the patterns of results suggested in Figures 2 and 3. We did so by drawing on analytic procedures that allowed us to summarize across multiple model parameters.

Our first aim was to assess whether there was coregulation generally. As noted above, it is difficult to draw firm conclusions about the presence or absence of coregulation from individual parameters alone. In light of this, we evaluated coregulation using a model comparison approach: We tested whether our original model, which included cross-partner effects (indicated by subscript p), fit the data better than a model that omitted these cross-partner effects. We reasoned that if our original model provided a better fit to the data, this would indicate that the partner effects mattered, thereby suggesting coregulation. If, however, our original model did not provide a better fit for the data compared to a model that omitted partner effects, this would indicate that the partner effects did not play a role in more accurately representing the data, thereby indicating the processes being examined purely reflected self-regulation and not coregulation.

Visualizing the influence of partner effects. First, we visualized the predicted physiological trajectories for the typical male and female partner from the model that omitted partner effects, and we compared these trajectories to those from our original model. As shown in Figure 4, there were a number of noteworthy differences. Allowing for cross-partner influence (top panel) resulted in different patterns of cycling: The inclusion of cross-partner effects resulted in more rapid cycling for both partners (e.g., in the support discussion in which the male partner received support, each partner completed roughly three cycles within the first five minutes once partner effects were taken into consideration, as compared to only two cycles when they were not). Cross-partner influence appeared to increase concurrent synchronization of partners' responses, as can be seen in the projected

trajectories during the male partner's support discussion (upper right-hand panel), a pattern that was not observed when partner effects were omitted.

Moreover, the inclusion of cross-partner effects resulted in greater damping (amplitudes reducing towards equilibrium faster) for both partners when they received support. The cross-partner effects also produced more variable amplitudes over time for the female partner. In the female partner's support discussion, the female partner shows an irregularity in amplitude around the 5-min mark, and in the male partner's support discussion, the female partner shows an alternating pattern of higher and lower amplitudes within the first five minutes. This pattern of varying amplitudes arises when partner effects are non-zero.

Figure 4. Results for the typical couple (fixed effects) during each discussion, from the original model (top row) and a version of the model omitting cross-partner effects (bottom row). Results for the typical female partner are displayed in red (lighter lines), and results for the typical male partner are displayed in blue (darker lines). The horizontal line at $IBI = 0$ indicates baseline IBI for each partner. F Receives Support = support discussion in which female partner received support. M Receives Support = support discussion in which male partner received support. Heavier lines up to the 5-minute mark show model predicted results during the actual discussion period, and fainter lines after the 5-minute mark show projections for the typical couple had their discussion lasted for up to 15 minutes.

Model Comparison. We next examined whether accounting for cross-partner influence provided a more veridical representation of the data. We used a Bayesian model comparison approach called Leave-One-Out (LOO). LOO is a cross-validation procedure that is frequently used to select better fitting models (Vehtari, Gelman, & Gabry, 2017; Vehtari, Simpson, Yao, & Gelman, 2019). The LOO approach does not assume that any of the models being compared is the “true” model and is instead concerned with identifying the best fitting model of those considered. Practically, LOO is a procedure that involves fitting a given model to all but one data point in the dataset and generating a prediction for the omitted data point (specifically, an estimate of the expected log posterior predictive distribution), and then repeating the procedure for every data point in the dataset. The results are then aggregated as a way of evaluating the model fit. LOO is designed to prevent over-fitting, meaning that a well-fitting model with a large number of parameters will be penalized when assessed in a LOO framework. We used a version of LOO with Pareto smoothing, a technique to enhance computational efficiency and precision of estimation. Similar to other model comparison approaches, a lower LOO value indicates a relatively better model fit.

Results indicated that our original model provided a substantially better fit for the data in comparison to a model that omitted partner effects and only modeled self-regulation processes. This difference in the LOO metric was 1,041.90 ($SE = 76.40$). Translated into a standardized metric, this amounted to a difference of 13.60 z-score units (1042/76).

Pseudo-Dyad Approach. To further establish that coregulation involves an *interpersonal* process, we reran our analysis using pseudo dyads. We randomly paired each participant with a new partner from a different dyad. We then fit our original model and a version of the model that omitted partner effects (as described above) and compared the fit of these models using LOO. The procedures were the same as described previously, with the only difference being that dyad members were randomly paired. If the difference in model fit is greater for real dyads compared to pseudo dyads, this can be taken as further evidence

that an *interpersonal* regulation process is at play (i.e., that cross-partner effects matter more for model fit in real dyads). As expected, we found the improvement in model fit was substantially greater for real dyads (difference in model fit in LOO metric = 222.25, $SE = 12.45$, 95% CI [197.92, 246.64]; 17.85 z-score units). This provided further evidence that coregulation involves more than two individuals self-regulating together—it speaks to coregulation as an *interpersonal* process.

Aim 2: Is coregulation more likely during support discussions?

We then examined whether patterns of coregulation differed according to discussion. We used two approaches: (1) a model comparison approach to assess whether there were differences in coregulation by discussion; and (2) an approach in which we examined posterior distributions across multiple parameters and computed probabilities for combinations of effects to reveal potential implications of these differences for couples' trajectories.

Model Comparison. We first examined whether allowing discussions to differ in their coregulation effects provided a more accurate representation of the data compared to imposing common coregulation effects during all discussions. We again used LOO cross-validation. We compared the fit of our original model, which allowed all parameters to vary across discussions, to the fit of a model that did not allow for different effects by discussion (i.e., a model that assumed a common regulatory trajectory across all discussions).

Results indicated that our original model that allowed effects to differ by discussion provided a substantially better fit for the data compared to a model that assumed a common process across all discussions. This difference in the LOO metric was 808.10 ($SE = 84.10$), corresponding to a difference of 9.60 z-score units (808/84). This improvement in model fit indicated that there are differences in effects across discussions.

Going further, we also compared the fit of our original model to the fit of a model that

allowed *actor (self)* effects to vary across discussions but did not allow *partner* effects to vary. If the original model provides a better fit compared to this restricted model, this would suggest there are meaningful differences in partner influence across discussions. Indeed, the original model fit the data better than a model that forced coregulation to be the same across discussion phases. This difference in the LOO metric was 220.10 ($SE = 32.40$), corresponding to 6.80 z-score units ($220/32$). This improvement in model fit further suggested that coregulation effects varied across the discussions.

Posterior Probabilities. Next, we turned to the posterior distributions for our model parameters. This provided a way to assess the probability of *combinations* of effects and, consequently, the nature of the coregulation process during the different discussions.

This second approach involved examining samples from the posterior distributions for multiple parameters. Because Bayesian estimation yields a distribution of possible parameter values, the values that make up the distribution (posterior samples) can be examined directly. We capitalized on this feature of Bayesian estimation to probe patterns of effects.

From a regulation standpoint, one important pattern of effects concerns the magnitude and sign of the self and partner damping parameters: Negative damping values suggest that amplitudes stabilize towards equilibrium, and larger negative values indicate more pronounced damping (i.e., better regulation). Other parameter values being equal, larger negative values across both self- and partner damping parameters would give rise to a “better” regulatory trajectory, with greater convergence towards an equilibrium level. This possibility is visualized in Figure 5. The left hand panel shows the predicted trajectory during one discussion when all damping parameters are -1 SD below a mean damping value, and the right hand panel shows the predicted trajectory when all damping parameters are +1 SD above a mean damping value. In the former case, amplitudes decreases towards equilibrium, thereby indicating a more stabilizing regulation process.

Figure 5. Simulated system trajectories when self- and partner damping effects are -1 SD below their mean (left hand panel) and +1 SD above their mean (right hand panel). Starting values are below equilibrium, holding all other coefficients at their mean values across the two plots. The horizontal line at IBI = 0 indicates baseline IBI for each partner.

Accordingly, we reasoned that a way of understanding patterns of coregulation could be to assess the probability that at least two of the four damping parameters during each discussion showed stronger (more negative) effects¹¹. First, to establish a reference point for assessing stronger damping, we computed an overall mean damping effect, by averaging all 12 damping (ζ) parameter values across partners and discussions (for each of the three discussions, there are two self damping effects and two partner damping effects), $M_{\zeta} = -0.03$. For each posterior sample, we coded whether each of the four damping coefficients (the two self-regulation damping effects, ζ_{ax} , ζ_{ay} and the two partner regulation damping effects ζ_{px} , ζ_{py}) were below this value.

Then, within each discussion, we computed the probability that two of more of these parameter values fell below the overall mean damping value across discussions. We selected two out of four as our cutoff because this would indicate that at least half of the damping

¹¹Probability distributions were simulated using procedures specified by Gelman (2009), which involved converting the binary distribution of “yes” and “no” codes into a single beta distribution (also see Carpenter, 2009). As noted above, this also allowed us to compute 95% intervals around the probability estimates to facilitate comparison of probabilities across phases.

parameter values fell beyond this threshold¹². A potential limitation of this approach is that it does not take into account the relative size of the damping effects to each other.

Results indicated that the probability that at least two or more (out of four) damping parameters per discussion were more extreme than the overall mean damping effect was 0.934 [0.930, 0.938] for the male recipient support discussion, 0.872 [0.866, 0.877] for the female recipient support discussion, and 0.415 [0.408, 0.423] for the control discussion.

Moreover, as shown in Figure 6, this probability was higher when the male (vs. female) partner received support, difference in probability = 0.062, 95% CI [0.056, 0.069]. Thus, the probability of stabilizing damping trajectories across parameters was highest during the support discussion when the male partner received support, and lower during the control discussion and female partner's support discussion. Additional analyses drawing on the posterior samples to examine patterns of effects are provided in the Supplemental Materials.

Aim 3: Do dyads differ in their coregulation effects?

With our third aim, we explicitly examined the extent to which dyads differed in their physiological dynamics across discussions. Through our use of multilevel modeling, we obtained estimates of dyad-specific effects (random effects), in addition to estimates of parameter values for the typical dyad. These random effects speak to the degree of between-dyad heterogeneity and are useful because they allow one to assess the generalizability of the results and can signal the presence of potential moderators, even if those moderators are not measured or modeled directly.

To assess the extent to which random effects are meaningfully large, we adopted Bolger et al.'s (2019) rule of thumb, which suggests that heterogeneity is noteworthy if the ratio of a

¹²In response to reviewer feedback, we also performed an equivalent analysis assessing the probability that all four damping parameter values fell below this threshold. Details are in the Supplemental Materials.

Figure 6. Difference between support discussions in probability of two or more damping parameter values falling below the overall mean damping parameter value across partners and discussions. Larger positive values indicate a higher probability of two or more stronger damping effects during the support discussion when the male (vs. female) partner received support. The solid point is the posterior mean for this probability difference, and the bar is the 95% credibility interval for this probability difference.

random effect to its corresponding fixed effect is .25 or greater; this would indicate that, in the population, 95% of subjects could be expected show effects ranging from half the size of the average effect to 50% larger than the average effect. We computed these ratios (random / fixed) for all parameters and found that all ratios exceeded .25, thereby indicating noteworthy heterogeneity. Additional analyses quantifying the extent of between-dyad heterogeneity using directional posterior probabilities are provided in the Supplemental Materials.

Figure 7 illustrates this between-dyad heterogeneity with model-predicted trajectories for a subset of six dyads showing a variety of coregulation patterns. Individual dyads are displayed along the rows, and the three discussions are displayed along the columns. Heterogeneity is apparent even in this small number of dyads. While some show patterns

similar to the fixed effects (e.g., Dyad 6 during the male partner's support discussion), others show very different patterns (e.g., Dyad 3 during the female partner's support discussion), suggesting there may be important moderating processes in self- and coregulatory dynamics. Investigating the sources and implications of this heterogeneity would be an important and interesting step to explore in future studies¹³.

Figure 7. Panel plots illustrating model predicted trajectories for six dyads (rows), across discussions (columns). X-axes show discussion duration (5 minutes). Y-axes have been scaled on a per-dyad basis for clarity of presentation. Female partners are displayed in red, and male partners are displayed in blue. The horizontal line at IBI = 0 indicates baseline IBI for each partner. F Receives Support = support discussion in which female partner received support. M Receives Support = support discussion in which male partner received support.

General Discussion

This research examined physiological coregulation during couples' social support discussions. Overall, we found patterns of regular cycling and damped oscillations towards equilibrium for both partners. These processes differed across discussions: On average, male

¹³To further investigate heterogeneity in coregulation, we conducted a latent profile analysis that suggested three types of coregulation patterns, generally differing in the extent and direction of partner influence. More details of this analysis and visualizations of the latent profiles are provided in the Supplemental Materials.

partners showed relatively more stabilizing trajectories during the discussion in which they received support, but this was less apparent for female partners receiving support.

We also investigated three aims to gain insight into couples' coregulation effects. First, we found evidence for coregulation as an interpersonal regulation process: Taking cross-partner effects into account provided a substantially better representation of the data relative to omitting cross-partner effects. Moreover, these gains in model fit when accounting for cross-partner effects were more pronounced for real couples than randomly paired couples. We then examined patterns involving multiple self- and partner damping effects to better understand the nature of regulation dynamics during each discussion. This indicated that stabilizing patterns were more likely to occur when the male partner received support. Finally, we found widespread between-dyad heterogeneity in coregulation, suggesting that a "one-size-fits-all" view of coregulation may not be warranted.

Contributions to Emotion Literature

These results offer new insights into coregulation and into physiological and emotional linkage more broadly. This was the first investigation, to our knowledge, to explicitly examine such processes in the context of social support discussions in adulthood. Although social support discussions have known importance to intrapersonal and interpersonal emotion regulation (Reeck et al., 2016; Rimé, 2009), our results speak to the role of social support in engendering dyadic coregulation between interaction partners.

Our findings also provide evidence that coregulation processes are important, and more likely to involve stabilizing patterns of influence, when a person has experienced a disruption to equilibrium. Indeed, during support discussions, which were characterized by greater emotional and physiological displacement from equilibrium, coregulation trajectories involved stabilization towards an equilibrium level, although this was more pronounced when the

male partner received support. This is some of the first direct evidence, that we know of, that situations involving greater perturbations to equilibrium may engender a more pronounced coregulation process. These findings may also offer an explanation for some of the mixed findings in the literature: An absence of coregulation may be due to individuals already being at equilibrium and not needing to coregulate with a partner to regulate themselves, rather than due to a lack of emotional interdependence *per se*. Moreover, this study generally found evidence for damping during the discussions. Prior work examining physiological coregulation in couples during other types of interactions (e.g., eye-gazing, imitation) has not found such damping effects (Helm et al., 2012). Thus, social support discussions might engender regulation processes that are specific to individuals' needs in this context, namely returning to equilibrium.

This work also revealed between-dyad heterogeneity in coregulation effects. We found that although some couples showed coregulation effects similar to that of the average couple, other couples differed markedly in these effects. That coregulation processes are heterogeneous can also help explain null or inconsistent findings in prior work. Ultimately, knowledge regarding the presence and extent of between-dyad heterogeneity can help researchers plan future studies (e.g., accounting for heterogeneity has direct implications for statistical power; Bolger & Laurenceau (2013)) and develop theories about what moderating variables might explain these differences in coregulation, a point we elaborate on shortly.

Contributions to Close Relationships Literature

This work also contributes to knowledge of close relationships. Separate lines of research have proposed that social support and coregulation may each play a role in explaining how relationships matter for emotional stability and well-being (Butler & Randall, 2013; Saxbe, Beckes, Stoycos, & Coan, 2019; Uchino, 2009). Physiological linkage in couples has also been shown to predict marital satisfaction over time (Levenson & Gottman, 1985).

As coregulation is a specific form of physiological linkage, it may also contribute to important relationship outcomes. Thus, this research makes an advance by revealing that social support and coregulation may work in tandem to benefit individual and dyadic well-being.

Our results also suggested that coregulation during social support differed according to the gender and role, such that coregulation tended to involve a more pronounced stabilizing process when the average male partner received support (or when the female partner *provided* support) compared to when the average female partner received support. This may offer novel insights into known gender differences in relationships. In particular, available evidence suggests that men tend to experience greater health benefits from being involved in romantic relationships compared to women (Kiecolt-Glaser & Newton, 2001; T. W. Smith et al., 2011). Differential patterns of coregulation during support receipt might play a role in explaining this disparity. These results are also consistent with prior work suggesting that men and women differ in the responsiveness of the support they give to their (opposite-gender) partners (Bodenmann et al., 2015; Neff & Karney, 2005; Neff et al., 2020). It is possible that differential coregulation processes mediate such effects, whereby social support discussions in which female partners give support (and male partners receive it) more effectively entrain partners' physiological and emotional responses, ultimately helping the dyad regulate more efficiently as unit. Over time, such processes could bolster the development of effective individual self-regulation and help individuals cope with difficult situations. Although such processes have been examined among parent-child dyads and shown implications for individual self-regulation in childhood (Calkins, 2011; Feldman, 2007), comparable effects in adult close relationships have not (yet) been a focus of research in this area.

Limitations, Open Questions, and Future Directions

Despite the contributions of this research, there are a number of open questions that still need to be investigated

Generalizability of results. One important open question concerns the generalizability of these findings. This study examined mostly younger, heterosexual couples. Therefore, results may not be generalizable to other groups, cultural contexts, developmental stages, or types of relationships. Notably, our sample included some non-heterosexual couples, but there were not enough of these couples to meaningfully examine how coregulation processes might differ in heterosexual vs. non-heterosexual couples. Examining whether similar patterns of coregulation emerge during social support discussions in different populations would be an exciting and important avenue for future research.

Mediators and Moderators. The present investigation focused on coregulation of physiological responses during support discussions. Focusing on physiology offered several advantages both methodologically (e.g., by allowing us to obtain intensively-sampled measurements during naturalistic discussions) and theoretically (e.g., physiological regulation is thought to act as a foundation for the development of emotional and behavioral regulation (Calkins, 2011)). An interesting next step would be to investigate antecedents and mediators of these effects—that is, how fluctuations in physiology give rise to coregulation. Such variables might include emotional expressions, touch, or conversation dynamics (e.g., differences in turn-taking, breathing patterns) that vary according to context.

The present study revealed important heterogeneity in coregulation processes, both in terms of gender differences and between-dyad differences. However, more work is needed to understand where, specifically, these differences come from.

First, it is not clear from this study why the typical male and female partners differed in their coregulation trajectories, and whether such differences were purely due to gender or were instead due to other factors related to gender. For instance, it is possible that men and women differed systematically in the issues they chose to discuss, for example, in terms of the severity of the issue. Indeed, in exploratory analyses, we observed that female partners reported feeling significantly more negative about the issues they chose to discuss during the

support discussions compared to male partners (see Supplemental Materials). It is interesting to note that despite saying they felt more negative about their issue, female partners showed less physiological disruption from equilibrium (baseline) compared to male partners. Perhaps these kinds of differences in negative affect partially account for some of the differences in the coregulation trajectories seen in the support discussions.

Men and women might also differ in their behaviors when receiving vs. providing support, which could influence the degree of coregulation occurring. For example, earlier work found gender differences in the degree of emotional expression during other types of couples' discussions (e.g., Carstensen, Gottman, & Levenson, 1995). As these possibilities suggest, the differences we found when male vs. female partners received support could be due to a host of other variables, rather than entirely due to gender per se. Future research could resolve these questions by having couples exchange support for a problem that is held constant across couples, such as by having one partner receive support in response to standardized laboratory stressor, and testing whether similar gender differences emerge.

We also found substantial between-dyad heterogeneity in coregulation effects, and an interesting and important avenue for future work will entail examining theoretically meaningful moderators that can explain this heterogeneity. The present studies reveal that within-dyad differences in coregulation dynamics come from the types of discussions couples have—i.e., the discussions are themselves moderators of coregulation dynamics.

Beyond that, there are likely other interpersonal, psychological, and emotional variables that moderate couples' coregulation processes. Past work has already shown that variables like relationship satisfaction and attachment style can moderate couples' coregulation dynamics (e.g., Helm et al., 2012) and linkage more generally (Levenson & Gottman, 1985). Regarding the coregulation dynamics revealed in the present investigation, given the specific emotional context of social support discussions, a critical consideration is whether the same variables that moderate coregulation dynamics during support discussions are the same or

different from those that moderate coregulation dynamics during non-support discussions. For instance, perceptions of partner responsiveness or support quality (Maisel & Gable, 2009; Zee et al., 2020) could be important for shaping coregulation during support discussions, but might not be as relevant to coregulation during non-support discussions. Overall, more theorizing is needed to develop targeted hypotheses about which variables might matter most for moderating coregulation processes during different types of dyadic interaction.

Equilibrium. An additional open question concerns our operationalization of equilibrium. In our study, we operationalized equilibrium as participants' average IBI during a baseline period. This baseline was obtained while participants rested quietly alone, so it is reasonable to consider this a true-to-life set point. However, it could be argued that this is not equivalent to the "baseline" that people experience in their daily lives. For example, social baseline theory posits that humans (and other animals) expect to be around others, and that being with people is our "baseline" state (Coan & Maresh, 2014). Our data also do not speak to whether returning to this particular equilibrium is beneficial or desirable; future research examining what an optimal equilibrium might be in various contexts could help to refine understanding of coregulation and what it means to maintain an "equilibrium" level. Given that coregulation is conceptualized as *dyadic* process, it would also be interesting to consider whether couples have a specific *dyadic* baseline as their equilibrium set point.

Physiological Measures. This research focused exclusively on coregulation of partners' inter-beat interval (IBI), which has been used as a focal measure in other studies of coregulation (Helm et al., 2012). IBI does not provide a high degree of specificity about the nature of the underlying psychological or emotional process (Cacioppo et al., 2000; Mauss & Robinson, 2009). Future work examining additional physiological and emotional measures (e.g., pre-ejection period to better tap into "pure" arousal) could provide further insights into the nature and function of coregulation in social support discussions and other contexts. Moreover, examining coregulation patterns across additional physiological and emotional

channels could bolster understanding of whether coregulation is a diffuse, multi-modal process, or whether it is targeted and operates on specific emotional channels.

It is also important to acknowledge that psychological states and stress exposure cannot be directly inferred from single measures of physiology alone (Repetti & Robles, 2016). To address this limitation, our study included information about interpersonal context by manipulating couples' discussions and confirmed key differences in the emotional context across discussions via observational coding data (see Supplemental Materials). However, as most of our conclusions were based physiological data, future research should examine whether similar patterns of coregulation emerge using non-physiological measures, such as intensively coded behavioral data or repeated-measures self-report data.

Modeling Considerations. Lastly, our investigation drew on dynamical systems modeling to examine coregulation. These models offer many advantages for examining coregulation; for a summary and guidance for implementing these models, see Butler & Barnard (2019) and the *rties* package for R. However, some considerations are warranted. First, these models are sensitive to the size of the embed dimension—i.e, the size of the window used to compute derivatives. There are differing perspectives on selecting an embed dimension, and in our study, we selected an embed dimension *a priori* to balance issues of measurement precision with the temporal properties of the cardiovascular process under examination. However, results could differ if other embed dimensions were used.

Second, the model trajectories also depend heavily on the choice of start values. That is, even if model parameters remain exactly the same, using different start values can result in markedly different trajectories (Boker & Nesselroade, 2002). We selected meaningful start values (observed IBI values at the start of each discussion) as a way to address this issue, but it is important to acknowledge that other trajectories might emerge if we were to select different start values. Our analyses on the posterior distributions and the model comparison approaches we used are not affected by start values. Nevertheless, the issue of start values is

always a consideration when working with these models.

Finally, our models drew on intensively sampled cardiovascular data in small enough time windows to capture oscillations in participants' responding. Physiological and other kinds of data aggregated into larger windows could potentially obscure oscillations by essentially averaging over moment-to-moment variation. When working with coupled oscillator models, it may be important to consider whether the time interval of the relevant variable(s) is small enough to reveal patterns of interest.

Conclusions

Coregulation has been proposed to play an important role in accounting for the beneficial effects of close relationships. The present work furthers this notion by demonstrating the emergence of physiological coregulation during social support discussions in romantic couples and by highlighting between-dyad differences in this process. Thus, coregulation appears to be an important channel through which supportive relationships help people manage their emotional and physiological responses to difficulties, and may contribute to better well-being and dyadic functioning over time.

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Physiological Coregulation during Social Support Discussions - Supplemental Materials

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Overview

This Supplement presents additional details and analyses, including analysis of IBI time trends, full model output with individual parameter estimates, details about tests of heterogeneity, and additional tests performed on the posterior distributions.

Illustration of how coregulation differs from reactivity

Figure 1 shows an example of how regulation differs from a process involving emotional escalation/de-escalation or reactivity; we present one self-regulatory trajectory for one individual for clarity of presentation but the general concept also extends to coregulation trajectories among dyads. The solid line illustrates a regulation process, in which feedback loops pull responses towards an equilibrium level. The dashed line illustrates escalation—a potential trajectory that could occur in the absence of a regulation process to bring responses back to equilibrium. As this figure implies, a regulation process can inhibit escalation and, in doing, so help stabilize responses around an equilibrium level. In this way, coregulation captures a fundamentally different process than escalation or reactivity; whereas coregulation involves moment-to-moment fluctuations in responding, reactivity typically involves sustained increases or decreases in levels of physiology over longer time windows (e.g., the course of a laboratory task).

Figure 1: Illustration of differences in escalation vs. regulation. A single trajectory is presented for clarity of presentation.

Details on physiological data collection procedures

We collected heart rate data using Biopac's MP150 and ECG module. We placed two electrocardiogram leads in a Lead II configuration on the torso (one on the right upper torso below the collar bone, and one on the lower left torso below the ribs). We also fitted participants with mylar band sensors (two strips each on the neck and the torso) to assess respiration and impedance cardiography. However, these assessments have not been processed or analyzed in regards to the present research question.

Complete heart rate data during the discussions were available for 85% of dyads in the sample (for more on exclusions and missing data, see the Results section).

HRV data were first scored in 30-second intervals in connection with a separate hypothesis. Data were scored by three scorers, with two scoring only baseline data. A third scorer, who was the primary scorer, reviewed all previously scored files and scored HRV data during discussion phases to help ensure consistency of scoring decisions. HRV data were then rescored in 10-second intervals in connection with the present hypotheses. This round of scoring drew the previously scored 30-second data and was reviewed by the same primary scorer.

Validating the emotional context

Initial IBI Values by Discussion

As a first step, we examined participants' IBI values at the start of each discussion. We had anticipated that, when they were receiving support, participants should show more pronounced perturbations away from equilibrium (reflected by larger decreases in IBI relative to baseline) at the start of the discussion, compared to the start of the control discussion. Indeed, participants' average IBI was lower (indicating a faster heart rate) at the start of the support discussion when they received support relative to the control discussion, female partners: $\mu_{diff} = -22.48$, 95% CI [-38.63, -6.72]; male partners: $\mu_{diff} = -11.64$, 95% CI [-27.89, 3.64]. Note that although the credibility interval for male partners' difference in IBI included zero, the Bayesian posterior distribution of possible values for this difference (i.e., the percentage of posterior samples falling below 0, as discussed in detail shortly) indicated a 0.93 probability that IBI was lower at the start of the support discussion relative to the control discussion. This provided empirical support for our assumption that prompting participants to share a stressful event as part of the social support discussions was more disequilibrating compared to engaging in the control discussion.

Expressions of Positive and Negative Affect by Discussion

Next, we drew on observational coding assessing participants' verbal and nonverbal expressions of positive and negative emotion. For each type of discussion two coders¹ blind to hypotheses watched video footage of participants' discussions and indicated the amount of positive and negative emotion each partner expressed. Coders were instructed to take into account frequency, magnitude, and duration when making their ratings (1 = *Not at all evident*, 7 = *Extremely evident*). Coders provided ratings in 30-second intervals, for a total of up to 10 observations per participant per discussion. To assess emotional disequilibrium, we examined differences in positive and negative emotion expressed during the first 30-seconds of the discussions only. There was acceptable inter-rater reliability in coders' ratings during the first 30-second period of each discussion ($ICCs \geq 0.76$).

As expected, we found that both the typical male and typical female partner expressed less positive emotion during the first 30-seconds of the support discussions, both when receiving support (male: $b = -1.49$, 95% CI [-1.67, -1.32]; female: $b = -1.69$, 95% CI [-1.86, -1.52]) and providing support (male: $b = -1.50$, 95% CI [-1.66, -1.33]; female: $b = -1.84$, 95% CI [-2.01, -1.67]), compared to during the control discussion. Partners also expressed more negative emotion during the discussion in which they received support compared to both the control discussion (male: $b = 0.24$, 95% CI [0.10, 0.39]; female: $b = 0.48$, 95% CI [0.34, 0.61]) and the discussion in which they provided support (male: $b = 0.38$, 95% CI [0.24, 0.52]; female: $b = 0.53$, 95% CI [0.4, 0.67]).

Collectively, these results illustrate the distinct emotional contexts of the discussions, with participants tending show more disequilibrium at the start of the discussion in which they received support.

¹Observational coding was carried out in connection with several hypotheses that were not directly related to the research question discussed in this paper. One group of two coders provided ratings of couples' control discussions, and a separate group of two coders provided ratings of couples' support discussions. The two groups of coders received identical instructions for coding positive and negative affect and were trained to apply the coding scheme by the same person. A disadvantage of having separate groups of coders is that between-coder differences cannot be fully ruled out as a contributor to differences in emotional expression across types of discussions. However, advantages of having separate groups of coders are that (a) this reduces the possibility of carry-over effects, in which participants' behaviors in the support discussions might influence ratings given in the control discussion and vice versa, and (b) this circumvents coder demand characteristics, by preventing coders from shifting their ratings based on assumptions they might have about how the discussions were intended to differ. We note that differences in emotional expression found across discussions are also generally consistent with the differences in IBI initial values found across discussions.

IBI Time Trends

An assumption of coupled oscillator models is that the underlying time series is stationary and does not involve linear increases or decreases in level over time. We assessed the presence of linear time trends by regressing IBI values on time, allowing time trajectories to differ according to discussion type and treating all effects as random. This analysis revealed extremely small changes in IBI from the start to the end of the discussion for the average female and male partners across discussions: female partner: $\mu_{diff} = 10.57$, 95% CI [3.00, 18.04]; male partner: $\mu_{diff} = 10.27$, 95% CI [3.32, 17.11]. This corresponded to a 1% change in IBI for each partner during the entire discussion period, or a difference of 1 beat per minute when converted into a heart rate metric. We therefore used baseline centered IBI values in our analysis, because this offered theoretical advantages by allowing us to assess deviations from participants' actual equilibrium [Boker2012].

Table 1: IBI Time Trends (fixed effects)

Term	Estimate	Lower	Upper
F Intercept	791.02	767.99	812.09
M Intercept	806.12	778.77	833.12
F Time	10.57	3.00	18.04
F Effect 1 (Control vs. F Receives)	-3.96	-14.94	7.25
F Effect 2 (M Receives vs. F Receives)	11.62	3.37	19.87
F Time X Effect 1	-19.19	-33.01	-5.19
F Time X Effect 2	-12.65	-23.38	-1.76
M Time	10.27	3.32	17.11
M Effect 1 (Control vs. F Receives)	-17.01	-24.81	-9.04
M Effect 2 (M Receives vs. F Receives)	0.001	-7.59	7.59
M Time X Effect 1	5.26	-4.86	15.33
M Time X Effect 2	15.43	3.09	27.80

Note:

Discussion phases are effect coded such that intercepts and main effects correspond to average levels of IBI and changes in IBI over time, respectively, averaging across discussion phases. Effect 1 is the comparison of Control to F Receives and Effect 2 is the comparison of M Receives to F Receives. Time is coded 0 to 1, with 0 corresponding to the first time point and 1 corresponding to the last time point. Thus, intercept estimates correspond to the average IBI values for the typical male and female partners during the first time point of a discussion, and the coefficients for Time correspond to the total average change in IBI across the the discussion for each partner. To facilitate interpretation, IBI values can be converted to heart rate (HR; beats per minute) using the formula $HR = 60000/IBI$. For the typical female and male partners during a typical discussion, heart rate only changed by -1 ($60000/(791.02+10.57)$ - $60000/791.02$) and -0.94 ($60000/(806.12+10.27)$ - $60000/806.12$) beats per minute, respectively.

Table 2: IBI Time Trends (random effects)

	Term	Estimate	Lower	Upper
1	F Intercept	105.71	91.00	122.80
2	F Time	32.37	26.60	39.17
3	F Effect 1	48.72	40.74	57.83
4	F Effect 2	31.14	24.26	38.82
5	F Time X Effect 1	52.12	40.56	65.19
6	F Time X Effect 2	30.75	16.80	44.14
7	M Intercept	127.82	110.39	148.27
8	M Time	29.58	24.15	35.98
9	M Effect 1	31.85	25.61	38.90
10	M Effect 2	28.22	21.67	35.69
11	M Time X Effect 1	30.41	17.68	42.65
12	M Time X Effect 2	43.52	31.51	56.23

Note:

Discussion phases are effect coded such that intercepts and main effects correspond to average levels of IBI and changes in IBI over time, respectively, averaging across discussion phases. Effect 1 is the comparison of Control to F Receives and Effect 2 is the comparison of M Receives to F Receives. Time is coded 0 to 1, with 0 corresponding to the first time point and 1 corresponding to the last time point. Thus, intercept estimates correspond to the average IBI values for the typical male and female partners during the first time point of a discussion, and the coefficients for Time correspond to the total average change in IBI across the the discussion for each partner.

Table 3: IBI Time Trends (random effects)

	Term	Estimate	Lower	Upper
13	F Intercept, F Time	-0.09	-0.30	0.13
14	F Intercept, F Effect 1	0.12	-0.08	0.33
15	F Time, F Effect 1	0.02	-0.21	0.26
16	F Intercept, F Effect 2	0.09	-0.15	0.32
17	F Time, F Effect 2	0.08	-0.18	0.34
18	F Effect 1, F Effect 2	0.22	-0.05	0.46
19	F Intercept, F Time X Effect 1	-0.10	-0.33	0.13
20	F Time, F Time X Effect 1	-0.14	-0.38	0.13
21	F Effect 1, F Time X Effect 1	-0.67	-0.80	-0.51
22	F Effect 2, F Time X Effect 1	-0.10	-0.37	0.19
23	F Intercept, F Time X Effect 2	0.24	-0.05	0.52
24	F Time, F Time X Effect 2	-0.11	-0.44	0.21
25	F Effect 1, F Time X Effect 2	-0.17	-0.48	0.19
26	F Effect 2, F Time X Effect 2	-0.41	-0.68	-0.06
27	F Time X Effect 1, F Time X Effect 2	0.10	-0.27	0.44
28	F Intercept, M Intercept	0.13	-0.06	0.32
29	F Time, M Intercept	-0.05	-0.27	0.17
30	F Effect 1, M Intercept	0.05	-0.16	0.25
31	F Effect 2, M Intercept	-0.08	-0.30	0.15
32	F Time X Effect 1, M Intercept	0.06	-0.18	0.29
33	F Time X Effect 2, M Intercept	0.06	-0.24	0.36
34	F Intercept, M Time	0.13	-0.09	0.35
35	F Time, M Time	0.12	-0.12	0.37
36	F Effect 1, M Time	-0.04	-0.27	0.20
37	F Effect 2, M Time	0.007	-0.25	0.27
38	F Time X Effect 1, M Time	0.008	-0.25	0.27
39	F Time X Effect 2, M Time	-0.08	-0.41	0.26
40	M Intercept, M Time	-0.27	-0.47	-0.06
41	F Intercept, M Effect 1	-0.09	-0.31	0.13
42	F Time, M Effect 1	0.03	-0.22	0.29
43	F Effect 1, M Effect 1	0.02	-0.22	0.25
44	F Effect 2, M Effect 1	-0.16	-0.42	0.12
45	F Time X Effect 1, M Effect 1	-0.13	-0.39	0.14
46	F Time X Effect 2, M Effect 1	0.38	0.06	0.68

Table 3: IBI Time Trends (random effects) (*continued*)

	Term	Estimate	Lower	Upper
47	M Intercept, M Effect 1	0.01	-0.21	0.24
48	M Time, M Effect 1	-0.18	-0.43	0.07
49	F Intercept, M Effect 2	-0.02	-0.26	0.21
50	F Time, M Effect 2	0.14	-0.14	0.39
51	F Effect 1, M Effect 2	-0.05	-0.31	0.21
52	F Effect 2, M Effect 2	-0.06	-0.33	0.22
53	F Time X Effect 1, M Effect 2	-0.04	-0.32	0.25
54	F Time X Effect 2, M Effect 2	0.24	-0.12	0.57
55	M Intercept, M Effect 2	-0.11	-0.34	0.13
56	M Time, M Effect 2	-0.15	-0.42	0.11
57	M Effect 1, M Effect 2	0.32	0.04	0.56
58	F Intercept, M Time X Effect 1	0.12	-0.17	0.40
59	F Time, M Time X Effect 1	0.009	-0.31	0.33
60	F Effect 1, M Time X Effect 1	0.28	-0.02	0.57
61	F Effect 2, M Time X Effect 1	0.21	-0.15	0.55
62	F Time X Effect 1, M Time X Effect 1	-0.07	-0.41	0.26
63	F Time X Effect 2, M Time X Effect 1	-0.22	-0.59	0.23
64	M Intercept, M Time X Effect 1	0.12	-0.17	0.40
65	M Time, M Time X Effect 1	-0.07	-0.40	0.26
66	M Effect 1, M Time X Effect 1	-0.25	-0.53	0.11
67	M Effect 2, M Time X Effect 1	-0.14	-0.50	0.26
68	F Intercept, M Time X Effect 2	0.19	-0.04	0.42
69	F Time, M Time X Effect 2	-0.14	-0.40	0.13
70	F Effect 1, M Time X Effect 2	0.16	-0.11	0.41
71	F Effect 2, M Time X Effect 2	0.18	-0.11	0.46
72	F Time X Effect 1, M Time X Effect 2	0.11	-0.18	0.38
73	F Time X Effect 2, M Time X Effect 2	-0.26	-0.60	0.11
74	M Intercept, M Time X Effect 2	0.22	-0.02	0.44
75	M Time, M Time X Effect 2	0.15	-0.11	0.40
76	M Effect 1, M Time X Effect 2	-0.15	-0.42	0.15
77	M Effect 2, M Time X Effect 2	-0.48	-0.69	-0.20
78	M Time X Effect 1, M Time X Effect 2	0.60	0.28	0.84
79	F Residual	47.65	46.90	48.43
80	M Residual	44.13	43.42	44.86
81	Residual Correlation	0.10	0.07	0.12

Table 3: IBI Time Trends (random effects) (*continued*)

Term	Estimate	Lower	Upper
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Note:

Discussion phases are effect coded such that intercepts and main effects correspond to average levels of IBI and changes in IBI over time, respectively, averaging across discussion phases. Effect 1 is the comparison of Control to F Receives and Effect 2 is the comparison of M Receives to F Receives. Time is coded 0 to 1, with 0 corresponding to the first time point and 1 corresponding to the last time point. Thus, intercept estimates correspond to the average IBI values for the typical male and female partners during the first time point of a discussion, and the coefficients for Time correspond to the total average change in IBI across the the discussion for each partner.

Coupled Damped Oscillator Model Output

Fixed Effects

Figure 2: Summary of Fixed Effects by Discussion Condition. Estimates are posterior means (unstandardized), with 95-percent credibility intervals in brackets. Along the rows, F Receives = support discussion in which female partner received support. M Receives = support discussion in which male partner received support. Along the columns, F = Effect on female partner's responses, M = Effect on male partner's responses.

Figure 3: Summary of Differences Between Conditions (Fixed Effects). Estimates are posterior means (unstandardized), with 95-percent credibility intervals in brackets. Along the rows, F Receives = support discussion in which female partner received support. M Receives = support discussion in which male partner received support. Along the columns, F = Effect on female partner's responses, M = Effect on male partner's responses.

Random Effects

Figure 4: Summary of Random Effects by Discussion Condition. Estimates are posterior means (unstandardized), with 95-percent credibility intervals in brackets. Along the rows, F Receives = support discussion in which female partner received support. M Receives = support discussion in which male partner received support. Along the columns, F = Effect on female partner's responses, M = Effect on male partner's responses.

Figure 5: Summary of Differences Between Conditions (Random Effects). Estimates are posterior means (unstandardized), with 95-percent credibility intervals in brackets. Along the rows, F Receives = support discussion in which female partner received support. M Receives = support discussion in which male partner received support. Along the columns, F = Effect on female partner's responses, M = Effect on male partner's responses.

Correlations Among Random Effects

Table 4: Correlations among Random Effects

	Correlation	Estimate	Lower	Upper
1	F Cycling (self), F Damping (self)	-0.03	-0.34	0.29
2	F Cycling (self), F Cycling (partner)	0.04	-0.15	0.23
3	F Damping (self), F Cycling (partner)	0.14	-0.21	0.45
4	F Cycling (self), F Damping (partner)	-0.09	-0.37	0.22
5	F Damping (self), F Damping (partner)	0.00	-0.32	0.32
6	F Cycling (partner), F Damping (partner)	0.12	-0.20	0.42
7	F Cycling (self), F Cycling (self) X Control	-0.03	-0.25	0.20
8	F Damping (self), F Cycling (self) X Control	0.05	-0.28	0.36
9	F Cycling (partner), F Cycling (self) X Control	0.29	0.09	0.48
10	F Damping (partner), F Cycling (self) X Control	0.14	-0.18	0.43
11	F Cycling (self), F Damping (self) X Control	-0.07	-0.38	0.25
12	F Damping (self), F Damping (self) X Control	0.00	-0.32	0.33
13	F Cycling (partner), F Damping (self) X Control	0.10	-0.22	0.41
14	F Damping (partner), F Damping (self) X Control	0.02	-0.31	0.34
15	F Cycling (self) X Control, F Damping (self) X Control	0.10	-0.22	0.40
16	F Cycling (self), F Cycling (self) X M Receives	-0.20	-0.43	0.05
17	F Damping (self), F Cycling (self) X M Receives	0.03	-0.30	0.34
18	F Cycling (partner), F Cycling (self) X M Receives	-0.05	-0.27	0.17
19	F Damping (partner), F Cycling (self) X M Receives	-0.13	-0.43	0.20
20	F Cycling (self) X Control, F Cycling (self) X M Receives	0.05	-0.22	0.30
21	F Damping (self) X Control, F Cycling (self) X M Receives	0.04	-0.28	0.36
22	F Cycling (self), F Damping (self) X M Receives	-0.01	-0.34	0.31
23	F Damping (self), F Damping (self) X M Receives	-0.01	-0.35	0.32
24	F Cycling (partner), F Damping (self) X M Receives	0.07	-0.26	0.38
25	F Damping (partner), F Damping (self) X M Receives	-0.03	-0.35	0.30
26	F Cycling (self) X Control, F Damping (self) X M Receives	-0.02	-0.34	0.30
27	F Damping (self) X Control, F Damping (self) X M Receives	0.01	-0.32	0.34
28	F Cycling (self) X M Receives, F Damping (self) X M Receives	0.04	-0.29	0.36
29	F Cycling (self), F Cycling (partner) X Control	-0.11	-0.33	0.13
30	F Damping (self), F Cycling (partner) X Control	0.00	-0.31	0.31
31	F Cycling (partner), F Cycling (partner) X Control	-0.14	-0.35	0.09
32	F Damping (partner), F Cycling (partner) X Control	0.00	-0.31	0.30

Table 4: Correlations among Random Effects (*continued*)

	Correlation	Estimate	Lower	Upper
33	F Cycling (self) X Control, F Cycling (partner) X Control	-0.19	-0.42	0.05
34	F Damping (self) X Control, F Cycling (partner) X Control	-0.02	-0.33	0.30
35	F Cycling (self) X M Receives, F Cycling (partner) X Control	-0.13	-0.38	0.14
36	F Damping (self) X M Receives, F Cycling (partner) X Control	0.02	-0.31	0.35
37	F Cycling (self), F Damping (partner) X Control	-0.10	-0.41	0.23
38	F Damping (self), F Damping (partner) X Control	0.00	-0.33	0.32
39	F Cycling (partner), F Damping (partner) X Control	0.09	-0.24	0.41
40	F Damping (partner), F Damping (partner) X Control	-0.03	-0.36	0.30
41	F Cycling (self) X Control, F Damping (partner) X Control	0.03	-0.30	0.35
42	F Damping (self) X Control, F Damping (partner) X Control	0.02	-0.32	0.35
43	F Cycling (self) X M Receives, F Damping (partner) X Control	0.01	-0.31	0.33
44	F Damping (self) X M Receives, F Damping (partner) X Control	0.00	-0.33	0.33
45	F Cycling (partner) X Control, F Damping (partner) X Control	0.03	-0.29	0.34
46	F Cycling (self), F Cycling (partner) X M Receives	0.05	-0.21	0.30
47	F Damping (self), F Cycling (partner) X M Receives	0.02	-0.31	0.34
48	F Cycling (partner), F Cycling (partner) X M Receives	0.03	-0.23	0.29
49	F Damping (partner), F Cycling (partner) X M Receives	-0.06	-0.37	0.27
50	F Cycling (self) X Control, F Cycling (partner) X M Receives	0.01	-0.26	0.28
51	F Damping (self) X Control, F Cycling (partner) X M Receives	-0.01	-0.34	0.31
52	F Cycling (self) X M Receives, F Cycling (partner) X M Receives	0.10	-0.19	0.38
53	F Damping (self) X M Receives, F Cycling (partner) X M Receives	0.06	-0.28	0.38
54	F Cycling (partner) X Control, F Cycling (partner) X M Receives	-0.02	-0.30	0.25
55	F Damping (partner) X Control, F Cycling (partner) X M Receives	-0.01	-0.33	0.32
56	F Cycling (self), F Damping (partner) X M Receives	-0.05	-0.33	0.24
57	F Damping (self), F Damping (partner) X M Receives	0.03	-0.31	0.34
58	F Cycling (partner), F Damping (partner) X M Receives	0.02	-0.27	0.30
59	F Damping (partner), F Damping (partner) X M Receives	0.00	-0.33	0.32
60	F Cycling (self) X Control, F Damping (partner) X M Receives	-0.09	-0.37	0.21
61	F Damping (self) X Control, F Damping (partner) X M Receives	-0.01	-0.34	0.32
62	F Cycling (self) X M Receives, F Damping (partner) X M Receives	-0.18	-0.47	0.13
63	F Damping (self) X M Receives, F Damping (partner) X M Receives	0.00	-0.33	0.32
64	F Cycling (partner) X Control, F Damping (partner) X M Receives	0.21	-0.10	0.49
65	F Damping (partner) X Control, F Damping (partner) X M Receives	0.02	-0.30	0.34

Table 4: Correlations among Random Effects (*continued*)

	Correlation	Estimate	Lower	Upper
66	F Cycling (partner) X M Receives, F Damping (partner) X M Receives	-0.10	-0.40	0.21
67	F Cycling (self), M Cycling (self)	-0.16	-0.35	0.03
68	F Damping (self), M Cycling (self)	-0.03	-0.34	0.28
69	F Cycling (partner), M Cycling (self)	-0.05	-0.23	0.14
70	F Damping (partner), M Cycling (self)	0.04	-0.25	0.33
71	F Cycling (self) X Control, M Cycling (self)	-0.14	-0.35	0.08
72	F Damping (self) X Control, M Cycling (self)	0.02	-0.29	0.33
73	F Cycling (self) X M Receives, M Cycling (self)	0.08	-0.16	0.31
74	F Damping (self) X M Receives, M Cycling (self)	0.01	-0.31	0.33
75	F Cycling (partner) X Control, M Cycling (self)	0.14	-0.08	0.35
76	F Damping (partner) X Control, M Cycling (self)	0.11	-0.22	0.41
77	F Cycling (partner) X M Receives, M Cycling (self)	-0.05	-0.28	0.19
78	F Damping (partner) X M Receives, M Cycling (self)	0.00	-0.26	0.28
79	F Cycling (self), M Damping (self)	-0.03	-0.35	0.30
80	F Damping (self), M Damping (self)	-0.02	-0.35	0.32
81	F Cycling (partner), M Damping (self)	-0.03	-0.36	0.30
82	F Damping (partner), M Damping (self)	0.01	-0.32	0.34
83	F Cycling (self) X Control, M Damping (self)	0.00	-0.32	0.32
84	F Damping (self) X Control, M Damping (self)	-0.01	-0.34	0.32
85	F Cycling (self) X M Receives, M Damping (self)	-0.05	-0.38	0.28
86	F Damping (self) X M Receives, M Damping (self)	-0.01	-0.34	0.31
87	F Cycling (partner) X Control, M Damping (self)	0.03	-0.29	0.35
88	F Damping (partner) X Control, M Damping (self)	0.00	-0.32	0.33
89	F Cycling (partner) X M Receives, M Damping (self)	-0.02	-0.35	0.31
90	F Damping (partner) X M Receives, M Damping (self)	0.00	-0.33	0.33
91	M Cycling (self), M Damping (self)	0.00	-0.32	0.32
92	F Cycling (self), M Cycling (partner)	0.13	-0.06	0.31
93	F Damping (self), M Cycling (partner)	0.12	-0.22	0.43
94	F Cycling (partner), M Cycling (partner)	0.58	0.43	0.71
95	F Damping (partner), M Cycling (partner)	0.05	-0.23	0.33
96	F Cycling (self) X Control, M Cycling (partner)	0.23	0.03	0.43
97	F Damping (self) X Control, M Cycling (partner)	0.08	-0.23	0.39
98	F Cycling (self) X M Receives, M Cycling (partner)	-0.01	-0.24	0.23
99	F Damping (self) X M Receives, M Cycling (partner)	0.07	-0.26	0.39

Table 4: Correlations among Random Effects (*continued*)

	Correlation	Estimate	Lower	Upper
100	F Cycling (partner) X Control, M Cycling (partner)	-0.12	-0.32	0.09
101	F Damping (partner) X Control, M Cycling (partner)	0.07	-0.23	0.37
102	F Cycling (partner) X M Receives, M Cycling (partner)	0.07	-0.16	0.30
103	F Damping (partner) X M Receives, M Cycling (partner)	-0.03	-0.29	0.24
104	M Cycling (self), M Cycling (partner)	-0.01	-0.19	0.16
105	M Damping (self), M Cycling (partner)	-0.05	-0.37	0.28
106	F Cycling (self), M Damping (partner)	0.05	-0.26	0.36
107	F Damping (self), M Damping (partner)	0.01	-0.32	0.34
108	F Cycling (partner), M Damping (partner)	-0.05	-0.35	0.26
109	F Damping (partner), M Damping (partner)	-0.10	-0.43	0.25
110	F Cycling (self) X Control, M Damping (partner)	-0.06	-0.36	0.26
111	F Damping (self) X Control, M Damping (partner)	-0.02	-0.34	0.31
112	F Cycling (self) X M Receives, M Damping (partner)	0.05	-0.26	0.37
113	F Damping (self) X M Receives, M Damping (partner)	0.02	-0.32	0.35
114	F Cycling (partner) X Control, M Damping (partner)	-0.08	-0.38	0.24
115	F Damping (partner) X Control, M Damping (partner)	-0.04	-0.37	0.29
116	F Cycling (partner) X M Receives, M Damping (partner)	-0.01	-0.33	0.31
117	F Damping (partner) X M Receives, M Damping (partner)	-0.08	-0.40	0.26
118	M Cycling (self), M Damping (partner)	-0.06	-0.36	0.25
119	M Damping (self), M Damping (partner)	-0.01	-0.34	0.32
120	M Cycling (partner), M Damping (partner)	0.00	-0.31	0.30
121	F Cycling (self), M Cycling (self) X Control	-0.05	-0.25	0.16
122	F Damping (self), M Cycling (self) X Control	0.00	-0.31	0.32
123	F Cycling (partner), M Cycling (self) X Control	-0.15	-0.35	0.05
124	F Damping (partner), M Cycling (self) X Control	-0.05	-0.34	0.25
125	F Cycling (self) X Control, M Cycling (self) X Control	-0.29	-0.50	-0.07
126	F Damping (self) X Control, M Cycling (self) X Control	-0.04	-0.34	0.27
127	F Cycling (self) X M Receives, M Cycling (self) X Control	0.04	-0.21	0.28
128	F Damping (self) X M Receives, M Cycling (self) X Control	0.01	-0.32	0.33
129	F Cycling (partner) X Control, M Cycling (self) X Control	0.08	-0.15	0.31
130	F Damping (partner) X Control, M Cycling (self) X Control	-0.02	-0.33	0.30
131	F Cycling (partner) X M Receives, M Cycling (self) X Control	-0.09	-0.35	0.17
132	F Damping (partner) X M Receives, M Cycling (self) X Control	0.11	-0.18	0.38
133	M Cycling (self), M Cycling (self) X Control	-0.27	-0.44	-0.08
134	M Damping (self), M Cycling (self) X Control	-0.02	-0.34	0.30

Table 4: Correlations among Random Effects (*continued*)

	Correlation	Estimate	Lower	Upper
135	M Cycling (partner), M Cycling (self) X Control	-0.21	-0.39	-0.02
136	M Damping (partner), M Cycling (self) X Control	0.03	-0.28	0.34
137	F Cycling (self), M Damping (self) X Control	0.01	-0.33	0.34
138	F Damping (self), M Damping (self) X Control	-0.01	-0.33	0.32
139	F Cycling (partner), M Damping (self) X Control	0.00	-0.33	0.33
140	F Damping (partner), M Damping (self) X Control	0.01	-0.32	0.34
141	F Cycling (self) X Control, M Damping (self) X Control	0.02	-0.31	0.35
142	F Damping (self) X Control, M Damping (self) X Control	0.00	-0.32	0.33
143	F Cycling (self) X M Receives, M Damping (self) X Control	-0.02	-0.34	0.31
144	F Damping (self) X M Receives, M Damping (self) X Control	-0.01	-0.34	0.33
145	F Cycling (partner) X Control, M Damping (self) X Control	-0.01	-0.35	0.31
146	F Damping (partner) X Control, M Damping (self) X Control	0.00	-0.33	0.33
147	F Cycling (partner) X M Receives, M Damping (self) X Control	0.00	-0.34	0.33
148	F Damping (partner) X M Receives, M Damping (self) X Control	-0.01	-0.34	0.32
149	M Cycling (self), M Damping (self) X Control	0.02	-0.30	0.34
150	M Damping (self), M Damping (self) X Control	-0.01	-0.34	0.32
151	M Cycling (partner), M Damping (self) X Control	0.00	-0.33	0.33
152	M Damping (partner), M Damping (self) X Control	0.00	-0.34	0.33
153	M Cycling (self) X Control, M Damping (self) X Control	-0.05	-0.37	0.28
154	F Cycling (self), M Cycling (self) X M Receives	-0.09	-0.29	0.13
155	F Damping (self), M Cycling (self) X M Receives	0.01	-0.30	0.32
156	F Cycling (partner), M Cycling (self) X M Receives	0.14	-0.06	0.34
157	F Damping (partner), M Cycling (self) X M Receives	0.08	-0.22	0.37
158	F Cycling (self) X Control, M Cycling (self) X M Receives	0.17	-0.06	0.39
159	F Damping (self) X Control, M Cycling (self) X M Receives	-0.01	-0.32	0.31
160	F Cycling (self) X M Receives, M Cycling (self) X M Receives	-0.13	-0.38	0.12
161	F Damping (self) X M Receives, M Cycling (self) X M Receives	0.00	-0.32	0.32
162	F Cycling (partner) X Control, M Cycling (self) X M Receives	0.13	-0.11	0.36
163	F Damping (partner) X Control, M Cycling (self) X M Receives	-0.03	-0.34	0.28
164	F Cycling (partner) X M Receives, M Cycling (self) X M Receives	0.00	-0.25	0.25
165	F Damping (partner) X M Receives, M Cycling (self) X M Receives	0.13	-0.15	0.40
166	M Cycling (self), M Cycling (self) X M Receives	-0.38	-0.54	-0.20
167	M Damping (self), M Cycling (self) X M Receives	0.00	-0.32	0.32
168	M Cycling (partner), M Cycling (self) X M Receives	0.03	-0.16	0.21
169	M Damping (partner), M Cycling (self) X M Receives	-0.07	-0.37	0.25

Table 4: Correlations among Random Effects (*continued*)

	Correlation	Estimate	Lower	Upper
170	M Cycling (self) X Control, M Cycling (self) X M Receives	0.19	-0.02	0.40
171	M Damping (self) X Control, M Cycling (self) X M Receives	0.00	-0.33	0.32
172	F Cycling (self), M Damping (self) X M Receives	-0.03	-0.35	0.30
173	F Damping (self), M Damping (self) X M Receives	-0.01	-0.34	0.32
174	F Cycling (partner), M Damping (self) X M Receives	-0.02	-0.34	0.31
175	F Damping (partner), M Damping (self) X M Receives	0.00	-0.32	0.33
176	F Cycling (self) X Control, M Damping (self) X M Receives	-0.03	-0.36	0.30
177	F Damping (self) X Control, M Damping (self) X M Receives	-0.01	-0.34	0.32
178	F Cycling (self) X M Receives, M Damping (self) X M Receives	-0.05	-0.38	0.28
179	F Damping (self) X M Receives, M Damping (self) X M Receives	-0.01	-0.34	0.32
180	F Cycling (partner) X Control, M Damping (self) X M Receives	0.05	-0.28	0.38
181	F Damping (partner) X Control, M Damping (self) X M Receives	0.00	-0.34	0.32
182	F Cycling (partner) X M Receives, M Damping (self) X M Receives	0.00	-0.32	0.33
183	F Damping (partner) X M Receives, M Damping (self) X M Receives	0.02	-0.31	0.34
184	M Cycling (self), M Damping (self) X M Receives	0.01	-0.31	0.33
185	M Damping (self), M Damping (self) X M Receives	-0.01	-0.34	0.32
186	M Cycling (partner), M Damping (self) X M Receives	-0.04	-0.35	0.28
187	M Damping (partner), M Damping (self) X M Receives	-0.01	-0.34	0.32
188	M Cycling (self) X Control, M Damping (self) X M Receives	0.01	-0.31	0.34
189	M Damping (self) X Control, M Damping (self) X M Receives	0.01	-0.32	0.33
190	M Cycling (self) X M Receives, M Damping (self) X M Receives	0.00	-0.33	0.32
191	F Cycling (self), M Cycling (partner) X Control	-0.11	-0.32	0.10
192	F Damping (self), M Cycling (partner) X Control	-0.07	-0.38	0.25
193	F Cycling (partner), M Cycling (partner) X Control	-0.14	-0.34	0.07
194	F Damping (partner), M Cycling (partner) X Control	0.00	-0.30	0.29
195	F Cycling (self) X Control, M Cycling (partner) X Control	-0.17	-0.39	0.06
196	F Damping (self) X Control, M Cycling (partner) X Control	-0.07	-0.38	0.25
197	F Cycling (self) X M Receives, M Cycling (partner) X Control	-0.16	-0.40	0.08
198	F Damping (self) X M Receives, M Cycling (partner) X Control	0.00	-0.33	0.32
199	F Cycling (partner) X Control, M Cycling (partner) X Control	0.51	0.30	0.69
200	F Damping (partner) X Control, M Cycling (partner) X Control	0.01	-0.30	0.32
201	F Cycling (partner) X M Receives, M Cycling (partner) X Control	-0.01	-0.27	0.25
202	F Damping (partner) X M Receives, M Cycling (partner) X Control	0.14	-0.14	0.41

Table 4: Correlations among Random Effects (*continued*)

	Correlation	Estimate	Lower	Upper
203	M Cycling (self), M Cycling (partner) X Control	0.17	-0.05	0.38
204	M Damping (self), M Cycling (partner) X Control	0.05	-0.28	0.37
205	M Cycling (partner), M Cycling (partner) X Control	-0.41	-0.59	-0.22
206	M Damping (partner), M Cycling (partner) X Control	-0.12	-0.42	0.22
207	M Cycling (self) X Control, M Cycling (partner) X Control	0.00	-0.22	0.22
208	M Damping (self) X Control, M Cycling (partner) X Control	0.01	-0.32	0.33
209	M Cycling (self) X M Receives, M Cycling (partner) X Control	0.13	-0.09	0.35
210	M Damping (self) X M Receives, M Cycling (partner) X Control	0.06	-0.27	0.38
211	F Cycling (self), M Damping (partner) X Control	0.10	-0.24	0.42
212	F Damping (self), M Damping (partner) X Control	-0.01	-0.33	0.32
213	F Cycling (partner), M Damping (partner) X Control	-0.01	-0.32	0.30
214	F Damping (partner), M Damping (partner) X Control	-0.01	-0.34	0.31
215	F Cycling (self) X Control, M Damping (partner) X Control	-0.04	-0.36	0.27
216	F Damping (self) X Control, M Damping (partner) X Control	-0.02	-0.36	0.31
217	F Cycling (self) X M Receives, M Damping (partner) X Control	-0.04	-0.36	0.28
218	F Damping (self) X M Receives, M Damping (partner) X Control	0.01	-0.33	0.34
219	F Cycling (partner) X Control, M Damping (partner) X Control	-0.02	-0.34	0.30
220	F Damping (partner) X Control, M Damping (partner) X Control	-0.06	-0.39	0.28
221	F Cycling (partner) X M Receives, M Damping (partner) X Control	0.03	-0.29	0.35
222	F Damping (partner) X M Receives, M Damping (partner) X Control	0.03	-0.31	0.35
223	M Cycling (self), M Damping (partner) X Control	-0.04	-0.35	0.29
224	M Damping (self), M Damping (partner) X Control	-0.01	-0.35	0.32
225	M Cycling (partner), M Damping (partner) X Control	0.02	-0.29	0.33
226	M Damping (partner), M Damping (partner) X Control	-0.02	-0.35	0.30
227	M Cycling (self) X Control, M Damping (partner) X Control	-0.03	-0.34	0.29
228	M Damping (self) X Control, M Damping (partner) X Control	0.00	-0.34	0.33
229	M Cycling (self) X M Receives, M Damping (partner) X Control	-0.02	-0.33	0.30
230	M Damping (self) X M Receives, M Damping (partner) X Control	0.00	-0.33	0.33
231	M Cycling (partner) X Control, M Damping (partner) X Control	-0.04	-0.36	0.28
232	F Cycling (self), M Cycling (partner) X M Receives	0.12	-0.17	0.39
233	F Damping (self), M Cycling (partner) X M Receives	0.00	-0.33	0.33
234	F Cycling (partner), M Cycling (partner) X M Receives	-0.05	-0.33	0.22
235	F Damping (partner), M Cycling (partner) X M Receives	0.01	-0.31	0.32

Table 4: Correlations among Random Effects (*continued*)

	Correlation	Estimate	Lower	Upper
236	F Cycling (self) X Control, M Cycling (partner) X M Receives	0.08	-0.23	0.37
237	F Damping (self) X Control, M Cycling (partner) X M Receives	0.01	-0.32	0.33
238	F Cycling (self) X M Receives, M Cycling (partner) X M Receives	-0.02	-0.31	0.29
239	F Damping (self) X M Receives, M Cycling (partner) X M Receives	0.00	-0.33	0.33
240	F Cycling (partner) X Control, M Cycling (partner) X M Receives	-0.02	-0.32	0.28
241	F Damping (partner) X Control, M Cycling (partner) X M Receives	-0.02	-0.34	0.31
242	F Cycling (partner) X M Receives, M Cycling (partner) X M Receives	0.17	-0.15	0.46
243	F Damping (partner) X M Receives, M Cycling (partner) X M Receives	0.05	-0.27	0.35
244	M Cycling (self), M Cycling (partner) X M Receives	-0.02	-0.30	0.27
245	M Damping (self), M Cycling (partner) X M Receives	0.00	-0.33	0.33
246	M Cycling (partner), M Cycling (partner) X M Receives	-0.02	-0.31	0.27
247	M Damping (partner), M Cycling (partner) X M Receives	-0.05	-0.37	0.28
248	M Cycling (self) X Control, M Cycling (partner) X M Receives	-0.09	-0.37	0.21
249	M Damping (self) X Control, M Cycling (partner) X M Receives	0.01	-0.32	0.34
250	M Cycling (self) X M Receives, M Cycling (partner) X M Receives	0.01	-0.28	0.30
251	M Damping (self) X M Receives, M Cycling (partner) X M Receives	-0.01	-0.33	0.32
252	M Cycling (partner) X Control, M Cycling (partner) X M Receives	0.12	-0.19	0.41
253	M Damping (partner) X Control, M Cycling (partner) X M Receives	0.01	-0.32	0.34
254	F Cycling (self), M Damping (partner) X M Receives	-0.02	-0.34	0.29
255	F Damping (self), M Damping (partner) X M Receives	0.01	-0.32	0.34
256	F Cycling (partner), M Damping (partner) X M Receives	0.03	-0.28	0.33
257	F Damping (partner), M Damping (partner) X M Receives	-0.03	-0.36	0.30
258	F Cycling (self) X Control, M Damping (partner) X M Receives	0.09	-0.24	0.41
259	F Damping (self) X Control, M Damping (partner) X M Receives	0.00	-0.32	0.33
260	F Cycling (self) X M Receives, M Damping (partner) X M Receives	0.10	-0.24	0.41
261	F Damping (self) X M Receives, M Damping (partner) X M Receives	0.02	-0.31	0.34
262	F Cycling (partner) X Control, M Damping (partner) X M Receives	-0.06	-0.37	0.26

Table 4: Correlations among Random Effects (*continued*)

	Correlation	Estimate	Lower	Upper
263	F Damping (partner) X Control, M Damping (partner) X M Receives	0.00	-0.33	0.33
264	F Cycling (partner) X M Receives, M Damping (partner) X M Receives	0.02	-0.30	0.33
265	F Damping (partner) X M Receives, M Damping (partner) X M Receives	-0.14	-0.47	0.21
266	M Cycling (self), M Damping (partner) X M Receives	-0.03	-0.34	0.28
267	M Damping (self), M Damping (partner) X M Receives	0.00	-0.32	0.33
268	M Cycling (partner), M Damping (partner) X M Receives	0.03	-0.28	0.33
269	M Damping (partner), M Damping (partner) X M Receives	-0.02	-0.35	0.31
270	M Cycling (self) X Control, M Damping (partner) X M Receives	-0.04	-0.35	0.28
271	M Damping (self) X Control, M Damping (partner) X M Receives	0.00	-0.33	0.33
272	M Cycling (self) X M Receives, M Damping (partner) X M Receives	0.03	-0.28	0.34
273	M Damping (self) X M Receives, M Damping (partner) X M Receives	-0.01	-0.34	0.32
274	M Cycling (partner) X Control, M Damping (partner) X M Receives	-0.06	-0.37	0.26
275	M Damping (partner) X Control, M Damping (partner) X M Receives	-0.01	-0.34	0.31
276	M Cycling (partner) X M Receives, M Damping (partner) X M Receives	-0.03	-0.36	0.29
277	Residual Correlation	0.09	0.06	0.11

Note:

The support discussion in which the female partner received support (F Receives) is the reference group. Control refers to a dummy variable indicating differences between the control discussion and female recipient support discussion (Control = 1, F Receives = 0). M Receives refers to a second dummy variable indicating differences between the male recipient and female recipient support discussions (M Receives = 1, F Receives = 0).

Analysis of Between-Dyad Heterogeneity using Posterior Probabilities

We further assessed heterogeneity through the use of directional posterior probabilities. Directional posterior probabilities refer to the percentage of posterior sample values falling above or below a particular threshold. We reasoned that if a substantial percentage of posterior samples for the fixed/random ratio exceeds .25, this can be taken as further evidence for the extent of heterogeneity. For other work using this approach, see Zee et al. [-@Zee2020b]. Indeed, we found that the probability that the fixed/random ratio exceeded .25 ranged from 0.48 to 1, with a median probability of 0.99. Taken together, the random effect estimates revealed, with a high degree of certainty, that coregulation processes are heterogeneous. Within the population, some dyads can be expected to show patterns of coregulation that resemble the patterns found for the average dyad, but many dyads can be expected to show markedly different patterns.

Tests on Posterior Samples: Damping Parameters

In response to reviewer feedback, we also performed an equivalent analysis assessing the probability that all four damping parameter values fell below the mean damping value across discussions and parameters.

Results indicated that the probability that all four damping parameters per discussion were more extreme than the overall mean damping effect was 0.018 [0.016, 0.021] for the male recipient support discussion, 0.078 [0.074, 0.082] for the female recipient support discussion, and 0.002 [0.001, 0.002] for the control discussion. This indicated that the probability of all four damping parameters falling beyond this threshold was highest when the female partner received support. However, the probabilities were all low, suggesting it was highly *improbable* that all four parameter values fall beyond this threshold, in any experimental phase. Considering both the analysis using at least two of the damping parameters and the trajectories implied in the visualizations, the evidence pointed more heavily in favor of a damping process being the most likely to occur when the male partner received support.

Additional Tests on Posterior Samples

In addition to the test presented in the main text, we also conducted an additional examination of the model’s posterior distributions to understand patterns of effects across multiple parameters. Through simulation, we identified a possible pattern of cross-partner coregulatory influence involving the signs of the cross-partner cycling effects. As shown in Figure 6, these simulations suggested that the simultaneous presence of opposite-sign partner cycling (η_p) coefficients (one negative coefficient and one positive coefficient) can generate a pattern of *dysregulation*. Other parameter values being equal, these opposite-sign parameters push partners away from equilibrium, manifested as increasing amplitudes over time. Thus, a possible way of characterizing beneficial patterns of coregulation could be to assess whether there is a lower probability of opposite-sign partner cycling coefficients, or, put differently, by a *higher* probability of *same*-sign partner cycling coefficients.

We note that in conducting further simulations, we noticed that this pattern was more apparent in the context of larger partner cycling effects (in absolute terms), that fell beyond the range of our observed effects. This pattern was less clear for smaller partner cycling effects. Nevertheless, our analysis is reported here for transparency.

For each posterior sample, we coded whether the two partner cycling parameters (η_{px} , the male partner’s effect on the female partner; η_{py} , the female partner’s effect on the male partner) were both negative in sign, both positive in sign, or of opposite signs. We then computed a probability of these patterns of partner cycling effects across all posterior samples for each discussion. As noted above, a limitation of this approach is that it does not take capture the magnitude of the partner cycling effects or the relative size of these effects to each other.

There was a reliable difference between the male recipient support discussion and the other discussions. The probability of same-sign partner cycling coefficients was 0.72 during the male recipient support discussion, 0.65 during the female recipient support discussion, and 0.64 during the control discussion.

Breaking this down further, a similar pattern of results was found for the probability of both partner cycling coefficients being negative. The probability of same-sign partner cycling coefficients was 0.66 during the male recipient support discussion, 0.55 during the female recipient support discussion, and 0.21 during the control discussion.

Although somewhat difficult to interpret because the patterns may depend on the overall magnitude of the effects and other parameter values, the results from this analysis were generally in line with those discussed in the main text: The probability of more beneficial patterns of coregulation occurring appeared to be higher during the support discussion when the male partner received support, and lower during the control discussion and female partner’s support discussion.

Figure 6: Simulated system trajectories when partner cycling coefficients are of opposite sign (left panel), both negative (middle panel), and both positive (right panel), and starting values are below equilibrium, all other coefficients equal across plots. For purposes of illustration, partner cycling effects = $|0.06|$. The remaining parameter values are set to the values of the fixed effects from the control discussion for all plots.

Latent Profile Analysis

To better understand between-dyad heterogeneity in our results, we conducted a latent profile analysis at the suggestion of a reviewer. We entered dyad-specific values for each of the 24 model parameters, specifying three latent profiles; the choice of three latent profiles was based on the lowest resulting BIC estimate, a type of model fit statistic where lower values indicate a better fitting model [Masyn2013]. This generated parameter values for each of the three latent profiles, and we used these values to visualize predicted trajectories. We used common start values (the mean observed initial IBI values for each partner for each phase, the same start values used in our visualization of the fixed effects) in order to more clearly examine differences in trajectories identified in the latent profile analysis.

The resulting profiles are displayed in the figure below. Based on visual inspection, the three profiles seem to reflect the following patterns:

Profile 1: Partners showed relatively synchronous patterns of fluctuations (except during the female recipient support discussion) but relatively weak cross-partner influence, indicated by consistent patterns of cycling and damping over time, with few alterations to amplitudes.

Profile 2: Both the male partner and female partner seemed to have a pronounced effect on each other's responses during the support discussions, indicated by varying amplitudes and frequencies in each partner's trajectories.

Profile 3: The male partner's responses had a particularly pronounced effect on the female partner's responses, indicated by varying amplitudes and frequencies in the female partner's trajectories, but the female partner appeared to have relatively little influence on the male partner's trajectories.

Figure 7: Predicted coregulation trajectories for three types of dyads revealed through latent profile analysis. Results for the typical female partner are displayed in red, and results for the typical male partner are displayed in blue. The horizontal line at IBI = 0 indicates baseline IBI for each partner. F Receives Support = support discussion in which female partner received support. M Receives Support = support discussion in which male partner received support.

Results of Analysis Using Data from Heterosexual Couples Only

We conducted a version of our analysis in which data from non-heterosexual couples was excluded ($n = 81$ heterosexual couples, vs. $n = 92$ couples for the full analytic sample). Coregulation trajectories for each partner are visualized below, and predictions from the two models are overlaid to facilitate comparison.

Results for the typical female partner are displayed in red (full sample) and gray (heterosexual sample only), and results for the typical male partner are displayed in blue (full sample) and black (heterosexual sample only). As can be seen by the high degree of overlap in corresponding pairs of lines, removing the non-heterosexual couples from the sample did not change our conclusions. Thus, we retained all couples with available data in our main analysis. Unfortunately, where was insufficient data to test for explicit differences between heterosexual vs. non-heterosexual couples. Nevertheless, panel plots illustrating model predicted trajectories for four example non-heterosexual dyads are provided on a following page.

Figure 8: Comparison of results for the typical couple from a model including all couples (red and blue lines) vs. a model including heterosexual couples only (black and gray lines). Results for the typical female partner or Partner A are displayed in red (full sample) and gray (heterosexual sample only), and results for the typical male partner or Partner B are displayed in blue (full sample) and black (heterosexual sample only). The horizontal line at $IBI = 0$ indicates baseline IBI for each partner. F Receives Support = support discussion in which female partner received support. M Receives Support = support discussion in which male partner received support.

Panel Plots - Non-heterosexual Couples

Figure 9: Panel plots illustrating model predicted trajectories for four example non-heterosexual dyads (rows), across discussions (columns). X-axes show discussion duration (5 minutes). Y-axes have been scaled on a per-dyad basis for clarity of presentation. Partner A (arbitrarily assigned) is shown in purple, and Partner B (arbitrarily assigned) is shown in dark green. The horizontal line at $IBI = 0$ indicates baseline IBI for each partner. Partner A Receives = support discussion in which Partner A received support. Partner B Receives = support discussion in which Partner B received support.

Gender Differences in Issues Discussed during Support Discussions

In exploratory analyses, we examined whether, on average, male and female partners differed in how they felt about the issues they chose to talk about during the support discussions.

Before the start of the support discussions, participants provided a brief description of their issue and indicated how negative they felt about it (1 = *Not at all*, 7 = *Extremely*; 5 items, $\alpha = .78$). Female participants reported feeling more negative about their issue compared to male participants, $b = 0.54$, 95% CI [0.20, 0.89].

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