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Staying Together: A Bidirectional Delay–Coupled Approach to Joint Action

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Abstract

To understand how individuals adapt to and anticipate each other in joint tasks, we employ a bidirectional delay–coupled dynamical system that allows for mutual adaptation and anticipation. In delay–coupled systems, anticipation is achieved when one system compares its own time-delayed behavior, which implicitly includes past information about the other system's behavior, with the other system's instantaneous behavior. Applied to joint music performance, the model allows each system to adapt its behavior to the dynamics of the other. Model predictions of asynchrony between two simultaneously produced musical voices were compared with duet pianists' behavior; each partner performed one voice while auditory feedback perturbations occurred at unpredictable times during live performance. As the model predicted, when auditory feedback from one musical voice was removed, the asynchrony changed: The pianist's voice that was removed anticipated (preceded) the actions of their partner. When the auditory feedback returned and both musicians could hear each other, they rapidly returned to baseline levels of asynchrony. To understand how the pianists anticipated each other, their performances were fitted by the model to examine change in model parameters (coupling strength, time-delay). When auditory feedback for one or both voices was removed, the fits showed the expected decrease in coupling strength and time-delay between the systems. When feedback about the voice(s) returned, the coupling strength and time-delay returned to baseline. These findings support the idea that when people perform actions together, they do so as a coupled bidirectional anticipatory system.

Keywords: Synchronization; Interpersonal coordination; Dynamical systems

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1. Introduction

Human behaviors such as conversational speech and ensemble music demonstrate fine-grained temporal coordination between individuals, during which they anticipate and adapt to each other (Repp & Su, 2013). Coupled nonlinear dynamical systems provide a possible physical mechanism for how this occurs (Haken et al., 1985; Stepp, 2009; Stepp & Turvey, 2010, 2015). Ensemble music performance is an ideal domain for examining the mechanisms of coordination between individuals (Demos et al., 2017; Goebl & Palmer, 2009; Wing et al., 2014). To achieve synchronization or simultaneity of the resulting sound, musicians rely on both the auditory outcomes of their own actions and those of their partner's actions to adapt to and anticipate each other (Loehr & Palmer, 2011; Palmer, 2013; van der Steen & Keller, 2013). We take the perspective that partners form a bidirectional dynamical system in which they share information through acoustic events (Demos et al., 2012, 2017). To instantiate this, we employ a dynamical systems model that allows for the adaptation between individuals through mutual anticipation of temporal events. We compare the model's predictions with how pianists who are skilled at achieving tight synchronization in the presence of temporal fluctuations perform together during auditory feedback perturbations (implemented as the removal and return of sound) to test how people adapt to and anticipate each other's actions.

The dynamical systems explanation for how two people might anticipate each other is based on the principles of physics-based models, which require that the systems be coupled, that is, transfer information between individuals (Haken et al., 1985; Kugler & Turvey, 1987; Pikovsky et al., 2001; Schuster & Wagner, 1989). Model simulations of unidirectionally coupled systems can generate adaptation and anticipatory behaviors when a driver system (master) is coupled with a driven system (slave) (Stepp & Turvey, 2010; Voss, 2000). In these coupled driver-driven systems, anticipation occurs by the driven system comparing its time-delayed self-feedback with instantaneous feedback from the driver system (Stepp & Turvey, 2010).

Empirical studies on unidirectional anticipatory behavior in human perceptual–motor synchronization tasks such as visual target-tracking and pendulum swinging have shown that participants tend to anticipate (get ahead of) a master (driver) system (Stepp, 2009; Washburn et al., 2017). When participants tracked a visual dot moving chaotically on a computer screen, only after a perceptual–motor delay was added between the movement of the participants' hand and the resulting movement of their computer marker was their synchronization anticipatory (Stepp, 2009). This anticipatory behavior is a type of strong anticipation (Dubois, 2002; Stepp & Turvey, 2010; Washburn et al., 2017) in which the driven system's anticipation is derived by comparing its time-delayed self-feedback, which is partly driven by the master (driver) system, with instantaneous feedback from the driver's system. This differs from cognitivist approaches which adopt a weak anticipation perspective (Dubois, 2002; Stepp & Turvey, 2015), in which anticipation is based on an internal model of the environment (van der Steen & Keller, 2013). While strong anticipation has been modeled with delay–coupled oscillator models (Stepp & Turvey, 2010; Voss, 2000, 2001), weak anticipation has been implemented in linear regression equations for phase and period error correction (van der Steen & Keller, 2013; Vorberg & Schulze, 2002; Vorberg & Wing, 1996; Wing et al., 2014). Empirical work has demonstrated strong anticipation in visual–motor bidirectional coupling tasks (Washburn et al., 2015). As in Stepp (2009), participants were required to coordinate a visual dot with a master dot and engage in circle drawing, but this time they had to coordinate their moving dot with a human partner, who was designated as the producer (i.e., master/driver). The coordinating (driven) partner showed more anticipation of the producer (master) when perceptual delays were added, demonstrating that in bidirectional (asymmetric) visuo–motor master–slave systems, anticipatory synchronization can occur.

In contrast to previous studies of strong anticipation, the primary mode of perceptional–motor coupling in music performance is in the auditory (rather than visual) domain. Movement synchronization with an external rhythmic cue has been shown to be superior in speed and accuracy for auditory than for visual stimuli, even when the temporal regularity is controlled across stimulus modalities (Repp & Penel, 2002, 2004; see Comstock et al., 2018, for review). Both in the presence and absence of visual cues to their partner's actions, ensemble musicians can maintain synchrony, measured by musical tone onsets, within tens of milliseconds (Palmer et al., 2019). We model the anticipatory nature of performers' musical tone onsets, which are event-driven (non-continuous) measures of performance synchrony that have been the focus of coordination models of string ensembles (Wing et al., 2014), vocal ensembles (Palmer et al., 2019), and piano duets (Goebl & Palmer, 2009). Another distinction from previous studies of strong anticipation is a focus on skilled performers: Experienced musicians show greater synchronization than novices when tapping with a regular (driving) metronomic cue, and experienced musicians tend to anticipate the cue less than inexperienced musicians (Repp & Su, 2013). Unlike the participants in circle drawing tasks (Stepp, 2009; Washburn et al., 2015), musicians commonly practice for many years in order to improve their synchronization skills. We propose to account for this fine auditory–motor synchronization with a mutual anticipation and adaptation model (MAAM) that generates predictions tested in an experiment on joint action in music performance. First, we describe the model and simulations; then we describe the experiment and MAAM model fits of musicians' responses to bidirectional and unidirectional perturbations during duet performance.

2. Mutual anticipation and adaptation model

A previously existing unidirectional model that accounts for anticipation is described by the generalized Eq. 1, where x describes the driver and y describes the driven system (Stepp & Turvey, 2010). Model simulations showed anticipatory behavior when a driver chaotic system, based on a Rössler system, was coupled with a driven simple harmonic oscillator (Stepp & Turvey, 2010). The harmonic oscillator was coupled to its driver using delay coupling (Pyragas, 1992), which is based on coupling strength and time–delay parameters. Whereas the driver oscillator receives no feedback (information about the partner system), the driven oscillator receives the instantaneous state of the driver, which is compared through an error term ($x - y_\tau$) to its own state at a specific time-delay. The time-delay (τ) affects the degree of anticipation of the driven system to the driver. The coupling (k) controls the settling time, that is, how long it takes the driven system to reach a stable amount of anticipation (which is often τ) relative to the driver.

$$\begin{aligned} \dot{x} &= f(x) \\ \dot{y} &= f(y) + k(x - y_\tau) \end{aligned} \tag{1}$$

In Eq. 1, the function $f(x)$ defines the uncoupled behavior of the system and can be chosen so that the time response of the differential system $\dot{x} = f(x)$ is oscillatory. In Eq. 1, y_τ is defined as the delayed state, $y(t - \tau)$, where τ is the amount of delay (in time) and t is the current time, and k is the coupling matrix between the two oscillators/systems. The term $k(x - y_\tau)$ generates the delayed-feedback. The degree of anticipation (i.e., how much the driven system precedes the driver) thus depends on the parameters of time-delay, τ, and coupling strength, k, and the underlying driver system chosen, $f(x)$ (for example a chaotic oscillatory Rössler system).

For many human joint action tasks, such as music performance, conversational speech, or team sports, we cannot always label one person as driver and the other as driven, because either the driver and driven parts are not easily recognizable in such systems or because they switch their roles as driver or driven systems, yielding conditions that might generate mutual anticipation. To resolve this problem (Driessen et al., 2011; Schuster & Wagner, 1989), another delay–coupling to the driver system from Eq. 1 was added to create Eq. 2:

$$\begin{aligned} \dot{x} &= f(x) + k_1(y - x_{\tau_1}) \\ \dot{y} &= f(y) + k_2(x - y_{\tau_2}) \end{aligned} \tag{2}$$

This new system is bidirectional because both components, x and y, are delay–coupled, which allows them to share information. In short, Eq. 2 creates a model in which mutual anticipation results in each component adapting its behavior to the dynamics of the other component. The degree of adaptation is influenced by each coupling term k_1 and k_2 that can be determined independently, thus making them either equally coupled (both are equal driver and driven) or unequally coupled (both are driver and driven, but one is more of a driver). The bidirectional system can be converted back to a unidirectional system by setting $k_1 = 0$ or $k_2 = 0$. In addition, the delays for each system (τ_1 and τ_2) can vary, allowing each system to anticipate each other to different degrees. This allows for the simulation of more natural, complex relationships between people engaged in joint action, in which one person might drive more than the other, but both partners are still adapting to one another.

We propose here a simple form of the model in which the same phase dynamics of a constant velocity harmonic oscillator are used for both $f(x)$ and $f(y)$, consistent with the assumptions of other delay–coupled models (Driessen et al., 2011; Washburn et al., 2015). The constant velocity harmonic oscillator was chosen to better understand the behavior of the model analytically,[1] and to allow comparisons with previous models. The experimental materials and task mirrored this simplifying assumption by examining natural coordination in rhythmically simple (isochronous) musical passages. Performances of more complex musical forms (Demos et al., 2016, 2018) might require a more complex oscillator (Large, 1996), a focus for later study.

We term Eq. 3 the Mutual Anticipation and Adaptation Model (MAAM) and report the model in terms of phase, $\dot{\theta}_1$ of each of the two systems. In Eq. 3, θ_1 and θ_2 denote the phase of the two oscillators and $\dot{\theta}_1$ and $\dot{\theta}_2$ denote the rate of phase change in time. Instantiating the model in phase and using simple matched harmonic oscillators will allow us to simulate pianists' behavior.

$$\begin{aligned} \dot{\theta}_1 &= \omega_1 + k_1(\theta_2 - \theta_{1,\tau_1}) \\ \dot{\theta}_2 &= \omega_2 + k_2(\theta_1 - \theta_{2,\tau_2}) \end{aligned} \tag{3}$$

2.1. MAAM predictions

Next, the dynamical predictions from the MAAM model simulations were generated for comparison with performance timing data collected from pairs of pianists who attempted to perform together synchronously. Simulation procedures were designed to mirror the experiment with pianists, depicted in Fig. 1. Each of the pianists performed a single musical voice or part (which we refer to as upper and lower voice) as they sat next to each other: The performer playing the upper voice (left of each box in Fig. 1), the melody, was told he or she would set the initial pace or tempo (thus assuming the driver role). In the experiment, auditory feedback resulting from one or both performers' actions (indicated by arrows in Fig. 1) was unpredictably removed from both partners' noise canceling headphones for a short period (called the perturbation window) and returned unpredictably (called the recovery window), to examine how synchronization changed. To mirror these periods in the model, we allow the model's coupling parameters to change as the model simulated the tone onset times of each performer during perturbation and recovery windows.

2.2. Model simulations

2.2.1. Simulation predictions

We examine asynchrony predictions (not phase measurements) of the model based on a logical set of parameters. Asynchrony is defined as the time of system 1's response minus time of system 2's response (i.e., upper voice − lower voice in milliseconds). Thus, asynchrony indexes how much one system is ahead of the other in time, which can later be compared with pianists' observed asynchrony of tone onsets. For a systematic set of simulations designed to address the effect of each parameter in Eq. 3, see Fig. S2 and Table S2 in Supporting Information.

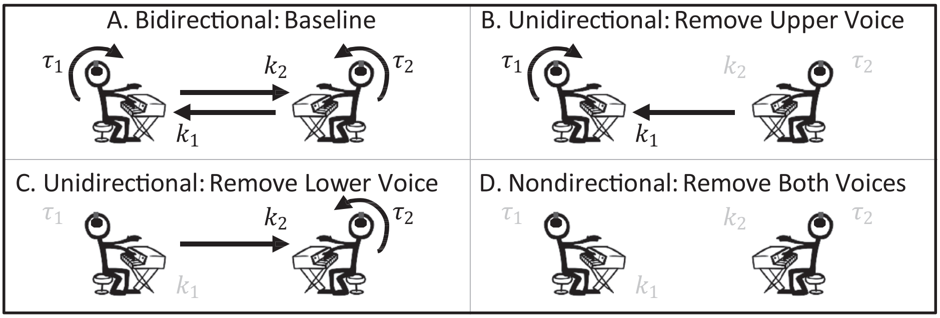

Fig. 1. Depiction of mutual anticipation/adaptation model applied to duet music performance, based on auditory feedback removal (arrows) affecting coupling (*k*) and time delay (τ) factors. Driver system expected to show reduced coupling and time delay in absence of feedback. (A) Full auditory feedback (mutual driver/ driven); (B) removal of upper voice feedback (driver = lower voice); (C) removal of lower voice feedback (driver = upper voice), (D) removal of both voices' feedback (no driver). Note: Pianists were sitting side by side on the same piano during the experiment.

2.2.2. *Frequency of each oscillator, ω*

We assume that, in the context of a joint (duet) performance, two musicians attempt to perform at the same frequency, but there may be natural frequency differences between them, such that one tends to play slightly faster than the other, consistent with empirical findings of frequency differences ($\omega_1 - \omega_2$) between performers that influence synchronization (Loehr & Palmer, 2011; Zamm et al., 2016). For desynchronization to occur, we assume a slight difference between the voices, and the oscillator frequencies were set to $\omega_1 = 2\pi/250$, $\omega_2 = 2\pi/251$ rad/ms (larger values are faster).

2.2.3. *Delay and coupling,* k, *τ*

We assume an asymmetrical relationship in the degree of delay–coupling between the performers because one part or voice of joint performance can be more important than other parts (Palmer & van de Sande, 1993). As we instructed in our study that the pianist performing the upper voice sets the pace of the performance, we assume the performers will show an asymmetry in anticipation. This asymmetry between the parts can be accomplished in different ways. Either the upper voice can be less strongly coupled to the lower voice, that is, $k_1 < k_2$, or the delay term can be smaller for the upper voice than for the lower voice, that is, $\tau_1 < \tau_2$. For simplicity, we assume moderate and equal coupling, $k_1 = k_2 = 2.5$, and we set $\tau_1 = 10$ ms and $\tau_2 = 20$ ms to account for the predicted anticipation. These values create a scenario in which performers mutually anticipate each other, but the pianist performing the lower voice anticipates the upper voice more.

The model's simulations were applied to four hypothetical musical duet synchrony conditions in which auditory feedback was removed from no voices (Baseline), from one voice (Unidirectional; upper or lower), or from both voices (Non-directional) of the duet performance as heard by both musicians. The results of the model simulations in Fig. 2A are described next.

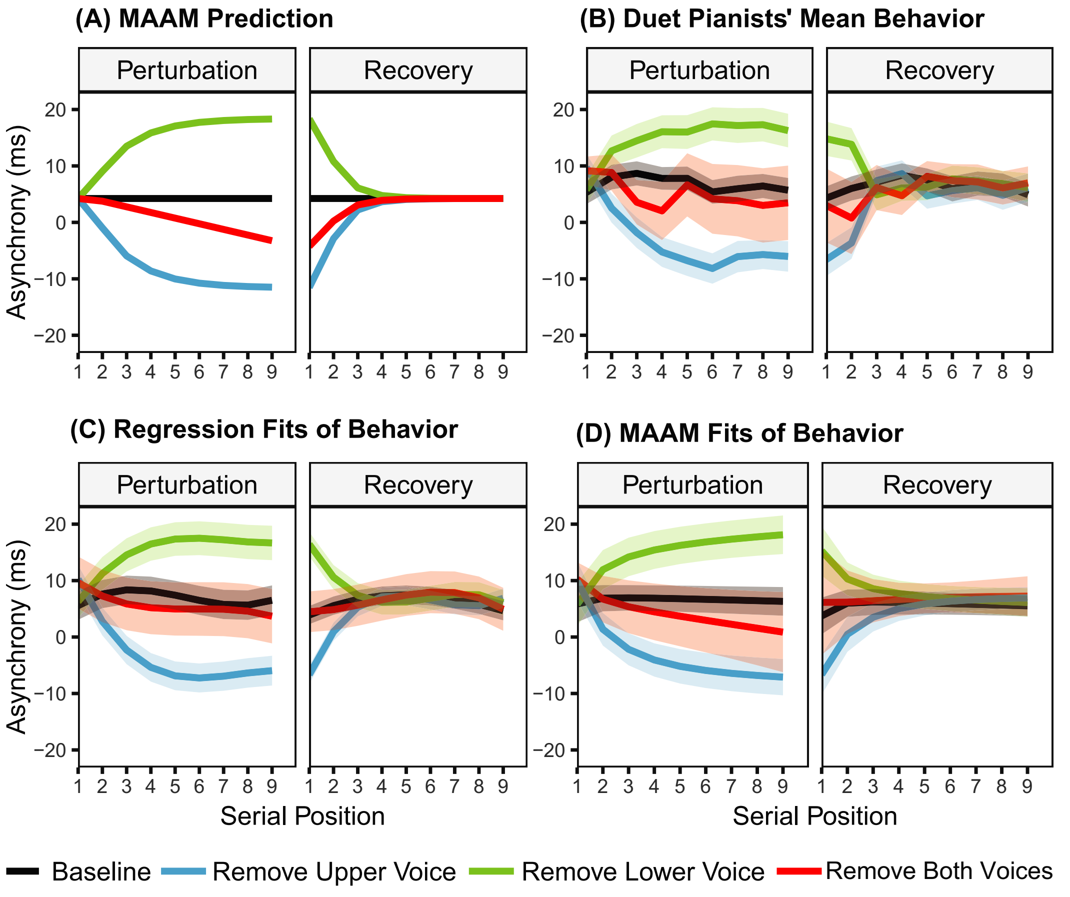

Fig. 2. Each panel shows the asynchronies (Upper–Lower Voice) by auditory feedback condition, window of feedback (Perturbation/ Recovery), and serial position (first nine notes). Panel (A) shows the MAAM simulated values (prediction). Panel (B) shows the mean results from duet pianists (behavior). Panel (C) shows mixed regression fits of duet pianists' behavior (statistical fit). Panel (D) shows the MAAM fits to experimental values. Ribbons in (B)–(D) represent two standard errors on each side of the mean.

2.3. *Methods*

Although MAAM is defined for continuous oscillators, it can also be applied to discrete periodic phenomena. To simulate tone onset times when keys are struck on a piano keyboard, we assigned discrete times whenever the simulated oscillator reached a fixed phase in its cycle (specifically, $\theta = 0°$ on a circle). The MAAM simulation requires the setting of three parameters (ω, k, τ) for each of the two systems, for a total of six parameters.

We set a constant-velocity (harmonic) oscillator to represent the underlying phase dynamics of each pianist's part. Although nonlinear oscillators are most likely a better estimation of the underlying dynamics of the human motor system, the model's behavior is more easily understood using harmonic oscillators.

2.3.1. Simulation procedure

The model's behavior was examined in two time windows in the musical sequence (using specific parameter values defined below). After letting the model reach a stable phase, a perturbation window was initiated by changing the coupling parameter (k) for a fixed number of tones (n = 9, corresponding to the maximal window length of perturbed sequence events presented in each trial) beginning at the point where the pianists' auditory feedback was to be removed. Next, to initiate a recovery window, the coupling parameter (k) was reset to allow the model to return to a new stable state for another fixed number of musical tones (n = 9) beginning at the point where the pianists' auditory feedback was to be returned. The coupling (k) between each system of Eq. 3 was manipulated during the perturbation windows in four different conditions: In the full coupling (baseline) condition, we introduced full auditory feedback, meaning there was no change in the coupling parameters during the simulation. Next, we tested a unidirectional condition by setting one system to have no coupling ($k = 0$), but the other coupling parameter remained unchanged (either lower- or upper-voice auditory feedback was removed). Finally, we perturbed both coupling parameters in a non-directional condition by setting them to $k = 0$ (both lower- and upper-voice auditory feedback was removed).

2.4. Results

2.4.1. Bidirectional (Baseline)

As seen in Fig. 2A, the lower voice anticipated (preceded) the upper voice. The initial stable asynchrony (serial position 1 of the perturbation window in the Baseline) was +4.32 ms. This initial asymmetry between the equally coupled voices was the result of the imbalance in delay parameters and difference in frequencies.

2.4.2. Unidirectional (Remove upper voice)

Feedback from the simulated upper voice was removed, which should force the lower voice to become the driver and the upper voice to become the driven system (i.e., $k_1 = 2.5$ and $k_2 = 0$), while the other parameters remained unchanged from the baseline. The upper voice now must do all the adaptation, and the asynchrony values switch from being positive to negative, which show that the lower voice is now the driver, as expected.

2.4.3. Unidirectional (Remove lower voice)

Feedback from the simulated lower voice was removed, which should force the upper voice to become the driver and the lower voice to become the driven system (i.e., $k_1 = 0$ and $k_2 = 2.5$), while the other parameters remained unchanged from the baseline. The lower voice is now the only voice adapting, and it anticipates the driver even more than in the baseline condition, which is shown by the asynchrony increasing from +4.23 to a maximum of +18.36 ms.

2.4.4. Non-directional (Remove both voices)

When both systems were perturbed, neither can adapt (i.e., $k_1 = 0$ and $k_2 = 0$) so they revert to their natural frequencies (ω_1, ω_2) in the absence of feedback from the other system. The asynchrony decreases linearly from 4.23 to −1.70 ms, a reflection of their intrinsic frequency difference (ω_1 is faster than ω_2).

2.5. Discussion

Simulation of perturbations to the MAAM model from bidirectional coupling to unidirectional coupling resulted in the expected change: The driven system anticipated the driver. The degree to which one system anticipated the other was related to the time-delay parameter (τ), and the trajectory (slope) after the perturbation began toward its stable rate of anticipation (see Figs. S1 and S2), as determined in part by the coupling parameter (k) and the difference in frequencies ($\omega_1 - \omega_2$). Differences in these parameters across systems also create differences in the initial amount of asynchrony between the systems (see Fig. S2 and Table S2 for impact of each parameter). In short, these three parameters allow the model to predict that there will be a change in asynchrony between the performers when one or more systems are perturbed. We test these model predictions (Fig. 2A) next in duet pianists' behavior by perturbing one or more systems with auditory feedback removal.

3. Piano duet experiment

3.1. Method

3.1.1. Participants

Thirty-two adult pianists with at least 10 years of piano experience (*M* years of private piano instruction = 13.22, *SD* = 5.06) were recruited from the Montreal music community. A screening task first required participants to play the musical piece with notation available twice without error, to ensure they were familiar with the music; all participants passed the screening task. Fifteen of the randomly matched pairs had never seen/meet their partner prior to the experiment; one pair said they had met but did not know each other.

3.1.2. Equipment

Pianists performed on a digital stage piano with weighted keys (Roland RD-700) for both solo (alone) and duet (side-by-side) performances at the same piano. Participants received auditory feedback about their performance and that of their partner through Bose QuietComfort 20 Acoustic Noise Canceling headphones (in ear). Pianists wore noise-canceling in-ear headphones to prevent sound from their partners' keypresses. Piano (GM2-001, no reverberation) and metronome (GM2-232) sounds were generated by a Roland Mobile Studio Canvas Sound Module (SD-50). The FTAP program (Finney,

2001) was used to generate auditory feedback and to record the MIDI keystroke timing with 1 ms resolution on a Linux (Fedora) computer (Dell T3600).

3.1.3. Stimulus materials

The musical stimulus was based on a modified excerpt of the opening section from K275/K300e, 12 variations on "Ah, vous dirai-je, Maman" by W. A. Mozart (1781) that consisted entirely of eighth notes performed by both hands, to render the stimulus rhythmically isochronous, as seen in Fig. 3. The excerpt was notated to be performed in repetition. Participants were sent the music notation prior to the experiment and were asked to practice it with the indicated fingering and tempo.

Sections in the musical stimulus during which the auditory feedback was removed (9–12 or 17–20 notes long) are referred to as perturbation windows, and sections immediately following the perturbation windows during which auditory feedback was restored (13–16 notes long) are called recovery windows. Perturbation windows were placed pseudo-randomly in different locations across the trials to make sure no specific location was overrepresented, and with the additional rule that the perturbation windows could not begin in the first bar of the musical excerpt.

3.1.4. Design

The study used a within-subjects design with independent variables of auditory feedback manipulation (baseline [full sound], remove upper voice, remove lower voice, remove both voices), length of feedback removal (short or long), and window of feedback (perturbation or recovery). The study occurred in two parts: The Solo setting was always followed by a Joint setting. In the Solo setting, each person performed the experiment alone by playing both voices of the musical piece using two hands. In the Joint setting, each person was assigned to perform one voice of the musical piece (upper or lower voice). Halfway through the Joint setting, the partners switched upper/lower voices (and hands). The order of voice/ hand assignment within the joint performances was counterbalanced across subjects.

The auditory feedback heard by pianists over headphones was manipulated during the perturbation windows in four different conditions: In the full sound (baseline) condition, pianists heard the auditory feedback associated with their keystrokes (no change). In the remove upper voice condition, auditory feedback from the upper voice was removed from both partners' headphones. In the remove lower voice condition, feedback from the lower voice was removed from both headphones. In the remove-both-voices condition, feedback from both voices was removed from both headphones. The stimulus locations within the perturbation windows at which an auditory feedback manipulation occurred differed in each performance, and equal numbers of perturbations began on strong and weak metrical beats across all trials.

The order of conditions was fixed: Solo performances (1 block of trials) preceded Joint performances (2 blocks of trials). Each trial contained 6 perturbation-recovery windows for each of the feedback removal conditions (upper voice, lower voice, both voices), and 12 "perturbation-recovery" windows from the full-sound condition (matched for stimulus

Fig. 3. Modified version of "Ah, vous dirai-je, Maman" by W. A. Mozart with fingerings and tempo as provided to the participants.

location), yielding a total of 36 perturbation/recovery window pairs per block. The order of presentation of the three feedback removal conditions (upper voice, lower voice, both voices) and their lengths were pseudo-randomly ordered and distributed evenly across the experimental trials for each pair, with the constraint that no two window lengths repeated. Thus, the type of feedback removal could not be associated with a particular stimulus location.

3.1.5. Procedure

Solo trials: Upon arrival, participants completed consent forms and individually completed the solo performance setting, while their partner waited outside (unable to hear or see their partner). Each participant performed the Solo trials which were cued by a 600-ms quarter-note metronome for four beats at the beginning of each trial. Participants were instructed to repeat the music three times (for four times total) without pausing in each trial until they were cued by a cymbal sound that the trial had ended. The participants completed two solo trials with full auditory feedback, without pitch errors. Following these trials, participants performed four additional solo trials that contained auditory feedback perturbations. If pianists made a pitch error during the manipulation of auditory feedback, they began the same trial again and were given two additional opportunities to complete it.

Joint trials: Participants were assigned randomly to the left or right end of the piano keyboard, sitting side by side. The person sitting on the right side was asked to play the upper-frequency voice with their right hand and the person sitting on the left side was asked to play the lower-frequency voice with their left hand. The participant playing the upper voice was informed that they were in charge of maintaining the pace after the 4-beat 600-ms quarter-note metronome cue stopped at the beginning of each trial. Participants were instructed to repeat the music three times (for four times total) without pausing in each trial until they were cued by a cymbal sound that the trial had ended. The Joint performance conditions followed the same order of trials as the Solo condition: First, there were two performances with full auditory feedback and then four performances containing auditory feedback removal. After the first assignment of performer to voice (upper/lower voice) was completed in the joint condition, the participants swapped positions and the entire set of joint conditions was repeated, with the order of the trials changed and the feedback removal type again pseudo-randomly ordered. The entire experiment lasted about 90 min and pianists received $20 for their participation.

3.2. Data analysis

3.2.1. Performance errors

Because pitch errors (deletions, additions) can alter the relationship between the number of produced events and the number of auditory feedback events delivered, they were removed from analysis. If a pitch error occurred within a perturbation window, both performers' voices were removed from analysis for the perturbation window and the corresponding recovery window. If a pitch error occurred only within a recovery window, only that recovery window was removed from analysis. These resulted in loss of 18.84% of data for solo (two-handed performance); 10.24% for joint (one-handed performances).

3.2.2. Asynchronies

The asynchronies in tone onsets were defined as "upper voice onset – lower voice onset" for tones notated as simultaneous in the musical score. Asynchronies larger than three standard deviations from the mean asynchronies in the remove-both-voices auditory feedback condition (the most difficult condition) were excluded from all conditions (0.054% for Joint; 0.59% for Solo). The asynchronies were then averaged across trials within auditory feedback, serial position, and window of feedback.

3.2.3. Baseline measures

To compare asynchronies during feedback removal conditions with those during normal feedback (Baseline condition with full sound), the Baseline trials (each with 4 repetitions) were divided into 12 windows of feedback (perturbation/recovery) that matched the stimulus locations of the windows in the auditory feedback removal conditions.

3.2.4. Mixed regression models

We used mixed models to examine the effects of auditory feedback perturbations on the asynchronies (Singer & Willett, 2003) using the lme4 version 1.1-8 package in R (Bates et al., 2015). The analysis was conducted separately for the solo and joint settings.

The following fixed-effect variables were dummy coded: auditory feedback condition (full sound; removal of upper, lower, or both voices), length of feedback removal (short or long), and window of feedback (perturbation/recovery). Serial position was entered as a fixed-effect (orthogonal polynomial) continuous factor (Mirman, 2016). The fixed-effects structure was constructed hierarchically through the addition of increasingly complex terms, and deviance tests (−2 log likelihood) were used to ensure that increasingly complex terms were warranted. The random-effects structure for each model, following the procedures of Barr et al. (2013), was constructed to include auditory feedback condition (full sound, removal of upper, lower, or both voices), length of feedback removal (short or long), window of feedback (perturbation/recovery), and serial position and reduced in complexity until the models would converge. The random variables in the solo conditions were analyzed relative to each participant; the random variables in the joint conditions were analyzed relative to the participant playing the upper voice (role was nested within pair), to account for differences due to assignment of individual to musical voice. We employed a two-step significance testing process for the fixed effects: First, to assess whether the model was an improved fit and then to assess the significance of individual predictors as *z*-values (Barr et al., 2013). We examined the asynchronies during the short and long perturbation/recovery windows for the first nine serial positions (the maximal window length across all conditions), to directly compare the initial degree of disruption and the return to baseline synchrony.

3.2.5. Statistical testing

We ran forward-fitted mixed-effect regression to test the differences between the auditory feedback (A), window of feedback (W), length of feedback removal (L), and third-order orthogonal polynomials: linear (S1), quadratic (S2), and cubic terms (S3) of serial position (Mirman, 2016). In Tables 1 and 2 we report the incremental models and their deviance tests to determine the best fitting model, analysis applying to capture the curvilinear changes in asynchrony over the serial positions in the perturbation windows.

3.3. Results

3.3.1. Solo performances

Fig. 4 presents the mean asynchrony values (tone onset times for upper − lower voice) by auditory feedback condition in the solo performances for the first nine serial positions in the Perturbation and Recovery windows within the music performance. Table 1 shows that the fixed effects of auditory feedback condition and window of feedback explained the variance above and beyond the random factors (Regression model 1.1); however, the asynchronies in the recovery windows were not different from the perturbation windows, and the altered auditory feedback conditions did not differ from the baseline condition (t's $< |1.4|$). The model fitting procedure indicated that the auditory feedback perturbations had no effect on the asynchronies between the hands of a single performer; the mean asynchrony across all conditions was $M = 2.12$ ms, $SD = 12.10$. Thus, the auditory

Table 1
Hierarchical mixed regression comparisons for asynchronies of solo performances

Model Comparison	Change in DF	Deviance	χ^2	p
Regression 1.1		29,589	10.527	.032
Regression 1.2 [vs. 1.1]	+1	29,589	0.0589	.8081
Regression 1.3 [vs. 1.1]	+5	29,584	4.932	.2943
Regression 1.4 [vs. 1.1]	+3	29,588	0.7828	.8536
Regression 1.5 [vs. 1.1]	+5	29,586	3.045	.693

Note. Regression 1.1 = A + W
Regression 2.2 = A + W + L
Regression 3.3 = A + W + L + A × L
Regression 4.4 = A + W + A × W
Regression 5.5 = A + W + A × W + S^1 + A × S^1

perturbations did not result in a change to the driver/driven system in solo performance from the baseline condition, where the same individual controls both parts.

3.3.2. *Joint performances*

Fig. 2B presents the mean asynchrony values (upper − lower voice) by auditory feedback condition in the duet performances for the first nine serial positions in the Perturbation and Recovery windows within the music performance. The duet performances showed that the removal of auditory feedback from either voice increased the asymmetry (i.e., the asynchrony values relative to the Baseline condition became larger). When auditory feedback was removed from one performer, the asynchrony changed in direction so that the performer whose feedback was removed anticipated the timing of their partner (i.e., became the driven system). When both voices were removed (Non-directional condition), the mean asynchrony values changed only slightly, likely due to averaging across negative and positive asynchrony values; this interpretation is supported by the standard error bar around the mean asynchronies values, shown in Fig. 2B. When auditory feedback was returned during the Recovery window of Fig. 2B, asynchrony values returned quickly to baseline levels in all conditions.

As seen in Fig. 2B, the duet performance asynchronies show a curvilinear change at the onset of the perturbation window, and another curvilinear pattern at the onset of the recovery window. To test the change statistically, we included in a regression model the serial position main effects and interactions, in linear, quadratic, and cubic functions. The best fitting statistical model in shown in Fig. 2C and can be found in Table 2. The individual parameter fits from the regression model for each window of feedback are shown in Table 3. Similar to both the model simulations (Fig. 2A) and the empirical findings (Fig. 2B), the statistical model (Fig. 2C) confirms the change in driver-driven roles that alter the sign of the asynchrony in Unidirectional feedback conditions, relative to the Baseline and Non-directional (no feedback) conditions.

Table 2
Hierarchical mixed regression comparisons for asynchronies of duet performances

Model Comparison	Change in DF	Deviance	χ^2	*p*
Regression 2.1		37,113	54.699	<.0001
Regression 2.2 [vs. 2.1]	+1	37,114	0.599	.4389
Regression 2.3 [vs. 2.1]	+5	37,115	0.00	.9999
Regression 2.4.[vs. 2.1]	+3	36,956	157.82	<.0001
Regression 2.5 [vs. 2.4]	+8	36,814	142.3	<.0001
Regression 2.6 [vs. 2.5]	+8	36,716	97.77	<.0001
Regression 2.7 [vs. 2.6]	+8	36,691	24.67	.0018

Note. Regression 2.1 = A + W
Regression 2.2 = A + W + L
Regression 2.3 = A + W + L + A × L
Regression 2.4 = A + W + A × W
Regression 2.5 = $A + W + A \times W + S^{1} + A \times S^{1} + W \times S^{1} + A \times W \times S^{1}$
Regression 2.6 = $A + W + A \times W + S^{1,2} + A \times S^{1,2} + W \times S^{1,2} + A \times W \times S^{1,2}$
Regression 2.7 = $A + W + A \times W + S^{1,2,3} + A \times S^{1,2,3} + W \times S^{1,2,3} + A \times W \times S^{1,2,3}$

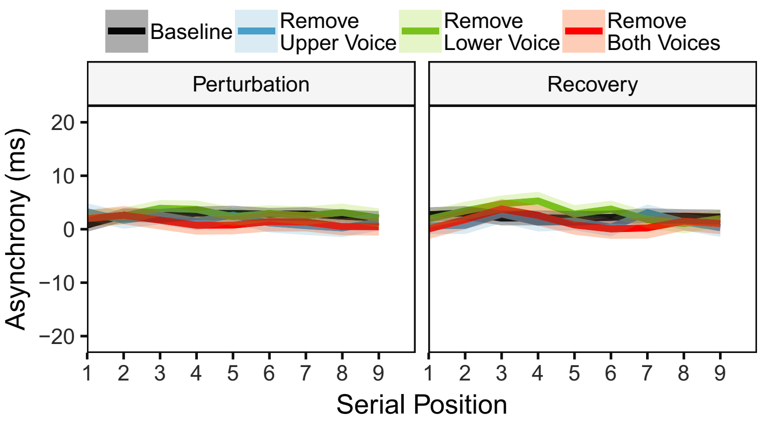

Fig. 4. Solo performance mean asynchronies (Upper–Lower Voice) by auditory feedback condition, window of feedback (Perturbation/ Recovery), and serial position (first nine notes). Ribbons represent two standard errors on each side of the mean.

3.4. Discussion

The empirical study of duet music performances demonstrated several important outcomes that tested MAAM's model predictions. First, the duet performances yielded a positive overall asynchrony (lower voice preceded upper voice), consistent with the instruction given to the pianists that the person performing the upper voice controlled the pace or tempo of the performance (i.e., the driver).

Second, when auditory feedback from only one voice was removed (the Unidirectional conditions) during duet performance, the temporal coordination between performers

Table 3
Fits of Regression model 2.7 from Table 2 to each duet pair's asynchronies and regression parameter estimates by auditory feedback condition, window of feedback, and serial position (first nine positions) in joint performances

	Bidirectional		Unidirectional				Non-Directional	
	Baseline		Remove Upper Voice		Remove Lower Voice		Remove Both	
	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*
Perturbation								
Intercept	6.22***	1.71	−9.81***	1.11	8.14***	1.11	−0.98	2.02
Linear Term	−25.66	37.37	−274.76***	51.49	214.18***	51.49	−72.47	51.69
Quadratic Term	−34.13	36.41	257.35***	51.49	−111.27*	51.49	76	51.69
Cubic Term	54.23	36.41	−115.93*	51.49	−9.57	51.49	−90.11	51.69
Recovery								
Intercept	−0.38	1.08	8.10***	1.08	−5.91***	1.08	0.46	1.09
Linear Term	36.82	51.49	462.29***	72.81	−369.37***	72.81	101.51	73.41
Quadratic Term	−45.05	51.49	−355.90***	72.81	315.71***	72.81	−64.63	73.41
Cubic Term	−47.12	51.49	221.30***	72.81	−91.79	72.81	47.53	73.41

*$p < .05$; **$p < .01$; ***$p < .001$.

converted from a bidirectional to a unidirectional system. This was evidenced by the change in asynchronies which became more positive (increase in asymmetry) when the lower voice was removed (the upper voice became the driver) and became more negative when the upper voice was removed (the lower voice became the driver). Consistent with MAAM's predictions, when one partner's auditory feedback was removed, the directionality of the asynchrony between the two performers changed: the tone onsets of the individual whose voice was removed preceded the tone onsets of their partner, and the performer whose voice was removed was driven by the performer whose voice was heard (i.e., driver) in the resulting unidirectional model.

A dynamical systems approach interprets the perturbations caused by the removal of auditory feedback as breaking the bidirectional coupling that normally forms between individuals in joint (duet) performance. When auditory feedback was removed from one performer, a transition to a unidirectional state occurred in which the partner whose feedback was not removed became the driver. The driver therefore sets the pace for their silent, driven partner who anticipated the driver. This pattern of unidirectional adaptation and anticipation also occurs when musicians are asked to perform with a regular metronome (Loehr et al., 2011); a unidirectional coupled system emerges with the performer (the driven) consistently preceding the metronome (the driver) (Repp & Su, 2013). In these unidirectional coupled systems, the quasi-periodic driver's behavior is anticipated by the driven system, which uses feedback about its own states to anticipate. We suggest that this change in coupling between bidirectional and unidirectional states underlies the behavioral shift observed in the asynchrony of pianists' joint performances when auditory feedback was removed from one performer.

The solo performances showed no effect of removal of auditory feedback on the mean asynchronies. This replicates previous findings that temporal variability does not change during removal of auditory feedback in well-practiced solo performance (Finney & Palmer, 2003). These findings suggest that auditory feedback is not necessary for performers to coordinate between their hands, most likely because the two hands of a performer are synergistically linked through the (same) motor system via proprioceptive and tactile information from each limb (Latash, 2008).

4. MAAM model fitting of experimental data

In this section, the MAAM equations were fitted to the experimental asynchronies from the duet performances to gain further insights into how the performers may have anticipated and adapted to each other's actions. We estimated the parameters of the MAAM for each performer (k, τ, ω) that could have yielded the resulting human behavior observed for each pair.

4.1. Predictions

We predicted that the coupling and/or time-delay parameters of the individual whose feedback is heard, when the feedback from the other voice was removed (Unidirectional condition), should decrease relative to the values in the Baseline condition, as there is decreased information sharing (Eq. 1). The voice whose feedback is removed (the unheard performer) has to do all the work for the pair to remain synchronous when the sound returns during the Recovery window. Thus, the coupling and/or delay terms could either remain the same as in the Baseline condition or could become larger, to help increase the degree of anticipation. By allowing the parameters to be free, we can examine when MAAM predicts which of these possibilities will occur. In addition, when no voices are heard (Non-directional condition), we expect both coupling and delay parameters to decrease relative to Baseline. Frequency differences should match the changes in directionality; for one system to anticipate the other, that system would have to also change its frequency, ω. Finally, during the Recovery, all of the parameter estimate values should return to Baseline levels.

4.2. Method

We fit MAAM to each pair's asynchrony measures averaged across trials within condition and window. The goal was to reduce the noise, but while fitting the data at the pair level; this resulted in 128 trials being tested (16 Duet pairs × 2 Windows [Perturbation/Recovery] × 4 Feedback conditions [Baseline/Unidirectional (2)/Non-directional]).

We allowed all parameters to be free but bounded ($k = 0$ to 7, $\tau = 0$ to 20 ms; $\omega_1 - \omega_2 = -2\pi/0.005$ to $2\pi/0.005$ rad/s). An additional parameter, the degree of initial asynchrony between the voices, which was bounded between −5 to 5 ms, was needed to

Table 4
Hierarchical mixed regression model comparisons for MAAM fitted parameter

Model Comparison	Fit	k_1	k_2	τ_1	τ_2	$\omega_1 - \omega_2$	Initial Asynch
3.2 vs. 3.1	Deviance	480.82	547.4	712.97	555.13	347.51	480.82
	χ^2	21.74	20.04	13.69	23.83	57.18	21.74
	p	<.0001	0.0002	0.0034	<.0001	<.0001	<.0001

Note. Regression 3.1 = A + W
Regression 3.2 = A + W + A × W

allow for the initial asynchrony difference from zero that occurs at the start of each condition (as seen in Fig. 2B). Fitting was accomplished in two stages. First, the fits of a global parameter search were made (genetic algorithm); second, those parameters were passed to a local parameter search (constrained nonlinear multivariate function). The fit was assessed using a weighted-least-squares function with the first serial position weighted by 4 and the final position by 2, the minimal weighting that captures the curvilinear relationship of the data (supported by statistical analysis seen in Fig. 2C) without the inclusion of more complex fit functions. Only four trials (3.1%) were removed from subsequent analysis because the fitting process failed. MAAM model goodness of fits were assessed with AIC, and the mean and SD of the AIC values are reported for each condition in Table 4.

4.2.1. Statistical testing

The statistical procedures (mixed regression models) were identical to those used in the analysis of the empirical music performance data, except that the fitted MAAM parameters were examined separately, resulting in six total mixed models (3 parameters per duet partner). The same hierarchical procedure for each parameter was applied, to ensure comparable results with the statistical fits of the experimental data. We report the incremental models and their deviance tests to determine the best fitting model. The contributions of auditory feedback (A) and window of feedback (W) were assessed. The results of the model fits are shown in Table 4. For all parameters, the best fitting regressions (3.1) that included the interaction (A × W) as indicated by the significant deviance test (p's < .01).

4.3. Results

Fig. 2D shows the MAAM model fits to the grand mean of duet pairs' experimental asynchronies by condition. The model fits yielded results similar to both the mean experimental data (Fig. 2B) and the statistical fit (Fig. 2C). Table 5 shows the parameter means and standardizations of the model fits to the experimental data (with significance values reported from regression 3.1) and the results are summarized below.

4.3.1. Bidirectional (Baseline)

The coupling observed for the upper voice (melody) to the lower voice (accompaniment) is significantly smaller than that of the lower voice to the upper voice,

Table 5
Parameter means and standard deviations of MAAM to asynchronies of duet performances by auditory feedback condition, window of feedback, and serial position (first 9 positions). Subscripts: 1 = Upper voice and 2 = Lower voice

	Bidirectional		Unidirectional				Non-Directional	
	Baseline		Remove Upper Voice		Remove Lower Voice		Remove Both	
Parameter	Mean	*SD*	Mean	*SD*	Mean	*SD*	Mean	*SD*
Perturbation								
k_1	2.06***	2.09	2.93	2.19	0.75*	1.06	1.97	2.66
k_2	3.41***	2.74	0.82**	1.74	3.38	2.75	1.52*	2.09
τ_1	8.66***	4.30	6.85	4.31	5.99	4.35	3.79**	3.51
τ_2	13.39***	4.81	8.11**	3.82	13.85	6.06	7.04***	5.79
$\omega_1 - \omega_2$	−0.62	1.94	2.13***	2.91	−2.75	1.97	0.38	3.32
Initial Asynch	−0.51	1.35	0.92	0.87	−0.91**	1.62	0.61	0.62
Mean AIC	31.63	3.81	32.59	6.57	36.29	5.05	44.55	7.36
Recovery								
k_1	2.24	2.53	0.66**	0.82	1.74	1.81	1.26	2.07
k_2	3.36	3.05	3.34**	1.98	1.35	1.86	1.97	2.60
τ_1	7.28	4.61	6.79	4.11	5.51	5.04	6.14*	3.89
τ_2	11.18	4.22	7.68	4.73	9.37*	3.92	9.44*	4.48
$\omega_1 - \omega_2$	0.59	1.57	−1.14***	1.57	−1.61	2.80	−1.16*	2.60
Initial Asynch	−0.8	1.43	−0.9	0.73	0.83	0.78	0	1.44
Mean AIC	31.22	6.72	36.47	4.72	35.35	5.30	42.01	6.72

Note. Significance values from Regression model 3.1.
$^*p < .05$; $^{**}p < .01$; $^{***}p < .001$.

$t(14) = -3.79$, $p < .01$, suggesting that the lower voice was more dependent on the upper voice than vice versa (Rasch, 1979) and consistent with instructions to performers that the upper voice determines the tempo. There is a larger asymmetry in the delay parameters, with the upper voice's smaller delay indicating greater anticipation of the lower voice, $t(14) = -2.82$, $p < .05$. Furthermore, there was a slight negative frequency difference, but it did not differ from zero, indicating the upper voice was estimated to play slightly ahead of (faster than) the lower voice.

4.3.2. Unidirectional (Remove upper voice)

As predicted, when auditory feedback from the upper voice was removed, the lower voice could not couple to it and showed a significant decrease in coupling term and delay from baseline, while the upper voice did not differ from baseline in coupling or delay. Furthermore, there was the predicted speed change from the Baseline condition reflected in the positive frequency difference (upper voice – lower voice), indicating the lower voice was now estimated to be playing faster than the upper voice. When auditory feedback returned during the Recovery, the lower voice returned to Baseline levels for both coupling and delay values, as predicted, but the frequency difference was a slight overshoot and the coupling terms an undershoot. In short, MAAM's estimates showed the system was settling during Recovery, but not completely.

4.3.3. Unidirectional (Remove lower voice)

As predicted, when the lower voice was removed, the upper voice could not couple to it and showed a significant decrease in coupling term; the delay term decreased but not significantly from Baseline values, while the lower voice remained unchanged from Baseline values for both coupling and delay terms. Furthermore, there was the predicted speed change from baseline reflected in the larger negative frequency difference, indicating the upper voice was now estimated to be playing faster than the lower voice. When auditory feedback returned during the Recovery, as predicted, the lower and upper voices parameters returned, but not fully, to their Baseline level.

4.3.4. Non-directional (Remove both)

Only the lower voice showed the predicted significant decrease in coupling, but both voices showed the predicted significant decrease in delay. There was no change in speed, which is expected given that neither performer is trying to anticipate the other. When auditory feedback returned during the Recovery, only the delay values significantly increased from the Perturbation window. The frequency difference became more negative and significantly overshot the baseline.

4.4. Discussion

The MAAM model provided qualitatively and quantitatively good fits to experimental findings from musical duet synchronization during unidirectional coupling (only one partner's auditory feedback was sounded) and bidirectional coupling (both partners' auditory feedback was sounded). Furthermore, the coupling parameters (k) approached zero during unidirectional perturbation trials; that is, the driver system did not couple with the driven system, consistent with when $k = 0$ for the driver system in Eq. 3 which would then reduce to Eq. 1 (Driessen et al., 2011; Stepp & Turvey, 2010, 2017; Voss, 2000, 2001). Finally, we saw changes in the coupling (k) and delay parameters (τ), as well as the frequency difference ($\omega_1 - \omega_2$), between performers in the Unidirectional and Non-directional feedback perturbation conditions in the expected directions, with at least a partial return to baseline levels during the return of auditory feedback in the Recovery windows. In short, these estimates represent how the three degrees of freedom (k, τ, ω) for each individual in a duet pair can allow for adaptation and anticipation in music performance and may be extended to any behavior that relies on tight temporal coordination.

The effect of delay parameters τ in modeling asynchronies between performers is analogous to effects of network transmission delays of sound across ensemble performers. In particular, Chafe et al. (2010) found reduced asynchronies among performers when the auditory feedback from their partner (presented over headphones) was delayed for approximately 11 ms, compared with shorter or longer time delays. Note that Chafe et al.'s (2010) manipulation of time delay was applied for each musician to only the partner's feedback, compared with the current study (in which the auditory feedback from both partners is manipulated simultaneously—at no delay). Chafe's network delays also differ from studies in which sensory feedback delays were applied to one partner's actions but were transmitted to both partners (Washburn et al., 2015). Nonetheless, the tendency to anticipate a partner's timing in the presence of delayed information is consistent with the general function of the delay mechanism in the strong anticipation models discussed here. We propose that, for the highly refined auditory–motor system of expert musicians, these delay mechanisms might develop internally over time through experience.

The computational model fits of MAAM to the experimental data accounted for the perturbation windows that yielded unidirectional and bidirectional feedback conditions. The model also accounted for the recovery windows quantitatively, but failed to capture the qualitative shape (see Fig. 2D vs. B). This may be because the model sets parameters for the whole window across events, consistent with other computational model fitting procedures (Loehr et al., 2011; Wing et al., 2014). For example, Wing et al. (2014) fitted their correction gain parameters (similar to MAAM's coupling parameter k) for each pair of ensemble musicians over the entire trial; in their model, the gain weights the error correction of each performer relative to other performers. Future versions of the MAAM model could allow for coupling and delay to vary as a function of musical or event importance, for example, when the melody (primary voice) shifts from upper to lower voice in multi-voiced music.

The current study used a perturbation design to measure behavioral disruption and recovery following switches between bidirectional and unidirectional coupling. The recovery period for skilled musicians was captured in a very short time series (within about 4 events), consistent with the strength of auditory–motor coupling exhibited in musical ensemble synchronization (Goebl & Palmer, 2009) and in conversational speech turn-taking (Schultz et al., 2016; Wilson & Wilson, 2005). Long-term dependencies that influence visuomotor coordination have been identified in longer (unperturbed) time series, such as fractal dimensionality underlying successful gait coordination. Almurad et al. (2017) recently found that synchronized walking (stride matching) among younger and older adults was most successful when the fractal dimensionality ($1/f$ noise) of the gait time series was matched across partners. This complexity matching (West et al., 2008) is proposed to increase information exchange between interacting systems that share similar complexities (Marmelat & Delignières, 2012). The MAAM model fits to individual data may be improved by consideration of these long-term dependencies. Future studies may measure pianists' finger movements over long (uninterrupted) time periods for related evidence of complexity matching that influences successful coordination.

The study of temporal coordination in skilled musicians presents a case of high-achieving synchronizers. Pianists in the current study exhibited mean asynchronies of <10 ms between hands in solo performances, as well as between partners in (unperturbed) duet performances. Asynchronous behavior of (less skilled) participants in unperturbed dot tracking visuomotor tasks, in contrast, averaged about 100 ms in the two-person task

(Washburn et al., 2015). Asynchronies as large as 100 ms are rare in an auditory–motor synchronization task whose temporal demands require participants to produce rapid events on the order of 200–300 ms apart; 100-ms feedback delays have been shown to disrupt music performance timing (Gates et al., 1974). This study thus represents performance of a highly adaptive system typical of auditory–motor performance by ensemble musicians (Palmer et al., 2019; Wing et al., 2014) and conversational speakers' turn-taking (Schultz et al., 2016; Wilson & Wilson, 2005). Future studies may examine novice ensemble performance, to test changes in time-delay and coupling parameters that may develop with expertise.

4.4.1. Conclusion

Theories of coordination implemented in dynamical systems models provide a way of understanding the mechanisms of anticipatory synchronization in tasks that require temporal coordination. The delay–coupled model stems from theories of physics that explain synchronization in physical (non-cognitive) chaotic systems. This approach allows for a powerful unified language of mental and physical systems that explains the low-level mechanisms of how people coordinate their actions (Alderisio et al., 2017; Driessen et al., 2011; Stepp & Turvey, 2010). Furthermore, the model indicates how a change in coupling between partners can result in a change in anticipatory behavior. When people perform actions together under normal sensory feedback conditions, they seem to do so as a coupled bidirectional system; when forced into a unidirectional system, they behave the same way that any cognitive or physical (non-cognitive) system would behave by anticipating the driver system.

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Conflict of interest

Authors have no conflicts of interest.

Note

1. The Supporting Information derives the model behavior analytically, provides special cases, and includes additional simulations (see Fig. S1 and Table S1).

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Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article:

Appendix S1. Supplementary materials include supplemental text, Figures S1 to S2, and Tables S1 to S2.

Supplementary Information for

Staying together: A bidirectional delay-coupled approach to joint action

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This PDF file includes:

Supplementary text
Figures S1 to S2
Tables S1 to S2

Empirical analysis of MAAM
A set of simulations was generated to test MAAM's main principles of anticipation and adaptation. The parameters for two interacting systems were set to differ in terms of τ and ω (parameters: $\tau_1 = 20$ ms, $\tau_2 = 5$ ms, $\omega_1 = \frac{2\pi}{40}$ *rad/s*, $\omega_2 = \frac{2\pi}{20}$, $\theta_1(0) = 10\ \theta_2(0) = -10$). Both an uncoupled model ($k_1 = 0$, $k_2 = 0$) and a coupled model ($k_1 = 5$, $k_2 = 15$) were simulated. Results of the simulations are shown in Figure S1. The uncoupled model (left panel) simulation shows the phase of each system slowly diverging. The difference between the phrase of the two systems (the relative phase) is related to the asynchrony (difference in time between keypresses) that occurs between two pianists. In other words, the asynchrony between pianists is expected to grow. The coupled model simulation (right panel) shows the system quickly converging to stable rate of asynchrony, but with a small phase difference (≈1.05 rad). As shown in the coupled system (right panel), the oscillators rapidly converged to linear behavior with equal slopes and different intercepts.

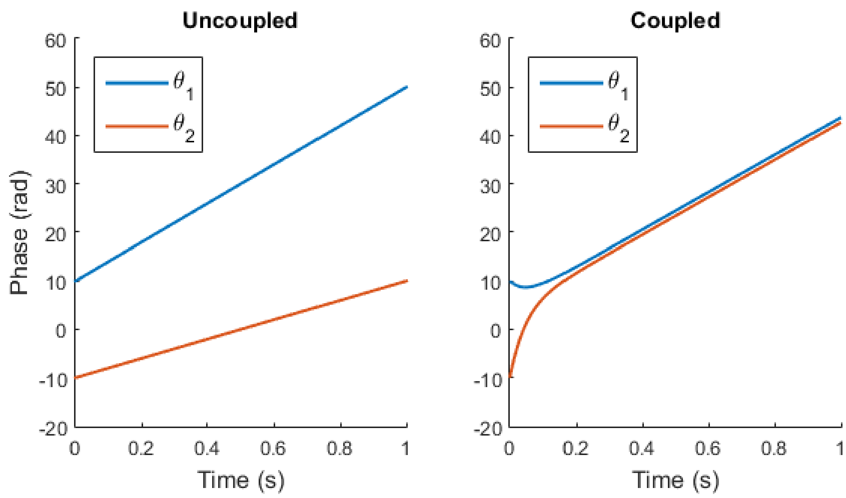

Figure S1. Simulation of uncoupled and coupled systems using MAAM. The y-axis represents the phase of each oscillator.

Analysis of steady-state phase of Fig S1
MAAM allows us to find the steady state of the phase relationship between the coupled oscillators. An analytical solution to the phase dynamics was based on the assumption that the steady-state behavior of the two oscillators with the same frequency but different intercepts is linear (See Figure S1). In equation 2.1, we denote time by t, the intercepts by $\tilde{\theta}$ and the frequency after synchronization by ω. Therefore, the phase, θ, of each system can be defined by frequency at a particular time point, relative to initial phase. This will be useful to help solve for asynchrony between the systems.

$$\theta_1 = \omega t + \tilde{\theta}_1 \\ \theta_2 = \omega t + \tilde{\theta}_2 \tag{2.1}$$

Taking the derivative of equation 2.1, we obtain equation 2.2.

$$\dot{\theta}_1 = \dot{\theta}_2 = \omega \tag{2.2}$$

If 2.1 is substituted into MAAM (Eq. 3), equations 2.3 are generated, which both equal ω, because of equation 2.2,

$$\begin{aligned} \omega &= \omega_1 + k_1\big(\omega t + \tilde{\theta}_2 - \omega(t - \tau_1) - \tilde{\theta}_1\big) \\ \omega &= \omega_2 + k_2\big(\omega t + \tilde{\theta}_1 - \omega(t - \tau_2) - \tilde{\theta}_2\big) \end{aligned} \tag{2.3}$$

which simplifies to equations 2.4.

$$\begin{aligned} \omega &= \omega_1 + k_1\big(\omega\tau_1 + \tilde{\theta}_2 - \tilde{\theta}_1\big) \\ \omega &= \omega_2 + k_2\big(\omega\tau_2 + \tilde{\theta}_1 - \tilde{\theta}_2\big) \end{aligned} \tag{2.4}$$

Equations 2.4 could be solved for ω, $\tilde{\theta}_2 - \tilde{\theta}_1$, by writing them in the matrix form 2.5,

$$\begin{bmatrix} 1 - k_1\tau_1 & -k_1 \\ 1 - k_2\tau_2 & k_2 \end{bmatrix} \begin{bmatrix} \omega \\ \tilde{\theta}_2 - \tilde{\theta}_1 \end{bmatrix} = \begin{bmatrix} \omega_1 \\ \omega_2 \end{bmatrix} \tag{2.5}$$

and taking the inverse of the coefficient matrix $\begin{bmatrix} 1 - k_1\tau_1 & -k_1 \\ 1 - k_2\tau_2 & k_2 \end{bmatrix}$ which leads to the following solution for ω in equation 2.6 and for phase difference $\tilde{\theta}_2 - \tilde{\theta}_1$ in equation 2.7

$$\omega = \frac{k_2\omega_1 + k_1\omega_2}{k_1 + k_2 - k_1k_2(\tau_1 + \tau_2)} \tag{2.6}$$

$$\tilde{\theta}_2 - \tilde{\theta}_1 = \frac{(1 - k_1\tau_1)\omega_2 - (1 - k_2\tau_2)\omega_1}{k_1 + k_2 - k_1k_2(\tau_1 + \tau_2)} \tag{2.7}$$

Note from equation 2.1 that $\tilde{\theta}_2 - \tilde{\theta}_1 = \theta_2 - \theta_1$, because the phase difference remains in the steady state over time, which yields 2.8.

$$\theta_2 - \theta_1 = \frac{(1 - k_1\tau_1)\omega_2 - (1 - k_2\tau_2)\omega_1}{k_1 + k_2 - k_1k_2(\tau_1 + \tau_2)} \tag{2.8}$$

Thus, in the limit, as time goes to infinity, phase converges to a steady-state phase. The asynchrony, therefore, can be defined as the horizontal distance between the parallel lines in Figure S1. We define t_1 and t_2 to be the times at which the two oscillators reach the same phase, and their difference divided by the slope to be the asynchrony (A) as seen in equation 2.9.

$$A = \frac{\tilde{\theta}_2 - \tilde{\theta}_1}{\omega} = \frac{\theta_2 - \theta_1}{\omega} \tag{2.9}$$

Next, we replace the phase difference ($\tilde{\theta}_2 - \tilde{\theta}_1$) and synchronization frequency (ω) in equation 2.9 by using equations 2.6 and 2.4, which leads to equation 2.10 to define asynchrony in terms of the original parameters.

$$A = \frac{(1 - k_1\tau_1)\omega_2 - (1 - k_2\tau_2)\omega_1}{k_2\omega_1 + k_1\omega_2} \tag{2.10}$$

These equations and in particular the equations 2.6, 2.8 and 2.10 describe the stable behavior of the coupled oscillators and their delay/anticipation with respect to each other without the need to solve the delayed ordinary differential equations.

Special Cases of MAAM

The challenge of working with a non-linear model such as MAAM is that we need to simulate its behavior using parameters to see its behavior. Under a specific set of scenarios, however, the behavior of MAAM can be solved analytically. This occurs when there is no difference in oscillator intrinsic frequency, or the couplings or delays are equal. These special cases help us to understand the behavior of the model. These scenarios give us a better sense of how the delays and coupling lead to anticipation in different applications. We provide this set of cases where asynchrony (A) and frequencies can be solved with Eq. 3 (main paper) and equation 2.10 after the models have reached stable behavior (ω), given the systems' natural frequencies (ω_0).

Table S1. Special cases of the mutual adaptation and anticipation model.

Scenario	Equation #	Equation #
$\boldsymbol{\omega_1 = \omega_2 = \omega_0}$ [Equal intrinsic frequency]	$\omega = \frac{(k_1 + k_2)\omega_0}{k_1 + k_2 - k_1 k_2(\tau_1 + \tau_2)}$ $A = \frac{k_2\tau_2 - k_1\tau_1}{k_2 + k_1}$	3.1
$k_1 = k_2 = k_0$ [Equal coupling]	$\omega = \frac{\omega_1 + \omega_2}{2 - k_0(\tau_1 + \tau_2)}$ $A = \frac{\left(\frac{1}{k_0} - \tau_1\right)\omega_2 - \left(\frac{1}{k_0} - \tau_2\right)\omega_1}{\omega_1 + \omega_2}$	3.2
$\omega_1 = \omega_2 = \omega_0$ and $k_1 = k_2 = k_0$ [Equal intrinsic frequency & coupling]	$\omega = \frac{2\omega_0}{2 - k_0(\tau_1 + \tau_2)}$ $A = \frac{\tau_2 - \tau_1}{2}$	3.3
$\omega_1 = \omega_2 = \omega_0$ and $k_1 = k_2 = k_0$ and $\tau_1 = \tau_2 = \tau_0$ [Equal intrinsic frequency, coupling, & delay]	$\omega = \frac{\omega_0}{1 - k_0\tau_0}$ $A = 0$	3.4

$\boldsymbol{k_1 = 0}, \boldsymbol{k_2 \neq 0}$ [Unidirectional coupling]	$\omega = \omega_1$ $A = \tau_2 + \frac{\omega_2 - \omega_1}{k_2 \omega_1}$	3.5
$\boldsymbol{k_2 = 0}, \boldsymbol{k_1 \neq 0}$ [Unidirectional coupling]	$\omega = \omega_2$ $A = -\tau_1 + \frac{\omega_2 - \omega_1}{k_1 \omega_2}$	3.6
$\boldsymbol{\omega_1 = \omega_2 = \omega_0}$ and $\boldsymbol{k_1 = 0}, \boldsymbol{k_2 \neq 0}$ [Equal intrinsic frequency with unidirectional coupling]	$\omega = \omega_1$ $A = \tau_2$	3.7
$\boldsymbol{\omega_1 = \omega_2 = \omega_0}$ and $\boldsymbol{k_2 = 0}, \boldsymbol{k_1 \neq 0}$ [Equal intrinsic frequency with unidirectional coupling]	$\omega = \omega_2$ $A = -\tau_1$	3.8

These last two special cases are important because they represent one-way coupling in near-identical oscillators[1] and give us a better sense of how the delays τ_1 and τ_2 could be interpreted in different applications. We provide additional simulations of some of these special cases as well as other logic simulations to help understand the analytical behavior of MAAM relative to the experimental manipulations with the duet performances.

Systematic Simulation Testing Results

When the parameters of MAAM are not of the special cases defined above, we must simulate MAAM to understand its behavior. This section shows the results of systematic testing of different parameter values of (ω, κ, τ) to investigate different assumptions about how performance might change (see Table S2 for the parameters for the simulation and results).

Simulation procedure. The simulation procedure was the same as reported in the main paper; we provide a shortened summary of that procedure here. After each parameter is set for each simulation, we examine the behavior of the model in two time windows in the musical sequence (perturbation & recovery window), each with a fixed number of musical tones (n = 9). We examine asynchrony predictions of the model where asynchrony is defined as the time of system 1 response minus the time of system 2 response[2] (i.e., upper – lower voice). A negative asynchrony means system 1 anticipated system 2 (upper voice plays before lower voice), thus system 2's timing behaves more like the driver. A positive asynchrony means system 2 anticipated system 1 (lower voice plays before upper voice), thus system 1's timing behaves more like the driver.

The coupling (k) between each system (see Eq. 3 of the main text) was manipulated during the perturbation windows in four different conditions: In the full coupling (baseline) condition, we introduced a baseline (i.e., full-feedback), meaning no change in the coupling

[1] Since the purpose of the MAAM presented in Eq.3 (main text) is anticipated synchronization, it is expected that the natural frequencies of the oscillators, ω_1 and ω_2, are close to each other.

[2] When they reach a particular phase, θ = 0.

parameters during the simulation. Next, we tested a unidirectional condition by setting one system to have no coupling (k = 0), but the other coupling parameter remained unchanged (i.e., remove either lower or upper voice auditory feedback). Finally, we perturbed both in which both coupling parameters were set to k = 0 (i.e., no auditory feedback).

Simulation Goals

Simulations 1 and 2. The goal of simulations 1 and 2 is to understand the impact of the frequency parameters (ω_1, ω_2). We start with the assumption that each performer would couple equally ($k_1 = k_2 = 5$) with their partner, show the same time delay ($\tau_1 = \tau_2 = 10$), but have slightly different frequencies[3]. Simulation 1: $\left(\omega_1 = \frac{2\pi}{250} rad/s, \omega_2 = \frac{2\pi}{251}\ rad/s\right)$ and Simulation 2: $\left(\omega_1 = \frac{2\pi}{251} rad/s, \omega_2 = \frac{2\pi}{250}\ rad/s\right)$. In musical terms this means that both the person playing the upper voice and the person playing the lower voice are anticipating and adapting to each other in equal amounts, but one tends to play slightly faster than the other (Zamm, Wellman, & Palmer, 2016). The slight frequency difference should affect both overall degree of asynchrony and how fast the systems drift apart when both voices are perturbed. The differences in natural frequencies are maintained in simulations 3-6 (the upper voice has a slightly faster frequency than the lower voice) to keep the variables comparable to Simulation 1.

Simulations 3 and 4. The goal of Simulations 3 and 4 is to understand the impact of coupling parameters (k_1, k_2). We start with the assumptions that the duet performers have the same frequency differences and show the same time delays as in Simulation 1 ($\tau_1 = \tau_2 = 10$). Here we vary the coupling strength in Simulation 3 ($k_1 = 1$ and $k_2 = 5$) and Simulation 4 ($k_1 = 5$ and $k_2 = 1$). In musical terms, this means there is imbalance in the strength with which the upper voice and lower voice adapt to one another. In Simulation 3, the upper voice does not adapt as strongly to the lower voice as vice versa, while in Simulation 4 the lower voice does not adapt as strongly to the upper voice as vice versa.

Simulations 5 and 6. The goal of Simulations 5 and 6 is to understand the impact of the delay parameters (τ_1, τ_2). We start with the assumption that the two performers have frequency differences and show the same coupling strength values as in Simulation 1 ($k_1 = k_2 = 5$). Here we vary the delay rate in Simulation 5 ($\tau_1 = 5$ ms and $\tau_2 = 15$) and Simulation 6 ($\tau_1 = 15$ and $\tau_2 = 5$). In musical terms, this means there is imbalance in the amount that each performer uses their own past information to anticipate their partner. In Simulation 5, the lower voice anticipates the upper voice more than vice versa. In Simulation 6, the upper voice anticipates the lower voice more than vice versa.

Simulation Results

The results of the simulations are shown in Figure S2 and summaries of the simulation findings are shown in Table S2.

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[3] Periods can be transformed to inter-onset interval or frequency, $\omega = 2\pi/t = 2\pi f$

Table S2. Summary of Results from Figure S2, MAAM Simulations.

	Initial Parameters						Baseline	Unidirectional		Non-directional
	k_1	k_2	τ_1	τ_2	ω_1	ω_2	**Bidirectional**	**Perturb system 1**	**Perturb system 2**	**Perturb both**
1	5	5	10	10	250	251	*Symmetrical initial intercept:* Sim 1 was –.38 ms Sim 2 was +.38 ms	Slope change was equal for Sim 1, 2	Slope change was equal for Sim 1, 2	Asynchrony drift caused by frequency difference
2	5	5	10	10	251	250				
Goal of simulations 1 and 2: Impact of the frequency parameters. <u>Major Finding</u>: The faster system always anticipates the slower system.										
3	1	5	10	10	250	251	Asymmetries in *Initial intercept:* Sim 3 was +6.01 ms Sim 4 was -7.32 ms	Slope change was asymmetrical. Sim 3: System 1 more change Sim 4: System 2 more change.	Slope change was asymmetrical. Sim 3: System 2 more change. Sim 4: System 1 more change.	*Same as above*
4	5	1	10	10	250	251				
Goal of simulations 3 and 4: Impact of the coupling parameters. <u>Major Finding</u>: Coupling strength impacts the initial asynchrony level. Furthermore, whichever system is coupled more strongly, anticipates the other system more, creating an asymmetry seen during perturbations.										
5	5	5	5	15	250	251	Asymmetries in *Initial intercept:* Sim 5 was +4.62 ms Sim 6 was -5.38 ms	Slope change was equal for Sim 5, 6	Slope change was equal for Sim 5, 6	*Same as above*
6	5	5	15	5	250	251				
Goal of simulations 5 and 6: Impact of the delay parameters. <u>Major Finding</u>: Delay difference impacts the initial asynchrony level.										

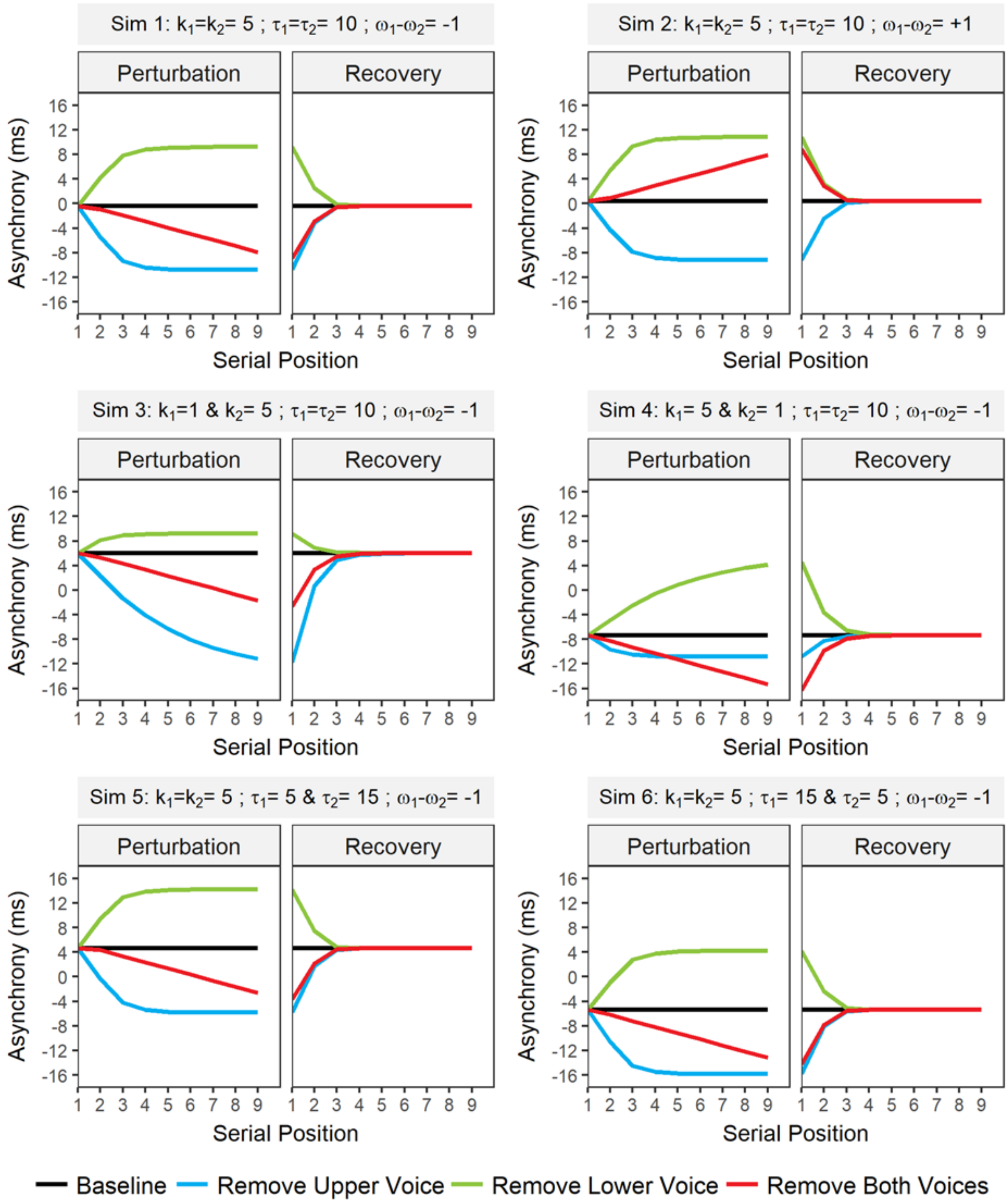

Figure S2. MAAM simulations 1-6 with initial parameters shown for each simulation.

References

Zamm, A., Wellman, C., & Palmer, C. (2016). Endogenous rhythms influence interpersonal synchrony. *Journal of Experimental Psychology: Human Perception and Performance*, *42*(5), 611–616. https://doi.org/10.1037/xhp0000201