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APPLICATION OF THE MATCHING LAW TO PITCH SELECTION IN PROFESSIONAL BASEBALL

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This study applied the generalized matching equation (GME) to pitch selection in professional baseball. The GME was fitted to the relation between pitch selection and hitter outcomes for five professional baseball pitchers during the 2014 Major League Baseball season. The GME described pitch selection well. Pitch allocation varied across different game contexts such as inning, count, and number of outs in a manner consistent with the GME. Finally, within games, bias decreased for four of the five pitchers and the sensitivity parameter increased for three of the five pitchers. The results extend the generality of the GME to multialternative natural sporting contexts, and demonstrate the influence of context on behavior in natural environments.

Key words: matching law, baseball, choice behavior, translational research

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In 1970, Herrnstein purported that "all behavior is choice" (p. 253). Thus, although an organism can emit a variety of responses at any given moment, only one is selected by prevailing contingencies of reinforcement. Under this view, choice entails a dynamic interplay between responses and their selection over time by reinforcement. Over the past four decades, researchers have made great strides in quantitatively modeling this dynamic interplay under controlled, laboratory conditions. In particular, one quantitative model of choice with robust empirical support is the generalized matching equation (GME; e.g., Baum, 1974; McDowell, 1989).

The GME describes the allocation of behavior across multiple response alternatives and may be written:

$$\log\left(\frac{B_i}{B_o}\right) = a \log\left(\frac{r_i}{r_o}\right) + \log b \qquad (1)$$

B_i and B_o represent the rate of a target response, and the rate of all other responding, respectively, and r_i and r_o represent the rate of reinforcement for the target response, and that for all other responses, respectively. As noted by McDowell (1989) the logarithmic form of the matching equation describes a straight line with a indicating the slope and log b indicating the y-intercept. The slope represents a measure of sensitivity to reinforcement and the y-intercept represents a measure of bias for one

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response alternative (Baum, 1974). The logarithmic form of the GME allows for comparatively easy interpretation of data through linear regression when the data is plotted in *x-y* coordinates. In addition, the logarithmic form of the GME has been successfully applied to situations with more than one alternative response (e.g., Elsmore & McBride, 1994; Kangas et al., 2009).

Previous studies have assessed behavior using the GME within a variety of naturalistic settings. For example, the GME has described the allocation of on-task (e.g., in seat) and off-task behavior (e.g., out of seat, audible nonvocal noise) in academic settings (e.g., Mace, Neef, Shade, & Mauro, 1994, 1996); allocation between problem behavior (e.g., aggression, self-injurious behaviors) and appropriate alternative behavior (e.g., vocal requests, taps on the arm) in clinical settings (C. S. W. Borrero et al., 2010; J. C. Borrero & Vollmer, 2002; Symons, Hock, Dahl, & McComas, 2003); and the distribution of social behavior during conversational exchanges based on differential levels of social reinforcement (e.g., J. C. Borrero et al., 2007).

Researchers also have used the GME to describe the allocation of behavior in collegiate and professional sports. For example, Vollmer and Bourret (2000) assessed the proportion of three-point shots to total shots taken as a function of points scored from three-point shots to total points scored. The authors found that the GME described shot allocation aggregated across the season well, with shot allocation within games being more variable. Similar results have been found with application of the GME to the ratio of passing plays to rushing plays in football with yards gained for each as the reinforcer (Reed, Critchfield, & Martens, 2006; Stilling & Critchfield, 2010).

Notwithstanding these successful applications of the GME, several areas of further inquiry have the potential to increase the utility of the GME in naturalistic settings. One area that has seen minimal attention is the analysis of antecedent variables that influence choice within natural environments. One exception is Stilling and Critchfield (2010) who observed a bias for running on first and second downs, and a bias for passing the football depending on the game situation (e.g., bias for running the football on first and second downs and passing on third downs). These changes in biases may suggest situation-specific effects that are not captured by analysis of play selection across the entire game.

The total number of response alternatives is also important to consider when extending matching into non-laboratory situations. Most applications of the GME in natural sporting environments have been restricted to two response alternatives (i.e., run vs. pass, two- vs. -three-point shot). Nevertheless, natural contexts allow for one of many responses, and thus more than one alternative response may be of interest to the researcher. For example, in the sport of baseball the majority of pitchers use three or more pitch types within most games.

Finally, it is unclear whether and how response and reinforcer characteristics change over time in natural contexts. For example, as a pitcher tires during a game his or her ability to throw a fastball may become more effortful. In addition, strikes and outs later in the game might be experienced as a higher quality reinforcer than earlier in the game. Response characteristics such as effort and reinforcement characteristics such as reinforcer magnitude have been demonstrated to influence the bias parameter of the GME (e.g., Baum, 1974). Similarly, the discriminability of reinforcement schedules may change, with discriminability increasing over the course of a game. Increased discriminability of reinforcement schedules has resulted in increased sensitivity to changes in reinforcement within laboratory settings (e.g., Madden & Perone, 1999).

The purpose of this study was to (a) evaluate whether the generality of the GME extends to pitch selection in professional baseball, (b) determine if pitch selection changes across specific game situations, and (c) assess how bias and sensitivity parameters change within games.

METHOD

Participants

Nine starting pitchers from three different Major League Baseball (MLB) teams (two National League teams and one American League team) were selected based on the favorite teams of the first and second author. Data were collected across all regular season games during the 2014 MLB season in which each of these nine pitchers were designated as the starting pitcher. During the season, four pitchers were moved to the baseball club's minor league system or to a relief pitcher role. Thus, data from five pitchers were used in the final analysis and all were from National League baseball teams.

Data Collection

Data were obtained by observing individual games using the Major League Baseball At-Bat application Version 3.1.1 for iPhone, iPad, and computer (2014). Antecedent data were collected for every pitch thrown across the following categories: the inning within which each pitch was thrown (inning), the batter's position within the lineup (batter), the specific count of balls and strikes at the time of the pitch (count), the general count of balls and strikes at the time of the pitch (count: ahead, even, or behind, AEB), the number of outs that had been recorded within that inning (outs), the difference in score between the pitcher's team and the opposing team (score differential), and the location of any runners on the base paths (runners).

Pitches were categorized as fast and straight (e.g., four-seam fastball, two-seam fastball), fast and breaking (e.g., slider, cutter), slow and straight (e.g., circle-changeup, palm ball), or slow and breaking (e.g., curveball). The degree of break on each pitch was easily observed and allowed data collectors to differentiate between straight and breaking pitch types (see interobserver agreement below). In addition, the posted speed on the At-Bat application allowed for differentiation between fast and slow pitch types. These categories were selected prior to the start of the study as each pitcher had a history of throwing at least one pitch from three or four of these categories. Visual examples of these categories are shown in Figure 1.

Once thrown, the speed of each pitch was shown on the screen. The speed of each pitch aided in determining whether it was a fast or slow pitch for each pitcher. Overall, fast pitches ranged from upper 80 miles per hour (mph;

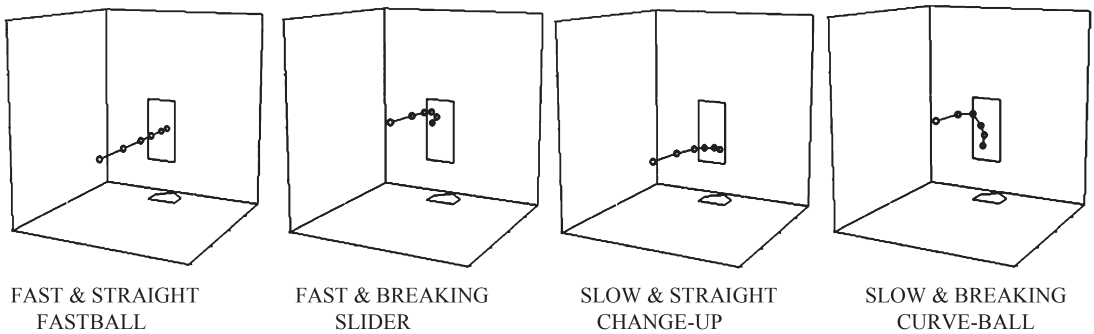

Figure 1. Example path of the baseball for each of the four categories measured within this study. Paths are those that would be observed for a right handed pitcher from the pitcher's point of view. The rectangle indicates the strike zone. Left handed pitchers would result in the mirror image.

128.7 kilometers per hour [kph]) to upper 90 mph (144.8 kph) with the specific range for each pitcher being idiosyncratic. Average fastball velocities in miles per hour during the 2014 season for participants 1–5 were 91.1 (146.6 kph), 95.4 (153.5 kph), 92.6 (149 kph), 89.6 (144.2 kph) and 92.0 (148 kph), respectively (fangraphs.com, 2016a; 2016b; 2016c; 2016d; 2016e). In addition, each pitcher threw a fastball as the first pitch to start each game. The initial miles per hour provided the data collector an approximate starting miles per hour that determined the remaining pitch categories. Slow pitches were defined as being slower by 5 mph (8 kph) or more than that pitcher's fast pitch. For example, participant 3 threw his fastball (fast and straight) between 91 and 99 mph (146.5 and 159.3 kph) during most games. His changeup (slow and straight) was between 83 and 88 mph (133.6 and 141.6 kph). This relative difference in speed was also used in determining whether a given breaking pitch was fast or slow (e.g., participant 3's slider was 86 to 89 mph [138.4 to 143.2 kph], whereas the curveball was 76 to 81 mph [122.3 to 130.4 kph]).

Each instance of a strike, ground/fly out(s), strikeout, fielder's choice, sacrifice, or an error on a position player or the catcher (if the pitch was called a strike) was counted as reinforcement. A fielder's choice or sacrifice occurs when a pitched ball is batted into play and either a runner on the base paths or the batter gets out, respectively, allowing the other player(s) to advance. These were scored as reinforcement, as an outcome beneficial to the pitcher's team occurred despite the batter still reaching base (fielder's choice) or other runners advancing on the base paths (sacrifice). Errors on position players were counted as reinforcement as the pitch induced a batted ball that would typically result in an out but failed to on that occasion (see Major League Baseball, 2016, for definition of an error in baseball). That is, the batter did not hit the ball well enough to get a hit, but due to a mistake by someone other than the pitcher, the batter reached base. No differential weight was assigned to 'outs' compared to 'strikes' for reinforcer amount.

Interobserver Agreement

Interobserver agreement (IOA) was calculated for 33% of all of the games scored. Interobserver agreement was calculated by scoring agreement for each of the antecedent, behavior, and consequence categories for every pitch of all games that were coded for IOA. Each pitch thrown therefore resulted in seven opportunities for agreement for the various aspects of the antecedent context, one opportunity for agreement for the type of pitch thrown, and a varied number of opportunities for agreement for the consequence, depending on what happened after each pitch. For example, if just a strike or ball was thrown then there was one opportunity for consequence agreement. If the play resulted in a base hit that scored one run, then there were three opportunities for consequence agreement in strike, single, and runs batted in. The overall percentage was then calculated by summing all antecedent, behavior, and consequence data that were in agreement and dividing that sum by the total number of opportunities for agreement. Interobserver agreement was 97% overall (range, 88.9%-100%) and 93% for behavior and consequence data only (range, 72.6%-100%).

Data Analysis

All five pitchers threw a fastball (fast and straight) on the majority of opportunities. Herrnstein (1970) provided two equations to calculate the smallest and largest proportions of responses that could occur given observed reinforcements and responses (Herrnstein, 1970; Equations 2 and 3). If a wide range is calculated, then patterns of responding described by the matching equation provide information about the choice behavior of the organism. If ranges are small, a pattern of responding consistent with matching would have little empirical content (Herrnstein, 1970). As such, the proportion of fastballs to all pitches was plotted as a function of the proportion of reinforcement for fastballs to all reinforcement. The range of possible responses was then calculated based on Equation 2 and Equation 3 from Herrnstein for each of the fastball proportions.

Then, the GME was fitted in several ways for each pitcher: with the number of fast and straight pitches as B_i, with fast and breaking as B_i, with slow and straight as B_i, and with slow and breaking as B_i. The total number of all other pitches was always B_o. The ratio of pitches and reinforcers was also aggregated and plotted for each individual game and for the season as a whole for each of the five pitchers and for each pitch type.

In addition, fast and straight data were replotted for each game and the season as a whole for several antecedent contexts. Contexts analyzed were inning, number of outs recorded in the inning, batter, count of balls and strikes, score of the game, and location of runners on the bases. Innings and outs were selected as they represented different within-game scales for which one might expect learning to occur. Fitting the GME to data plotted across innings allowed determination of whether changes in pitch ratio would be susceptible to changes in strikes and outs over the course of a game. Only innings 1 through 6 were used as all of the pitchers were relieved after the 6th inning for most of their starts. Outs of zero, one, and two were used for the context analysis of outs.

Other antecedent contexts were selected as the result of common game strategies (see Hample, 2007, for overview). Briefly, differential hitting abilities may result in different pitch ratios based on the position of the hitter in the lineup, a higher probability of breaking pitches is commonly observed when the pitcher is ahead rather than behind in the count, overall team success (i.e., pitcher winning, tied, or losing) may shift pitching strategy, and the position of the runners on the base paths may influence pitching strategy. Each context was identified to determine if pitching strategies common to various baseball contexts would correspond with descriptions of the GME.

RESULTS

Figure 2 shows proportional matching for the individual pitchers. In addition, the maximum and minimum values calculated from Herrnstein (1970) are plotted for each game. Relatively broad ranges of potential proportions were observed for four of the five participants. All five participants were observed to throw a proportion of fastballs similar to the proportion of strikes and outs over the course of the season.

We then determined how well the GME described pitch selection for these five professional baseball pitchers. Figure 3 shows the matching functions for all four pitch categories for the individual pitchers. Overall, the GME described pitch selection for each participant relatively well, accounting for an average proportion of variance (VAC) of 0.93 (range, 0.91-0.97). When separated by pitch type, we observed average VACs of 0.71 (range, 0.58-0.85), 0.76 (range, 0.31-0.92), 0.77 (range, 0.63-0.88), and 0.87 (range, 0.78-0.96) for fast and straight, fast and breaking, slow and straight, and slow and breaking pitches, respectively. Sensitivity parameters were also less than 1.00 for all five participants across almost all pitch types (only exception was slow and straight pitches for participant 2; a = 1.02). Bias toward fastballs was observed for participants 1 and 2, no bias was observed for participants 3 and 4, and a bias for nonfastballs was observed for participant 5.

We then determined if pitch selection changed across specific game situations. The season totals of fastballs compared to all other pitches

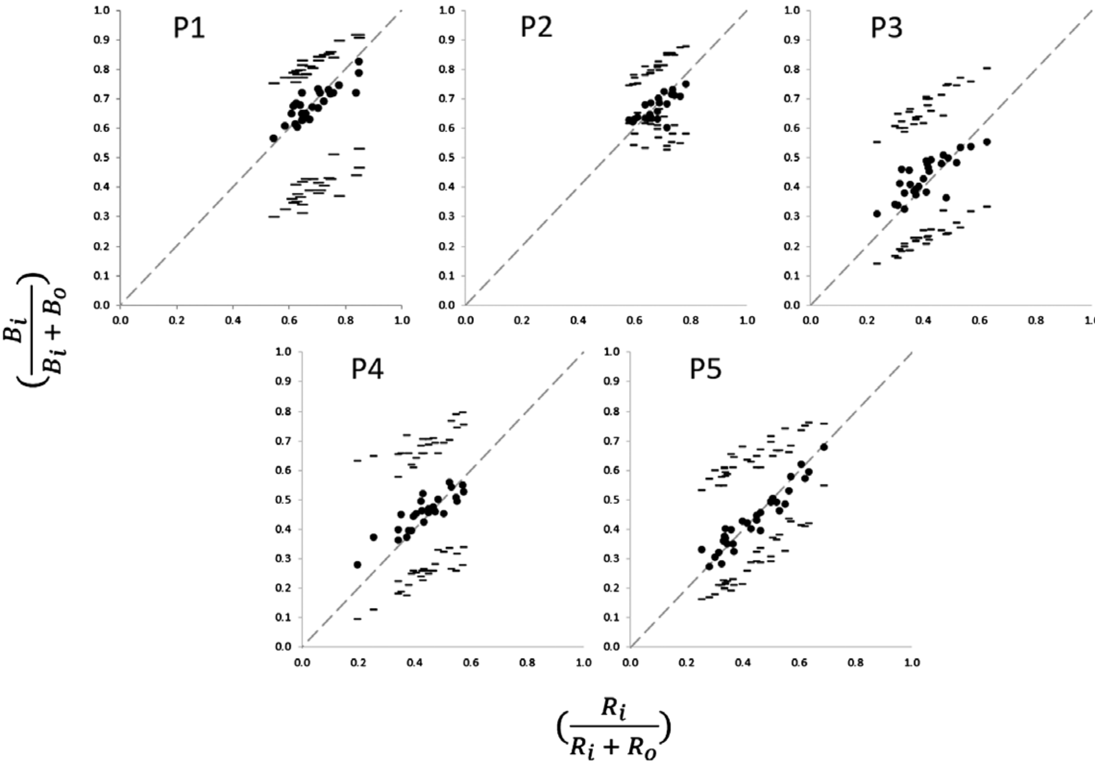

Figure 2. Results of the application of the proportional matching equation to pitch selection for each pitcher (e.g., P1). Closed circles represent a single regular season game for that pitcher. Horizontal black lines represent the maximum and minimum values each pitcher could have thrown in each game based on fits of Eq. (2) and Eq. (3) from Herrnstein (1970) to observed data. The dashed grey line represents bias equal to zero and sensitivity equal to 1 (i.e., "perfect matching").

within each antecedent context were plotted as a function of reinforcement for fastballs compared to all other pitches. For example, Figure 4 shows matching functions for the individual pitchers for the antecedent context of inning. Each data point shows pitch selection as a function of reinforcement contacted in a specific inning. The number of the marker corresponds to the inning of the game (i.e., 1 = first inning, 2 = second inning, etc.). Visual analysis of these data suggests that pitch selection changed across innings consistent with changes in reinforcement contacted across innings. Furthermore, four of the five participants threw more fastballs in the earlier innings of baseball games (i.e., innings 1–3) than in the later innings of baseball games (i.e., innings 4–6).

Figures 5 through 8 depict the influence of the remaining contexts on pitch selection. Figure 5 demonstrates the influence of position in the lineup of the batter from the opposing team. More fastballs were thrown to the number 9 batter and the least number of fastballs were thrown to the middle of the lineup (i.e., 4, 5, or 6 hitter). Figure 6 shows the influence of count on pitch selection. Four of the five pitchers threw more fastballs when behind in the count (i.e., more balls than strikes) and the least when ahead in the count. Figure 7 demonstrates the influence of outs recorded on pitch selection. Four of the five

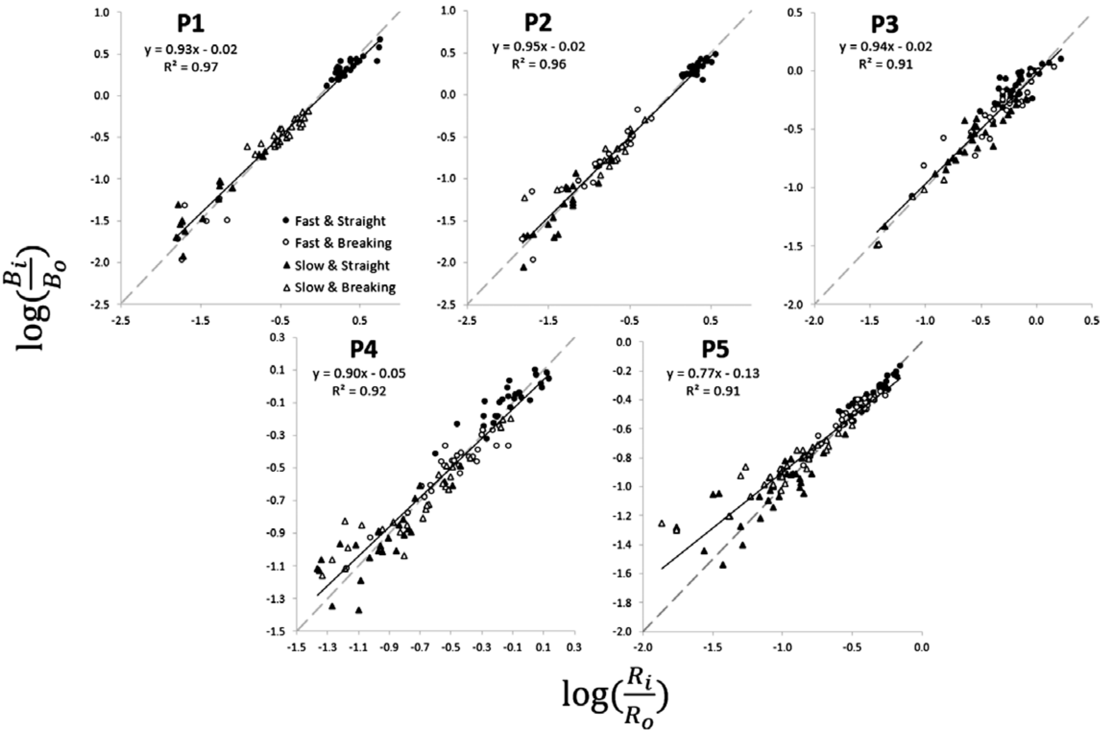

Figure 3. Results of the application of the GME to pitch selection for each pitcher (e.g., P1). Each data point represents a single regular season game for that pitcher. The dashed grey line represents bias equal to zero and sensitivity equal to 1 (i.e., "perfect matching").

participants threw more fastballs when there were no outs compared to one or two outs. Figure 8 shows the influence of score on pitch selection; all five participants threw more fastballs when the game was tied and the least number of fastballs when the pitcher was losing. Finally, the GME described pitch selection well for the context of position of runners on the bases. However, no systematic trend was observed for the position of runners on the base paths across starting pitchers and thus those plots are not shown.

We then determined how bias and sensitivity parameters changed over the course of a baseball game. Figure 9 shows bias, sensitivity, and VAC as a function of inning for each of the five participants. Three of the five pitchers showed a decrease in bias toward fastballs as a function of innings; bias for pitchers 3 and 4 did not systematically vary as a function of inning. Sensitivity parameters showed an increase as a function of innings for three of the five pitchers and remained relatively stable for pitchers 4 and 5. For participant 1, VAC was variable with no observed trend. An increase in VAC as a function of innings was observed for participant 2. Participants 3 and 5 were observed to have relatively little change in VAC across innings—excluding inning 3 for participant 5—and a decrease in VAC was observed for pitcher 4.

DISCUSSION

For all five pitchers, there was a relatively wide range of minimum and maximum values for the proportion of fastballs to all other types of pitches. However, all pitchers threw

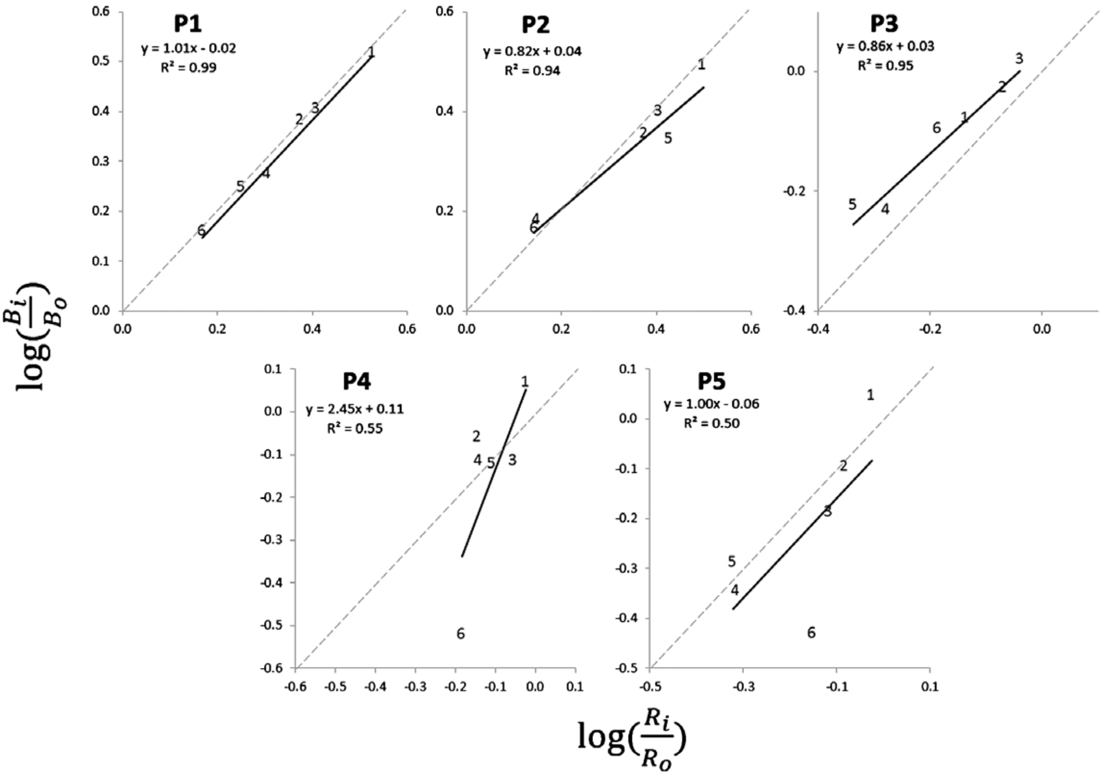

Figure 4. Results of fitting the GME to pitch selection for each pitcher (e.g., P1) based on the antecedent context of inning. Each data point represents the ratio of behavior and reinforcement for the entire season for the corresponding inning (i.e., 1 = first inning, 2 = second inning, 3 = third inning, 4 = fourth inning, 5 = fifth inning, and 6 = sixth inning). The dashed grey line represents bias equal to zero and sensitivity equal to 1 (i.e., "perfect matching").

proportions of fastballs to all pitches that matched the proportion of strikes or outs from fastballs to all strikes and outs. These data suggest that the observed matching relations for this study were not trivially true (Herrnstein, 1970).

The GME was fitted to pitch selection over the course of the season for five starting pitchers from MLB. Overall, the GME described the allocation of pitches as a function of strikes and outs. The VAC by the GME averaged 0.93 (range 0.91 to 0.97) for all pitches and 0.72 (range 0.58 to 0.85) for fastballs specifically. Three of the five pitchers showed bias for throwing fastballs with two pitchers showing little bias. All pitchers showed undermatching, which is common within laboratory studies of matching as well as studies fitting the GME to responding in sports contexts (Alferink, Critchfield, Hitt, & Higgins, 2009; Reed et al., 2006; Romanowich, Bourret, & Vollmer, 2007; Stilling & Critchfield, 2010; Vollmer & Bourret, 2000).

The present study found the generality of matching to extend to a naturally occurring context with multiple response alternatives. Previous research in sports and other applied settings has primarily fitted the GME to two response situations (e.g. 2- vs. 3-point shots, run vs. pass plays, problem behavior vs. appropriate behavior). In a laboratory setting, Elsmore and McBride (1994) found that the GME described changes in response and reinforcer ratios for an eight-alternative

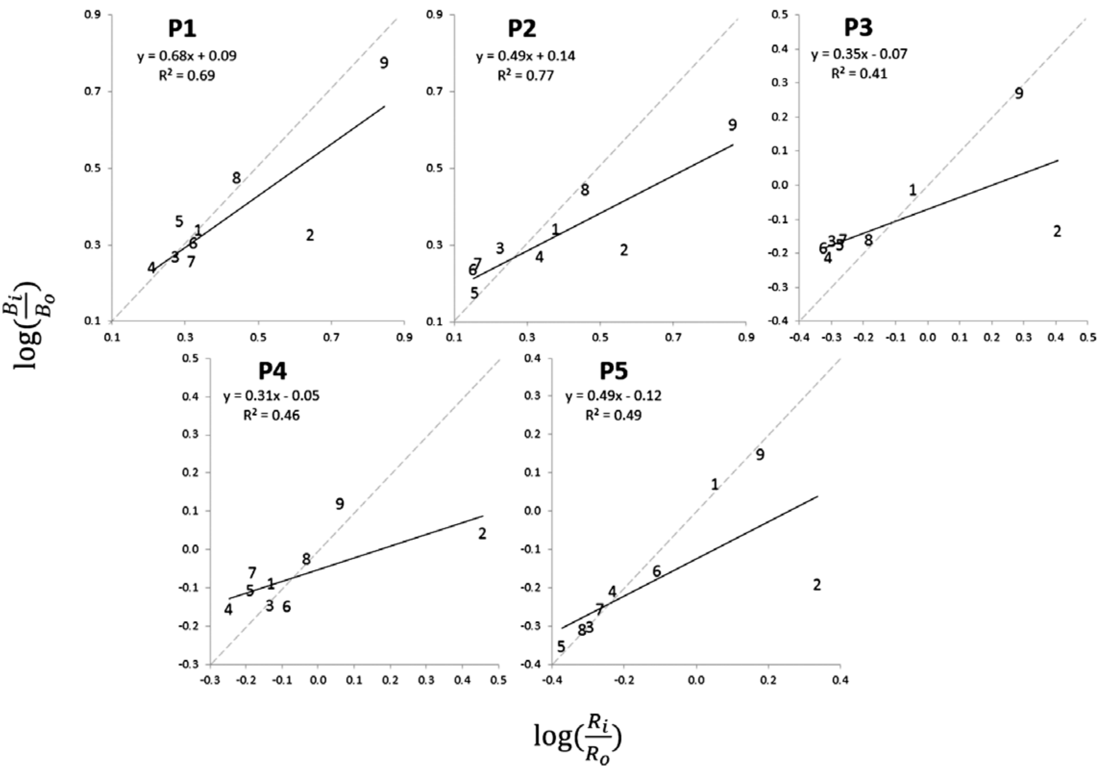

Figure 5. Results of fitting the GME to pitch selection for each pitcher (e.g., P1) based on the antecedent context of batter in opposing lineup. Each data point represents the ratio of behavior and reinforcement for the entire season for the corresponding batter (i.e., 1 = first batter, 2 = second batter, 3 = third batter, etc.). The dashed grey line represents bias equal to zero and sensitivity equal to 1 (i.e., "perfect matching").

concurrent schedule. The current study fitted the GME to response and reinforcer ratios in a natural four-alternative context. Applying the GME to a greater number of natural multioperant environments allows direct assessment of the generality of the model when the likely reinforcers are known (e.g., points in basketball, strikes/outs in baseball). Research fitting the GME to a variety of multioperant natural contexts will aid in identifying limits in the generality of the GME and variables influencing matching in natural contexts. This, in turn, would likely lead to increased social utility of the GME beyond the current state.

This study also assessed the influence of antecedent contexts on response allocation (Stilling & Critchfield, 2010). All five pitchers showed similar trends in pitch selection across innings, batter, and score. Specifically, the ratio of fastballs to other pitches decreased across innings of baseball games, increased for the number 9 batter compared to the middle of the lineup, and increased when the game was tied. Pitcher 5 was the only participant for whom the data deviated from trends in outs and count. The ratio of fastballs to other pitches increased with zero outs and when behind in the count for the other four pitchers.

The causal variable for trends in pitch selection across contexts is unclear. It is possible that the antecedent contexts, as opposed to reinforcer rates, played a causal role in determining pitch allocation. For example, a common rule for pitchers is to throw breaking

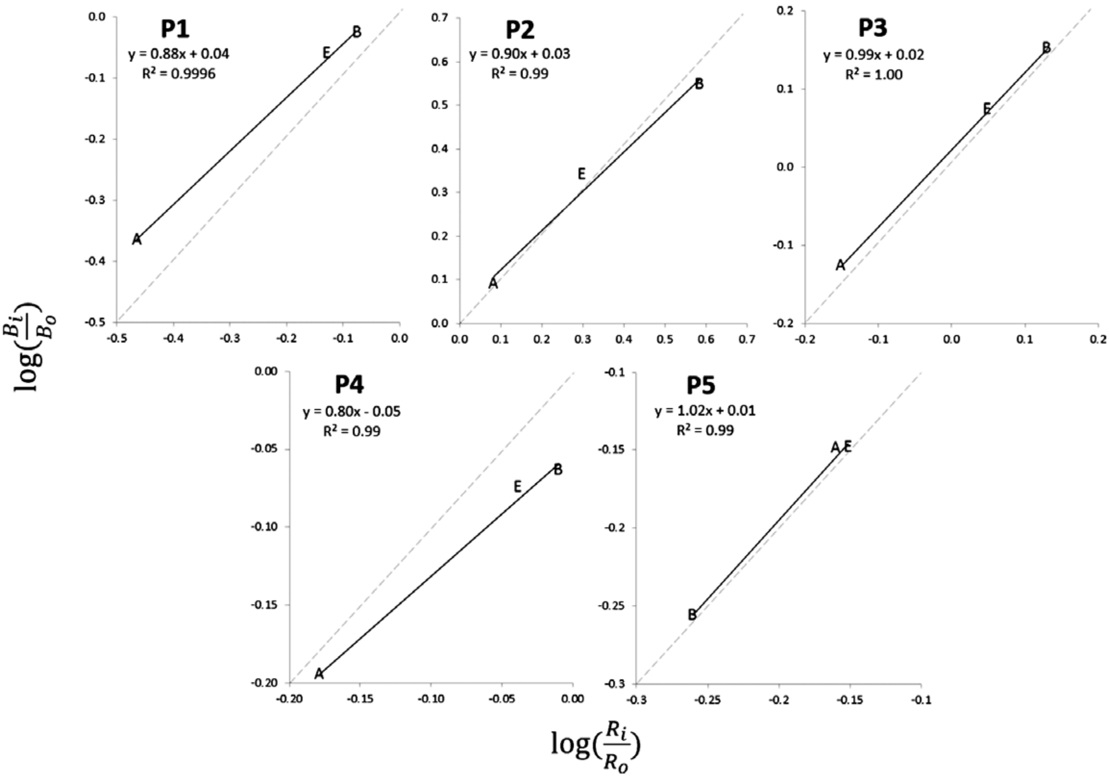

Figure 6. Results of fitting the GME to pitch selection for each pitcher (e.g., P1) based on the antecedent context of generic count. Each data point represents the ratio of behavior and reinforcement for the entire season for the corresponding generic count of the pitcher being ahead in the count (A), behind in the count (B), or an even count (E). The dashed grey line represents bias equal to zero and sensitivity equal to 1 (i.e., "perfect matching").

pitches aimed at the edges of the strike zone with a count of zero balls and two strikes. Breaking pitches may initially look like they will be in the strike zone, increasing the likelihood that the batter will swing to avoid striking out. However, as the pitch breaks towards the edge or outside of the strike zone, the batter is likely to either miss the ball or hit the ball poorly. Players 1–5 threw breaking pitches with zero ball and two strike counts on 103 of 173 (60%), 69 of 146 (48%), 115 of 129 (89%), 99 of 166 (60%), and 101 of 238 (42%) of opportunities throughout the season, respectively. This rule may play a role in pitch selection in contexts in which the pitcher is ahead in the count, and similar rules pertaining to game strategy in other contexts are likely to play a role in pitch selection. Nevertheless, it is interesting that reinforcer rates changed with pitch selection in a manner consistent with the GME across the various contexts (see Figures 3–7). However, it is unknown whether reinforcement within those contexts was driving pitch selection because we did not manipulate the contingencies directly. Rules or other variables may have been guiding pitch allocation within contexts with reinforcement coincidentally changing according to the GME.

Another interesting feature of the present study is that multiple individuals were involved in selecting pitches. The pitcher, the

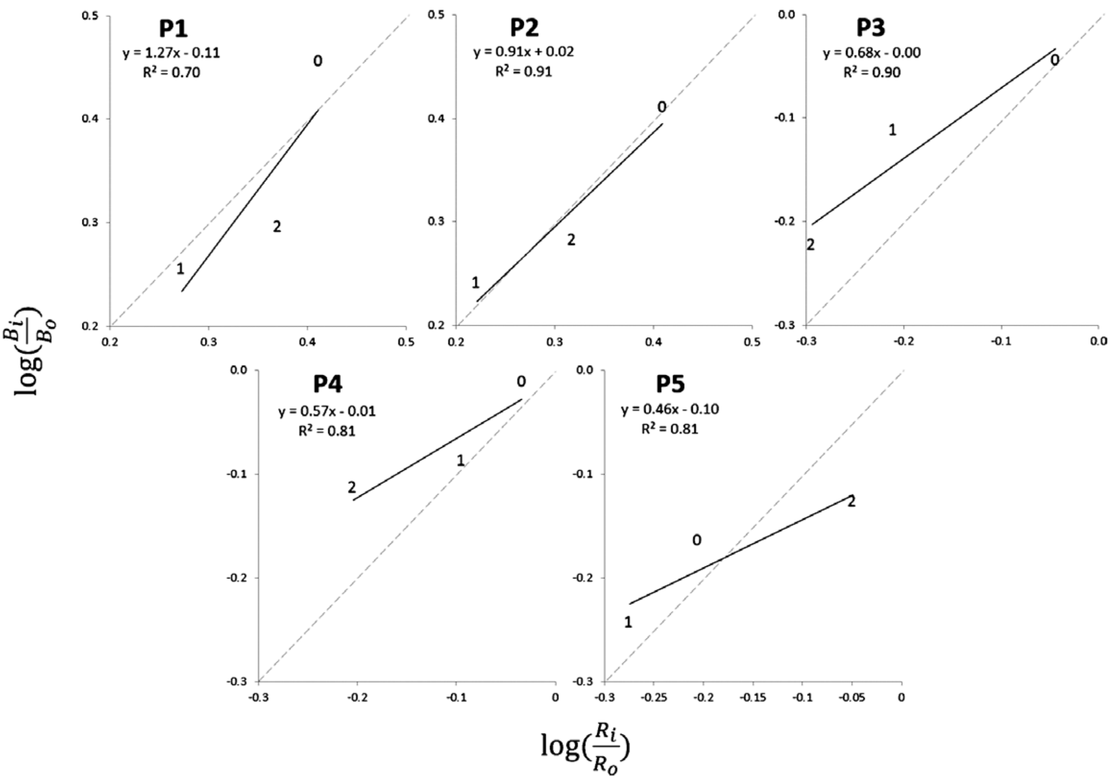

Figure 7. Results of fitting the GME to pitch selection for each pitcher (e.g., P1) based on the antecedent context of outs. Each data point represents the ratio of behavior and reinforcement for the entire season for the corresponding number of outs recorded to that point in the inning (i.e., 0 = zero outs recorded, 1 = 1 out recorded, and 2 = two outs recorded). The dashed grey line represents bias equal to zero and sensitivity equal to 1 (i.e., "perfect matching").

catcher, and/or the pitching coach may all play a role in pitch selection. The number of individuals involved likely depends on a number of variables such as the experience of the pitcher and catcher, and prespecified situations that would occasion a coach selecting the pitch sequence. Nevertheless, the GME described pitch selection well, despite the fact that multiple individuals may have contributed to the ultimate choice of which pitch was thrown.

Previous research has assessed changes in bias and sensitivity parameters as a function of time in natural contexts using statistical analyses at the group level (Stilling & Critchfield, 2010). This study analyzed how these parameters changed over time within a game for each participant. Reductions in bias over the course of a game indicated that pitchers were less likely to throw fastballs as the game progressed, independent of strikes and outs contacted by each pitch type. This suggests response or reinforcer characteristics may have changed over the course of a game. One possible example of this may be increased response effort to throw fastballs compared to other pitches over time. Fastballs are typically more effective the harder they are thrown, whereas breaking pitches are typically more effective the more the pitch breaks. The degree of break is not determined by how hard the ball is thrown. Rather, the degree of break is controlled by finger placement on the

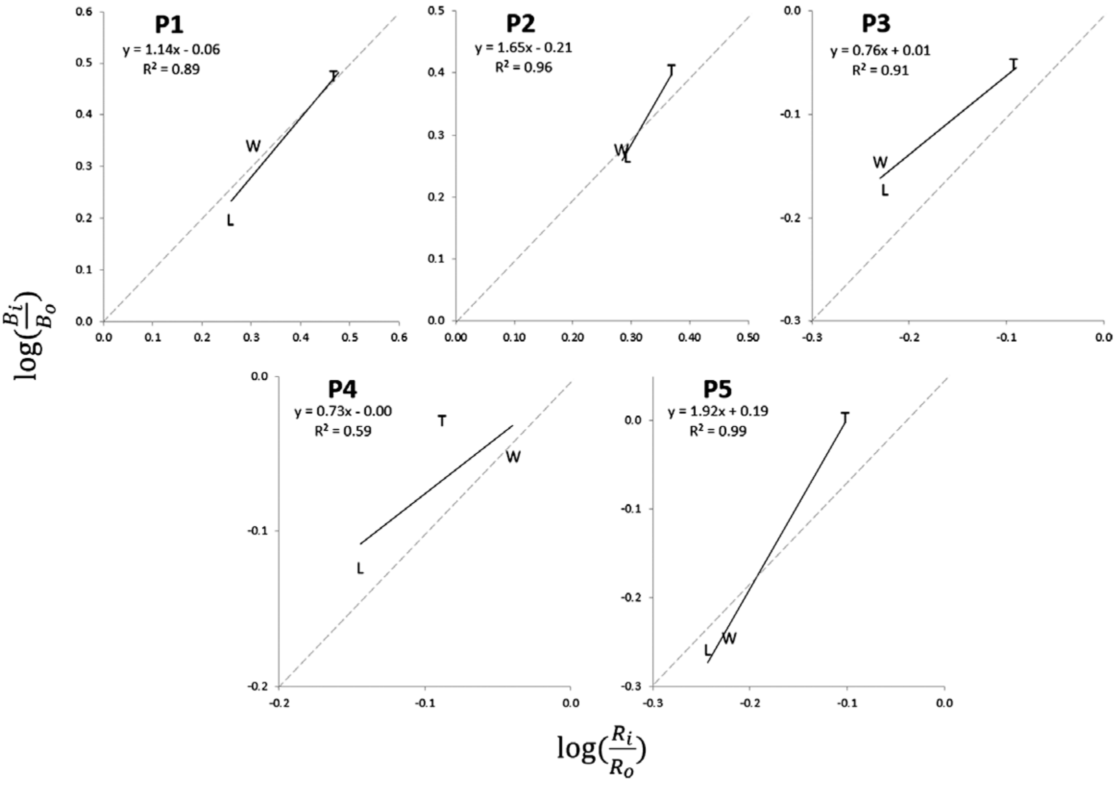

Figure 8. Results of fitting the GME to pitch selection for each pitcher (e.g., P1) based on the antecedent context of score. Each data point represents the ratio of behavior and reinforcement for the entire season for the corresponding score of the game at the time the pitch was thrown. T = tied game, W = the pitcher was winning, L = the pitcher was losing. The dashed grey line represents bias equal to zero and sensitivity equal to 1 (i.e., "perfect matching").

baseball, angle of the arm on pitch release, and the angular rotation of the ball as it is released from the hand of the pitcher. Fatigue throughout a game likely will decrease how hard one can throw a fastball but would not necessarily affect responses controlling degree of break on a pitch.

In this study, sensitivity describes the change in pitch selection as a function of change in the amount of strikes and outs contacted by each type of pitch. An increase in sensitivity over the course of a game indicated that pitcher behavior was more sensitive to change in strikes and outs in later innings compared to earlier innings. These results are consistent with previous laboratory research that has observed increases in sensitivity parameters within sessions (Aparicio & Baum, 2006, 2009; Davison & Baum, 2000; Rodewald, Hughes, & Pitts, 2010).

One limitation of this study stems from a common strategy in baseball to use sequences of pitches to "set up" the hitter. That is, throwing one or two specific pitches in specific locations such that the next pitch thrown will "fool the hitter" (i.e., increase the latency to accurate discrimination of the pitch type and result in the batter swinging poorly at the thrown ball). Multiple pitch sequences were not the unit of analysis within this study. Future research should attempt to incorporate pitch sequences to determine if matching occurs across

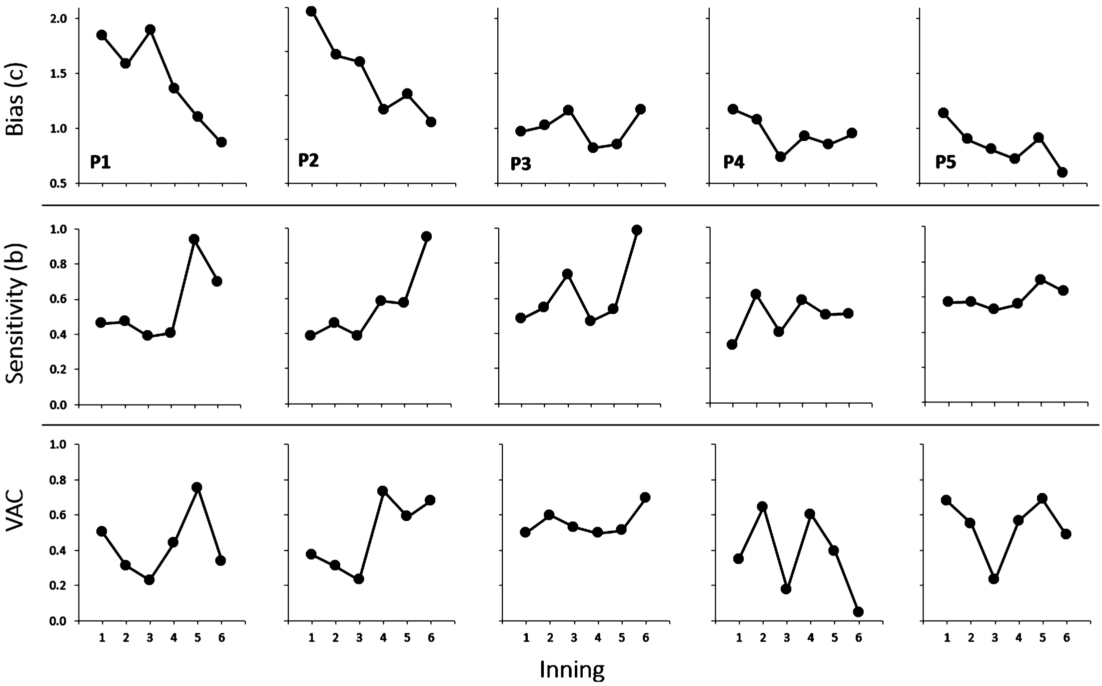

Figure 9. Changes in bias, sensitivity, and VAC as a function of changes in the antecedent context of 'inning' for each of the five participants.

sequences of responses coded as a single unit compared to individual pitches. In other words, the functional unit being selected by reinforcement contingencies in baseball may not be limited to single pitches, as was assumed in this study.

The generality of the GME can be tested by applying it to a greater number of natural contexts involving multiple response alternatives. Furthermore, understanding how different contexts influence the parameters of the GME will further increase the utility of the model. The GME described pitch selection generally and within specific contexts. Different game situations systematically influenced relative preference for throwing fastballs. Finally, reductions in bias and increases in sensitivity across innings within games suggest reinforcement and response parameters may have changed over time within baseball games.

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