Int. J. Sport Psychol., 2025; 56: 218-236
doi: 10.7352/IJSP.2025.56.218

Applying the matching law to Major League Baseball (MLB)

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The application of the generalized matching equation (GME) has been detailed in a variety of sports, including football, basketball, and others. However, only a limited number of studies have focused on Major League Baseball (MLB), and they typically have examined ≤ 5 players and/or focused on a single behavior. This paper increases the generalizability of such work by using newly available, state-of-the-art data from thousands of players to explore the GME in several scenarios within three aspects of a baseball game - defense, pitching and batting. We found that the GME accurately summarized response allocation in most scenarios, with r^2 ranging from 0.5 to 0.981, sensitivity ranging from 0.428 to 0.977, and bias ranging from -0.254 to 0.158. In addition, temporal trends in the applicability of the GME were examined within the context of changing philosophies in baseball strategy. These results indicate that the GME operated within several precisely defined dimensions of a baseball game and that analyses of this phenomenon can yield insight into prevailing trends in the sport. Furthermore, with the GME recognized as a ubiquitous phenomenon, teams can examine whether competitive advantages exist for GME adherence and adjust their strategies accordingly. From a psychological science perspective, this work helps establish the degree to which the GME generalizes to real-world contexts.

KEY WORDS: Matching Law, MLB, Baseball.

Introduction

A. What is the problem?

The matching law, first introduced by Herrnstein (Herrnstein, 1961), describes the relationship between the relative response rates and reinforce-

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Declarations of interest: None
in MLB Data Repository at https://baseballsavant.mlb.com
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ment rates for two concurrently available schedules of reinforcement. A common way to express this relationship is the generalized matching equation (GME):

$$\log\left(\frac{R_1}{R_2}\right) = s \cdot \log\left(\frac{r_1}{r_2}\right) + \log\,(b)$$

where *R*„ and *R*!, respectively, represent the relative response rates, r_1 and r_2 indicate the corresponding reinforcement rates, and the y-intercept, *log*(b), and *s* are constants called, respectively, the *bias* and *sensitivity* (McDowell, 2005). When $s = 1$ and $bias = 0$, response allocation is entirely governed by reinforcement rates, a scenario known as *ideal matching.*

For $bias \neq 0$, the bias represents a preference for one of the response alternatives, irrespective of reinforcement ratio. $s < 1$ corresponds to *undermatching*, where the ratio of responses is less than that what is predicted by the reinforcement ratio; *overmatching* ($s > 1$) represents the opposite pattern and is less common. The bias and sensitivity are typically determined empirically by fitting linear functions to log-transformed response/reinforcement ratio data with the r^1 value for this fit indicating the degree to which GME explains the ratio of responses.

Once verbal behavior has been acquired, humans and nonhumans often differ in operant performance, yet the matching law runs counter to this trend (Horne & Lowe, 1993).

Numerous studies have demonstrated that the GME accurately describes the relative allocation of behavior in many domains in both nonhumans (Baum, 1974, 1979; Schneider & Lickliter, 2010) and humans (Billington, 2003; Bulow & Meller, 1998; McDowell & Caron, 2010); although there have been no table exceptions (Davison & McCarthy, 2016; Takahashi & Iwamoto, 1986). In addition to being found across species and behavior domains, matching is robust at scale, having been observed at both individual and group levels (Poling, Edwards, et al., 2011). Typically, matching has been observed in controlled, laboratory settings and the degree to which these findings generalize to real-world contexts is an active area of research.

B. Research questions

A fruitful area for investigating matching in naturalistic settings has been sporting competitions, which is consistent with the more general recognition of athletics as a platform to study ecological decision dynamics (Araújo et al., 2006). Sporting events are attractive since competitions can often be broken

TABLE I
On Base Percentage By Handedness Matchups For The 2018 Season (Baseball Reference, 2019)

Pitcher	Hitter	On Base Percentage
RHP	RHB	0.308
RHP	LHB	0.330
LHP	RHB	0.323
LHP	LHB	0.305

into discrete events and a sport's rule structure provides a precise description of reinforcement alternatives available to participants.

Additionally, most top-tier sporting organizations keep detailed statistics, which allow response and reinforcement rates to be accurately recorded over long time periods. Matching was first investigated in basketball, where Vollmer & Bourret (Vollmer & Bourret, 2000) examined the ratio of two-point to three-point shot attempts versus shooting percentages throughout the season for 26 college athletes. A follow-up study analyzed a quasi-experiment that occurred when the National Basketball Association (NBA) moved the three-point line and thereby changed the reinforcement rate (Romanowich et al., 2007). Schenk & Reed (Schenk & Reed, 2020) duplicated this work with a direct experiment in a basketball video game and Alferink et al. (Alferink, Critchfield, Hitt, & Higgins, 2009) observed matching in the same domain at both the individual and team levels. In American football, matching has been associated with the ratio of passing to rushing plays (Reed, Critchfield, & Martens, 2006; Stilling & Critchfield, 2010) and point-after-touchdown options (Falligant et al., 2016). The allocation of types of hockey shots (Seniuk et al., 2015) and the location of strikes in mixed martial arts competitions (Seniuk et al., 2020) have also been found to follow the GME.

More than any other professional sport, Major League Baseball (MLB) has an affinity and tradition for quantifying outcomes, with statistical summaries of games published as newspaper box scores since the mid-19th century (Pesca, 2009). Despite this history, few studies have examined matching within an MLB context. Poling et al. (Poling, Weeden, Redner, & Foster, 2011) investigated the GME for the allocation of left versus right-handed at-bats versus the relative reinforcement for three outcomes – total bases (TB), runs batted in (RBI), and homeruns – for three elite switch hitters. Undermatching was found for all outcomes, which led the authors to conclude that the behavior ratio was dictated by traditional baseball rules rather than matching. Cox et al. (Cox, Sosine, & Dallery, 2017) turned their attention to pitchers, where they examined the relationship between pitch types (fast vs. slow, straight vs. breaking) and advantageous outcomes for five pitchers. The GME described the data well, with an average r^2 of 0.93 and four of the five participants demonstrating near ideal matching with $-0.05 \leq b \leq -0.02$ and $0.90 \leq s \leq 0.95$. GME also described how pitch allocation changed with various in-game scenarios such as pitcher fatigue, game score, inning, opposing batter's lineup location in the lineup, number of outs, and pitch count. More recently, Cox expanded his methodology to examine a much larger pool of players (Cox et al., 2021). Also, Falligant (Falligant et al., 2021) expanded on the GME by evaluating six "higher-skill pitchers" and six "lower-skill pitchers" separately.

Tangentially, Reed (Reed, 2016) applied matching theory to the Twitter interactions between MLB teams and fans.

C. Hypotheses

The MLB studies outlined above examined ≤ 5 players, applied the GME on an individual basis, and/or considered a single domain (e.g. pitching). This latter property is consistent with other studies that have examined matching in sporting competitions. Taken together, these characteristics limit the degree to which the generalizability of matching in sports can be assessed. In this study, we hypothesized that adherence to the GME was a more universal phenomenon that could be observed in several aspects of MLB-related behaviors.

D. Aims of the study

First, to determine if the GME applied at a macro rather than individual scale, we assessed matching within MLB data at the group level. Second, we identified behaviors in three domains of a baseball game – defense, pitching, and batting – and investigated whether response allocations followed the GME. To perform this work, we used state-of the-art data associated with a technological revolution that has recently occurred in MLB, which now allows the game to be quantified in ways that were unimaginable in the recent past (Verducci, 2019). This dramatic increase in data allowed us to observe outcomes for a large number of players in exceptionally specific scenarios. We also examined trends in matching over time, to explore the possibility that MLB teams have used the wealth of newly-available data to encourage players to adjust their behavior. By assessing the prevalence of the GME in multiple domains, each rife with idiosyncratic factors that add noise to response rates, this study provides critical information about the generalizability of matching at the group level in uncontrolled, real-world settings.

Materials And Methods

A. Study design and sample

At the beginning of the 2015 season, MLB introduced *Statcast*, which revolutionized the sport by tracking every play and allowing "for the collection and analysis of a massive amount of baseball data, in ways that were never possible in the past" (MLB Advanced Media, 2019). This level of detail was achieved by installing two pieces of equipment in every stadium: a Trackman Doppler radar system, that tracks everything related to the baseball at 20,000 frames per second, and a Chyron Hego six-camera stereoscopic system that tracks players' positions and movements. *Statcast* data is publicly available via the *Baseball Savant* database (Willman, 2019). *Baseball Savant* allows users to create precise, complex queries concerning pitch type, pitch result, infield alignment, situation, and more, which provides data at an unprecedented level of detail.

As detailed below, five *Baseball Savant* queries were created within three domains of a baseball game – defense, pitching, and batting – where players make a clear decision between behaviors with distinct reinforcement rates. Data was extracted from 2015 through 2018, covering 550, 395 events and 1930 players. For each identified scenario, we first provide background information concerning context within current baseball philosophy and then outline the selection of GME parameters (i.e. response and reinforcement alternatives) and analysis inclusion criteria.

B. Procedures and statistical analyses

Defense - Shift Analysis

In baseball, a standard defensive alignment consists of a left fielder (LF), center fielder (CF), right fielder (RF), third baseman (3B), shortstop (SS), second baseman (2B), and first baseman (1B) playing in the approximate locations shown in Figure 1a. In recent years, an abundance of data has allowed teams to create spray charts that accurately quantify the probability that a batter will hit the ball to various areas of the field (see Figure 1c). In an effort to increase the likelihood of recording an out, teams often use this information to deploy fielders in non-standard alignments, called shifts, that place defenders in the locations where the ball is mostly likely to be hit Figure 1b illustrates a popular shift alignment, where the 2B has been moved to the outfield and the SS covers the standard 2B position. The shift strategy was once reserved for only the most accomplished hitters, but advances in data analytics have resulted in it becoming an increasingly integral part of the game. Managers must be judicious in deploying the shift, though, as shifting the defenders also leads to defensive vulnerabilities in other parts of the field that batters can exploit.

Response alternatives for this analysis were defined as instances of a defensive team deploying a standard alignment versus an infield shift during a batter's at-bat; reinforcement was defined as whether an out was recorded during the at-bat. Since infield shifts are designed to combat groundball hits, only outcomes that were recorded on groundballs were included in our analysis. Response/reinforcement ratios were calculated on an individual batter basis, with only those players having 50 instances of both an infield shift and standard alignment deployed against in a given season being included.

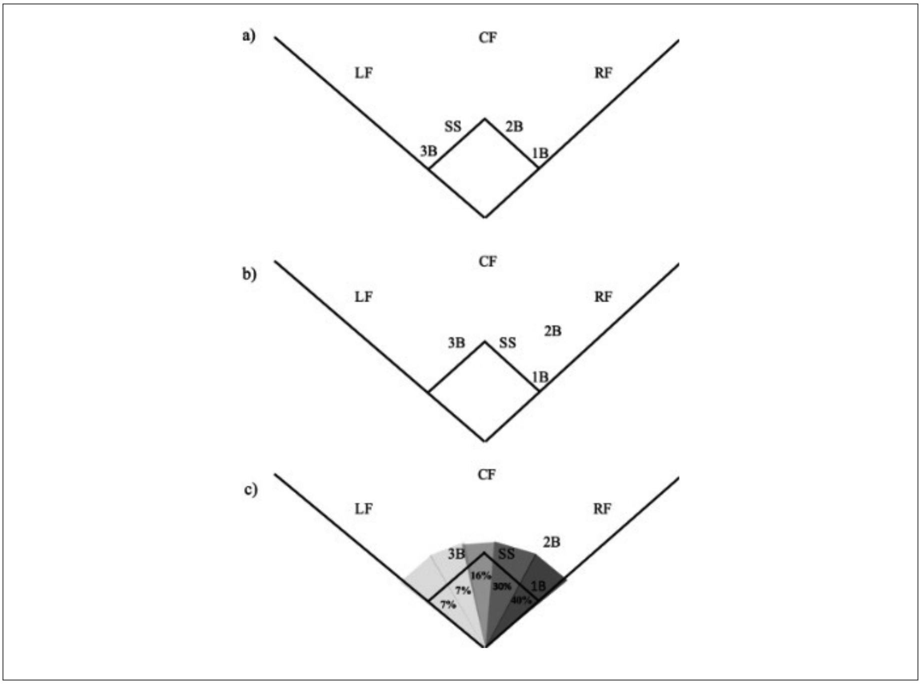


Figure 1. a) Standard defensive alignment; b) Shifted defensive alignment; c) Sample spray chart illustrating the percentage of a batter's balls hit to various locations of the field.

Pitching - Full Count Pitch Selection

A full count is a crucial situation in baseball in which a batter has three balls and two strikes against them. If the pitcher throws a fourth ball, the batter advances to first base via a base-on-balls (or walk), but if the pitcher records a third strike, the batter is ruled out by strikeout. This small margin for error makes strategical choices about this pitch incredibly critical. Broadly speaking, pitchers have three options to choose from when delivering a pitch: fastball, off speed pitch, or breaking pitch. A fastball is easier to throw as a strike but also easier to hit, while off speed and breaking pitches are difficult to accurately locate, thus risking a base on balls, but could result in a batter swinging and missing, resulting in a strikeout. From a GME perspective, full counts are an interesting scenario since they force a meaningful outcome (batter advances or not) that ends the at-bat, while other pitch counts do not.

For this analysis, responses were grouped into two classes on a per pitcher basis: throwing a fastball versus a breaking/off-speed pitch in a full count. Reinforcement was considered to be any outcome (strikeouts, batted out, etc.) that did not result in a hit or base on balls. During a full count, when a batsman hits a foul ball, i.e. outside the confines of the field boundaries, the count remains the same and the scenario is repeated; therefore, full count foul balls were eliminated from this analysis. Data were retained for only those pitchers with a minimum of 25 fastballs and 25 breaking/off-speed pitches in full-count scenarios (excluding foul balls) in a given season.

Pitching - Four-Seam versus Two-Seam Fastball

An aspect of pitching that has been revolutionized by baseball's recent technological advances is the spin rate of the baseball as it leaves the pitcher's hand. Prior to the widespread use of the Trackman system, spin rate was a non-consideration, but it is now broadly recognized as an important indicator of pitch quality. A large consequence of this development is that the low-spin two-seam fastball, in which the pitcher grips the ball along the seams, is now considered to be largely inferior to the high-spin four-seam fastball.

The response alternatives examined in this analysis were two-seam versus four-seam fastballs, summarized at the pitcher level over a given season. Only pitchers that threw a minimum of 100 of both types of fastballs throughout a season were included. Two different reinforcement criteria were used. First, we considered a swing and miss by the batter as a reinforcer, since it is typically this metric by which the superiority of the four-seam fastball is established. We then re-ran the analysis using the recording of an out as the reinforcer, which was expected to be a stronger consequence.

Pitching – Fastball Location

One way in which hitters have made use of newly available data analytics is by recognizing the true value of a homerun relative to other outcomes (e.g. a double) and, therefore, adjusting their swing to make homeruns more likely, at the expense of increasing their chance of recording an out. They have begun to "…prioritize slugging over batting average, [as] they seek higher launch angles with a more upward swing path to the ball— perfect for elevating low pitches" (Verducci, 2019). This is more difficult to achieve with a high pitch, so as an adjustment, pitchers now throw more fastballs in the upper part of the strike zone, to obtain a swing and miss.

Baseball Savant separates where a pitch is thrown into 14 zones, as shown in Figure 2. This analysis concentrated on the reinforcement from throwing a fastball high in the zone, operationalized as zones (1, 2, 3, 11, 12) versus low in the zone, operationalized as zones (7, 8, 9, 13, 14), aggregated at the pitcher level. Although pitchers could throw an off-speed or breaking pitch high in the zone, due to the shape and speed of these pitches they are not in the best interest of the pitcher and are avoided. Pitchers who threw at least 100 types of each fastball in a given season were included in the analysis. As was the case for two-versus four-seam fastballs, two different reinforcement criteria were used, swing-and-miss and out.

Batting – Switch Hitting

Most batters hit either right-handed (RHB) or left-handed (LHB), but some hitters, called switch hitters, are able to hit from either side. For switch hitters, the choice of which way to bat is usually based on whether the pitcher is left (LHP) or right-handed (RHP), since opposite-handed matchups are more advantageous for hitters (platoon advantage).

This analysis was similar to that of Poling et al. (Poling, Weeden, et al., 2011), described in the introduction, but for many more players. Response alternatives were described as batting from the left versus right side, with reinforcement defined as a hit or walk during the

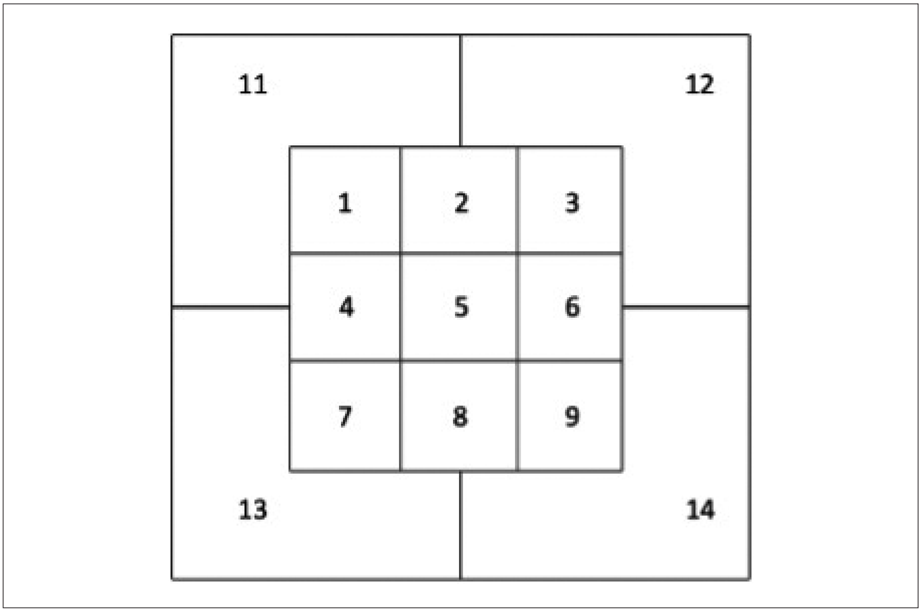


Figure 2. Pitch location zones, as outlined by Baseball Savant.

at-bat. Switch hitters are relatively rare, so data was combined over the 2015-2018 season and only switch hitters with 200 or more plate appearances from each side of the plate during this time-period were included.

Results

A. Defense – Shift Analysis

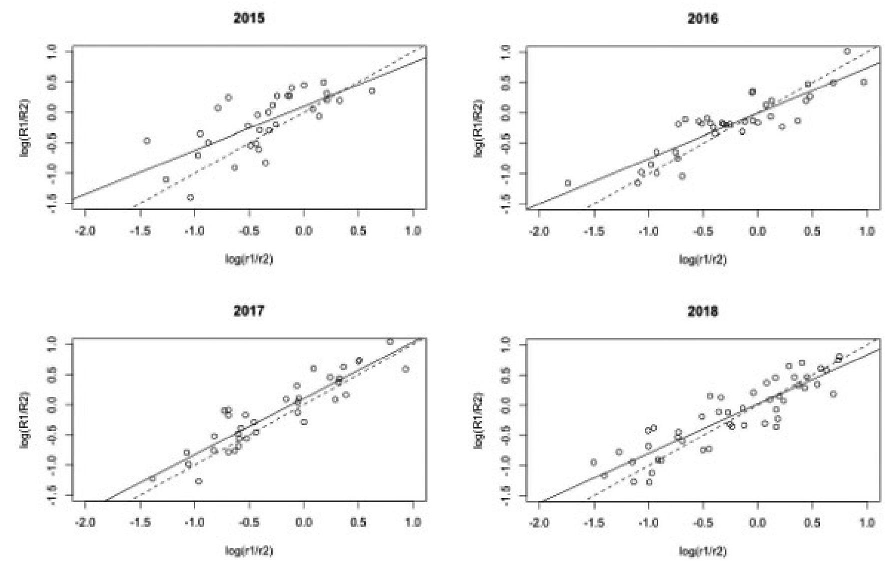
The query for this analysis resulted in a total of 29,909 events analyzed for 154 players across the 2015-2018 seasons. Results for GME fits are shown in Figure 3 with temporal changes in GME parameters summarized as well. Excluding 2015, the r^2 values indicate that the GME accurately described the relationship between response and reinforcement ratios. There appears to be a trend towards higher sensitivity to reinforcement with time.

B. Pitching – Full Count Pitch Selection

The query for this analysis resulted in a total of 32,427 pitches analyzed for 348 pitchers across the 2015-2018 seasons, with results shown in Figure

4. Temporal changes from 2015-2018 are summarized further in Figure 4 as well. Based on the r^2 values, the GME performed reasonably well at summarizing the relationship between responses and reinforcement.

Undermatching was present and there was consistent bias towards throwing fastballs. Major temporal trends in these parameters were not found.

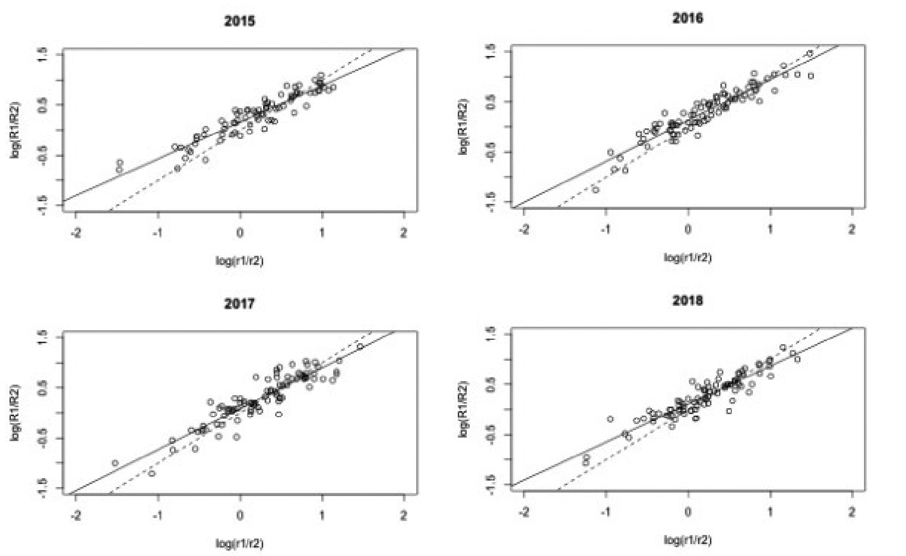


GME Linear Fit Results				
Year	**Players**	**r^2**	**Sensitivity**	**Bias**
Reinforcer = Swing-And-Miss				
2015	32	0.5	0.721	0.097
2016	38	0.774	0.747	-0.0059
2017	36	0.826	0.932	0.105
2018	48	0.793	0.817	0.017

Figure 3. Defensive shift regression results. R_1= shift deployed; R_2= standard alignment deployed; r_1= Outs recorded with shift; r_2= Outs recorded *with standard alignment.*

C. Pitching – Four-Seam Versus Two-Seam Fastball

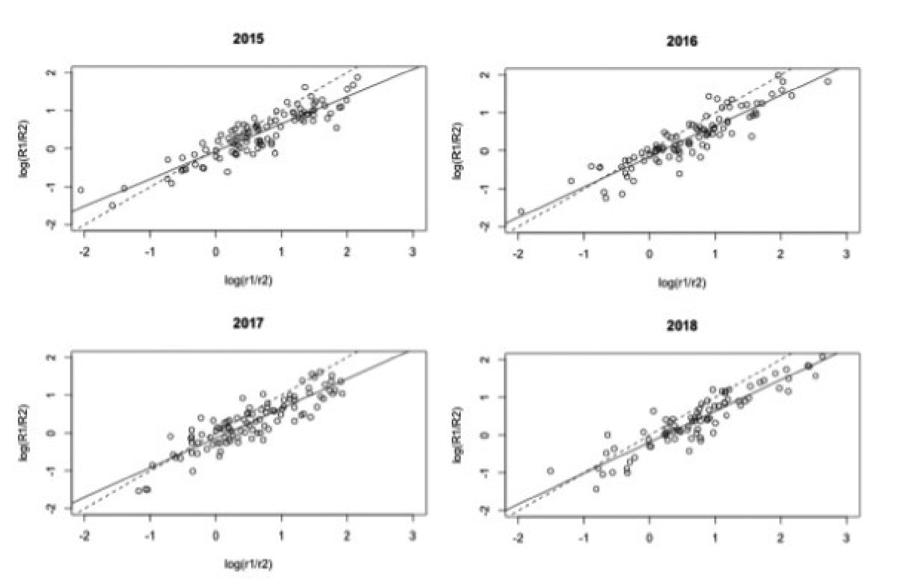
The queries for these analyses resulted in a total of 221,360 pitches analyzed for 375 pitchers when using swing-and-miss as a reinforcer and 60,414 pitches analyzed for 161 pitchers when using out recorded as reinforcers across the 2015-2018 seasons. There are more outcomes for the former since there are many more pitches for which a swing-and-miss, rather than an out, are recorded. Results are shown in Figure 5 and Figure 6. The r^2, sensitivity, and bias significantly improved towards perfect matching when considering out recorded as a reinforcer, relative to a swing and miss. Bias increased in the



GME Linear Fit Results				
Year	*Players*	*r^2*	*Sensitivity*	*Bias*
2015	78	0.864	0.729	0.158
2016	90	0.874	0.814	0.126
2017	91	0.832	0.814	0.085
2018	89	0.845	0.756	0.107

Figure 4. Full count pitch selection regression results. R_1= fastballs thrown; R_2= non-fastballs thrown; r_1= outs recorded w/ fastball; r_2= outs recorded w/ non-fastball.

negative direction with time (only marginally for out as a reinforcer), which interestingly signifies a bias towards two-seam fastballs. The number of play-



GME Linear Fit Results				
Year	*Players*	*r^2*	*Sensitivity*	*Bias*
Reinforcer = Swing-And-Miss				
2015	100	0.812	0.720	-0.07
2016	92	0.817	0.802	-0.150
2017	101	0.777	0.782	-0.138
2018	82	0.838	0.822	-0.186
Reinforcer = Out Recorded				
2015	50	0.970	0.946	-0.009
2016	40	0.981	0.948	-0.031
2017	43	0.981	0.957	-0.043
2018	28	0.979	0.977	-0.029

Figure 5. Four-seam versus two-seam fastball regression results. R_1= 4-Seam pitches; R_2= 2-Seam pitches; r_1 Swing-and-miss/Out on 4-Seam Pitch; r_2= Swing-and-miss/ Out on 2-Seam Pitch. Illustrated results show swing and miss as reinforcer.

ers that qualified for these analyses decreased greatly in 2018 as the philosophy of pitching moved towards more four-seam fastballs.

D. Pitching – Fastball Location

The queries for these analyses resulted in 291,741 pitches analyzed for 673 pitchers and 51,716 pitches analyzed for 174 pitchers for swing-and-miss and out as reinforcers, respectively. The results are shown in Figure 7 and Figure 8. Based on r^2 values, matching was much stronger when considering outs, rather than swing-and-miss, as a reinforcer. The same was true for sensitivity and bias. When using outs as the reinforcer, r^2 and sensitivity slightly decreased over time.

E. Batting – Switch Hitting

The query for this analysis resulted in 72,301 events analyzed for 45 hitters across the 2015-2018 seasons. The results of the regression are in Figure 9 illustrates these findings.

Generally, the GME characteristics were weaker in this domain than in

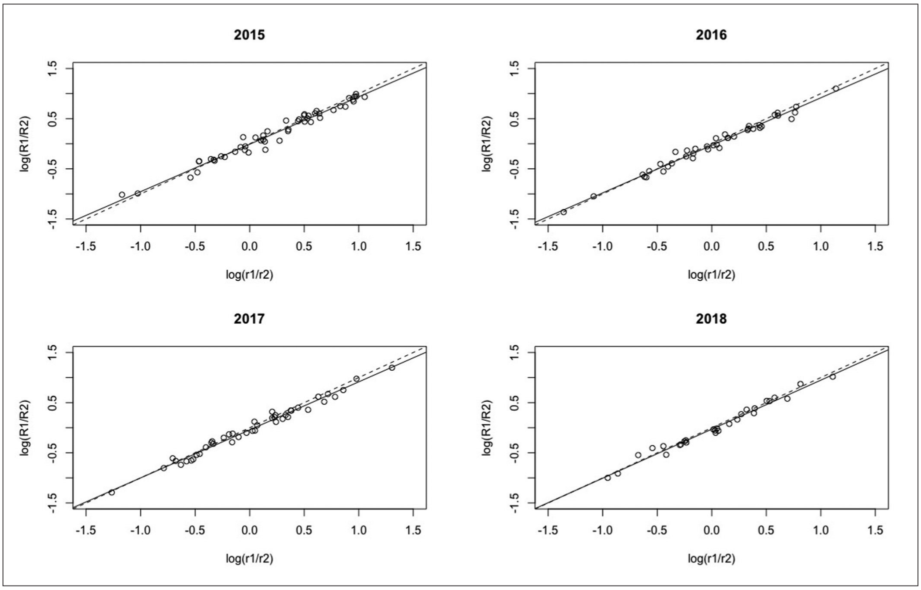
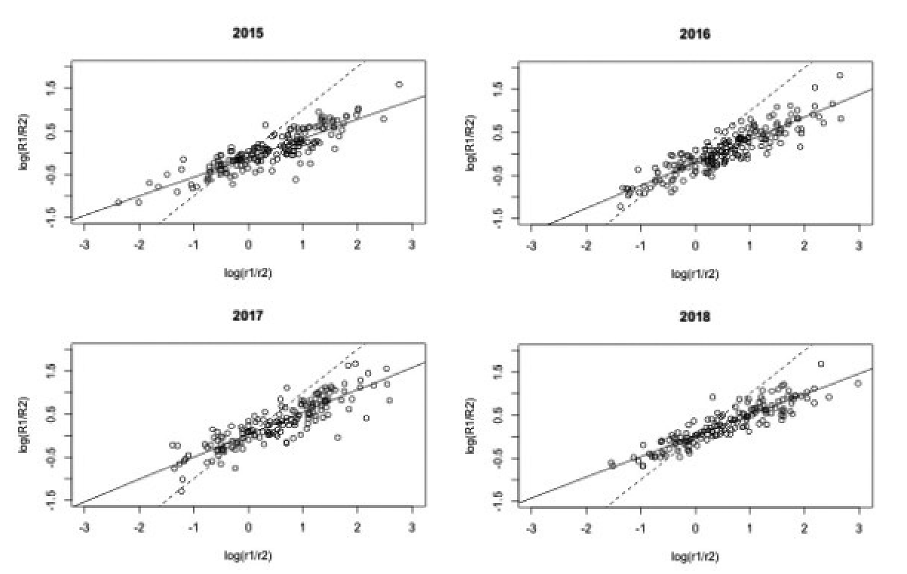


Figure 6. Illustrated *regression* results of four-seam versus two-seam fastball analysis (out recorded as *reinforcer).*

the others explored in this manuscript. The negative bias showed a bias towards LHB, unrelated to the reinforcement, which is likely due to more RHP than LHP in MLB and the presence of a non-reinforcement-based heuristic that dictates which option a batter should choose (RHB vs LHP and LHB vs. RHP).



GME Linear Fit Results				
Year	Players	r^2	Sensitivity	Bias
Reinforcer = Swing-And-Miss				
2015	177	0.750	0.446	-0.113
2016	185	0.788	0.530	-0.205
2017	158	0.752	0.520	0.025
2018	153	0.816	0.428	0.021
Reinforcer = Out Recorded				
2015	58	0.974	0.922	-0.074
2016	44	0.963	0.945	-0.084
2017	40	0.964	0.925	-0.04
2018	32	0.936	0.865	-0.047

Figure 7. Fastball location regression results. R_1= Fastball high in the zone; R_2= Fastball low in the zone; r_1 *Swing-and-miss/Out from a fastball high in the zone;* r_2= *Swing-and-miss/Out from a fastball low in the zone. Illustrated results show swing and miss as reinforcer.*

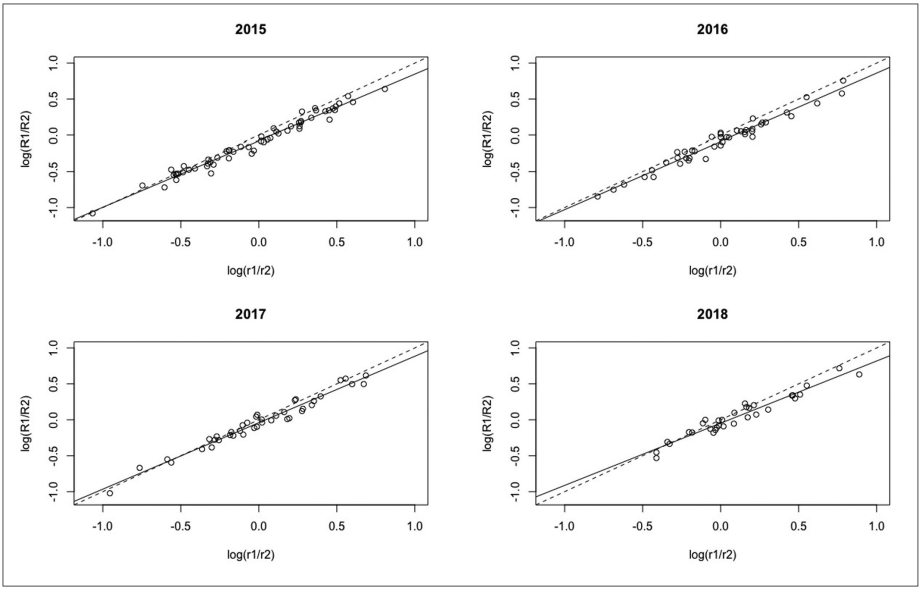
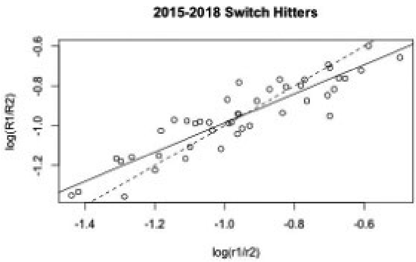


Figure 8. Illustrated regression results of fastball location analysis (out recorded as reinforcer).

Discussion

This study used state-of-the-art Statcast data to explore the degree to which the GME can be used to describe behavioral choices in three facets of a baseball game – defense, pitching, and batting. Statcast allowed analyses to probe several in-game scenarios with a level of precision that would not have been otherwise achievable, making this analysis unique in its multi-faceted examination of matching in a single sport. Our results point to the GME as a ubiquitous phenomenon within baseball by which teams quantify their decisions between various strategies and determine whether there is a competitive advantage associated with adherence (or non-adherence) to the GME. The GME framework also represents a tool that can be used to expose previously unrecognized biases towards certain behaviors so that, if necessary, action can be taken to correct this bias. For example, if there is a bias towards deploying defensive shifts more frequently than this strategy is reinforced by recording an out, coaches could choose to implement a standard alignment more frequently.

The results for defensive shifts indicated that teams' defensive strategies are partially affected by reinforcement schedules. There was a trend towards



GME Linear Fit Results				
Year	*Players*	r^2	*Sensitivity*	*Bias*
2015-2018	45	0.827	0.733	-0.254

Figure 9. Switch hitting regression results. R_1= Right-handed at bat; R_2= Left-handed at bat; r_1 Hit or walk during right-handed at bat; r_2= Hit or walk during left-handed at bat.

higher sensitivity to reinforcement with time, which could reflect a learning process, whereby teams are discovering how to best make use of the massive volume of data inundating their organization. When present, bias was in the direction of shifting, which could possibly represent an over-correction by teams, or failure to recognize adjustments by batters to make the shift less advantageous (e.g. bunting to an under-positioned side of the infield).

In exploring pitchers' allocation of fastballs versus breaking/off-speed pitches in a full count, there was a slight bias towards fastballs. This is not surprising, as fastballs are easier to control and locate within the strikezone, which makes them more apt to force a batter to swing. Pitchers would likely prefer that a batter reach by attempting to make contact and record a hit, rather than automatically advance via a base-on-balls (walk). Walks are often called a "free pass," which likely reflects this bias.

The two-seam versus four-seem pitching results allowed us to explore the consequences of changes in baseball philosophy that are currently under way, specifically an increased focus on swing and misses. This trend is reflected by 2018 stats that showed eight less balls in play and six more strikeouts compared to 1988 (Verducci, 2018). Based on this development, we hypothesized that pitchers would be biased towards throwing more four-seam fastballs, which are known to have better success at inducing swing and misses. But when using swings and misses as the reinforcer, the opposite effect was found as there was a bias towards two seam-fastballs. This could be a result of pitchers abandoning the two seam-fastball, and thus not meeting the inclusion criteria (100 of each type of fastball) for analysis.

For swing-and-miss as a reinforcer, in 2015 100 pitchers met the criteria, while in 2018 only 82. In addition, two-seam fastball use decreased by 2.4% from 2015-2018 and four-seam fastball use increased by 2.3% (Willman, 2019). Another possible explanation for this bias is that, due to a history of training, some pitchers rely on the two-seam fastball as their primary pitch, so it may be a fallback in high leverage situations.

The trend towards more swings and misses was also explored via the pitch location analysis. When using swings and misses as a reinforcer, there was bias toward low pitches in 2015 and 2016, but not in 2017 and 2018. This result is consistent with a concurrent change in philosophy towards throwing high fastballs to induce swings and misses. This analysis had the most extreme undermatching, with a low of 0.428 in 2018, which might be explained by pitcher's resistance to changing pitching strategies. When the reinforcement criteria was switched to outs rather than swings and misses, there was little bias towards either option.

This likely reflects the increased importance of outs versus swings and misses and may indicate that the differences between these two options extend beyond swing and miss rates, as they are often described.

The switch-hitting results allowed us to explore the idea of platoon advantage (opposite handedness) for hitters. There was a negative bias towards hitting left-handed, which was most likely due to an over-representation of right-handed pitchers in the league.

There was also undermatching, which indicates that switch hitters could improve outcomes by more frequently batting from the same side as the pitcher throws. A switch hitter would likely forgo hitting left-handed against a right-handed pitcher (or vice versa) only when facing a knuckleball pitcher, which is rare. But the results indicate that, from a reinforcement standpoint, this strategy is not optimal We found that undermatching was present in all scenarios we examined ranging from 0.428 to 0.977, which is consistent with previous studies (Baum, 1979); although in some cases the fitted sensitivity was near to the ideal matching value of 1. Undermatching is often interpreted as a failure to optimally identify or respond to differences in reinforcement rates.

It is not surprising to see this effect in baseball, as often a specific scenario, rather than the history of reinforcement, can have a huge effect on the allocation of behavior. For example, if an offensive team was mounting serious scoring threat with runners on 1st and 3rd base with one out, the pitcher could neutralize this danger by inducing the batter to hit a ground ball into an inning-ending double play. Pitches thrown low in the strike zone are most likely to result in this outcome. Since two-seam fastballs are more likely to induce a groundball than a four-seam fastball, this option would be far more probable in this scenario, regardless of the history reinforcement. Similarly, if a team is ahead by several runs, pitchers are more likely to throw fastballs in a full count so that they can avoid walking batters and placing runners, that could eventually be converted to runs, on base. Despite these contextual factors, the widespread applicability of the GME indicates that differential reinforcement still plays a large role in determining behavioral response.

There were several limitations to this study. First, we did not account for levels of reinforcement within the game. A player's ultimate goal is to win the game and the reinforcement criteria we used (swings and misses, outs, hits, etc.) are intermediate outcomes encountered in pursuit of this goal. But not all of these outcomes are equal throughout a game. For instance, the reinforcement value of an out recorded late in the game where one team is leading by a large margin is not likely to be equal to that of an out recorded in a high-leverage situation of a close game. But our approach considered these outcomes to be equal.

A potential solution would be to weight specific outcomes by associated changes in run expectancy (Weinberg, 2014) or likelihood of winning the game, which would provide a more accurate representation of an event's reinforcement value. Second, while baseball contains an almost limitless number of behaviors and scenarios that could have been examined, we only explored five. While this number is greater than what has been examined in past studies of matching in sports, our results should not be considered a full characterization of the presence of matching in the game. There were several scenarios with discrete events and clearly discernable outcomes (e.g. stealing a base) that the data did not allow us to explore. Lastly, our results were calculated over several players over four years and analyses did not account for personal preferences, prevailing team philosophy, history of injury, and a host of other factors that almost certainly affect behavior allocation In conclusion, these results indicate that the GME operated within several precisely-defined dimensions of a baseball game, and that analyses of this phenomenon can yield insight into prevailing trends in the sport. As big data summaries begin to be incorporated into other sports, this approach can be extended to a multitude of other scenarios (e.g. fouling a poor free-throw shooter in basketball, field goal versus standard play in football) that could potentially help teams develop more effective strategies. More importantly, this work highlights the role that reinforcement plays in the determination of human behavior in naturalistic settings. Such research is useful in helping the public move towards an operant framework to explain behavioral outcomes.

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Manuscript submitted July 2024 . Accepted for publication Febbraio 2025.