Under Pressure: A Case Study of the Effects of External Pressure on MLB Players using Twitter Sentiment Analysis

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Submitted in partial fulfillment of the requirements for graduation
with honors in the Bryant University Honors Program
November 2020

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ABSTRACT

Performance under pressure and psychological momentum are well-documented topics in sports psychology, but most research focuses on "in-game" pressure. This study views pressure more broadly to examine how the external pressure of fans, quantified using the sentiment of tweets mentioning the players, can affect how MLB players perform.

Although external pressure is intangible, it can impact a player's psyche and performance. This investigation focuses on players Chris Sale and David Price. A new process was developed leveraging the Vader package in Python that can generate tweet sentiment to compare to several performance metrics from Baseball Reference.

Results proved to be promising with correlation analysis pointing to some association between sentiment and performance. There was also an observed difference in how both players handled the pressure depending on whether they played for a small or large market team. An anecdotal study of the 2018 season showed even more interesting differences between Sale's and Price's performance and Twitter sentiment. Price's performance and Twitter's sentiment moved in a cyclical manner throughout the season whereas Sale's results were much more consistent and less sensitive to change. Finally, a study focused on the impact of both pressure and past performance on future outings showed results consistent with past studies on the subject. For example, Sale was most likely to perform well under pressure if he preceded the start with a very good or bad outing rather than an average outing. Information like this could be useful for front offices and managers.

More analysis should be conducted to confirm and expand on the findings of this project. However, this case study can be used as a foundation for a new and innovative approach to player evaluation, ultimately complementing existing methods and informing decisions regarding otherwise intangible factors.

INTRODUCTION

Serving one of the largest markets in the MLB, Boston Red Sox players are heavily scrutinized by scores of media, talk-show hosts, Twitter trolls, and dedicated fans. Players who come to Boston can be beloved (David Ortiz, Brock Holt, Chris Sale) or hated (Pablo Sandoval, Carl Crawford, David Price) with equal intensity depending on their attitude and performance here. Some players seem to thrive under the pressure where others crack. This study aims to determine whether some players react differently to external pressure by comparing performance metrics to the sentiment of fan tweets.

Professional baseball is a multimillion-dollar industry. Some players are given contracts of 300 to 400 million dollars. When there is this magnitude of money involved, it is important that front offices make the right decision when it comes to choosing and supporting players. David Price ($217M), Carl Crawford ($142M), and Pablo Sandoval ($95M) are three recent Red Sox contracts that are widely viewed as mistakes despite the success all three players had on other teams. Conversely, David Ortiz initially signed with the Red Sox for $1.25M after being released and went on to have a Hall of Fame caliber career. If the Red Sox front office was able to understand the relationship between external pressure and performance, perhaps they could make better decisions initially or provide some sort of intervention to struggling players with bloated contracts.

LITERATURE REVIEW

Yogi Berra said that “baseball is ninety percent mental and the other half is physical”. Since the time he retired in 1965, the field of sports psychology has continuously advanced. It is from this field that most of the literature for this project will be drawn. Some of the key findings from past studies relate to how performance is affected by pressure and psychological momentum.

Performance Under Pressure

It is generally accepted that a graph depicting pressure or physiological arousal on the x-axis and performance on the y-axis would be a parabolic shape (Luiselli & Reed, 2011) (See

Figure 1). With minimal pressure, performance would suffer due to indifference or disinterest. As the amount of pressure increases, performance would improve until a maximum point is reached where an athlete is "locked in" at the top of their game and in a state of mind called "flow state". Eventually, more pressure will lead to feelings of anxiety and nervousness that will ultimately deteriorate performance (Williams, 2010).

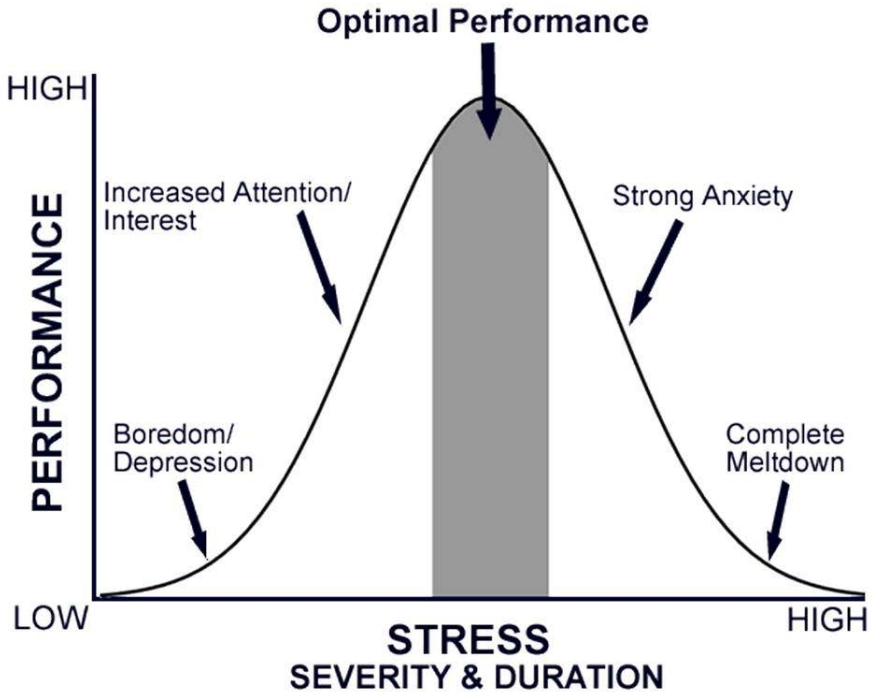


Figure 1: There is a parabolic relationship between performance and stress (Bradberry, 2014).

Martin (2019) provides several reasons why nervousness might interfere with performance. First, nervousness consumes energy that could be more efficiently utilized. Secondly, anxiety narrows an athlete's attention potentially preventing them from picking up on external cues. Lastly, the rush of adrenaline that accompanies anxiety can destroy the timing of skilled routines that are an important part of sports.

Masters et al. (1993) developed a "Reinvestment Scale" aimed at predicting who would perform the worst under stress. They theorized that those who scored higher on the reinvestment scale disrupted the "automaticity of skilled performance" by investing too much

of their attention to their action when under pressure. This supports the idea that "thinking too much" will hurt one's performance. The scale included three elements that would indicate whether a person is more susceptible to "deautomatization". They include rehearsal (a tendency to mentally rehearse emotional events), private self-consciousness (the amount of attention one pays to their thought processes), and public self-consciousness (the amount that a person is concerned with how others view them). The higher a person rates on any of these factors, the more likely they will succumb to pressure.

Psychological Momentum

Several studies have concluded that past performance is a significant factor when predicting whether a player will succeed under pressure. One study analyzed NFL games and found that the probability of failure was highest when the pressure was high and the play was preceded by a failure (Harris et al., 2019).

In a separate study that focused on individual baseball players completing simulated at-bats, findings were similar, showing an interaction effect between past performance and pressure. Interestingly, the study found that players on either a cold or hot streak were more likely to succeed under pressure as compared to those who were not on a streak. Researchers attributed this to the fact that in a cold streak, a player will shift their attitudinal focus inward and focus more on fundamental skills than external pressure. Conversely, those on a hot streak will have heightened self-confidence or perceived control that improves their external attitudinal focus and makes them more immune to the pressure. Additionally, those who succeeded under pressure performed much better after the pressure was removed (Gray et al., 2013).

Another relevant finding came from a study by Golding et al. (2017). Athletes and non-athletes were asked to pitch both with a crowd offering positive and negative criticism. Athletes were more affected by the criticism presumably because they care more about their performance, but the type of reaction and the magnitude was highly dependent on the person. This seems to suggest that some athletes are affected more by external pressure than others.

Other Findings

One article discussed different ways to measure fan passion including the extent to which a team occupies the fan's heart, mind, body, and soul. Fan passion could be a measure to determine how much pressure a player will be under and/or how likely they will be to interact with fans on social media (Wakefield, 2016).

The idea of clutch, having an innate ability to perform in high leverage situations, is a controversial one in baseball. There are many studies of clutch that have shown that given a large enough sample, those who perform best in high pressure situations are those that perform the best in low pressure. However, players like David Ortiz make it hard to believe that clutch doesn't exist, and many managers do believe that some players are more capable in high leverage situations (Perrotto, 2018).

This Investigation

Most of the aforementioned literature focuses on short-term, in-game pressure while this project hopes to expand the concept of pressure to include the continuous off-field pressure a player faces when playing in large markets like Boston, New York, or Los Angeles. Additionally, many of these articles were controlled experiments that did not include professional baseball players. This investigation will use Twitter sentiment analysis as a proxy for external pressure on professional baseball players and use actual game performance metrics to determine the interaction between pressure and performance.

RESEARCH QUESTIONS

The fundamental questions that this study will seek to answer are the following:

1. Can external fan pressure be quantified using tweets and is this measure related to player performance in a meaningful way?
2. Do some baseball players perform differently under high external pressure than others?

3. How can front offices predict how players will react to varying levels of external pressure?

RESEARCH METHODOLOGY

Player Selection

To answer the research questions presented, a case study was completed comparing Chris Sale and David Price. These players were selected because they are players who had similar careers prior to joining the Red Sox (See Appendix A) except for one important difference: their perceived reaction to external pressure. Both are left-handed pitchers who joined the Boston Red Sox between 2016 and 2017 after playing in smaller markets. They are within 3 years of age and before joining the Red Sox had very comparable statistics (David Price Stats, n.d.) (Chris Sale Stats, n.d.).

When the two came to Boston, however, their first few seasons were very different (See Appendix A). In general, David Price did not perform as expected and fans were very critical of him. In contrast, Sale began dominating and fans embraced him with open arms. It is possible that the difference stemmed from their reaction to the increased external pressure. Furthermore, this could be related to their social media habits. The largest differentiation between Price and Sale when they joined the Red Sox was that Price was an avid Twitter user who had publicized Twitter battles with others, including an Umpire while in Tampa Bay (Rymer, 2013). Sale, on the other hand, did not have any social media accounts and appeared to block out the noise (*It Doesn't Sound Like Chris Sale Will Be On Twitter, Social Media Any Time Soon*, 2016).

Compiling Data

The methodology for this case study included using tweets mentioning Sale and Price as a proxy for external pressure from fans. Using the Python package, GetOldTweets3, a process was developed for compiling tweet text, retweets, favorites, dates, and more with a user defined time-period and query (Mottl, 2018/2020). All tweets mentioning "David Price" and "Chris Sale" were collected from the time of their starting pitching debut (2010 and 2012,

respectively) until the end of 2019. Word Clouds were created from the resulting text using the wordcloud package and the data was cleaned to remove advertisements and other irrelevant tweets (See Figure 2) (Mueller, 2020).

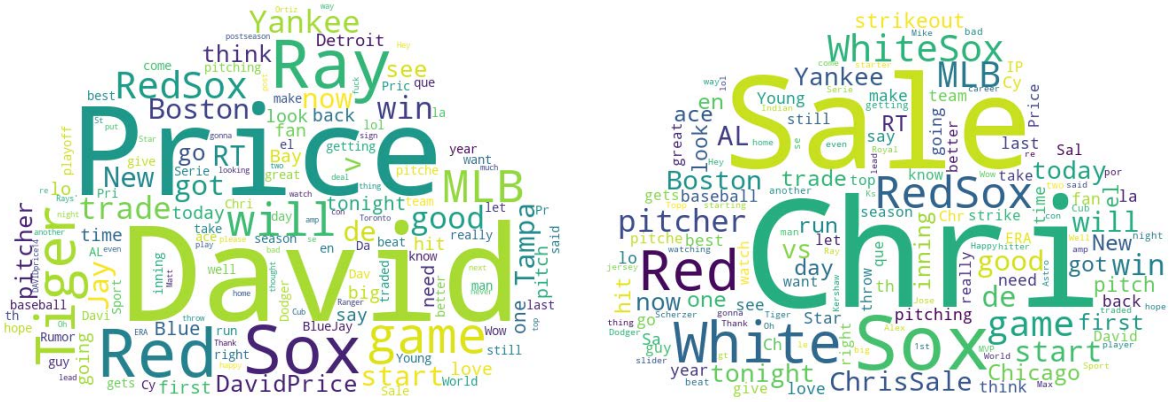


Figure 2: Word Clouds produced from tweets mentioning David Price and Chris Sale

Additionally, performance data from the same dates were collected from Baseball Reference game logs (*MLB Stats, Scores, History, & Records*, n.d.). The date, innings pitched (IP), earned run average (ERA), win probability added (WPA), and game score (GSc) from each pitcher's outings were compiled. WPA is a measure of how much a player's performance increased their team's chance of winning. A higher WPA indicated better performance especially in high leverage situations (Slowinski, 2010). GSc is a metric developed by Bill James to quantify a starting pitcher's overall performance. A GSc of 50 to 60 is considered about average whereas 80 plus is considered very impressive (*What Is a Game Score?*, 2020).

Sentiment Analysis

To determine the sentiment of the tweet text, the Vader Python package was employed (Hutto, 2020). This package is intended for sentiment analysis of social media posts. The package would break down tweets into individual words and categorize them as positive, negative, or neutral. Based on this categorization, a weighted average compound score was determined on a scale from -1 being most negative to 1 being most positive. This compound score is referred to interchangeably with sentiment during this study.

Grouping Data

Once the data was compiled, it was then grouped for analysis. Twitter sentiment data was grouped by date and again by the time periods between starts for Price and Sale. Sentiment and performance metrics were merged into one final data set that included various metrics about a particular start and the Twitter activity leading up to that start. A visualization of the data flow described can be found in Figure 3.

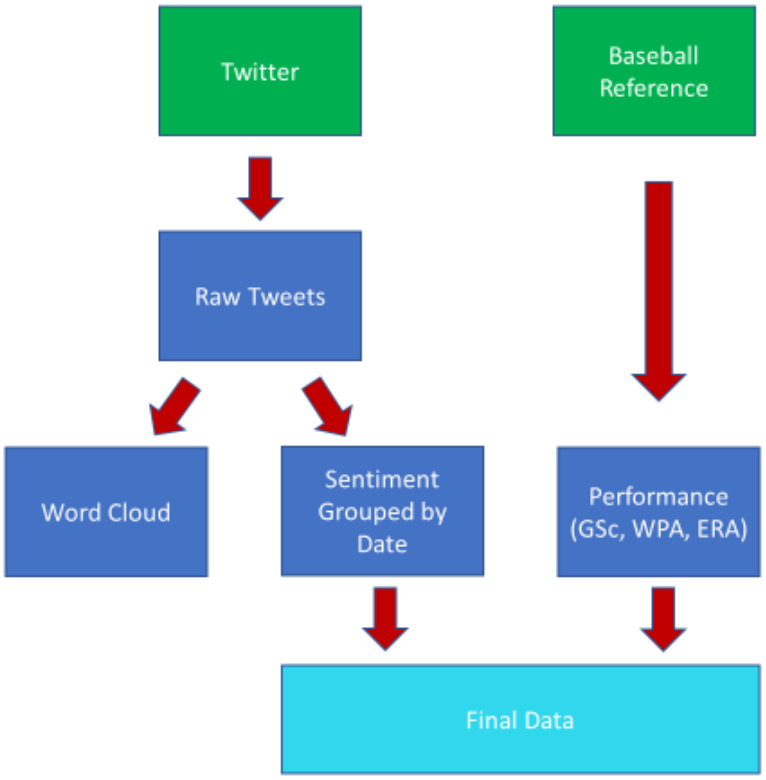


Figure 3: This figure shows the transformation of the source data from Twitter and Baseball Reference into a final data set for analysis.

DATA ANALYSIS & RESULTS

Correlation Analysis

To confirm that sentiment relates to a player's performance, correlations between performance and sentiment following each game were examined. Interestingly, after joining the Red Sox, the correlations between Price's performance and Twitter's reaction increased

substantially--especially when the performance included high leverage situations. As seen in Figure 4, the correlation between WPA and subsequent sentiment increased from .21 when playing for small market teams to .43 on the Red Sox. Conversely, the same statistic decreased from .43 to .31 for Chris Sale. Expressed differently, compared to Price's seasons with small market teams and Sale's seasons with the Red Sox, Price experienced higher degrees of Twitter responses for good or bad performances. This could translate to more pressure being placed on his performance in subsequent outings. It is also evidence that Twitter sentiment is associated with performance and could be a suitable surrogate for external pressure.

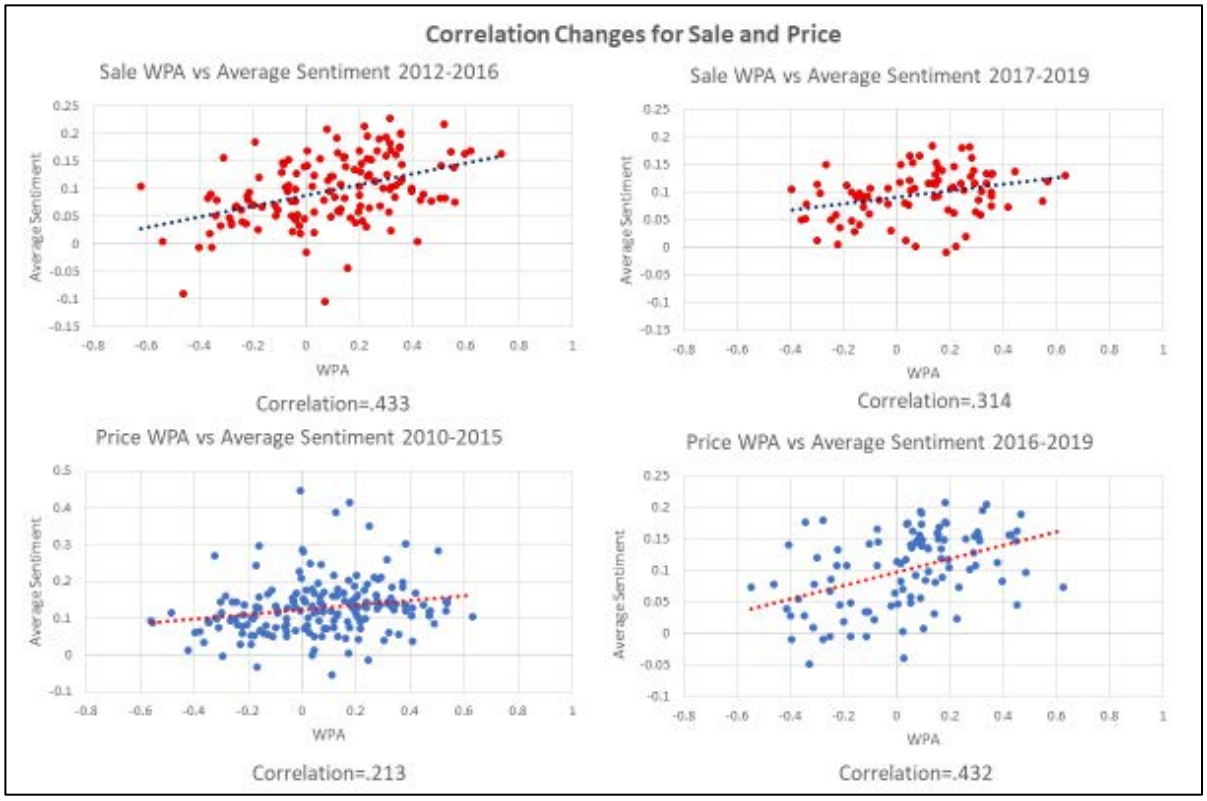


Figure 4: Correlation between WPA and Sentiment for Price and Sale before and after joining the Red Sox. While in Boston, Price experienced higher degrees of Twitter responses for good and bad performances which could lead to more pressure in future outings.

Sentiment preceding games and subsequent performance were then examined. The results show that there is a relationship between the two. Both pitchers exhibited some correlation

between the percent of tweets with negative sentiment leading up to a game and ERA of that game (.30 and .47 respectively).

This brief analysis shows that there may be some association between tweet sentiment and various performance metrics. Additionally, there is some proof that this association could be different depending on the player and whether they play for a small or large market team.

2018 Season

The next component of exploratory analysis included a detailed study of the 2018 season. Figures 5 and 6 show average daily tweet sentiment and Game Scores for every start during the 2018 season that ended in a Red Sox World Series title. This study was consistent with the findings of the correlation analysis that showed higher degrees of Twitter response for David Price than for Chris Sale.

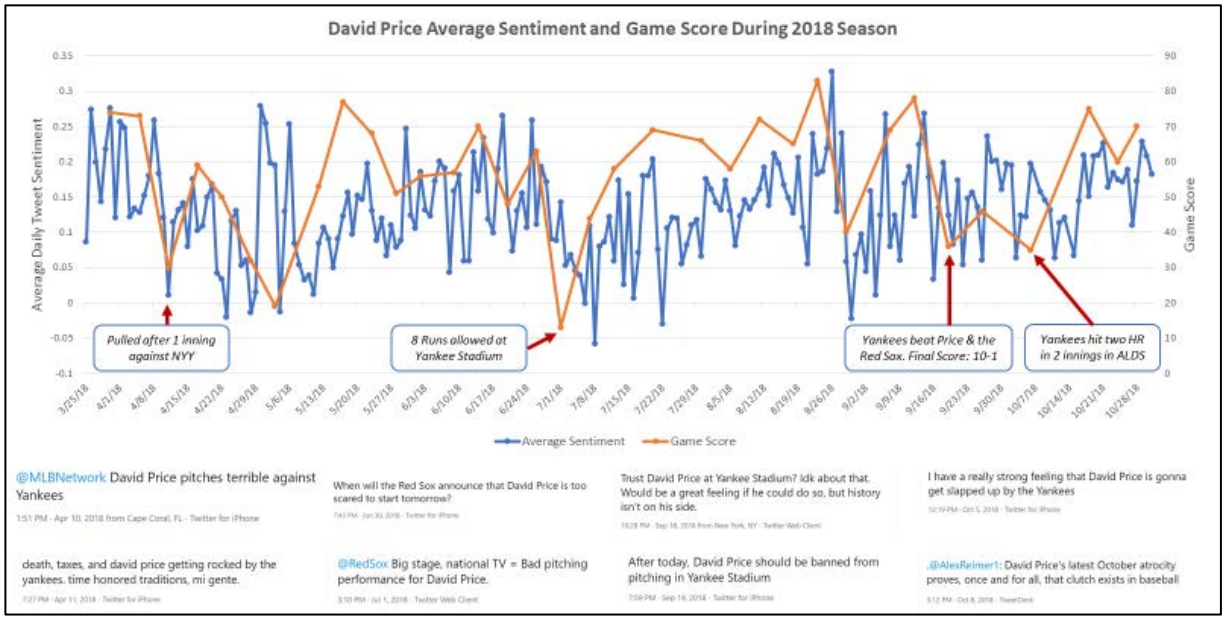


Figure 5: David Price 2018 Average Sentiment and Performance. Price's worst performances (usually against the Yankees) were often preceded by decreasing sentiment, potentially a signal of increased pressure.

Price's season appears cyclical with prolonged periods of overall increasing or decreasing sentiment that appears roughly consistent with his performance. The graph shows that Price's worst performances (usually against the Yankees) were preceded by decreasing sentiment, potentially a signal of increased pressure.

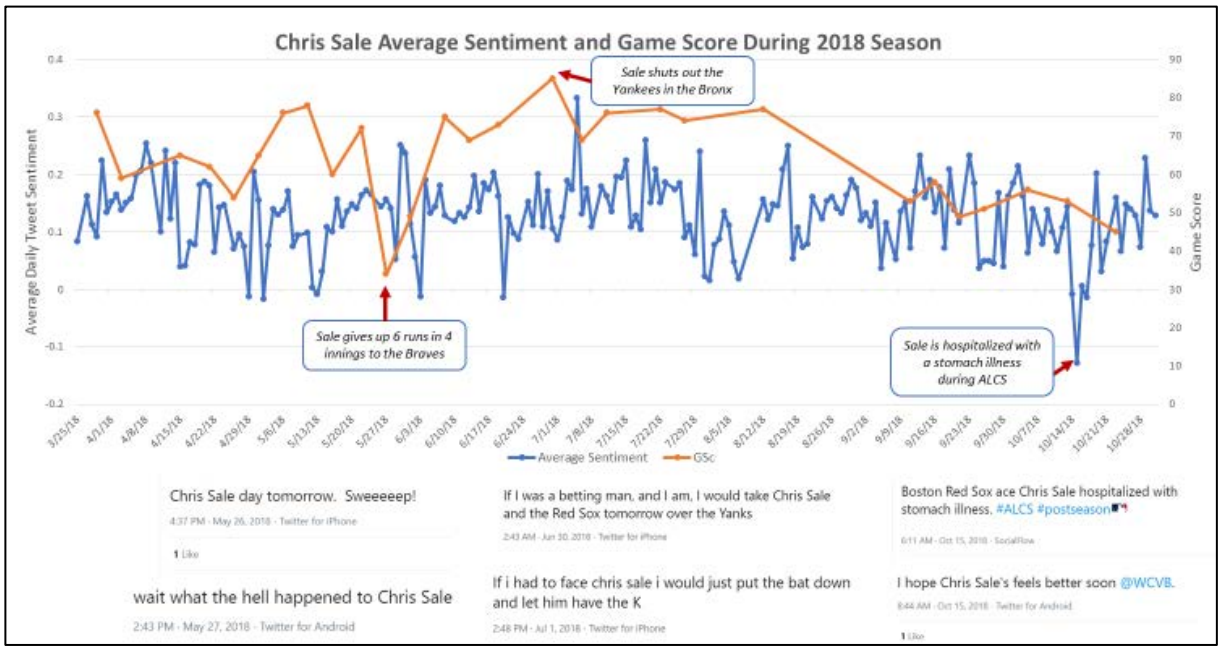


Figure 6: Chris Sale 2018 Average Sentiment and Performance. Sale's 2018 season was much less cyclical in sentiment and performance than Price's with brief spikes for extraordinary events.

Conversely, sentiment of tweets mentioning Sale held relatively constant over time and did not display the same cyclical nature as Price. Both performance and sentiment were relatively stable outside of brief spikes for extraordinary events such as a poor outing against the Braves, a shutout against the Yankees, and a stomach illness during the ALCS. This could potentially be related to the differing social media habits of the two players. Price is very active on Twitter so it makes sense that his performance and Twitter sentiment could be linked whereas Sale does not even have an account which could explain the lack of Twitter sensitivity.

Overall, this element of the case study showed compelling evidence that Twitter sentiment and performance are somehow related and that the relationship can be different depending on the player.

<u>Psychological Momentum and Pressure Study</u>

The final element of this case study aimed to test the results of three studies mentioned in the literature review above on psychological momentum and pressure. Psychological momentum can be defined as a person's propensity to perform better or worse based on their most recent

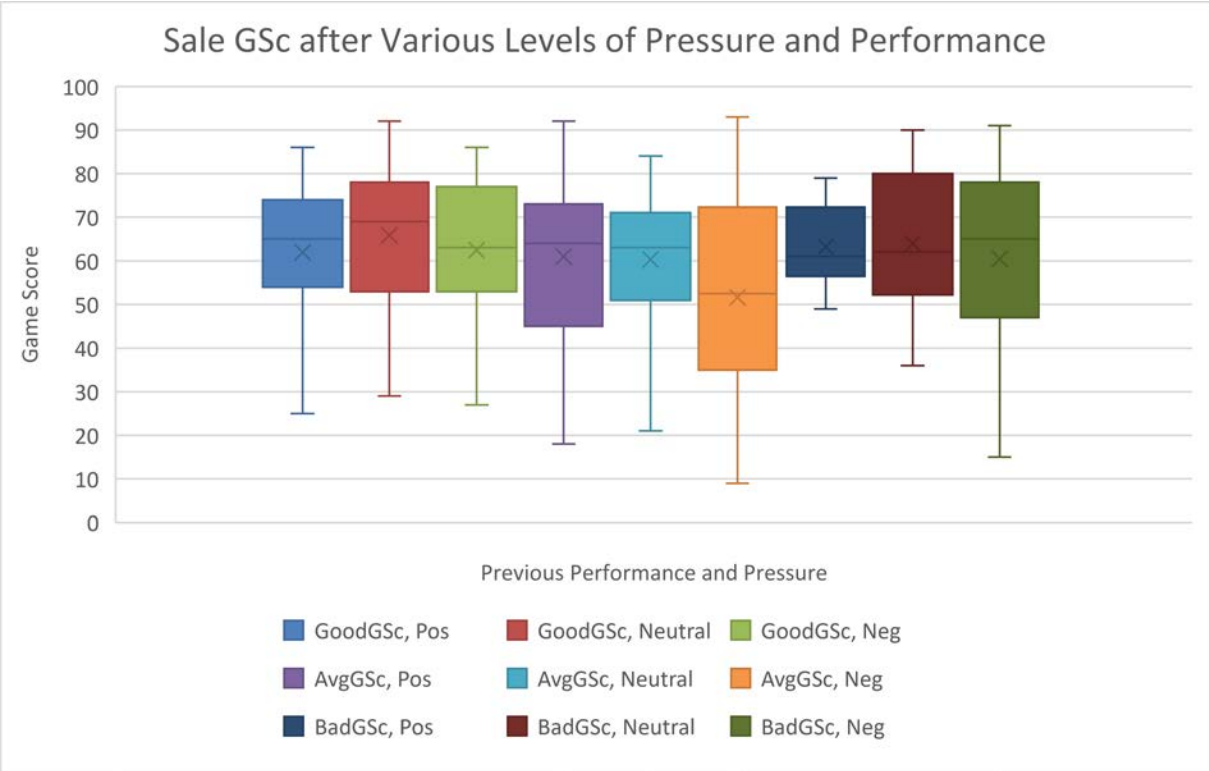
performance. Several studies have concluded that past performance and pressure have some sort of interaction effect that can impact future performance.

There were three main conclusions from the literature review that were examined in the context of the David Price and Chris Sale study:

1. Harris et al. concluded that the probability of poor performance is highest when the pressure is high and there was a preceding poor performance (2019).
2. Gray et al. concluded that players on either a hot or cold streak were more likely to perform well under pressure than an average player (2013).
3. Golding et al. concluded that athletes are more likely to be affected by criticism, but the type and magnitude of their reaction is highly dependent on the person (2017).

To examine these conclusions, each outing for David Price and Chris Sale was flagged as a Good, Bad, or Average performance based on Game Score. Game Score was used as a metric because it does the best job of quantifying a starting pitcher's overall performance. In Addition, Twitter sentiment leading up to a start was classified as largely positive, largely negative, or neutral. Nine groups of starts were then compiled based on the combination of previous performance and Twitter sentiment. Figure 7 shows box plots for both pitchers' performance.

Additionally, a single factor Analysis of Variance (ANOVA) hypothesis test was conducted to determine whether the means of any the groups were significantly different from one another. The ANOVA output for both pitchers is located in Appendix B. The p-values for both tests are below .20 indicating that there is an 80% chance that there are differences in mean game score among the nine groups referenced above and displayed in the box plots of Figure 7. Figure 8 shows ANOVA plots for both pitchers for further analysis.



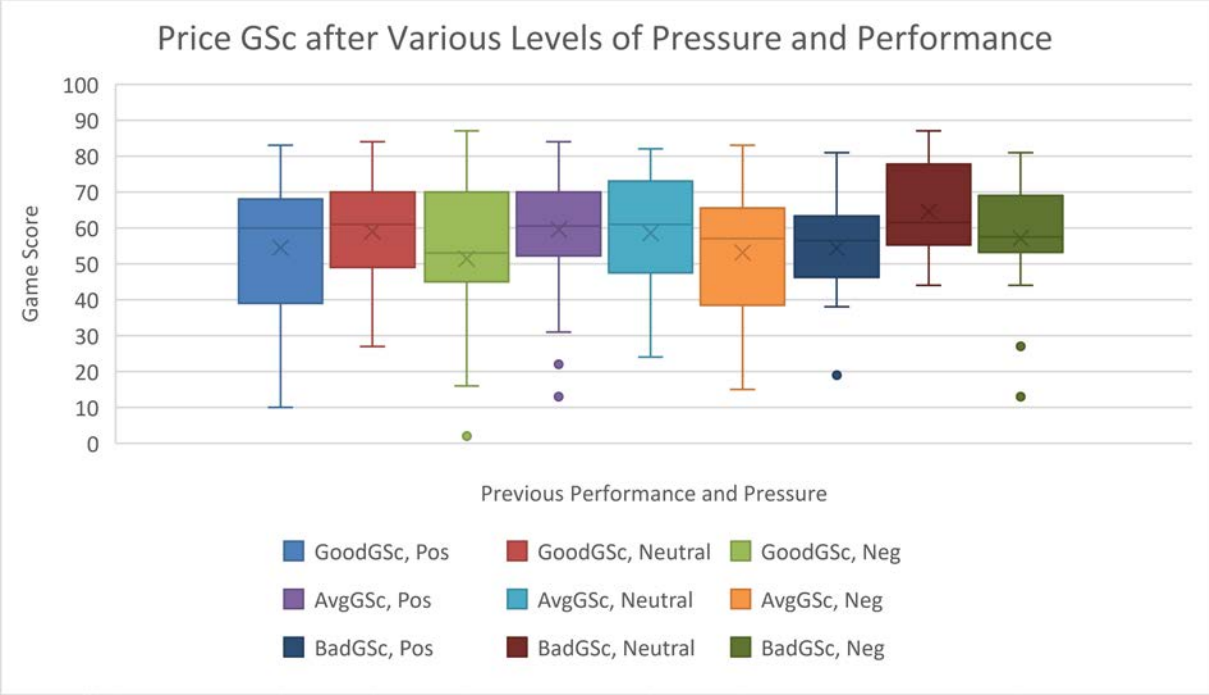


Figure 7: David Price and Chris Sale Performance after various levels of pressure and past performance.

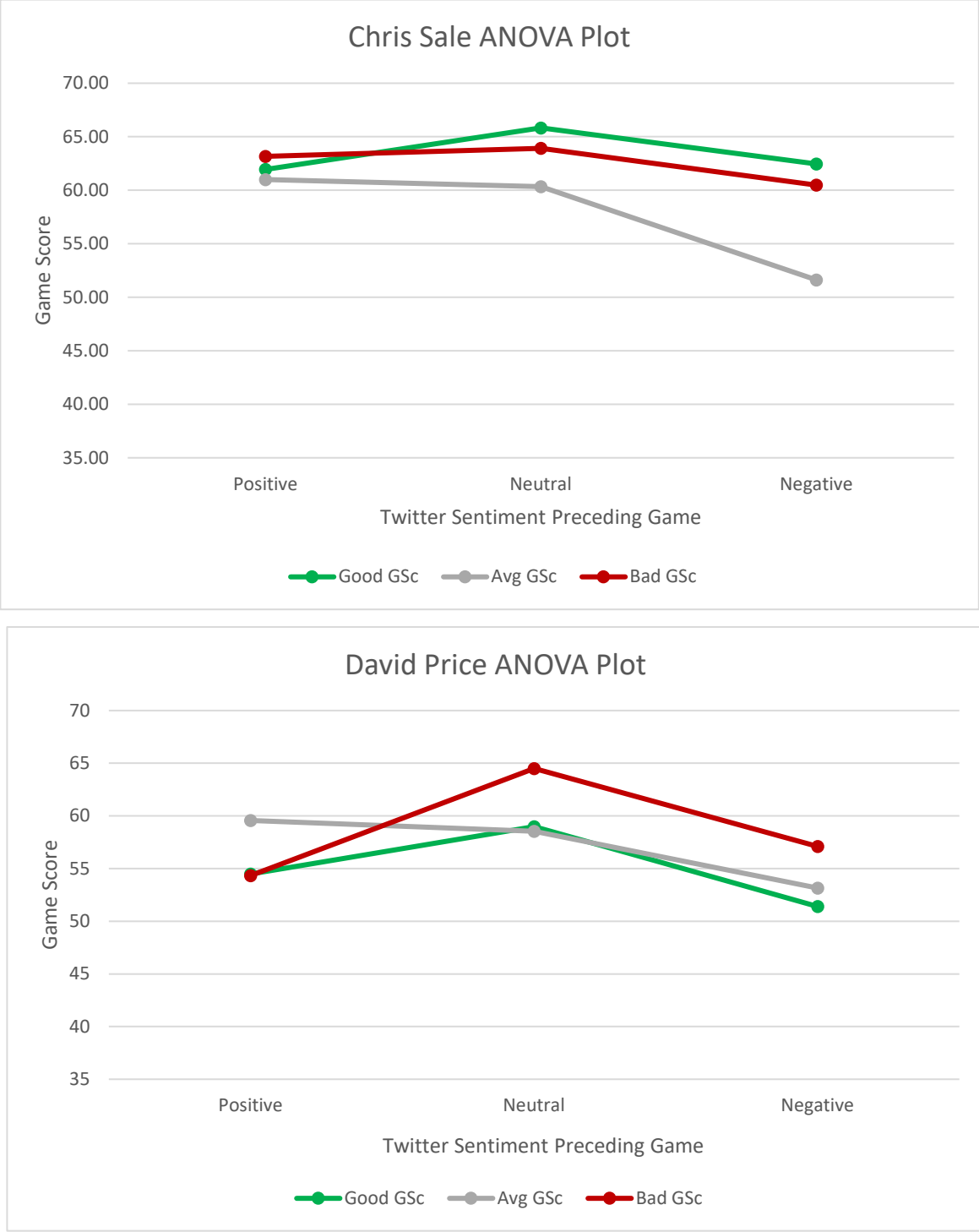


Figure 8: Analysis of Variance Plots for David Price and Chris Sale that show the mean GSc of starts after various combinations of prior performance and Twitter sentiment. Consistent with the literature review, both pitchers perform best under neutral sentiment, Chris Sale performs best under the pressure of negative sentiment when entering the game on a "cold streak" or "hot streak", and Price generally performs best after poor starts highlighting the differences between his and Sale's reactions to pressure and psychological momentum.

The above ANOVA plots display the mean game score for each group that contains outings flagged as following positive, negative, or neutral sentiment and good, bad, or average previous performance. Twitter sentiment is meant to be a proxy for pressure and previous performance indicates whether the player is entering the game on a "cold streak", "hot streak", or neither. Viewing these plots, one can not only learn about the individual relationships between future performance and past performance or pressure, but one can also visualize the interaction effect that could be occurring between the two independent variables.

This analysis yielded several key insights that were consistent with the literature review. First, as seen in Figure 8, both pitchers had their highest mean game scores after a period of neutral sentiment. In other words, the pitchers performed better when there was limited pressure from fans. Additionally, performance was generally the worst when there was negative sentiment from fans. This is consistent with the conclusion of Harris et al. that higher pressure was associated with worse performance.

Secondly, analysis of Chris Sale shows remarkable consistency with the findings of Gray et al. When viewing Sale's ANOVA plot in Figure 8, the spread between average previous GSc, and good or bad previous GSc increases substantially under negative sentiment. This indicates that when Sale experiences large amounts of external pressure, quantified by large volumes of negative tweets, he performs better when on a "cold streak" or a "hot streak" compared to starts following an average performance. This phenomenon is exactly what Gray et al reported.

Finally, viewing David Price's results supports the conclusions of Golding et al. Although there are some similarities between trends in Price's data and that of Sale, such as both pitchers performing relatively well after neutral sentiment, overall, it appears Price reacts quite differently than Sale does in similar conditions. For example, Price's highest average game scores were following bad performances. Furthermore, Price's worst average game score is following a good performance and period of negative sentiment. These findings support the idea that players react differently to pressure and psychological momentum. It is

easy to see how this concept could be extended to front offices so that they can find players who will react in desirable ways depending on the pressure associated with their team.

CONCLUSIONS

Overall, this case study serves as a compelling proof of concept for future research. It is impossible to draw far-reaching conclusions from a study with only two players; however, the findings presented can be used as building blocks for an entirely new area of player evaluation. Too often teams sign free agents or trade for players with impressive numbers without determining whether the player would be a good fit for their organization and their market. Twitter sentiment analysis could be a tool to compliment traditional methods and give front offices an edge.

The first research question presented in this analysis was whether external fan pressure could be quantified using tweets. It was further questioned if this proxy for pressure would have any relationship with player performance. Based on this study, the answer to both questions is yes. The new process for collecting, cleaning, and analyzing tweets mentioning players was successful and could be scalable to collect information on any modern player. Furthermore, correlation results were promising showing at least some association between pressure and performance for both Chris Sale and David Price and differences in that correlation depending on the player and the team they played for. Furthermore, ANOVA tests that included sentiment and psychological momentum produced results similar to what would be predicted by other scholars in the field. Finally, anecdotal information from the 2018 season showed compelling evidence that there could be a meaningful relationship between Twitter and player performance.

The second research question asked whether some players would perform differently under high external pressure than others. Again, this answer is yes based on the comparison of David Price and Chris Sale. The two lefty pitchers had strikingly similar resumes before joining the Red Sox, where external pressure undoubtedly increased. It is not difficult to imagine that their reaction to this external pressure could be the source of subsequent

differences in performance. Correlation analysis revealed that the association between tweet sentiment and metrics like WPA could be different depending on the player and whether they play for a big or small market team. For example, Price experienced higher degrees of Twitter responses based on his play with the Red Sox, which could have led to more pressure and worse performance in subsequent outings. Additionally, analysis of the 2018 season revealed that Price's performance and tweet sentiment was much more cyclical than that of Sale. Lastly, Sale performed in manners that were consistent with the findings of scholars mentioned in the literature review in the context of performance under pressure and psychological momentum, whereas Price deviated from this trend, potentially due to his fundamentally different reactions to pressure.

The final research question mentioned in this exploration related to how front offices could predict how players will react to various levels of external pressure. This question will unfortunately remain largely unanswered until a broader analysis is conducted expanding this study's initial findings. One cannot assume that the results of Chris Sale and David Price will apply to every Major League ballplayer. Future studies should include expansions to other players, teams, and positions.

Using data such as that which is presented here, front offices could profile players based on their performance under pressure. Large market teams could find players that will thrive under increased pressure and avoid players that will crumble. Conversely small market teams can find value in players that failed in the bright lights of New York or Boston not due to lack of talent, but due to their psychology. This study proves there is value in considering Twitter data when making baseball decisions, but it is not until more information is compiled and analyzed that macrotrends will be revealed allowing front offices to improve their decision making. Eventually, this study can be the basis of a movement towards front offices adding new players to their team who are better fits and providing improved support to current players throughout the season.

APPENDICES

Appendix A – Price vs. Sale Comparison before and after Red Sox Debut

Price vs. Sale Comparison at time of Red Sox Debut		
	David Price	**Chris Sale**
Position	Starting Pitcher	Starting Pitcher
Throws	Left	Left
Red Sox Debut	2016	2017
Age at Debut	30	28
Previous Teams	TBR, DET, TOR	CHW
Career ERA at Debut	3.09	3.00
Career FIP at Debut	3.20	3.06
Career WHIP at Debut	1.132	1.065
Career WAR at Debut	29.3	30.1
Cy Young Awards	1	0
Top 10 in Cy Young Voting	4	5
Top 25 MVP Voting	2	2
Previous All-Star Appearances	5	5
Acquired by Red Sox Through	Free Agency	Trade
Annual Salary Year 1 with Red Sox	$30M	$12M

Price vs. Sale Comparison after Joining Red Sox		
	David Price	**Chris Sale**
Position	Starting Pitcher	Starting Pitcher
Throws	Left	Left
Length of Tenure	4 seasons	3 seasons (and counting)
2020 Season	Traded to Dodgers and opted out of season	Tommy John Surgery
ERA	3.84	3.08
FIP	3.74	2.57
WHIP	1.204	0.970
WAR	10.4	15.2
Cy Young Awards	0	0
Top 10 in Cy Young Voting	0	2
Top 25 MVP Voting	0	2
All Star Appearances	0	2
2020 Expected Salary	$32M (50% LA, 50% BOS)	$30M

Appendix B – ANOVA Output

David Price ANOVA: Single Factor

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
GoodGSc, Pos	31	1689	54.484	347.458
GoodGSc, Neutral	55	3244	58.982	229.537
GoodGSc, Neg	20	1028	51.400	538.358
AvgGSc, Pos	46	2740	59.565	258.296
AvgGSc, Neutral	40	2342	58.550	247.741
AvgGSc, Neg	33	1754	53.152	316.070
BadGSc, Pos	12	652	54.333	256.970
BadGSc, Neutral	24	1548	64.500	170.783
BadGSc, Neg	28	1599	57.107	237.877

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	3,310.33	8	413.792	1.493	0.160	1.692
Within Groups	77,624.32	280	277.230			
Total	80,934.65	288				

Chris Sale ANOVA: Single Factor

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
GoodGSc, Pos	35	2168	61.943	263.997
GoodGSc, Neutral	47	3094	65.830	248.101
GoodGSc, Neg	26	1624	62.462	278.978
AvgGSc, Pos	11	671	61.000	484.400
AvgGSc, Neutral	39	2353	60.333	228.386
AvgGSc, Neg	24	1239	51.625	544.418
BadGSc, Pos	6	379	63.167	105.367
BadGSc, Neutral	12	767	63.917	264.992
BadGSc, Neg	27	1633	60.481	371.259

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	3,418.33	8	427.291	1.401	0.197	1.699
Within Groups	66,501.77	218	305.054			
Total	69920.09692	226				

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