Is Rivalry All About the Fans?

The Impact of Rivalry on Player Performance in Major League Baseball (MLB)

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Abstract:
Rivalry is a widely recognized and extremely visible facet of sports around the world. Defining sports for the casual fan and aggravating passions for the diehard, rivalry is an integral part of the fan experience. While empirical work has been done on the economic impact of rivalries across many sports, this paper sets out to explore the effect of rivalry as a motivating factor for individual actors in Major League Baseball. Looking at players in Major League Baseball across 3 key rivalries during the period 2001-2013, this paper for the first time performs a statistical analysis to attempt to isolate the effect of rivalry on individual offensive performance. While future studies are necessary to confirm any concrete conclusions, results suggest that there is no consistent, systematic effect of rivalry on player performance.

"All literary men are Red Sox fan--to be a Yankee fan in a literate society is to endanger your life."
—John Cheever, Pulitzer Prize Winning Author

Introduction

Rivalry is an undeniable force in the sports world. Discussed widely and visible to even the most casual of fans, it serves as a paradigm of intensity and engagement with the sport. Rivalry spreads beyond the field of play into the locales in which it is played, and permeates not just local and national media, but also water coolers and office spaces, dinner tables and households. It is an undeniable part of the sports fan experience and as such, is of interest from an academic perspective, particularly an economic one.

Increased attention and hype surround even the most banal of rivalry games, as fans expect a high quality, fierce battle with more at stake than the typical encounter. Leagues and media capitalize on this hype as an asset, fueling the excitement through incessant discussions and endless promotions in the weeks leading up to the encounter. Rivalry has a clear, demonstrable economic benefit for the teams and leagues involved, but does it have an actual impact on the athletes themselves, the direct participants in rivalry? With money and fanfare surrounding each encounter, does "rivalry" serve as a financial or psychological motivator for players, or is it an exogenous factor that has little to no effect on an individual actor's actions? In other words, "Is Rivalry All About the Fans?" and as the author of this paper is a "Yankee fan" and thus, bravely "endanger[ing] [his] life" by embarking on this academic inquiry, this paper sets out to explore this subject in the field of Major League Baseball.

Until now, little work has been done on the impact of rivalry in the context of professional sports, with no previous literature exploring its effect through the lens of Major League Baseball. Consequently, considerable time will be spent at the beginning of the paper exploring precedent literature and a background of Major League Baseball so as to develop the rationale and impulse behind its choice as a dataset of focus. Following this, the paper will contextualize the question of importance, presenting the economic incentives of "rivalry" in Major League Baseball. The crux of this paper will then explore the hypothesis in question, concluding with a discussion of results and future steps.

PART I: Development of Framework and Context

Hypothesis

Rivalry in Major League Baseball has a significant impact on the offensive performance of individual players and teams.

Literature Review

Definition of Rivalry

The present literature regarding the effect of rivalry on performance in sports is limited, with only one study to date as a point of reference by Kilduff, Elfenbein, Staw, 2008.[1] In this study, researchers at Washington University in St. Louis for the first time addressed and proposed an operational definition of rivalry. As the only in-depth study conducted on this topic, this paper will employ their "working" definition of rivalry. It is as follows:

> …a subjective competitive relationship that increases the psychological involvement of competitors beyond what the objective characteristics of the situation would predict. In other words, rivalry exists when an actor places greater significance on competition against certain other opponents as a direct result of his or her competitive relationships with these opponents, controlling for any objective stakes (financial, reputational, or otherwise)…relational as opposed to a series of isolated interactions.[2]

This suggests the role of "rivalry" as a motivating factor in competitive interactions between individuals, groups, and organizations. It suggests that it is relational, based on prior interactions, and grounded in a variety of different factors that are often independent between dyadic relationships. It is implicitly psychological, and defined to be so in their paper through a comprehensive review of psychological theories of competition.[3] Of particular note is "Social Comparison Theory," as it provides a basis for many of the studies they mention that explore "rivalry" as relational and competitive.[4] This

[1] Kilduff, Gavin J., Hilary A. Elfenbein, and Barry M. Staw. "The Psychology of Rivalry: A Relationally-dependent Analysis of Competition." The Academy of Management Journal 53.5 (2010): 1-68. Web.
[2] Kilduff, Elfenbein, Staw 8
[3] Kilduff, Elfenbein, Staw 4-10
[4] Kilduff, Elfenbein, Staw 10

definition of rivalry provides a strong grounding upon which to advance in addressing the issue of rivalry in Major League Baseball.

Review of Kilduff, Elfenbein, Staw Study

The definition says nothing about the actual effect of rivalry on individual actors or groups. It reviews many studies linking both positive and negative effects of increased motivation on “performance” and “effort”[5], and then conducts an analysis of their own to investigate the issue. In their analysis, they attempted to isolate the effect of rivalry on player “effort” in NCAA basketball. In choosing NCAA basketball as their grounds for exploration, they point to the existence of well-known rivalries, high stakes, homogeneity of teams, and a wealth of information available.[6] The same rationale applies to Major League Baseball. There are many well-defined and historical rivalries, billions of dollars surrounding the promotion and execution of games, similar teams drawing from similar talent pools, and a wealth of information available. Major League Baseball is an applicable dataset upon which to analyze rivalry.

Kilduff, Elfenbein, & Staw attempt to develop a “rivalry gauge” of sorts in NCAA basketball; measuring rivalry as a factor between over 200 different teams.[7] Through SOREMO analyses, they develop this network of rivalry as an independent measure between each individual dyad, and then apply it to their empirical analysis of the impact of rivalry on player “effort.” This rivalry gauge is beyond the breadth of this paper, as it will instead focus on 3 high-profile, well-recognized rivalries in Major League Baseball. Further discussion will follow on this point. Using this rivalry gauge, they measured the effect of rivalry on defensive “hustle” metrics following an ANOVA methodology. They conclude that rivalry has a significant positive effect on “effort” in NCAA basketball.[8]

This paper employs the operational definition of rivalry used from the Washington University in St. Louis study and utilizes the same rationale behind using a professional sports league as a data set, but

[5] Kilduff, Elfenbein, Staw 18
[6] Kilduff, Elfenbein, Staw 19
[7] Kilduff, Elfenbein, Staw 20
[8] Kilduff, Elfenbein, Staw 36

the similarities end there. The approach, methodology, and means of analysis in this paper are original, and the conclusions entirely independent.

Other Relevant Literature

Other relevant literature helps to tailor the idea of rivalry specifically to professional baseball. There have been a few studies examining rivalry through the lens of major league baseball, but they have largely come from a managerial firm perspective. For example, it has been shown that MLB teams within the same division and of similar skill levels—rivals under our definition—are less likely to trade or cooperate with each other than with otherwise unrelated teams.[9] Outside of baseball, but relevant to our discussion, is work done showing that parity amongst homogenous competitive groups increases the intensity of rivalry between individual groups, and that this effect is larger between groups that are relatively high performers.[10] This will be relevant for a discussion about degrees of rivalry in the "Results" section later on in the study. Most other empirical work on rivalry in sports lies outside of Major League Baseball. Work in the field of boxing suggests the importance of prior interactions on increased future effort[11], and recent work by Evan Osborne in a variety of sports suggests the complimentary role of fans in rivalry and their desire to see a rivalry develop[12]. This last study by Osborne is particularly relevant to this paper's discussion of the economic impact surrounding rivalry, as it corroborates the notion that rivalry is centered on and derived from fans.

Background

Major League Baseball

To fully understand the context behind the dataset examined, it will be useful to briefly explain the framework of Major League Baseball in its current state. As of 2012, there are 2 leagues, 3 divisions

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[9] Schneper, William D. "Cognition, Cooperation, and Rivalry: Patterns of Interorganizational Relationships in Major League Baseball." Diss. The Wharton School, University of Pennsylvania, 2005. 10-15, Web

[10] Garcia, Stephen M., Avishalom Tor, and Richard Gonzalez. "Ranks and Rivals: A Theory of Competition." Personality and Social Psychology Bulletin 32.7 (2006): 973-975. SAGE PUB. Web.

[11] Amegashie, J. A., and Edward Kutsoati. "Rematches in Boxing and Other Sporting Events." Journal of Sports Economics 6.4 (2005): 409. EconLit with Full Text. Web.

[12] Osborne, Evan. Rivalries. North American Association of Sports Economists. The College of Holy Cross, n.d.: 6-11. Web.

in each league with 5 teams each. Teams are organized geographically into divisions within each league: the East, West, and Central Divisions. Major League Baseball in its current state spreads across the entire United States with teams in 17 states, 1 Canadian Province, and 27 major cities. When including Minor League Baseball teams, or teams in the lower echelons, controlled by each major team, baseball spans across 41 of the 50 states, also with ties to Mexican Provinces and other parts of Canada.[13] As will be discussed in the follow sections, geography is an important contributor to the development of each of these rivalries.

Since 1961, each team has played 162 games in a season. As of 2001, the breakdown of games played by team was as follows: 72 games within division, 72 games with other teams in the league, and 18 interleague games.[14] This has changed recently in 2012, with there now being 76 games a year against teams in your division, but the sentiment is the same. Major League Baseball has increased the amount of games played against divisional foes because they recognize the value of rivalry.[15] Because of this, the dataset used will span from 2001-2013, which includes the greatest amount of rivalry games.

Rivalries

This study will take as its focus the three biggest rivalries in Major League Baseball. Developing a rivalry index that would develop a scale of rivalry for each interaction between teams is outside of the scope of this paper. As such, analysis will be based off of data from the three most historic and well-recognized rivalries in baseball: The New York Yankees (NYY) vs. the Boston Red Sox (BOS), the San Francisco Giants (SFG) vs. the Los Angeles Dodgers (LAD), and the Chicago Cubs (CHC) vs. the St. Louis Cardinals (STL).

Identified across 8 independent news sources as the biggest rivalries in baseball and similarly recognized by fans[16], these established rivalries provide a dataset of pure and concentrated rivalry upon which to base our conclusions. While a development of a rivalry index would provide clearer results, the

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[13] MiLB.com. "Teams by Geographical Location." MiLB.com. MLB.com, n.d. Web.
[14] Major League Baseball. 2012-2016 MLB BASIC AGREEMENT. N.p.: MLB, 11 Dec. 2011. PDF
[15] Donovan, John. "Division Races Tighten with Unbalanced Schedule." Sports Illustrated. CNN, 21 Mar. 2001. Web. 3 Dec. 2013
[16] ESPN, MLB.com, FanGraphs, Baseball-Reference, Forbes, Gallup, Sports Illustrated, MLB Network

intent is to isolate effects of rivalry robust enough to draw conclusions. Any strong effect of rivalry on player performance should be evident through an examination of these archetypes of rivalry.

As discussed, this paper will define rivalry as "…a direct result of his or her competitive relationships with these opponents, controlling for any objective stakes." Objective stakes in these three rivalries can refer to geographical proximity, prior competitive interactions, historical significance, and many other factors. To better define the stakes particular to each rivalry, it will be useful to review the respective histories and bases upon which they are formed. As a foundation, the head-to-head numbers historically and during 2001-2013—the time period our data draws from—are found in Chart 1 on the following page.[17]

New York Yankees vs. Boston Red Sox

Often labeled "the best rivalry in sports" this rivalry allegedly began in 1919, when fabled pitcher and batter for the Boston Red Sox, Babe Ruth, was traded to the New York Yankees for a money sum. Boston, at the time a thriving franchise, was unable to win a World Series title for 86 years following this trade. This drought soon became attributed to the "Curse of the Bambino."[18] Historically, these two teams are on uneven playing ground; the Yankees transformed into the winningest franchise in sports history during Boston's 86-year drought. Because of this, the city of Boston embroiled itself against New York, and banter and wars of words were daily in the popular media. The Yankees were ascribed the name "The Evil Empire" and perpetually cast in a negative light by the entire region of New England, and a definitive underdog mentality began to surround the entire affair. While historically at odds, their head-to-head records are still very close, and starting in 2004, when the Red Sox "broke the curse," the Red Sox have dominated the divisional rivalry, winning 3 World Series and overpowering the Yankees.[19]

[17] "Baseball-Reference.com - MLB Stats, Standings, Scores, History." *Baseball-Reference.com*. Baseball-Reference, n.d. Web. 19 Dec. 2013.
[18] "Red Sox-Yankees Is Baseball's Ultimate Rivalry." USATODAY.com. USATODAY, 20 Oct. 2004. Web. 1 Dec. 2013
[19] "Red Sox-Yankees Is Baseball's Ultimate Rivalry." USATODAY.com. USATODAY, 20 Oct. 2004. Web. 1 Dec. 2013.

San Francisco Giants vs. Los Angeles Dodgers

Stemming back farther than the Yankees vs. Red Sox rivalry, these two teams began warring in the late 19th century on the East Coast in New York City. The Dodgers were in Brooklyn and the Giants were at the Polo Grounds in Manhattan, but in 1957 the two teams decided to move westward together to the cities of Los Angeles and San Francisco, respectively, doing so under the premise of being rivals.[20] As the first two professional teams on the West Coast, their rivalry enveloped the state of California and attracted thousands of new fans.[21] Filled with brawls, playoff matchups, and an extremely similar head-to-head and overall performance record, this historic divisional rivalry has been marked by intensity but occasionally violence during its 100+ year duration. Most recently, the fatal beating of Bryan Stow outside of the Dodgers' Stadium and the stabbing of John Denver outside of the Giants' have marred the purity of the rivalry.[22] In the last 13 years, head-to-head and aggregate performance has been very close, with playoff accolades strongly favoring the San Francisco Giants.

Chart 1

New York Yankees	**ALL TIME**	Boston Red Sox
1901	Founded	1901
1147	Head-to-Head Wins	947
0.577	Team Win Pct. (Aggregate)	0.517
51	Playoff Appearances	21
40	Pennants	13
27	World Series Titles	8
New York Yankees	**SINCE 2001**	Boston Red Sox
124	Head-to-Head Wins	116
0.594	Team Win Pct.(since 2001)	0.561
11	Playoff Appearances	7
2	Pennants	3
1	World Series Titles	3
	Closest record since 2001 against teams in their league	
San Francisco Giants	**ALL TIME**	Los Angeles Dodgers
1883	Founded	1890
1201	Head-to-Head Wins	1174
0.538	Team Win Pct.	0.524
24	Playoff Appearances	27
22	Pennants	22
7	World Series Titles	6
San Francisco Giants	**SINCE 2001**	Los Angeles Dodgers
121	Head-to-Head Wins	120
0.526	Team Win Pct.	0.530
4	Playoff Appearances	5
3	Pennants	0
2	World Series Titles	0
	Closest record since 2001 against teams in their league	
Chicago Cubs	**ALL TIME**	St. Louis Cardinals
1870	Founded	1882
1110	Head-to-Head Wins	1076
0.511	Team Win Pct.	0.519
16	Playoff Appearances	26
16	Pennants	23
2	World Series Titles	11
Chicago Cubs	**SINCE 2001**	St. Louis Cardinals
106	Head-to-Head Wins	113
0.482	Team Win Pct.	0.560
3	Playoff Appearances	9
0	Pennants	4
0	World Series Titles	2
	Closest record since 2001 against teams in their league	

[20] Associated Press. "Giants-Dodgers: A Long and Sometimes Violent Rivalry." CBSNews. CBS, 27 Sept. 2013. Web.

[21] Associated Press. "Giants-Dodgers: A Long and Sometimes Violent Rivalry." CBSNews. CBS, 27 Sept. 2013. Web.

[22] Morrison, Pat. "Dodgers and Giants -- Rivals, Not Enemies." Los Angeles Times. Los Angeles Times, 27 Sept. 2013. Web. 17 Dec. 2013.

Chicago Cubs vs. St. Louis Cardinals

The longest lasting of the three rivalries to be examined, this was one of the earliest rivalries in Major League Baseball. Not as marred by controversy or violence over the years, this divisional rivalry is marked by tradition. As two of the bigger market teams in the Mid-West, they traditionally have competed for fans and radio rights in Illinois[23], and with one of the closest historic head-to-head records amongst all teams, they have seesawed back and forth over the course of the last century. Significant events fueling the rivalry include the Home Run Race in 1998 between Mark McGwire and Sammy Sosa to break Roger Maris' record for Home Runs in a season, drawing national media attention to the players and the rivalry.[24] Recent poor performance by the Chicago Cubs, an over 100 year drought of winning a World Series has taken away some fuel from the rivalry, and particularly in the last 13 years, the Cubs have performed very poorly in the division in relation to the Cardinals. Nevertheless, independent media outlets and fans continue to label it unanimously as one of the top rivalries in baseball.

Economic Impact of Rivalry

Having introduced past literature and background on the sport of baseball to serve as a foundation for our analysis, we now turn to a brief context for the hypothesis in question.

This study was motivated by a desire to explore the phenomena of rivalry, largely because of the economic implications it holds for the leagues and teams involved. If there is so much money surrounding it, is the quality of play higher—are the players performing at a higher level? As the following review of empirical work will demonstrate, "rivalry" as an institution has immense economic benefits in MLB, both directly and indirectly. This context is important in addressing the motivations behind the study, and in helping to explain the immense stature ascribed to "rivalry" as an institution throughout all sports. After a review of this empirical work, the following section will begin to address the analysis at hand.

The direct economic benefits of rivalry can be seen through work on attendance, ticket prices, concessions, and TV ratings. Many empirical studies have been done on the different determinants of

[23] "Regions of Cardinals and Cubs Fandom Based on Their Radio Networks." ArcGIS. N.p., 20 Aug. 2013. Web
[24] Smith, Gary. "Big Swingers." Sports Illustrated. N.p., 21 Dec. 1998. Web. 2 Nov. 2013.

attendance at Major League Baseball games, each suggesting the positive relationship between interdivisional rivalry and attendance.[25] [26] Work has even been done on the effect of attendance after the switch to 72 games against divisional opponents each year in 2001, suggesting that attendance is higher for each of the rivalries discussed in this paper.[27] Similarly, in aggregating basic ticket pricing information and surveying fans, it is clear that rivalry games demand higher ticket price markups.[28] Increased attendance and increased ticket prices leads to higher revenues, and similarly, increased attendance leads to greater revenues from concessions.[29] TV ratings of all three are significantly higher, and direct rivalry promotions are common, with each of these rivalry games often broadcasted on national television.[30]

Indirect economic benefits largely stem from increased marketing opportunities. The theory of “rival team saliency” posits that having a visible rival mobilizes a fan base and increases “team identification,” or association.[31] Similarly, teams and leagues will utilize rivalry in the “Marketing Habit Loop” popularized by Charles Duhigg, in which a rivalry game is discussed and hyped in the weeks prior across media platforms to motivate viewers and fans towards a tangible reward—a cup or trophy (i.e. Iron Bowl between Alabama & Auburn in college football). This Marketing Habit Loop feeds into viewership and fan commitment.[32] Lastly, the rivalry teams this study examines are each in the top 10 in Major League Baseball in revenues, net worth, popularity, most recognizable, and merchandise sales. This of course, represents a certain degree of correlation without causation, but the takeaway is the same. Rivalry

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[25] Lemke, Robert J., Matthew Leonard, and Kelebogile Tlhokwane. "Estimating Attendance at Major League Baseball Games for the 2007 Season." Journal of Sports Economics 11.3 (2010): 329. EconLit with Full Text. Web.
[26] Beckman, Elise M., Wenqiang Cai Cai, Rebecca M. Esrock, and Robert J. Lemke. "Explaining Game-to-Game Ticket Sales for Major League Baseball Games Over Time." Journal of Sports Economics 13.5 (2011): 544. 30 June 2011. Web. 25 Nov. 2013
[27] Click, James. "Checks and Balances: Looking at the Unbalanced Schedule." Baseball Prospectus. N.p., 19 Dec. 2003. Web. 3 Dec. 2013
[28] Kim, Hyung-Min. "The Relationship Between Fan's Interest and Media Coverage: Through Classification of the MLB Rivalry Types." Lecture. 19th Conference of the European Association for Sport Management. Madrid. EASM. Web
[29] Krautmann, Anthony C., and David J. Berri. "Can We Find It at the Concessions? Understanding Price Elasticity in Professional Sports." Journal of Sports Economics 8.2 (2007): 183-91. EconLit. Web. 13 Nov. 2013.
[30] Seldman, Robert. "ESPN's Sunday Night Baseball Early Season Schedule Features Rivalries." TVbytheNumbers. N.p., 12 Jan. 2011. Web. 17 Dec. 2013.
[31] Luellen, Tara B., and Daniel L. Wanna. "Rival Salience and Sport Team Identification." Sports Marketing Quarterly 19.2 (2010): 99. EconLit with Full Text. Web
[32] Palmer, Brian. "How Much Is a Sports Rivalry Worth?" Slate Magazine. N.p., Aug. 2013. Web. 17 Dec. 2013.

in baseball has undeniable economic benefits for the leagues and teams involved, both directly and indirectly. But do the players even care?

PART II: Analysis

Approach, Rationale & Assumptions

Approach & Rationale

This paper will be analyzing the offensive performance of individual players in "Rivalry" games versus their performance in "Non-Rivalry Games." Rivalry games will be defined as the games played against each team's singular rival in each pairing (i.e. New York Yankees vs. Boston Red Sox), while Non-Rivalry Games will be every other game in the season. Performance will be measured for individual players, entire teams, and across rivalries; aggregating game-by-game data and averaging it over different time periods. The general approach will be to identify if there are statistically significant differences between performance in Non-Rivalry Games and performance in Rivalry games for each athlete using "2-Tailed T-Tests" for Significance.

The rationale behind looking at the data in this way is as follows. In comparing an individual player's performance in Non-Rivalry games vs. Rivalry games, individual factors are inherently controlled for. Individual factors affect players equally across the course of a season, and thus potential anomalies in the data like steroid use, declining age, and injury years are implicitly addressed. Results of one player are compared to his own results in the same year, and as such, we immediately control for a large variety of individual factors.

The paper will only investigate the effect of rivalry on offensive performance—on the performance of "batters." Data collection for pitchers proved to be too difficult for the scope of this study, as there would not have been enough data points to draw meaningful statistical conclusions. This point will be discussed later in "Future Steps and Final Thoughts", but as a quick explanation: pitchers, for the most part only participate in game play every 5 days, while batters participate almost daily. As a result, in the 18 or so rivalry games played each year, a pitcher will often have between 3-5 data points, while a batter will have 14-18, with an average of 4 plate appearances in each. 3-5 data points would make it difficult to draw meaningful statistical results.

Assumptions

There are two important assumptions to review before delving into the data and the analysis. 1.) Because of the difficulty in aggregating pitchers' data briefly discussed above, this analysis will assume that pitching is constant. In other words, it will be assumed that the pitching offensive players face in Rivalry Games will be equivalent to the average pitching offensive players face in Non-Rivalry Games. 2.) Discussed in the "Background" section, this analysis will also assume that Rivalry is a constant, only present between the matchups specified in this paper. Limited time and resources preclude the creation of a scale of rivalry throughout all of Major League Baseball like that developed in the Washington University of St. Louis study, and as such, we will assume that the only Rivalry Games played in a season are those played between each defined pair of teams in these 3 rivalries.

Both assumptions are potentially confounding for our study, but through a detailed, controlled, and pointed analysis of the data in many different iterations, the hope is to draw conclusions robust and consistent enough across the data to conclude meaningful results about the actual impact of rivalry on player performance in Major League Baseball.

Data Collection

Offensive Performance Metric

This study will use "On-Base-Percentage plus Slugging Percentage (OPS)" as the offensive metric for performance. Unlike traditional metrics for offensive performance like "Batting Average (BA) "or "Runs Batted In (RBIs)" that only look at individual performance abilities, OPS measures a player's aggregate ability to reach base, hit for power, and hit for average.[33] The formulas for OPS are as follows:

[33] Sabermetrics Library. "OPS and OPS." FanGraphs. N.p., n.d. Web. 13 Oct. 2013.

$$OPS = OBP + SLG$$

$$OBP = \frac{H + BB + HBP}{AB + BB + HBP + SF}$$

$$SLG = \frac{1B + (2x2B) + (3x3B) + (4xHR)}{AB}$$

OPS is a sum of a player's On-Base-Percentage and their Slugging Percentage. On-Base-Percentage (OBP) is a measure of how many times a player gets on base (either from a Hit (H), a walk (BB) or if he is Hit by a Pitching (HBP)) divided by the amount of times he has an opportunity to get on base (through an At-Bat (AB), BB, HBP, or Sacrifice Fly (SF)). In essence, it measures what % of the time a player is able to reach base; looking at ability to hit, but also patience. Slugging percentage looks at the amount of Total Bases a player accumulates (weighing a single as 1 base, a double as 2 bases, a triple as 3 bases, and a Home Run as 4 bases) divided by the amount of opportunities he gets to hit. This also measures a player's ability to reach base, but more concretely looks at the amount of power he hits for, as a higher Slugging Percentage means a higher percentage of his hits were either doubles, triples, or Home Runs. An OPS of .900 is very good, while an OPS of 1.000 is exceptional.[34]

Other offensive performance metrics like Wins-Above-Replacement (WAR) may provide a more accurate indication of overall performance, including defensive performance and a normalization in comparison to a league average. These are problematic though because they more difficult to calculate on a game-by-game basis, and also, aren't a measure of pure offensive performance. OPS provides the best and simplest approximation of offensive performance, and will thus be the offensive metric of interest in this study.

Physical Data

All individual player data, team performance data, and head-to-head data was collected from Baseball-Reference.com. The Dataset for our analysis consisted of all players in the years 2001-2013[35] on

[34] Sabermetrics Library. "OPS and OPS." FanGraphs. N.p., n.d. Web. 13 Oct. 2013.
[35] 2001, the year when league structure switched to 18-19 yearly games against each divisional opponent

each of the 6 teams who had greater than 30 Plate Appearances in Rivalry games over the course of an individual season. 30 Plate Appearances was chosen as an approximation to be able to conclude normal distributions of data following the Central Limit Theorem. If players had greater than 30 Plate Appearances in a Rivalry Game, they also had consistently greater than 100 Plate Appearances in Non-Rivalry Games, also implying normality of data under the Central Limit Theorem.

OPS was calculated for each eligible player in each individual game, and from that, average OPS in Non-Rivalry Games and average OPS in Rivalry Games were tabulated. These calculations were all aggregated manually through a developed Excel template that filtered each individual player's yearly game log and calculated the relevant numbers. The template also calculated yearly average OPS in Non-Rivalry Games at Home/Away versus OPS in Rivalry Games at Home/Away. This information will be used in a later refined iteration of the analysis. Numbers were manually crosschecked with Baseball Reference to ensure accuracy of the template. Of note, Batting Average numbers were similarly calculated across the dataset, and in concluding the final numbers, were fairly correlated with the OPS numbers. This is logical, as Batting Average is inherent within the OPS calculation, but is mentioned here to confirm that OPS provides no significant conclusions outside of what would otherwise be expected, and is merely a more accurate depiction of offensive performance.

Over the course of 13 years and across the 6 teams, this yielded 329 Players and 754 Observations (eligible players played on average for 2.3 years in each rivalry). With an average of about 47 plate appearances in Rivalry Games each year, and an average of about 350 plate appearances in Non-Rivalry Games each year across all the data acquired for individual players, this yielded results spanning across over approximately 35,000 plate appearances in Rivalry Games and 260,000 plate appearances in Non-Rivalry Games. Similar numbers of results were tabulated for each team. There was an expectation of slightly lower numbers of eligible players for the Chicago Cubs and St. Louis Cardinals because they played in a division with 6 teams until 2012 (when Houston Astros moved to the American League), and thus only played each other 14-15 times a year until 2012. These differences did not appear in the data though, and any differences in data accumulation were evaluated as statistically negligible.

Methodology

The statistic employed for the "Analysis" in this paper is a manually calculated statistic we will label "OPS spread". It is the product of the below operation:

OPS Spread = Avg. OPS in Non-Rivalry Games in Year – Avg. OPS in Rivalry Games in Year

In essence, this transforms our analysis from a comparison between two sample sizes for each individual through a "Paired T-Test," to a test of significance from 0 on a single sample. In subtracting these two averages, we are calculating the average difference in performance between Non-Rivalry Games and Rivalry Games. We can perform this subtraction because of the assumption of normality made through the Central Limit Theorem; all players in the sample have at least 30 plate appearances in Rivalry Games and 100 plate appearances in Non-Rivalry Games. If "OPS Spread" is positive, we will conclude that rivalry has a negative effect on performance in that season, and if it is negative, we will conclude that rivalry has a positive effect on performance in that season. We will be testing if these OPS Spreads across teams, individuals, and other subsets of the data are significantly different from 0 using a simple "2 Tailed T-Test."

To normalize the data, the "OPS Spread" recorded for each eligible player will be averaged out over each season of data in the sample. As an example, Derek Jeter, a player for the New York Yankees, has 12 seasons worth of data during the relevant period 2001-2013, each with a different tabulated Average OPS Spread. These 12 data points will be averaged so as to normalize the data and allow direct comparison to other players in the sample. Later, this assumption will be broken down to isolate any changes in OPS spread over time lost through this averaging assumption.

Analyses of significance will be carried out through testing a variety of different Hypotheses. Each iteration used the same data, but with different controls and across different subsets of the data. Each Hypothesis tested will be presented with a brief explanation, followed by a brief discussion of the results. For all iterations, the null hypothesis was tested that "Rivalry in Major League Baseball has a significant impact on the offensive performance of individual players and teams." In other words, it was tested using a 2-Tailed T-Test whether the Average OPS spread given the following conditions was statistically significant from 0.

Results

Hypotheses 1a-b

The first set of Hypotheses are tested to isolate and identify any general effects or trends.

Hypothesis 1a: Testing average OPS Spread of All Players (2001-2013) *with no controls* within teams or across rivalries

For an introductory look at the data, this general hypothesis was tested looking at all players in the sample, testing if the OPS Spreads for each player over the entire period were significantly different from 0. This was not compared within teams or across rivalries.

Chart 2 - OPS Spreads

	Hypothesis 1a	Hypothesis 1b								
	ALL	NYY	BOS	NYY v. BOS	SFG	LAD	SFG v. LAD	CHC	STL	CHC v. STL
Mean	0.020	0.016	0.004	0.009	0.044	0.028	0.036	0.000	0.030	0.013
Std. Dev.	0.166	0.148	0.176	0.164	0.179	0.159	0.169	0.173	0.158	0.166
N =	329 players	44	54	98	59	60	119	61	51	112
T Value	2.213	0.723	0.154	0.562	1.903	1.347	2.324	-0.022	1.340	0.844
P Value	**0.028****	0.474	0.878	0.576	0.062	0.183	**0.022****	0.982	0.186	0.401

** Is significant at α = 0.05 significance level

With 329 players, the results can be seen in Chart 2 under the column, "Hypothesis 1a." Results suggest that without controlling within team or across rivalry, there is a significant negative effect of rivalry on player performance. The Mean is positive (0.020), implying that players on average performed better in Non-Rivalry Games than rivalry games, and significantly so, with a p-value of 0.028—significant at α = 0.05 significance level.

Hypothesis 1b: Testing average OPS Spread of All Players (2001-2013), *with controls* within teams and across rivalries

Fine-tuning our analysis, Hypothesis 1b then looks at results if we control within team, and then control across rivalry. This was done in an attempt to isolate any team or rivalry specific effects, as the results from Hypothesis 1a are too general to draw any meaningful conclusions. As an example, for the San Francisco Giants, we took each of the eligible players' average OPS Spread over the 2001-2013 time period, and tested that dataset's significance from 0 using a 2-Tailed T-Test. We did this for each team, and then did the same but across each rivalry (NYY v. BOS, SFG v. LAD, & CHC v. STL).

General results can be seen in Chart 2 under the column "Hypothesis 1b." As seen in the chart, while Hypothesis 1a suggested that rivalry has a significant negative impact on offensive performance, a closer look suggests that within each team, there is no significant effect of rivalry at the $\alpha = 0.05$ significance level. Across rivalries, there only appears to be a significant negative effect of rivalry across the San Francisco Giants and Los Angeles Dodgers matchup. We now look across different subsets of the data to further hone our analysis.

Hypothesis 2a-c

The second set of Hypotheses perform the same tests for significance, but across subsets of the aggregate data to try to isolate potential anomalies or outliers.

Hypothesis 2a: Testing average OPS Spread for Home / Away games of All Players (2001-2013), controlling within teams and across rivalries

General Results can be found in Chart 3 in the first two rows.[36] To summarize, controlling for Home and Away games was very much in line with conclusions taken from the first set of results. There were no significant effects of rivalry across the majority of data. There were again some significant effects across the LAD v. SFG rivalry; with no significant impact of rivalry in playing in Home games but a significant negative impact of rivalry in playing Away games—particularly for the Los Angeles Dodgers. This implies that Rivalry Games at Home don't affect performance of the Home team, but negatively affect performance of the Away team, particularly for the Dodgers. The only other statistically significant result was a significant negative effect of rivalry at Home for the New York Yankees. This last result is the first significant result present outside of the SFG v. LAD rivalry.

[36] Detailed results for this test are presented in Appendix. See Charts A & B.

Hypothesis 2b: Testing average OPS Spread for Players with over 3 years of "Exposure to Rivalry" (2001-2013), controlling within teams and across rivalries

With this iteration of the data, we tested the hypothesis that players who have been on the team longer—have been exposed to the rivalry for 3 years or more—will experience a greater effect of rivalry on offensive performance. 102 players across the sample set met this qualification.

As seen in Chart 3[37] in the row "Hypothesis 2b," the results appear to be consistent with previous tests. There again are statistically significant negative effects of rivalry on player performance within the SFG v. LAD rivalry and the teams involved, but no significant effect of rivalry within any other team or across any other rivalry. This implies that exposure to rivalry has no additional effect, or that it fails to amplify any actual effect of rivalry on performance.

Chart 3 - Results for Hypotheses 2a-c

	Results for Hypotheses 2a-c (Mean, p-values below)								
	NYY	BOS	NYY v. BOS	SFG	LAD	SFG v. LAD	CHC	STL	CHC v. STL
Hypothesis 2a (Home)	0.057**	0.022	0.038	0.052	-0.021	0.015	-0.03	0.012	-0.010
	(0.040)	(0.522)	(0.093)	(0.115)	(0.591)	(0.545)	(0.383)	(0.736)	(0.669)
Hypothesis 2a (Away)	-0.004	0.008	0.002	0.053	**0.063****	**0.058****	0.049	0.041	0.045
	(0.907)	(0.828)	(0.925)	(0.060)	(0.012)	(0.002)	(0.139)	(0.212)	(0.051)
Hypothesis 2b	0.024	0.026	0.025	**0.057****	0.010	**0.037****	-0.002	0.014	0.008
	(0.269)	(0.184)	(0.082)	(0.029)	(0.536)	(0.025)	(0.961)	(0.604)	(0.704)
Hypothesis 2c	0.039	0.041	**0.040****	0.021	0.018	0.019	-0.067	0.014	-0.085
	(0.136)	(0.135)	(0.033)	(0.451)	(0.526)	(0.320)	(0.340)	(0.842)	(0.233)

** Is significant at $\alpha = 0.05$ significance level

Hypothesis 2c: Testing average OPS Spread of All Players, only in years of "Best Rivalry," controlling within teams and across rivalries

Similar to Hypothesis 2b, this iteration of the data looks at only the years which were deemed to be "Best Rivalry" years. As mentioned in the literature review, work has been done throughout the field of psychology showing that parity increases the intensity of rivalry, and that this effect is larger between groups that are relatively high performers.[38] With this in mind, "Best Rivalry" years were determined by the following criteria. 1.) Seasonal Head-to-Head record—if the teams were within 3 games of each other

[37] Detailed results for this test are presented in Appendix. See Chart C.
[38] Garcia, Stephen M., Avishalom Tor, and Richard Gonzalez. "Ranks and Rivals: A Theory of Competition." Personality and Social Psychology Bulletin 32.7 (2006): 973-975. SAGE PUB. Web.

in their head-to-head matchup over the course of a season. 2.) Season Aggregate Record—if their overall records on the season were within 10 games of each other. 3.) Proximity of Finish—if the teams finished one spot away from each other in the standings, anywhere within the top 3 spots in the standings.[39] This yielded 8 years for the NYY v. BOS rivalry, 6 years for the SFG v. LAD rivalry, and 1 year for the CHC v. STL rivalry.[40] Breakdown of these calculations and year-by-year data are provided in the Appendix, Chart D.

General Results can be found in Chart 3.[41] Generally, there is again no significant impact of rivalry within any team, and no consistent effect of rivalry across the entire sample set. This iteration differs slightly in that there appears to be a significant negative effect of rivalry across the NYY v. BOS rivalry, and not across the SFG v. LAD rivalry. Testing of this Hypothesis though imply that even in "Best Rivalry" years, there is no explicit, robust effect of rivalry across all teams.

Hypotheses 3a-b

The third set of Hypotheses will try to control for effects over time that may have been lost in the averaging of OPS Spreads over the course of the 13-year period. These will not use the same T-Tests for significance from 0 as did the previous sets of Hypotheses.

<u>Hypothesis 3a:</u> Testing average OPS Spread of Select Individual Players over time

Averaging OPS Spreads could potentially eliminate different responses over time to Rivalry by individual players. As such, we will breakdown the individual "OPS Spread" numbers of select individual players over the entire 2001-2013 period. We have selected 3 players from each of the following teams thus far that we have seen statistically significant results for; the New York Yankees, Boston Red Sox, San Francisco Giants, and Los Angeles Dodgers. The 3 players were selected as having the most eligible seasons of data to analyze over time. We performed 2-Tailed T-Tests for each individual player on their average OPS Spread numbers each year. The results are in Chart 4.

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[39] The methodology behind these calculations year-by-year are provided in the Appendix. See Chart D.
[40] As mentioned, the CHC v. STL rivalry has suffered over the past 13 years in performance, as the Cubs have been significantly worse than have the Cardinals. Significance of this will be discussed in "Next Steps & Final Thoughts."
[41] Detailed results for this test are presented in the Appendix. See Chart E.

Chart 4 - Individual Effects Over Time

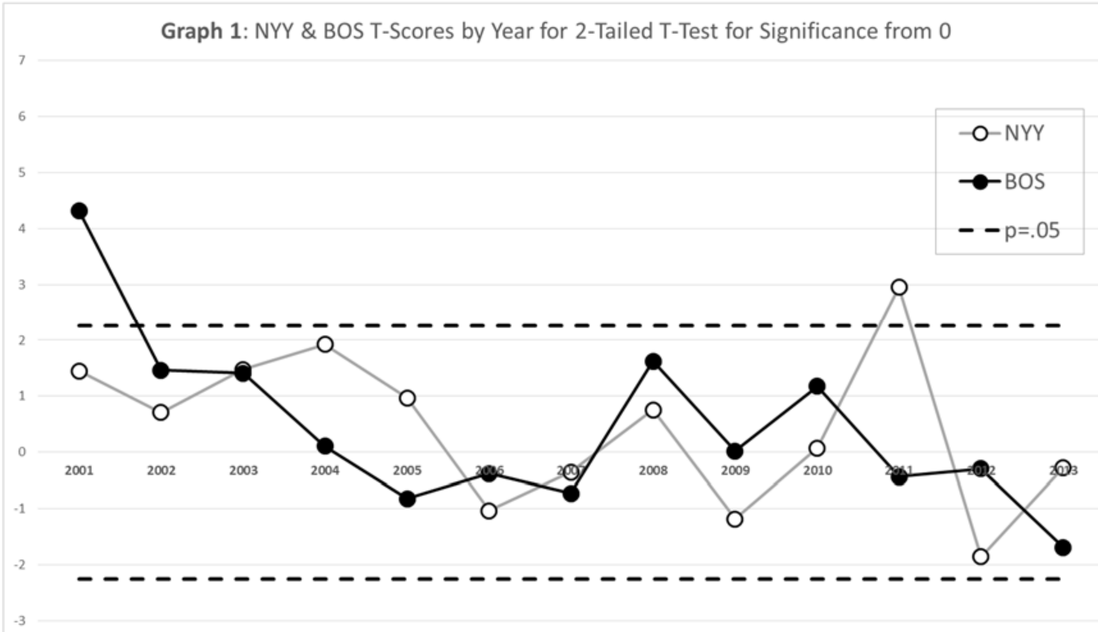
	New York Yankees			Boston Red Sox			San Francisco Giants			Los Angeles Dodgers		
2001-2013	Robinson Cano	Derek Jeter	Jorge Posada	David Ortiz	Jason Varitek	Dustin Pedroia	Barry Bonds	J.T. Snow	Pablo Sandoval	Andre Ethier	Matt Kemp	James Loney
Mean	-0.005	0.069	-0.008	-0.022	0.127	0.004	0.182	-0.066	0.063	0.026	0.008	0.116
Std. Dev.	0.135	0.177	0.227	0.110	0.220	0.145	0.449	0.235	0.236	0.086	0.212	0.128
T Value	-0.122	1.354	-0.116	-0.627	1.726	0.078	0.993	-0.624	0.598	0.846	0.104	2.229
P Value	0.906	0.203	0.910	0.546	0.123	0.941	0.366	0.567	0.582	0.425	0.921	0.076
"Best Rivalry"	Robinson Cano	Derek Jeter	Jorge Posada	David Ortiz	Jason Varitek	Dustin Pedroia	Barry Bonds	J.T. Snow	Pablo Sandoval	Andre Ethier	Matt Kemp	James Loney
Mean	-0.102	0.022	0.019	-0.007	0.122	0.065	0.015	-0.110	-0.090	0.085	0.091	0.071
Std. Dev.	0.091	0.193	0.249	0.121	0.252	0.023	0.629	0.246	0.338	0.116	0.354	0.132
T Value	-2.503	0.322	0.221	-0.143	1.287	5.598	0.040	-0.898	-0.375	1.038	0.364	0.759
P Value	0.067	0.757	0.832	0.891	0.246	**0.011****	0.972	0.436	0.771	0.488	0.778	0.587

** Is significant at α = 0.05 significance level

None of the players experience a significant impact of rivalry on their offensive performance when looking across all years of eligible data, and only one player experiences a significant negative effect of rivalry when controlling for only "High Rivalry" years of data. The impact of rivalry may fluctuate over time for reasons outside of the scope of this paper, but for none of these players does it do so to a statistically significant degree.

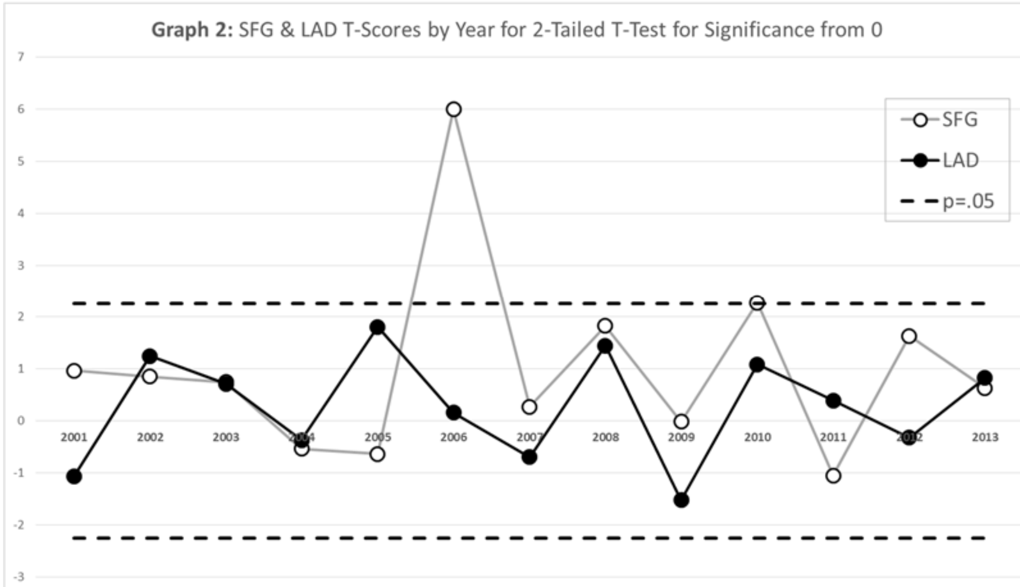
<u>Hypothesis 3b:</u> T-Scores for Individual Teams over time

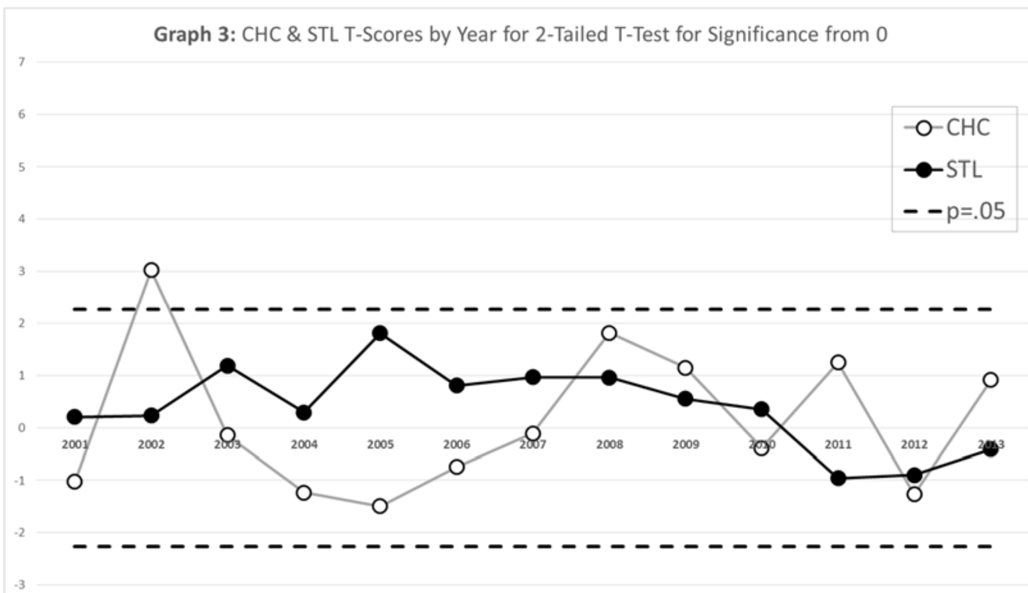
In this final analysis, we again eliminate the assumption of averaging over time, and look at the relative effect of rivalry on each individual team over the course of the 13 period. We calculate the T-Score for each team given the eligible players from that year, and plot these numbers over time for each individual team. As an example, we take the average OPS Spread from each eligible player on the Chicago Cubs' team in 2013, and calculate a 2-Tailed T-Score, measuring its significance from 0. We do this for each year, and plot it out over time. The following graphs (Graph 1, 2, & 3) present this data for each team in each of the 3 rivalries. The dotted lines spanning horizontally across each graph represent the T-score buffer lines for significance at the"α = 0.05" significance level given the appropriate degrees of freedom.



Graph 1 shows that for all but 1 of the years for both the Yankees and Red Sox, respectively, the T-Scores fall within the buffer of p=.05 significance. This suggests that for 12 of the 13 years in this data set, rivalry had no significant effect on player performance within that season. In looking closer at the significant years, the 2001 Boston Red Sox and 2011 New York Yankees, a potential explanation is evident. In 2001, the Boston Red Sox lost 13 of 18 games to the Yankees, and in 2011, the New York Yankees lost 12 of 18 games to the Boston Red Sox. These were two of the worst matchup years in their rivalry over the last 13 years, and can potentially be seen as outliers influencing the data. This corroborates our findings thus far. Rivalry does not appear to have a consistent effect on offensive performance. The following graphs for the other rivalries merely affirm this conclusion.

Looking at Graph 2, we see the results of this analysis for the SFG v. LAD rivalry. Similar to above, the majority of T-Scores fall within the buffer zone for significance except for one clear outlier. The 2006 San Francisco Giants lost 12 of 18 games against the Los Angeles Dodgers, falling in line with the trend from above. Looking now at Graph 3, the only significant point outside of the buffer zone is the 2002 Chicago Cubs, who similarly lost 12 out of 18 games to the St. Louis Cardinals.





Over time, all 6 of these teams have T-Scores that fall almost exclusively within the buffer zone with the exception of a few outlier years. Each of these statistically significant years represent the worst years of head-to-head matchups in the last 13 years for each team.[42] This suggests that these years may be skewing our results, as there appeared to be a statistically significant negative of effect of rivalry on performance because of potential outside factors. As will be discussed, most notably one of these potential outside factors may be the existence of superior pitching.

[42] See Appendix Chart C

Summary of Results

The first set of Hypotheses looked at the general data, testing for significance within teams and across rivalries. Results yielded statistically significant effects of rivalry only within the SFG v. LAD rivalry. The second set of Hypotheses tested different subsets of the data to isolate potential anomalies or outliers of the data caused by our analysis being potentially too broad. Results suggested minimal significance of rivalry again across the data; only isolating fairly consistent significant impact of rivalry within the SFG v. LAD rivalry and occasional significance within the NYY v. BOS rivalry. Through these first two sets of hypotheses, we only found significant results for the teams within the NYY v. BOS and SFG v. LAD rivalry; no significant effects of rivalry were found within any iterations of the CHC or STL data. The third set of Hypotheses looked at the effect of Rivalry on Individuals and Teams over time to address the averaging assumption made for the majority of the analysis. While Individuals had varying OPS spreads over time, none were affected significantly by rivalry over time. Interestingly, when looking across teams over time, only certain years suggested a significant negative effect of rivalry. This implied that there was no significant effect of rivalry over time for each team, but that certain outliers were potentially skewing the results. Of note, the years of significance for each were also years of historically poor performance in rivalry games.

Conclusions

The goal of all of these hypotheses was to look at the data in as many different ways as possible, and to attempt to identify results robust enough to draw conclusions from across the data. As one may have already concluded, there do not appear to be consistent, systemic effects of rivalry across rivalries, teams, and many different iterations of the data. This is a key, unexpected conclusion. As discussed earlier in the paper, rivalry is an enormous institution in the field of sports; it is widely recognized and embraced by fans and utilized by leagues and teams for economic purposes. The conclusion that it does not result in a higher level of play suggests a rejection of the initial hypothesis, lending credence to the idea that rivalry doesn't affect players at all, and that "Rivalry is All About the Fans."

The specific results across the individual Hypothesis Tests confirm this general takeaway, but also suggest a few interesting conclusions that may speak to an issue with the initial assumptions made. The SFG v. LAD rivalry has fairly consistent significant results across all iterations of the data, while the NYY v. BOS rivalry and CHC v. STL rivalry have little to none. This would appear to indicate that rivalry is a stronger, more present force for players in the SFG v. LAD rivalry. Conclusions from Hypotheses 2b-c corroborate this, as they suggest there is no additional effect of rivalry on player performance when controlling for individual exposure to rivalry and "High Rivalry" years, except in the SFG v. LAD rivalry. The stakes may be higher in the SFG v. LAD rivalry and it thus affects the players more, but more likely, these results speak to a flaw in assumptions made—in particular, the assumption of "pitching is constant."

As noted in the discussion of results for Hypothesis 3b, only a few years for each team across the time period 2001-2013 indicate statistically significant impacts of rivalry, and each of these significant years coincide with a year of historically poor performance in head-to-head rivalry games. These years appear to be clear outliers, and may have biased some of our results when looking at data through the averaging process, particularly those within the SFG v. LAD rivalry in which there is one large outlier of note. These results could be explained by certain factors negatively affecting performance that are outside of the scope of this study, or could be a result of a team that performed particularly poorly under the pressure of a rivalry game in one year more than others. What is more likely though, is that pitching played a role, and that our assumption of constant pitching influenced our results. In seasons where there are historically poor records in rivalry games, it is logical to assume that not only did the batters of the team in question perform poorly, but that also the pitchers of the opposing team performed very well. In other words, while poor batting is correlated with a poor record in rivalry games, so is high-quality opposing pitching, and a combination of the two may have contributed to these "outlier" years. Following this logic, these outlier years may not actually suggest as negative effect of rivalry on performance, and if pitching wasn't assumed to be constant, would fall more in line with our general results. This corollary is based purely on conjecture, but if true, may further suggest that rivalry has no impact on player performance across any iterations of the data.

The assumption about pitching made at the beginning of the paper was made largely because of limited resources and the limited scope of this paper. It ultimately may have affected all results in the same manner described above, and potentially even more so by not controlling for differences in pitchers in Non-Rivalry Games as well. Regardless of this though, one would have still expected to see a consistent, similar effect of rivalry across all games and different tests on the data, and this was clearly lacking. While a concrete rejection of the Hypothesis is difficult to make, what this paper succeeds in doing is severely bringing in to question the popularly held notion that rivalry is a motivator for athletes.

PART III: Future Steps & Final Thoughts

Future studies should first attempt to address the assumptions made at the start of this paper; namely 1.) Rivalry is Constant and 2.) Pitching is Constant. This first assumption was not deemed to be as problematic. From a statistical standpoint, rivalry can safely be considered to average out over the course of a season. If we assume that there are other games besides those with the primary rival that can be deemed "Rivalry Games," we can also assume that there are many others that may considered rivals at all, and that these games may result in potential demotivation (i.e. extremely poor performing teams with no historical relationship). With 18-19 Rivalry Games and 142-143 Non-Rivalry Games in a season, it is a safer assumption that any additional rivalry will cancel out over a 142-143 game period. However, with adequate resources and time, a rivalry gauge similar to that developed in Kilduff, Elfenbein, & Staw's study could be collected through national polls of newspapers, surveys of general managers and owners. Implementing this gauge to develop different degrees of rivalry would yield a more precise analysis on the exact effect of differing degrees of rivalry. Similarly, this would control for the assumption made that the three major rivalries used represent the same, intense level of rivalry. Because they are so widely accepted as rivals by the media, players, and fans though, this assumption was not deemed to be problematic.

Controlling for the Pitching assumption is the more important facet of this study to be addressed. The difficulty in doing so speaks to a general problem studies such as this face in trying to approximate the impact of "Context." Looking at the effect of something as broad as rivalry requires an extreme fine-tuning of the data. While this study attempted to analyze a variety of different subsets of the data, it may have still been too broad. Because there are so many external factors, many of which aren't easily reflected in numbers, researchers studying "context" need to control for as many factors as possible in their analysis. Ideally, one would look at the effect of rivalry on a certain batter, facing a certain type of pitcher, at a certain point in the season, given his past performance in the season (etc.), and compare that to an exact similar situation in a non-rivalry situation. It is difficult to find enough data points for pitchers in Rivalry Games alone, and aggregating data for these precise situations would be extremely difficult. One way to potentially address this though in future studies would be to develop a "Quality of Opponent" statistic. This statistic would weigh performance in Rivalry Games according to the quality of pitcher and team faced, and would control for important differences in a hitter's performance against Left and Right-Handed Pitchers, and across different ballparks. The Ballparks issue was controlled for in this paper through the examination of Home and Away performance in Rivalry vs. Non-Rivalry, but could be examined more effectively and precisely through the development of this "Quality of Opponent" statistic.

In conclusion, this paper does not claim to make any concrete conclusions about the effect—or lack of—of rivalry on offensive player performance. As one of the first known attempts in economic literature to quantify the effect of rivalry on offensive player performance in Major League Baseball, it provides a clear, comprehensive framework for future studies and explorations, and seriously brings into question the premise that rivalry brings out the best in players. As a follower of baseball and a Yankees fan, the results of this paper won't affect the author's commitment to following his favorite rivalry. Instead, the author will embrace the premise that the "Rivalry is All about the Fans," and regardless of the performance of his favorite team in the rivalry games, enjoy the hype and banter; continuing to point to the historical scoreboard listed in Chart 1—particularly at the 27 World Championships.

Appendix

Appendix Chart A - OPS Spreads (Home)

	Hypothesis 2a (Home)								
	NYY	BOS	NYY v. BOS	SFG	LAD	SFG v. LAD	CHC	STL	CHC v. STL
Mean	0.057	0.022	0.038	0.052	-0.021	0.015	-0.03	0.012	-0.010
Std. Dev.	0.179	0.250	0.221	0.252	0.299	0.278	0.262	0.257	0.259
N =	44	54	98	59	60	119	61	51	112
T Value	2.127	0.645	1.698	1.598	-0.540	0.607	-0.879	0.339	-0.429
P Value	**0.04****	0.522	0.093	0.115	0.591	0.545	0.383	0.736	0.669

** Is significant at $\alpha = 0.05$ significance level

Appendix Chart B - OPS Spreads (Away)

	Hypothesis 2a (Away)								
	NYY	BOS	NYY v. BOS	SFG	LAD	SFG v. LAD	CHC	STL	CHC v. STL
Mean	-0.004	0.008	0.002	0.053	0.063	0.058	0.049	0.041	0.045
Std. Dev.	0.241	0.262	0.251	0.212	0.190	0.200	0.256	0.231	0.244
N =	44	54	98	59	60	119	61	51	112
T Value	-0.117	0.219	0.094	1.919	2.581	3.167	1.500	1.265	1.971
P Value	0.907	0.828	0.925	0.060	**0.012****	**0.002****	0.139	0.212	0.051

** Is significant at $\alpha = 0.05$ significance level

Appendix Chart C - Exposure to Rivalry

	Hypothesis 2b								
	NYY	BOS	NYY v. BOS	SFG	LAD	SFG v. LAD	CHC	STL	CHC v. STL
Mean	0.024	0.026	0.025	0.057	0.010	0.037	-0.002	0.014	0.008
Std. Dev.	0.095	0.083	0.089	0.111	0.062	0.095	0.109	0.112	0.109
N =	20	17	37	21	15	36	12	17	29
T Value	1.138	1.381	1.785	2.349	0.634	2.350	-0.050	0.529	0.384
P Value	0.269	0.184	0.082	**0.029****	0.536	**0.025****	0.961	0.604	0.704

** Is significant at $\alpha = 0.05$ significance level

Appendix Chart D

Year		Games Won		Games Won		Season Wins	Season Losses	Finish	Season Result		Season Wins	Season Losses	Finish	Season Result
2001	NYY	13	BOS	5	NYY	95	65	1	Lost WS	BOS	82	79	2	
2002	NYY	10	BOS	9	NYY	103	58	1	Lost LDS	BOS	93	69	2	
2003	NYY	10	BOS	9	NYY	101	61	1	Lost WS	BOS	95	67	2	Lost ALCS
2004	NYY	8	BOS	11	NYY	101	61	1	Lost ALCS	BOS	98	64	2	Won WS
2005	NYY	10	BOS	9	NYY	95	67	1	Lost LDS	BOS	95	67	2	Lost LDS
2006	NYY	11	BOS	8	NYY	97	65	1	Lost LDS	BOS	86	76	3	
2007	NYY	10	BOS	8	NYY	94	68	2	Lost LDS	BOS	96	66	1	Won WS
2008	NYY	9	BOS	9	NYY	89	73	3		BOS	95	67	2	Lost ALCS
2009	NYY	9	BOS	9	NYY	103	59	1	Won WS	BOS	95	67	2	Lost LDS
2010	NYY	9	BOS	9	NYY	95	67	2	Lost ALCS	BOS	89	73	3	
2011	NYY	6	BOS	12	NYY	97	65	1	Lost LDS	BOS	90	72	3	
2012	NYY	13	BOS	5	NYY	95	67	1	Lost ALCS	BOS	69	93	5	
2013	NYY	6	BOS	13	NYY	85	77	3		BOS	97	65	1	Won WS
Year		Games Won		Games Won		Season Wins	Season Losses	Finish	Season Result		Season Wins	Season Losses	Finish	Season Result
2001	SFG	8	LAD	11	SFG	90	72	2		LAD	86	76	3	
2002	SFG	11	LAD	8	SFG	95	66	2	Lost WS	LAD	92	70	3	
2003	SFG	13	LAD	6	SFG	100	61	1	Lost LDS	LAD	85	77	2	
2004	SFG	9	LAD	10	SFG	91	71	2		LAD	93	69	1	Lost LDS
2005	SFG	10	LAD	9	SFG	75	87	3		LAD	71	91	4	
2006	SFG	6	LAD	13	SFG	76	85	3		LAD	88	74	2	Lost LDS
2007	SFG	8	LAD	10	SFG	71	91	5		LAD	82	80	4	
2008	SFG	9	LAD	9	SFG	72	90	4		LAD	84	78	1	Lost NLCS
2009	SFG	7	LAD	11	SFG	88	74	3		LAD	95	67	1	Lost NLCS
2010	SFG	10	LAD	8	SFG	92	70	1	Won WS	LAD	80	82	4	
2011	SFG	9	LAD	9	SFG	86	76	2		LAD	82	79	3	
2012	SFG	10	LAD	8	SFG	94	68	1	Won WS	LAD	86	76	2	
2013	SFG	11	LAD	8	SFG	76	86	3		LAD	92	70	1	Lost NLCS
Year		Games Won		Games Won		Season Wins	Season Losses	Finish	Season Result		Season Wins	Season Losses	Finish	Season Result
2001	CHC	9	STL	8	CHC	88	74	3		STL	93	69	2	Lost LDS
2002	CHC	6	STL	12	CHC	67	95	5		STL	97	65	1	Lost NLCS
2003	CHC	8	STL	9	CHC	88	74	1	Lost NLCS	STL	85	77	3	
2004	CHC	8	STL	11	CHC	89	73	3		STL	105	57	1	Lost WS
2005	CHC	10	STL	6	CHC	79	83	4		STL	100	62	1	Lost NLCS
2006	CHC	11	STL	8	CHC	66	96	6		STL	83	78	1	Won WS
2007	CHC	11	STL	5	CHC	85	77	1	Lost LDS	STL	78	84	3	
2008	CHC	9	STL	6	CHC	97	64	1	Lost LDS	STL	86	76	4	
2009	CHC	6	STL	10	CHC	83	78	2		STL	91	71	1	Lost LDS
2010	CHC	9	STL	6	CHC	75	87	5		STL	86	76	2	
2011	CHC	5	STL	10	CHC	71	91	5		STL	90	72	2	Won WS
2012	CHC	7	STL	10	CHC	61	101	5		STL	88	74	2	Lost NLCS
2013	CHC	7	STL	12	CHC	66	96	5		STL	97	65	1	Lost WS

Appendix Chart E - "Best Rivalry" Years

	Hypothesis 2c								
	NYY	BOS	NYY v. BOS	SFG	LAD	SFG v. LAD	CHC	STL	CHC v. STL
Mean	0.039	0.041	0.040	0.021	0.018	0.019	-0.07	0.014	-0.085
Std. Dev.	0.146	0.160	0.152	0.178	0.172	0.174	0.185	0.219	0.293
N =	33	35	68	41	39	80	8	10	18
T Value	1.52913	1.5294	2.175	0.7618378	0.6407605	1.000	-1.023	0.205	-1.236
P Value	0.136	0.135	**0.033****	0.451	0.526	0.320	0.340	0.842	0.233

** Is significant at $\alpha = 0.05$ significance level

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