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Improving Offensive Player Performance Measures for Assessing Free Agent Major League Baseball Players

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Improving Offensive Player Performance Measures for Assessing Free Agent Major League Baseball Players

An Undergraduate Honors Thesis to fulfill the requirement of graduating with Honors from the College of Engineering

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Abstract

Professional sports teams are important to their local economies, so successful franchises are significant contributors to their prosperity. This need for successful teams drives the owners and general managers to perform in-depth analyses on potential players to gain insight, so the best players can be chosen. Major League Baseball is one of the largest sports leagues in the world, so their analysis of players must be excellent to ensure they sign the best players and can compete at a high level.

Baseball is a complex sport with many different statistics evaluating nearly every part of a player's game. Because of its complexity, professional baseball relies on statistics more than any of the other professional sports. General managers and scouts for teams analyze players using a variety of statistics, so ensuring current statistics that meet their needs are available is vital. Continuously updating and developing new statistics is extremely important to keep professional baseball near the top of the professional sports world. This analysis develops a new offensive statistic for use by MLB teams when they consider what players to sign during free agency. The approach used attempts to improve an existing statistic then combines the improved statistic with another statistic to gain a new perspective on player analysis.

1. Introduction

Major League Baseball (MLB) is the largest professional baseball league and the second largest sports league in the world with over $10 billion in gross revenues in 2017 (Brown, 2017). Because of the scope and importance of the league to the local economies, it is important for teams to be well informed in their analysis of players. An important tool used by teams for analyses is statistics. Using statistics, teams analyze batters based not only on how well they hit, but also their ability to avoid getting out (Hakes & Sauer, 2006). The statistics, ranging from simple to very complex, have not always been valued like they are today. In the middle of the 20th century, Branch Rickey was the first baseball executive to find value in statistics when organizing his teams. He was a pioneer in baseball who created formulas that disproved myths and proved what really wins (Rickey, 1954). Rickey's ideas set the tone for what would come half a century later.

Two ways that teams acquire players are through free agency and through trading with other teams. Free agency is when teams make decisions regarding which players without current contracts to sign. Trading is when teams exchange players or other resources such as cash or future draft picks. Both trades and free agency decisions are risky because baseball is a very unpredictable sport that allows the lesser-skilled teams to win on any given day (Jia, Wong, & Zeng, 2013). MLB teams are always trying to gain an advantage in determining which players will benefit their team the most. Winning games is the ultimate goal in baseball, so choosing players who will help accomplish this is imperative. With the constant evolution of statistics to try to determine the most effective measures for player analysis, experimentation of new metrics to obtain a different perspective of players is important to develop the game for the future. The research I conducted aimed to first formulate a new statistic based on currently used metrics in an effort to improve how players are analyzed and second, to formulate a new statistic combining the first one I created and an existing one to find a new method for teams to evaluate free agent players they might like to sign.

2. Literature Review

At some level, statistics have always been measured in baseball. In baseball, statistics can be divided into two different categories: counting and rate. Counting statistics measure a player's total production without addressing how many plate appearances they have. On the other hand, rate statistics are calculated by taking the number of successes a player has by the number of opportunities (Use of Statistics, 2016). The use of statistics began with easy to quantify counting statistics such as home runs, and innings pitched. As baseball has grown on the national scale, the need for better statistical analyses has become necessary. In the 1970s, Bill James became one of the first people to analyze baseball players using in-depth statistics. James coined the term "sabermetrics" to define the analysis he was doing. James defined sabermetrics as "the search for objective knowledge about baseball" (Birnbaum). Sabermetrics was the beginning of development of many new rate statistics as well as a few, more complex, counting statistics.

The boom of sabermetrics sparked the interest of more people than just the few involved with Bill James' research. The desire to learn the most effective ways to identify the best players eventually moved onto a larger scale when the Oakland Athletics (A's) proposed the idea of *Moneyball*. Because all MLB teams do not have the same budget, the ability to analyze players effectively is especially important for less wealthy teams. The A's were the first team to prove how crucial statistical analysis is in baseball. The A's are a small market team, so their budget is not as large as other teams. Despite having either the lowest or second-lowest payroll in the

MLB for consecutive seasons, the A's fielded teams that were competitive with the teams with the highest payrolls (Lewis, 2003). The general manager of the A's, Billy Beane, realized the competitive disadvantage his team faced, so he became more creative in his analysis of players. The concept of Moneyball based the analysis of players on statistics not valued as highly by other teams such as on base percentage to sign free agents' or trade for players other teams overlooked.

Batting average has always been the statistic that is the most popular among casual baseball fans because of how easy it is to calculate and how clearly it impacts the game. Batting average is calculated by dividing the number of hits for a player by the number of at bats they have. It is important to note that walks and hit-by-pitch are not included in this calculation. Hitters who have high batting averages consistently reach base via a hit. The players who are viewed as being the best typically have one of, if not, the highest batting averages. Table 1 shown below describes the statistics that are most important to my research. These statistics are used to calculate more advanced statistics such as batting average.

Table 1: Common batting statistics

Hit (H)	When a batter hits a ball into fair territory and reached base safely without an error or fielder's choice.
Walk (BB)	When a pitcher throws four balls outside the zone and the hitter does not swing at any of them. The batter is awarded first base. Walks do not count as an at-bat.

Hit-by-pitch (HBP)	When a batter is struck by a pitched ball without swinging at it. Hit-by-pitch occurrences do not count as an at-bat.
At Bat (AB)	When a batter reaches base via a fielder’s choice, hit, or an error, or when a batter is put out on a non-sacrifice.
Plate Appearance (PA)	When a batter completes a turn at the plate.
Sacrifice Fly (SF)	When a batter hits a fly-ball out to the outfield or foul territory that allows a runner to score.
Sacrifice Bunt (SH)	When a batter successfully advances one or more runners by bunting the ball for an out.
Error (E)	When a fielder fails to make a play that the official scorer judges an average fielder would have made.
Run (R)	When a runner crosses the plate safely to score.
Stolen Base (SB)	When a runner takes a base to which they aren’t entitled.
Caught Stealing (CS)	When a runner is thrown out trying to steal a base.
Intentional Walk (IBB)	When a batter is walked on purpose.
Strikeout (K)	When a hitter swings or looks at the third strike of their at-bat.

Like batting average, On-base percentage (OBP) is another statistic used to measure player performance. As its name indicates, OBP measures how often a player gets on base divided by the total number of plate appearances the player has. It considers all plate appearances resulting in a hit, walk, or hit-by-pitch as positively affecting the value and all other plate appearances as negatively affecting the value. Errors negatively affect OBP even though the player did reach base safely. OBP is calculated using the formula below. Even though the importance of OBP is not as widely recognized by casual baseball fans, it is a very important statistic for small market MLB teams such as the A's. OBP allows teams to compete despite a low batting average because of their ability to get on base.

$$\text{On Base Percentage} = \frac{\text{Hits+Walks+Hit by Pitch}}{\text{At bats+Sacrifice Flies+Walks+Hit by Pitch}}$$

OBP was made immensely more popular by *Moneyball*. Getting on base more often causes multiple problems for the opposing defense. It not only provides the team a chance to score, but it also affects the pitcher's pitching motion as well as the defensive alignment (Lewis, 2003). Pitchers also are forced to throw more pitches, so they may become tired more quickly. These differences in the defense put more pressure on them and give the team on offense a better chance to score than simply having the runner on base.

Slugging percentage (SLG) is another statistic used to evaluate players. This statistic measures a player's ability to hit for power. Slugging percentage favors players who get more doubles, triples, and home runs known as extra base hits because these types of hits are worth more total bases per at-bat. This metric is measured on a scale from 0.000 – 4.000 with a higher value representing a better player.

$$\text{Slugging percentage} = \frac{\text{Total Bases}}{\text{At Bats}}$$

On-base plus slugging (OPS) is a statistic combining OBP and SLG. OPS is used to determine hitters who are well-rounded. A higher OPS indicates a player who is good at both hitting for power and getting on base. The formula for OPS is shown below.

$$\text{OPS} = \text{OBP} + \text{SLG}$$

While OPS is an interesting statistic that is fairly effective at evaluating players, it is not without its flaws. This statistic treats OBP and SLG as equal statistics in the calculation, but this equal treatment does not fairly analyze players (Slowinski, 2010). This unequal treatment was discussed in *The Book: Playing the Percentages in Baseball*. In this book, the authors explain how calculating OPS using a 1.7 multiplier for OBP makes sense because of how much more value it provides to the statistic (Tango, Lichtman, & Dolphin, 2007). My research aims to explore an alternate way to account for the added value OBP adds to the statistic by taking the current SLG formula and giving weight to walks. Walks are only given value currently in the OBP formula, so adding them to the SLG formula will help even out the disparity in how much value should be given to SLG and OBP when calculating OPS.

Bill James developed a new statistic to help evaluate players in more depth than just OPS as well. His statistic, runs created (RC), is used to predict how many runs a player or team will create based on their hitting statistics. Runs created allows teams to analyze players by seeing how much they would contribute to their team if they signed them. This statistic is especially important because it focuses on runs scored which is the goal of the offense in baaseball.

Rob Mains conducted a study of every team from 1914 to 2015 to see what the relationship was between runs per game, SLG, OBP, OPS, and BA (Mains, 2016). The results of his study are in Table 2 below. This table shows OPS is clearly the best indicator for runs scored by a team. Because the correlation coefficient is not perfect, my goal is to create a statistic that is even closer to the optimal value of 1.0.

Table 2: Rob Mains Correlation Results

Correlation Test	Correlation Coefficient
Runs per game vs. OBP	0.890
Runs per game vs. SLG	0.867
Runs per game vs. OPS	0.944
Runs per game vs. BA	0.812

Even though currently used statistics do a good job of measuring player performance, purely evaluating players by weighting each plate appearance equally does not seem fair. This is where situational hitting comes into play. Whether a player hits a home run in the first inning of a regular season game or in the ninth inning of Game 7 of the World Series, its statistical significance is the same. Situational hitting is a very important quality to teams. Hitters that are categorized as being more “clutch” are more attractive to teams because they perform better in high leverage situations. The abilities these players possess do not significantly change when presented with situations where they are required to be “clutch”, so they are sought after when building rosters. “Clutchness” is a newer statistic being measured. The measure assigns in-game situations a leverage index value and assesses players based on their performance in higher leverage situations. If they perform at or below their normal averages on any given statistic, they are said to not be very clutch. However, if they perform better in high leverage situations than they do in “normal” situations, they are clutch. Using the statistics previously mentioned, my research analyzes the best players and attempts to connect “clutchness“ to the newly developed statistic.

To connect “clutchness” to the statistic, I researched how often a player bats in a “clutch” situation on average. David Appleman writes about the leverage index which defines how important a particular situation in a game is based on different measures. In his article, he mentions that around 10% of all situations have a leverage index above 2 which indicates these situations are the highest leverage. This leverage index is used to create the currently existing clutch statistic on Fangraphs website.

For my research, I will use the statistic that is already developed to build an overall statistic that measures a player’s ability to perform in both “clutch” and “normal” situations. A detailed breakdown of the components of this statistic will be included in the methodology section below. This new statistic can be used alongside currently existing statistics such as OPS and batting average to give teams a different perspective on a certain player.

3. Methodology

This research project is broken down into three distinct phases: preliminary analysis, new statistical formulation, and comparative analysis. The primary software I used for performing the analysis was Excel. I used it to run correlations create new formulas and analyze the data for the comparative analysis.

3.1 Preliminary Analysis

The first phase is the initial data analysis phase. In this phase, I looked at currently used statistics and identified how well they currently operate and the players who are the best using the respective statistics. The insights gained from this initial analysis helped us better understand the relationship between each of the statistics of interest and the players that performed the best when analyzed using them.

"Clutchness" was the main statistic I investigated. To see which players were doing well in this category, I gathered data from the previous twenty seasons on all qualifying players. A qualifying player is simply a player who averages 3.1 plate appearances per game. This eliminates players who do not play as much from being rewarded for it. The data I gathered included the "clutchness" data as well as data on the batting average, slugging percentage, OPS, and other frequently used statistics. I ran correlations on this data to see if there was any relationship between "clutchness" and any of the other statistics of interest to me. Table 3 shows the results of the analysis.

Table 3: Clutchness vs. Common Statistics Correlation Results

Comparison	Correlation Coefficient
Clutchness vs. OBP	0.04466
Clutchness vs. SLG	-0.03528
Clutchness vs. OPS	-0.00668
Clutchness vs. BA	0.07075

This analysis showed exactly what I was expecting to see. The overall abilities of a player do not necessarily affect how clutch they are. This proves how important evaluating "clutchness" is. Just because a player performs well in 90% of the situations they face, does not mean they will perform well in high leverage situations. This initial analysis suggests creating a statistic using "clutchness" could be useful for analyzing player performance.

3.2 New Statistic Formulation

In the second phase, I altered one of the currently used statistics, OPS. The goal of the new statistic which I will call OPS* is to see if I could create a new statistic that more closely reflects a team's ability to score runs. When formulating the new statistic, I created four basic variations to implement different aspects of a player's performance. All variations of the statistic are very similar to OPS, but they add more complexity to the formula. Each of the variations was used to find the correlation between it and runs scored to see if an improvement from the original OPS formula was found.

The first, most basic variations were created to evaluate each of the statistics separately. Each of the statistics of interest (BB, HBP, IBB, SB) were plugged into the base slugging formula shown below. This formula was then added to the existing OBP formula to form the new OPS statistic.

$$\text{SLG Alternative} = \frac{\text{Total Bases} + \text{Candidate}}{\text{At Bats} + \text{Candidate}}$$

$$\text{OPS Alternative} = \text{OBP} + \text{SLG Alternative}$$

The first variation shown below gives more weight to walks in the slugging percentage formula. This extra weight is given to try to even out the apparent difference in weight between OBP and SLG. The formula for the statistic is shown below.

$$SLG^* = \frac{\text{Total Bases} + \text{BB}}{\text{At Bats} + \text{BB}}$$

$$OPS^* = OBP + SLG^*$$

The second variation gives more weight to HBP in the slugging percentage formula. Like the formula using walks, this formula was developed to give players credit for earning their way on base. Even though all players do not intentionally try to get hit, some players will crowd the plate each at bat and the addition of this statistic rewards them for their actions. The formula for the variation is shown below.

$$SLG\$ = \frac{\text{Total Bases} + \text{HBP}}{\text{At Bats} + \text{HBP}}$$

$$OPS\$ = OBP + SLG\$$$

The third variation accounts for intentional walks. Intentional walks are weighed separately from non-intentional walks because they are not “earned” in the same way. Intentional walks only occur in certain in-game situations, but I believed it was important to include them in the analysis because better players are typically intentionally walked more. The variation is shown below.

$$SLG\hat{} = \frac{\text{Total Bases} + \text{IBB}}{\text{At Bats} + \text{IBB}}$$

$$OPS^\wedge = OBP + SLG^\wedge$$

The next variation gives weight to stolen bases. This rewards faster players who bring added pressure to the pitcher and catcher because of their ability to essentially stretch their hit into a higher value hit by stealing a base. However, they will also be penalized for being caught stealing. The formula for this variation is shown below.

$$SLG' = \frac{\text{Total Bases} + SB - CS}{\text{At Bats}}$$

$$OPS' = OBP + SLG'$$

The final basic variation was designed to negatively affect players who strikeout often. Strikeouts do not provide any advantages to the team because the ball is not put in play. Putting the ball in play forces the other team to make a play and the possibility of reaching base or advancing a runner who is already on base increases. In 2019, the total number of strikeouts record was broken again just as it had been in each of the previous fourteen seasons. In the current era of baseball, players value the homerun more highly than ever, but with this greater effort to hit more homeruns often comes at the expense of more strikeouts. Because of this number continuing to climb, including a formula for strikeouts was necessary. To find the exact weight for what each strikeout should be worth, a sensitivity analysis was performed. The goal of this analysis was to get the best correlation value versus runs scored. The results of this analysis are discussed in the results section. The strikeouts formula is shown below.

$$\text{SLG\#} = \frac{\text{Total Bases - 0.07(K)}}{\text{At Bats}}$$

$$\text{OPS\#} = \text{OBP} + \text{SLG\#}$$

Once the initial analysis of each of the five candidate statistics were performed, the potential contributors to a final improved statistic were identified and this statistic was built. Variations with all possible combinations of the chosen statistics were formulated to find the final one. The final variation shown below includes stolen bases, walks, and strikeouts. The results of the experimentation to find this statistic are in the results section.

$$\text{SLG!} = \frac{\text{Total Bases + SB - CS + BB - 0.07(K)}}{\text{At Bats + BB}}$$

$$\text{OPS!} = \text{OBP} + \text{SLG!}$$

After the final variation of OPS was created, a new formula was created to evaluate the overall value of a player. This statistic combines the final OPS variation with the clutch statistic currently used. I called this statistic an Integrated Measure of Performance (IMP). This new statistic aims to evaluate a player's overall value for all situations. It gives a much greater weight to OPS! because this statistic describes a player's performance in any situation. Teams care more about a player's performance in general. For this statistic, I gave clutch situations a 10 percent weight and all other situations a 90 percent weight because most players find themselves in high level “clutch” situations roughly 10 percent of the time. The statistic I formulated is shown below.

$$IMP = 0.1 * Clutch + 0.9 * OPS!$$

3.3 Analysis

Finally, a two-part analysis was performed. The first part compared OPS with the multiple variations of the new statistic. This analysis was a process that occurred during and following the new statistical formulation phase. The first part of the analysis involved a correlation between the OPS variations and runs scored just as Rob Mains performed. For my research, I only used the data from the last 30 years instead of the more than one hundred seasons he used.

The second part of the analysis evaluated the IMP. I first looked at how the IMP changed over a player’s career. Because I had data from the last twenty seasons, I evaluated players who began their careers in the early 2000s for this analysis. I also looked at how the IMP rated players and compared this rating to their finish in the Most Valuable Player (MVP) race and their Wins Above Replacement (WAR) total for the season. WAR is used to summarize a player’s total contribution to their team into one statistic (Slowinski, 2010). WAR is known to be a very good statistic for determining how good a player is at a specific aspect of the game. WAR is divided into three different categories: Batting Runs, Base Running Runs, and Fielding Runs. For the purposes of our study, I will only be considering their batting runs because I did not look at fielding, and base running runs involves much more than just stolen bases.

4. Results

The results are divided into two sections: the results for the new statistical formulation and the results from the analysis of the IMP.

4.1 New Statistic Formulation

After doing the preliminary analysis using the existing statistics, I began the next phase of developing the new statistic. I first ran baseline correlations to see how well the existing SLG and OPS statistics predict runs scored. The data I used for these correlations spanned the last 30 seasons and included statistics for all teams in the league. After I had established the baseline, I began experimenting with the different statistics to see if I could improve on the SLG and OPS statistics.

I began by looking at each of the candidate statistics separately to see if they improved the correlation by themselves. The full tables of correlations are shown in Tables 4 and 5. I will now discuss each of the individual statistics and analyze the results of their testing.

The first addition to the statistic was walks. Because walks occur frequently and earning them has the potential to advance runners, it was no surprise that the SLG statistic improved significantly, and the OPS statistic improved slightly.

Next, I analyzed the impact of HBP. HBP is similar to walks in that it has the potential to advance runners, but because they do not occur as frequently, it is not surprising to see that it did not make the OPS or the SLG statistic any better.

I then looked at the intentional walks to see their impact. In a game, intentional walks are usually only given in situations where runners will not advance or high leverage situations. For this reason, it is not surprising that the OPS statistic did not improve. However, intentional walks did improve the SLG statistic because they are like walks and HBPs in that they runner reaches base safely.

Net stolen bases was the next statistic I investigated. Because players who steal bases are stretching their hit into essentially a hit that is worth one more base, it is not surprising that stolen bases help predict runs score more effectively in both formulas.

The final statistic was strikeouts. To find the final version of this formula that I wanted to use, I performed a sensitivity analysis with different percentages to subtract for each strikeout. After the analysis, I settled on seven percent for every strikeout because it created the OPS# value closest to the optimal value of 1.0. This formula proved to be effective for both SLG and OPS because as I mentioned earlier, runners cannot be advanced when a player strikes out, so strikeouts do not help score runs. Tables 4 and 5 show the results of the correlations. Figures 1 and 2 represent correlation plots showing Runs vs. SLG + BB and Runs vs. OPS + (SLG + HBP). The other correlation plots showing the results of these tests are shown in Figures 7-16 in the Appendix.

Table 4: Runs vs. Base Slugging Alternatives Correlation Results

SLG Alternative Correlation	Correlation Coefficient
Runs vs. SLG	0.90067
Runs vs. SLG + BB	0.93084
Runs vs. SLG + HBP	0.89673
Runs vs. SLG + IBB	0.90482
Runs vs. SLG + SB	0.90518
Runs vs. SLG – 0.1K	0.91492
Runs vs. SLG – 0.15K	0.91810
Runs vs. SLG – 0.05K	0.90913
Runs vs. SLG – 0.07K	0.91176

Table 5: Runs vs. Base OPS Alternatives Correlation Results

OPS Alternative Correlation	Correlation Coefficient
Runs vs. OPS	0.95253
Runs vs. OPS + (SLG + BB)	0.95470
Runs vs. OPS + (SLG + HBP)	0.95092
Runs vs. OPS + (SLG + IBB)	0.95189
Runs vs. OPS + (SLG + SB)	0.95393
Runs vs. OPS + (SLG - 0.1K)	0.95347
Runs vs. OPS + (SLG - 0.15K)	0.95213
Runs vs. OPS + (SLG - 0.05K)	0.95361
Runs vs. OPS + (SLG - 0.07K)	0.95370

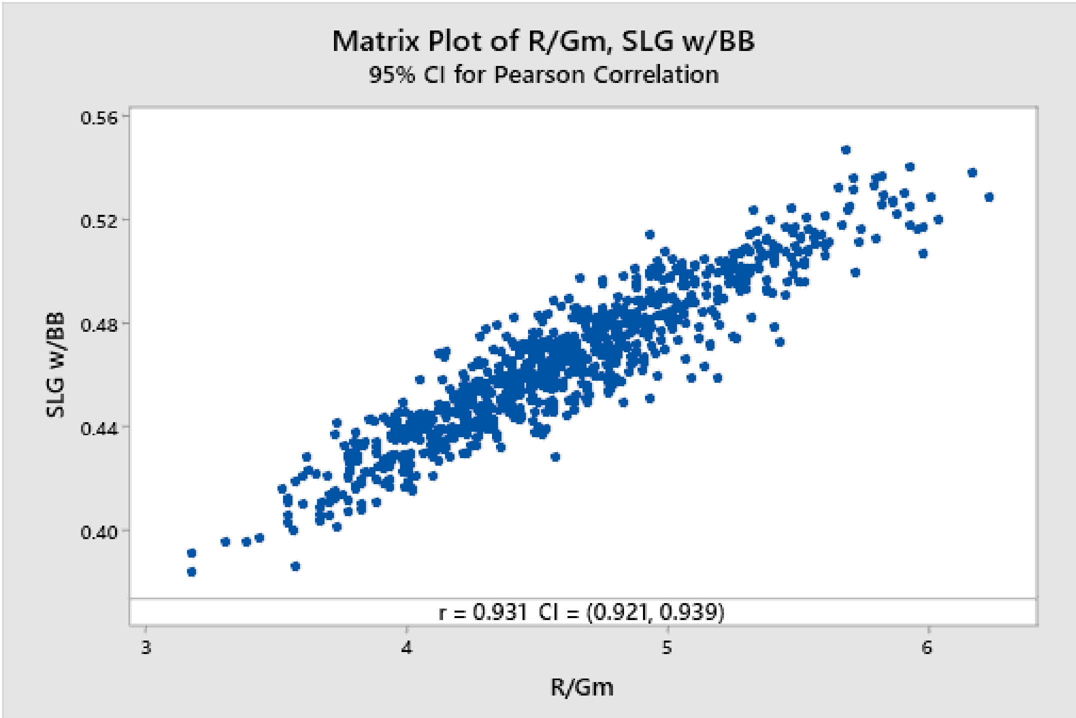

Figure 1: Correlation Plot for Runs vs. SLG w/BB

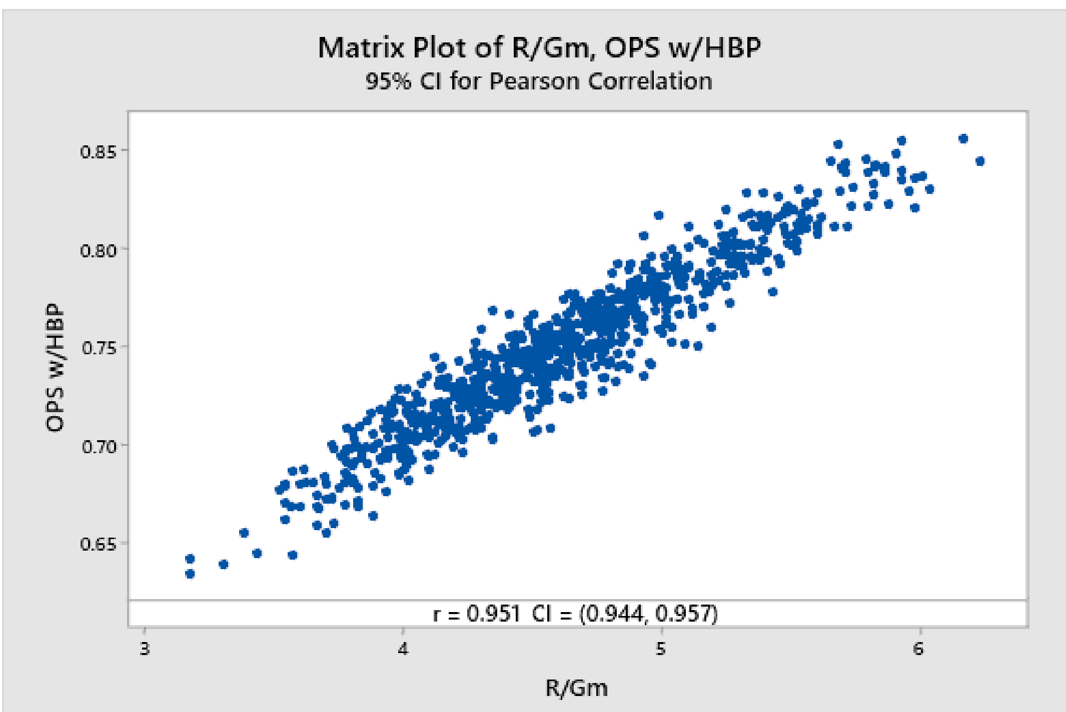

Figure 2: Correlation Plot for Runs vs. OPS w/HBP

The combined final statistic showed improvement from the existing OPS statistic, but not by very much. Because the existing statistic is already an excellent predictor of runs scored, there was not much room for improvement. Tables 6 and 7 show the correlation for the slugging percentage and OPS of each variation of the final statistic. They show that each of the combinations of two of the three best predictors were very good, but the one that was chosen at the end was the one combining all three. A plot of the final OPS correlation is also shown in Figure 3, and all other correlation plots for SLG! and OPS! are in the Appendix as Figures 17-23.

Table 6: Runs vs. SLG! Alternatives Correlation Results

SLG! Alternatives Correlation	Correlation Coefficient
Runs vs. SLG + BB + SB – CS	0.93371
Runs vs. SLG + BB – 0.07K	0.94026
Runs vs. SLG + SB – CS – 0.07K	0.91514
Runs vs. SLG + BB + SB – CS – 0.07K	0.94452

Table 7: Runs vs. OPS! Alternatives Correlation Results

OPS! Alternatives Correlation	Correlation Coefficient
Runs vs. OPS + (SLG + BB + SB - CS)	0.95574
Runs vs. OPS + (SLG + BB – 0.07K)	0.95560
Runs vs. OPS + (SLG + SB – CS - 0.07K)	0.95464

Runs vs. OPS + (SLG + BB + SB – CS - 0.07K)	0.95624

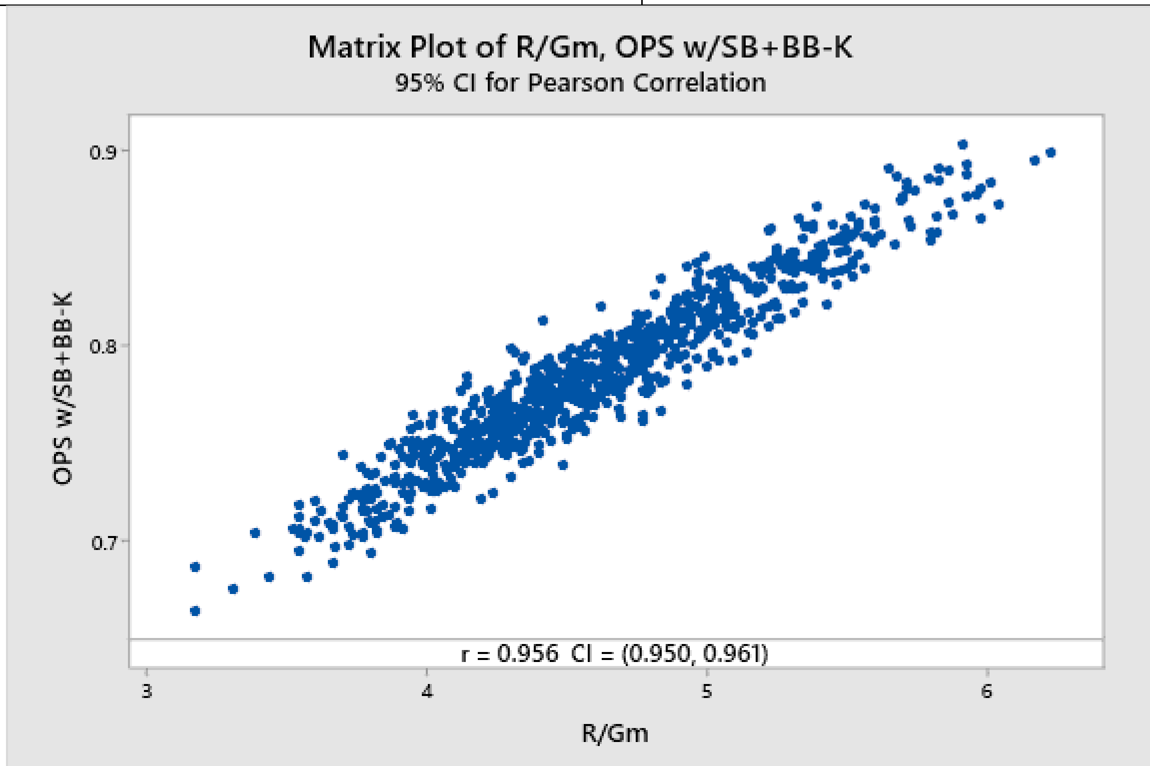

Figure 3: Correlation Plot for Runs vs. SLG w/SB + BB - K

4.2 IMP Evaluation

After the final variation of OPS was formulated, I began to formulate the IMP. The goal of the IMP was to create an overall statistic to evaluate players just as Bill James did with his runs created (RC) statistic. For each of the last five seasons, tables showing the top 10 players according to our IMP were created. Table 8 shows the 2019 leaders. The rest of the tables are in the appendix as Tables 16-19.

Table 8: 2019 IMP Leaders

Player	IMP
Christian Yelich	1.100
Matt Olson	1.067
Xander Bogaerts	1.017
Anthony Rendon	1.014
Bryce Harper	1.004
Anthony Rizzo	0.995
Mookie Betts	0.989
Michael Brantley	0.985
Max Muncy	0.985
Charlie Blackmon	0.971

Just like in every other sport, MLB players' abilities regress as they get older. This affects how well they perform in each of the main statistical categories. I decided to investigate how players typically regress according to the IMP I developed. I looked at a few players who began their careers in the early 2000s such as Albert Pujols, and I analyzed their regression over time. The three players I investigated, Albert Pujols, David Ortiz, and Carlos Beltran, showed different patterns in their IMP scores. Overall, all three players showed a few seasons where they peaked, then a gradual decline occurred. This was most noticeable in Albert Pujols. David Ortiz decline was less dramatic because he had seasons at the end of his career where he had much higher numbers than the surrounding seasons. Figure 4 shows the results of this analysis. Figure

5 also shows the same players' results for OPS over the same time period. The OPS analysis shows more of a gradual decline and no clear peak for the players like there was in the IMP. The peak in the IMP appears as though it was only caused by the players having peak "clutchness" years at the same time they were having good OPS seasons as shown by Figure 6. The underlying statistics for these analyses are shown in Tables 36-38 in the Appendix.

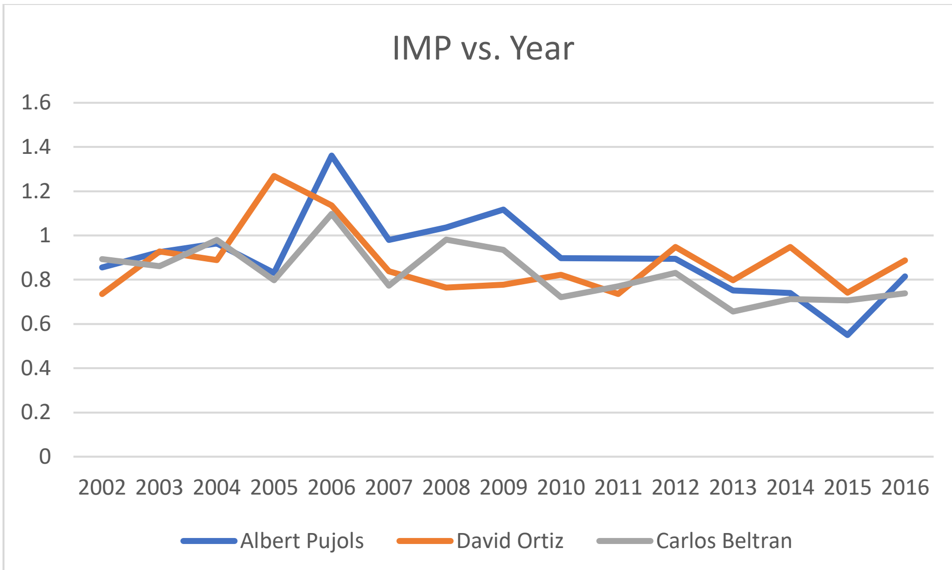

Figure 4: Graph Showing IMP Values Over Time

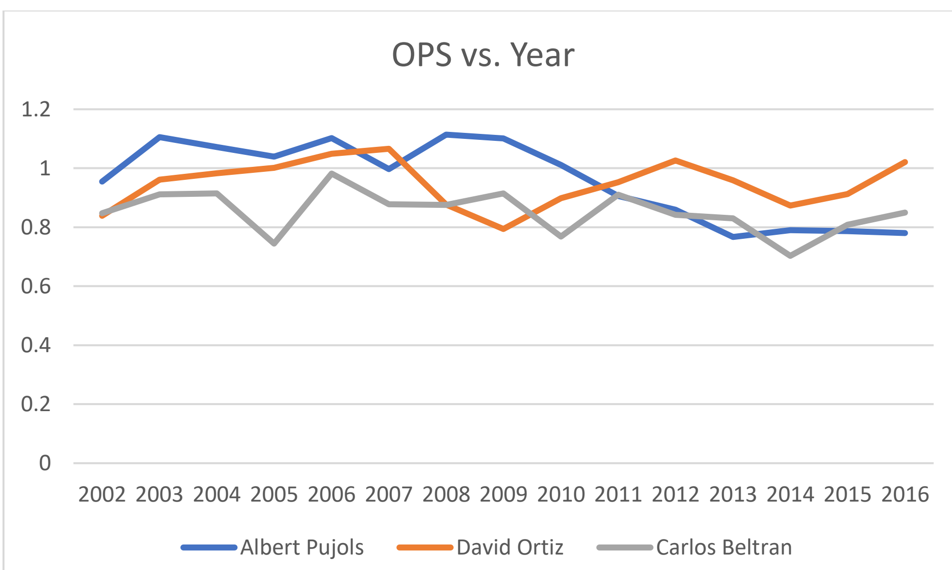

Figure 5: Graph Showing OPS Values Over Time

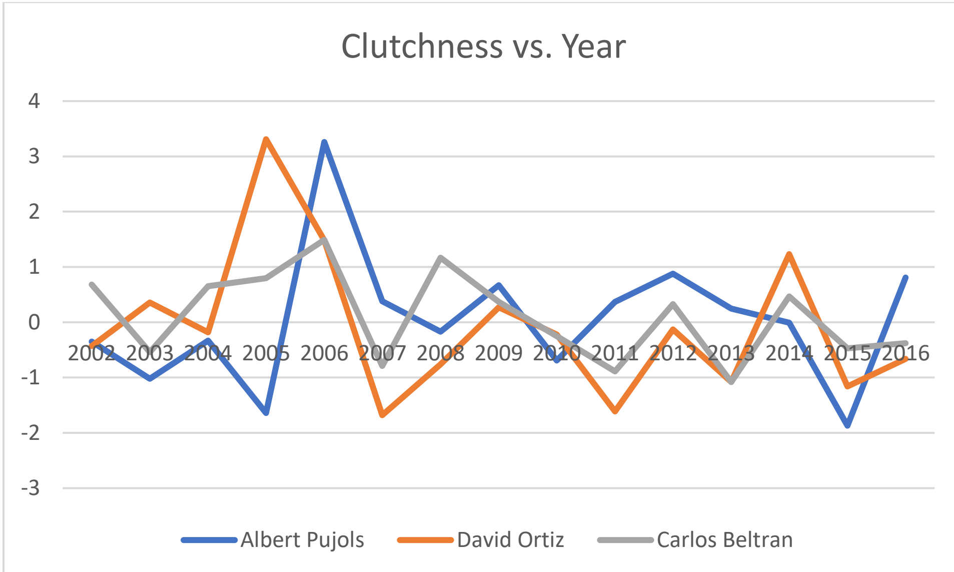

Figure 6: Graph Showing Clutchness Values Over Time

An analysis of how the top players ranked according to MVP voting and WAR was the final analysis of the IMP I created. For each of the last twenty seasons, I gathered the top five position players according to WAR total and the top five finishers in the MVP race. I then compared where they finished according to the IMP score. The goal of this comparison was for the sum of the rankings to be less than 50. This would mean that all five players on average were in the top 10 of the IMP ranking system. However, after looking at the results of this analysis, it appears as though the statistic I have developed is not a good predictor of who the MVP should be. For some seasons, the results did come out close to what I was hoping they would, but for others, they were very far off because at least one of the players was extremely “unclutch”.

I did not want to come to this conclusion based solely upon one or two bad seasons, so I continued investigating. I consistently found the results to be outside the desired range. Out of the ten separate races tested, only three qualified as being acceptable. The two tables below show the MVP races from two different seasons. Table 9 shows a fairly normal race where all the players placed moderately high in the IMP ranking, and their total ranking barely met the minimum requirement. Table 10 shows one of the extreme seasons where two of the players were extremely “unclutch”, so the overall IMP ranking was more than three times the desired outcome. The rest of the IMP Ranking Tables are shown as Tables 20-27 in the Appendix. For each of the tables, the order of finish for the MVP voting is the same as the order the players are listed in the table.

Table 9: 2017 NL MVP Race IMP Ranking

Player	IMP Ranking
Giancarlo Stanton	22
Joey Votto	5
Paul Goldschmidt	30
Nolan Arenado	1
Charlie Blackmon	7
Total	65

Table 10: 2017 AL MVP Race IMP Ranking Table

Player	IMP Ranking
Jose Altuve	14
Aaron Judge	65
Jose Ramirez	74
Mike Trout	4
Francisco Lindor	7

Total	164

Whenever I evaluated the players according to their WAR total for the season, the results were not much different than the MVP results. In general, players who have a higher WAR are better, so the media typically votes them at the top of the MVP race. Due to this, a maximum of only one or two players out of the top five changed from MVP to WAR for each of the seasons I analyzed. A table showing the WAR totals for the NL and AL in 2019 are shown below. There is only one player different from the MVP race above in both leagues, so the total is worse for both, but in general these changes did not affect the total significantly. Tables 11 and 12 show how the WAR leaders for both leagues did in our IMP Rankings for the 2019 season. The rest of the tables showing the results of this analysis are Tables 28-35 in the Appendix.

Table 11: 2019 NL WAR Leaders IMP Ranking

Player	IMP Ranking
Christian Yelich	1
Ketel Marte	21
Cody Bellinger	14
Anthony Rendon	2
Pete Alonso	22
Total	60

Table 12: 2019 AL WAR Leaders IMP Ranking

Player	IMP Ranking
Mike Trout	7
Alex Bregman	14
Marcus Semien	31
Xander Bogaerts	2
Rafael Devers	26
Total	80

I also created a table to analyze the top 20 players in five different categories of interest for my research. In Table 13, the leaders for each of five categories are shown. For the first three categories, the top players are not undervalued by teams. OPS and offensive WAR are well-known among the decision makers, and OPS! is not a huge variation from OPS, so their analysis using it would probably not change too much. The last two columns show statistics that would not be at the top of the list for general managers when they analyze players. The IMP showed six players who did not appear on any of the three main lists, so they may be undervalued. One player, Matt Olson, was even rated as the second-best player according to my IMP. Using the IMP to analyze players could allow teams to sign them at much lower cost. Finding these players was the one of the main goals I had when I created this statistic.

Table 13: 2019 Offensive Leaders

OPS	OPS!	oWAR	Clutchness	IMP	Normalized IMP
Christian Yelich	Christian Yelich	Mike Trout	Matt Olson	Christian Yelich	Christian Yelich
Mike Trout	Mike Trout	Alex Bregman	Alex Gordon	Matt Olson	Mike Trout
Cody Bellinger	Cody Bellinger	Marcus Semien	Jose Iglesias	Xander Bogaerts	Anthony Rendon
Nelson Cruz	Alex Bregman	Christian Yelich	Michael Brantley	Anthony Rendon	Cody Bellinger
Alex Bregman	Anthony Rendon	Xander Bogaerts	Jean Segura	Bryce Harper	Alex Bregman
Anthony Rendon	Nelson Cruz	Cody Bellinger	Matt Chapman	Anthony Rizzo	Nelson Cruz
Ketel Marte	Juan Soto	Ketel Marte	Bryce Harper	Mookie Betts	Mookie Betts
George Springer	Ketel Marte	Anthony Rendon	Shin-Soo Choo	Michael Brantley	Xander Bogaerts
Nolan Arenado	George Springer	Rafael Devers	Kevin Newman	Max Muncy	Juan Soto
Juan Soto	Nolan Arenado	Pete Alonso	Xander Bogaerts	Charlie Blackmon	Anthony Rizzo
Pete Alonso	Mookie Betts	Jorge Polanco	Adam Frazier	Freddie Freeman	Freddie Freeman
Charlie Blackmon	Freddie Freeman	Mookie Betts	Evan Longoria	Ronald Acuna Jr.	Nolan Arenado
Xander Bogaerts	Carlos Santana	DJ LeMahieu	Max Muncy	Shin-Soo Choo	George Springer
J.D. Martinez	Xander Bogaerts	George Springer	David Fletcher	Trea Turner	Ketel Marte
Freddie Freeman	Anthony Rizzo	Yoan Moncada	Wilson Ramos	Matt Chapman	Bryce Harper
Josh Bell	J.D. Martinez	Nolan Arenado	Anthony Rizzo	Nolan Arenado	Carlos Santana
Eugenio Suarez	Josh Bell	Trevor Story	Charlie Blackmon	Kris Bryant	Max Muncy
Anthony Rizzo	Pete Alonso	Juan Soto	Trea Turner	Mike Trout	Matt Olson
Austin Meadows	Trevor Story	Ronald Acuna Jr.	Ronald Acuna Jr.	Bryan Reynolds	Ronald Acuna Jr.
Jorge Soler	Josh Donaldson	Matt Chapman	Paul Goldschmidt	Carlos Santana	Charlie Blackmon

After I ran the analysis on the IMP, I realized that normalizing the "clutchness" part of the IMP had the potential make the statistic better. Because most players have OPS scores between 0 and 1 while the range for clutchness is typically -2 to 2. Because the formula treats them like they are the same, the analysis made it seem as though a normalization would make the formula better. Normalizing "clutchness" will create a more fair balance of "clutchness" and day-to-day performance. When I normalized "clutchness" by dividing it by two, the resulting correlation coefficient versus runs scored was 0.31414. I then normalized it again by dividing "clutchness" by four. The resulting correlation coefficient versus runs scored was 0.50938. Both of these values being closer to the optimal value of 1.0 indicate that normalization may be a better process for developing this statistic. Further sensitivity analysis could be done in the future to improve the statistic. Table 14 shows the 2019 players rankings according to the second normalization and compares the rankings to the original IMP. This table ranks the higher ranked OPS! and WAR players much higher than the original IMP.

Table 14: 2019 Normalized IMP Leaders

Player	Normalized IMP	Original IMP Ranking
Christian Yelich	1.072	1
Mike Trout	1.004	18
Anthony Rendon	0.968	4
Cody Bellinger	0.959	24
Alex Bregman	0.947	31
Nelson Cruz	0.933	21
Mookie Betts	0.916	7
Xander Bogaerts	0.915	3
Juan Soto	0.911	28
Anthony Rizzo	0.909	6

5. Conclusion

Baseball is a continuously evolving game. Players change their approaches frequently to gain an advantage. These nuances are what make baseball so unique. Every player plays the game differently, so new statistics are being created frequently to evaluate players according to their specifications. The performance measure I created can be used to look at players in a different way than they previously have been. Combining regular and clutch performance gives teams a new way to look at players.

Table 14 shows the correlation values for each of the main overall offensive statistics used. WAR is clearly the best, and the new OPS statistic created is the second best. While the IMP is not very good at predicting runs scored, it can still be used alongside other statistics to evaluate the situational capabilities of players and to find players who may be undervalued.

The normalized IMP rating system would be a better rating system for MLB players. The normalization gives less value to "clutchness", so while more of the best players will still be at the top of the rankings, some undervalued players will still be shown because of their "clutch" ability.

Table 15: Runs vs. Offensive Statistics

Correlation	Correlation Coefficient
Runs scored vs. OPS	0.95259
Runs scored vs. OPS!	0.95356
Runs scored vs. WAR	0.99180
Runs scored vs. IMP	0.197823
Runs scored vs. Normalized IMP	0.50938

6. Future Work

This research can be furthered by finding an even better statistic to predict runs scored or to better predict another measure of player performance and make the baseball statistics field even better. The analysis showed that adding the "clutchness" statistic made some players much better and some much worse. Finding the balance between OPS! and "clutchness" for the IMP I created could make this an even more useful statistic. The normalization process I did after the rest of my analysis had been completed should be further investigated through a sensitivity analysis to find this balance.

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8. Appendices

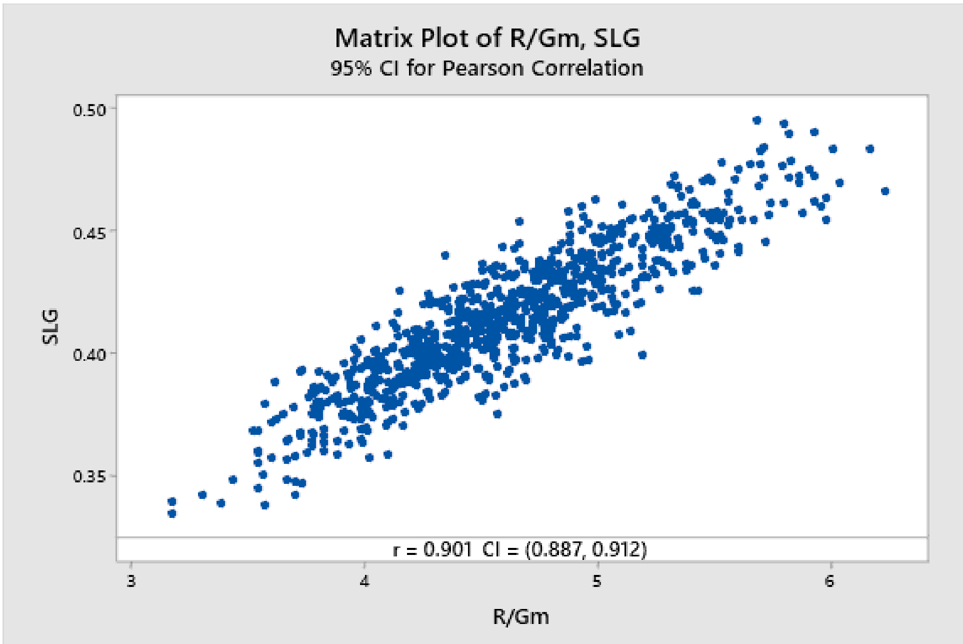

Figure 7: Correlation Plot for Runs vs. SLG

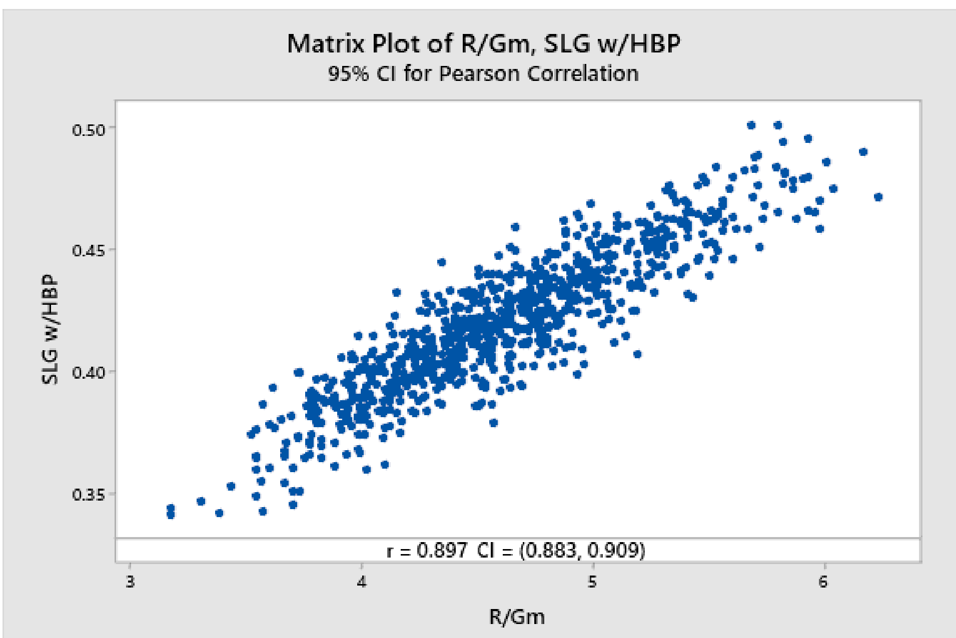

Figure 8: Correlation Plot for Runs vs. SLG w/HBP

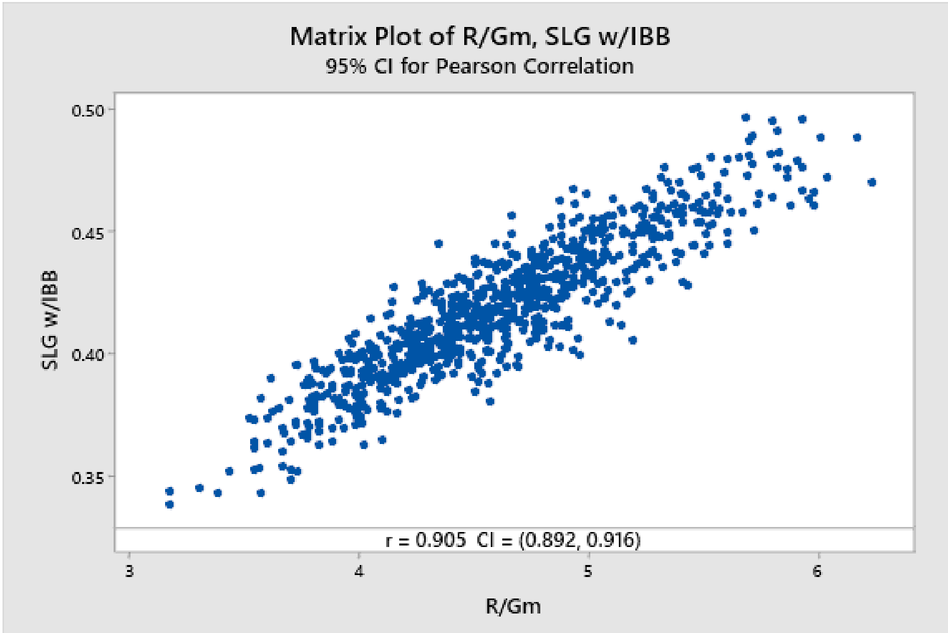

Figure 9: Correlation Plot for Runs vs. SLG w/IBB

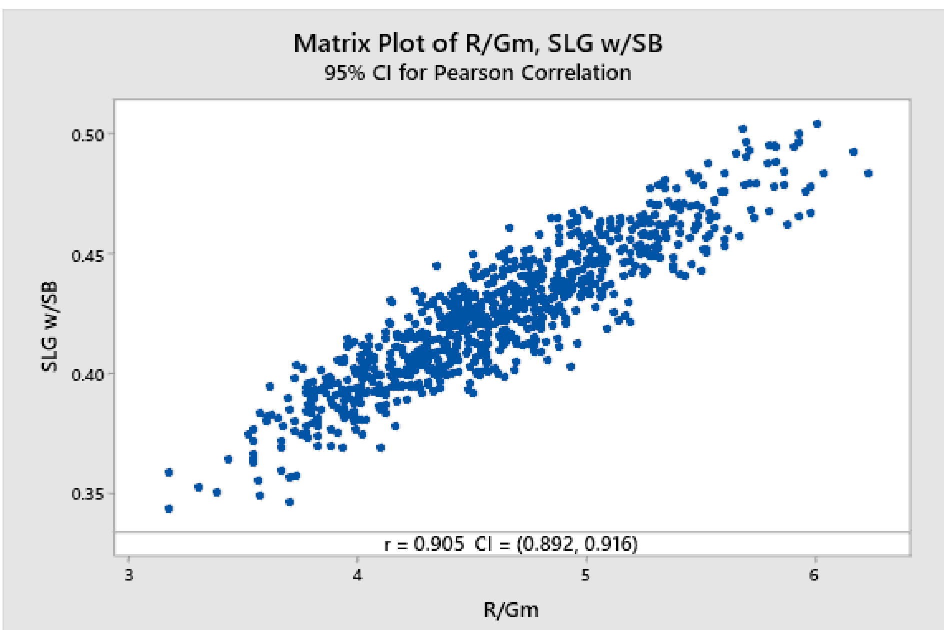

Figure 10: Correlation Plot for Runs vs. SLG w/SB

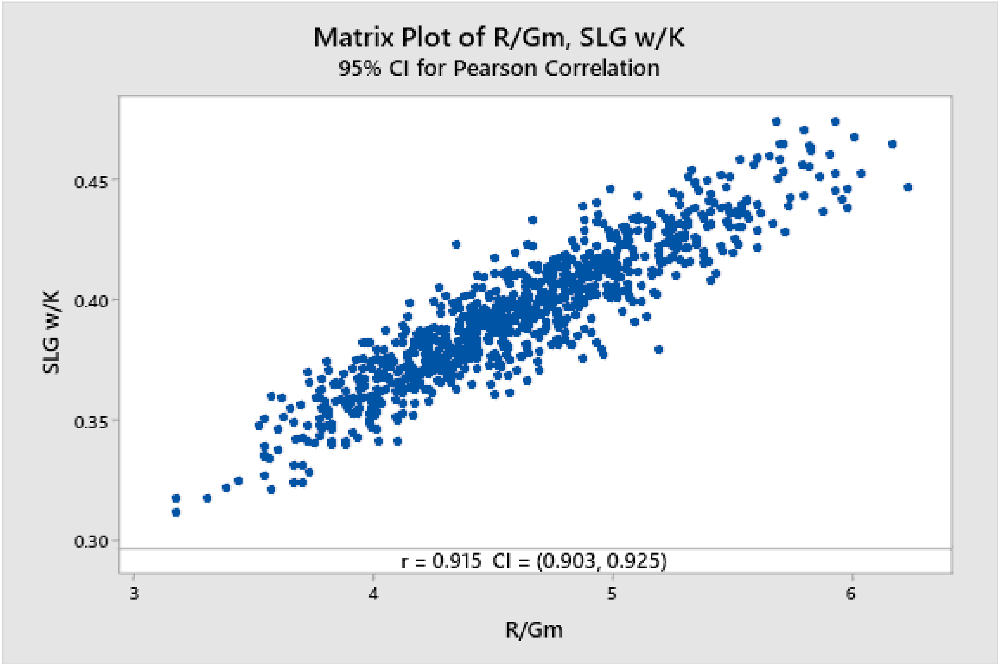

Figure 11: Correlation Plot for Runs vs. SLG w/K

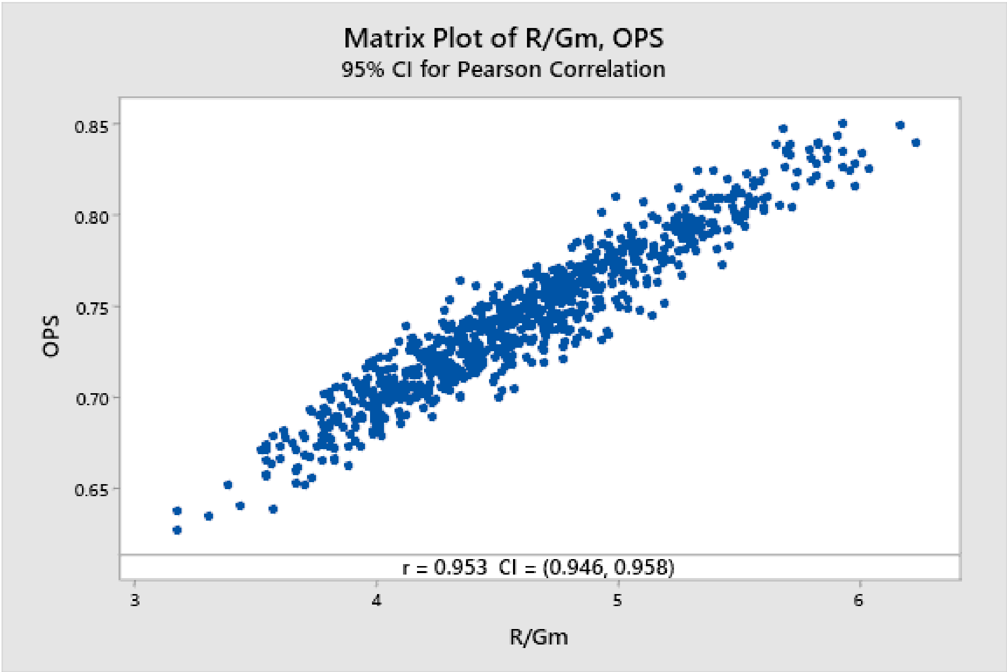

Figure 12: Correlation Plot for Runs vs. OPS

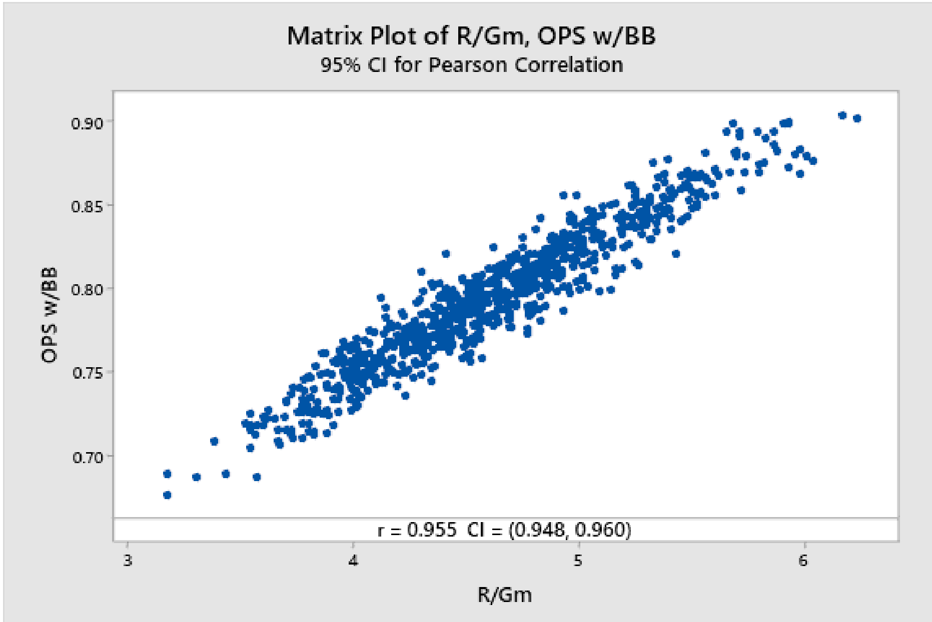

Figure 13: Correlation Plot for Runs vs. OPS w/BB

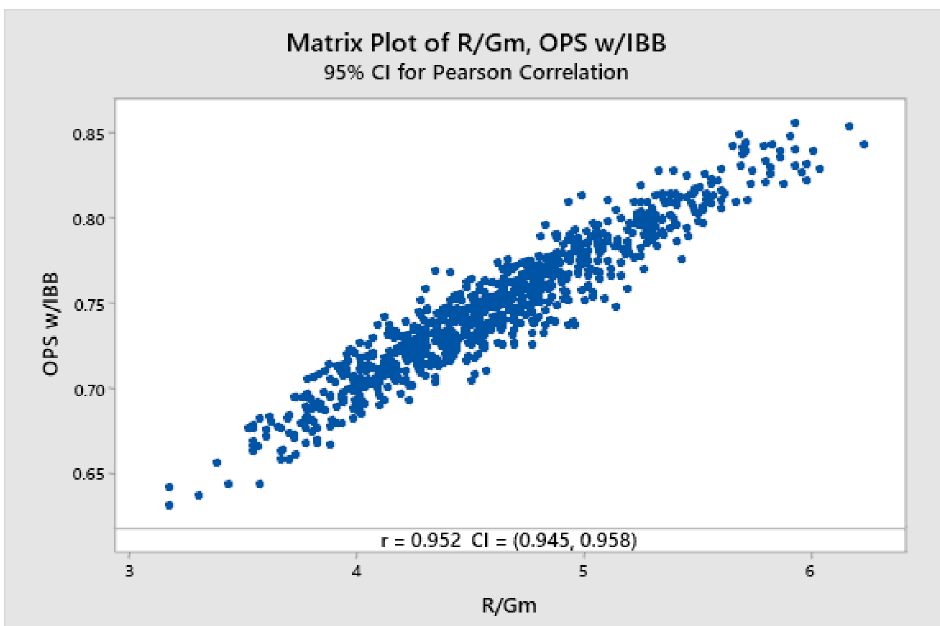

Figure 14: Correlation Plot for Runs vs. OPS w/IBB

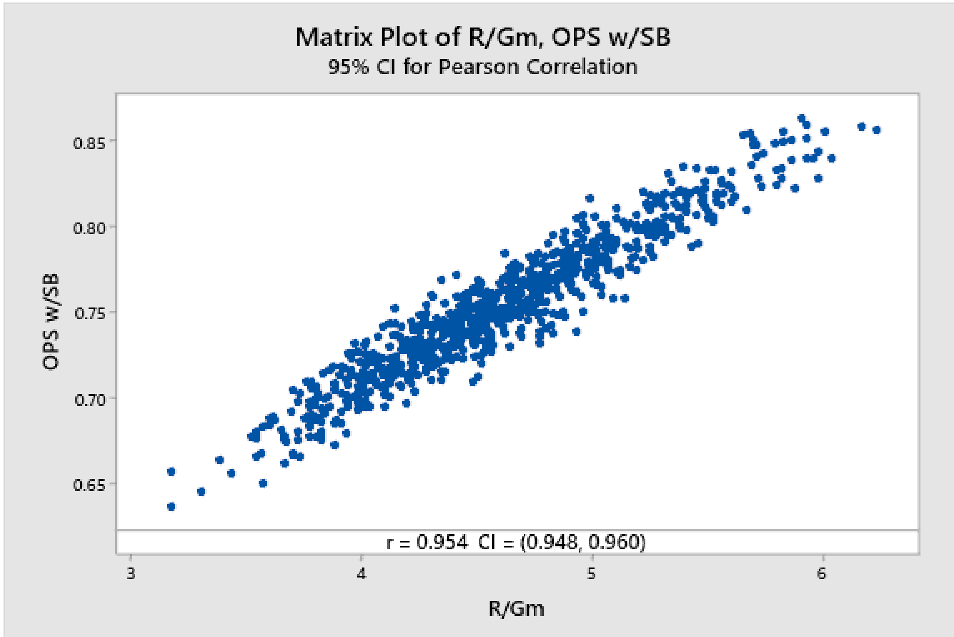

Figure 15: Correlation Plot for Runs vs. OPS w/SB

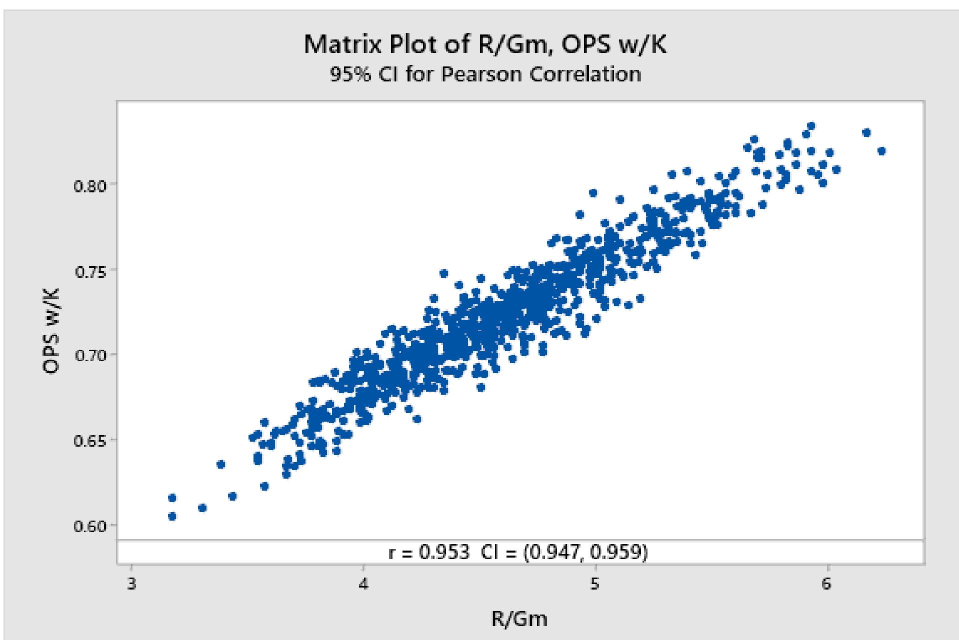

Figure 16: Correlation Plot for Runs vs. OPS w/K

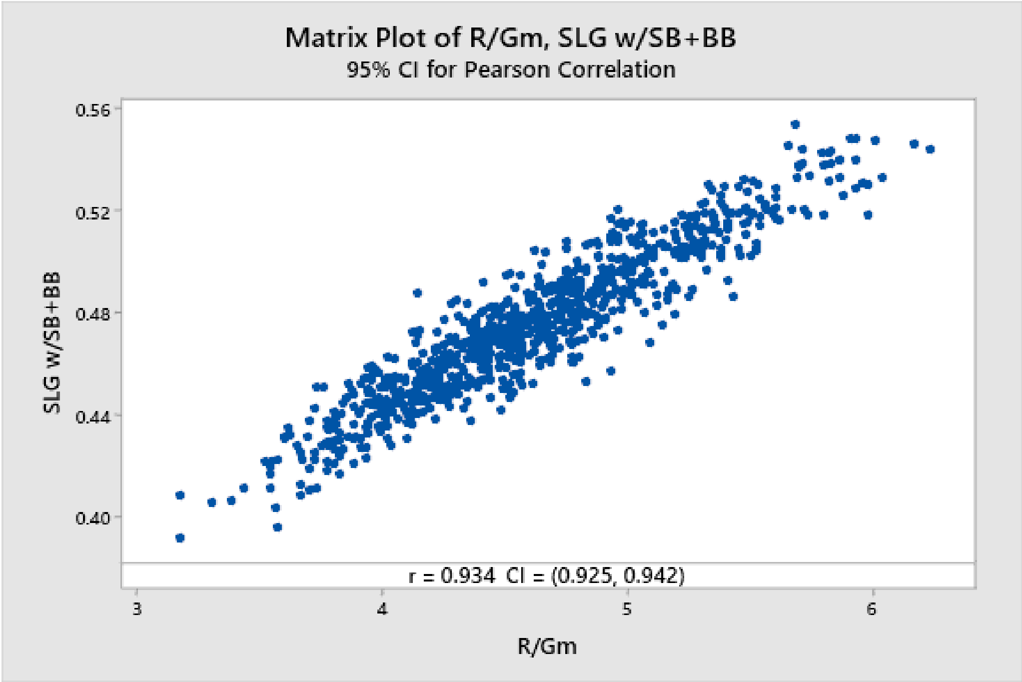

Figure 17: Correlation Plot for Runs vs. SLG w/SB + BB

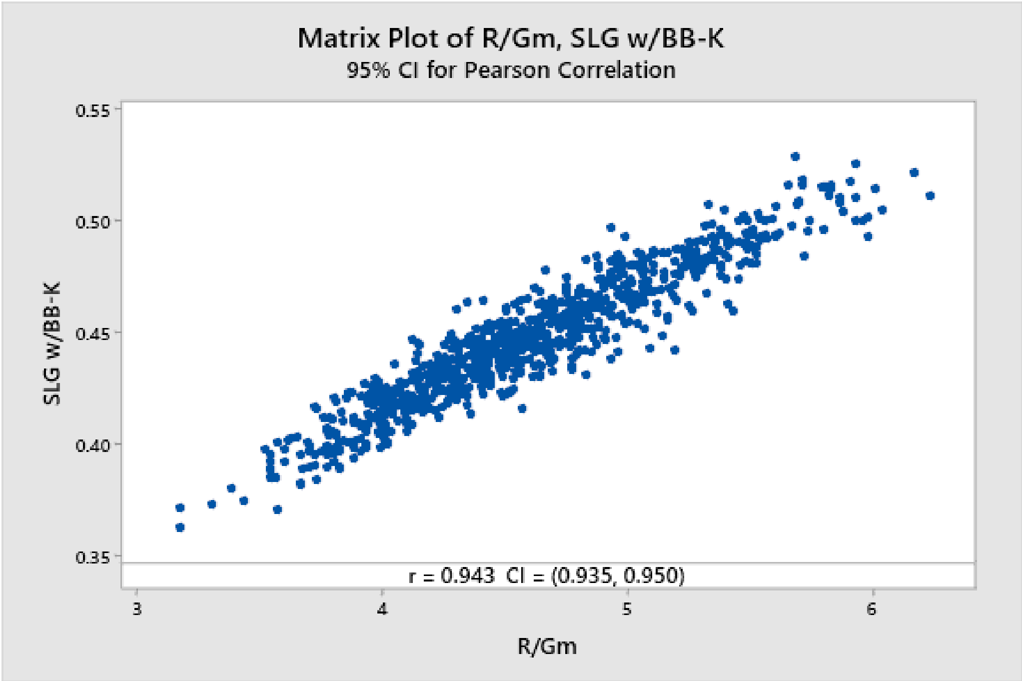

Figure 18: Correlation Plot for Runs vs. SLG w/BB - K

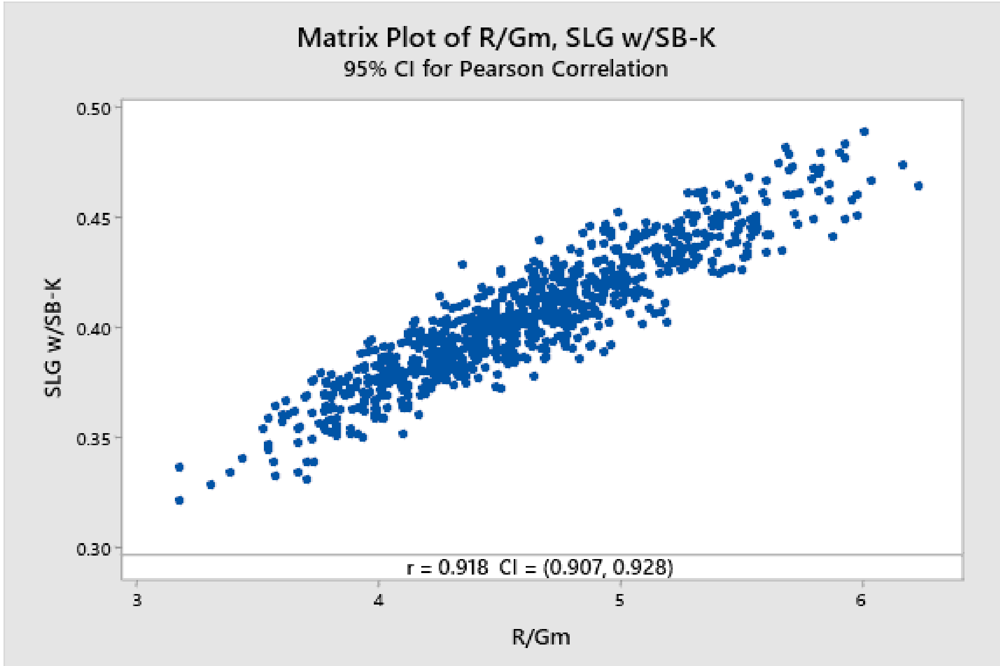

Figure 19: Correlation Plot for Runs vs. SLG w/SB - K

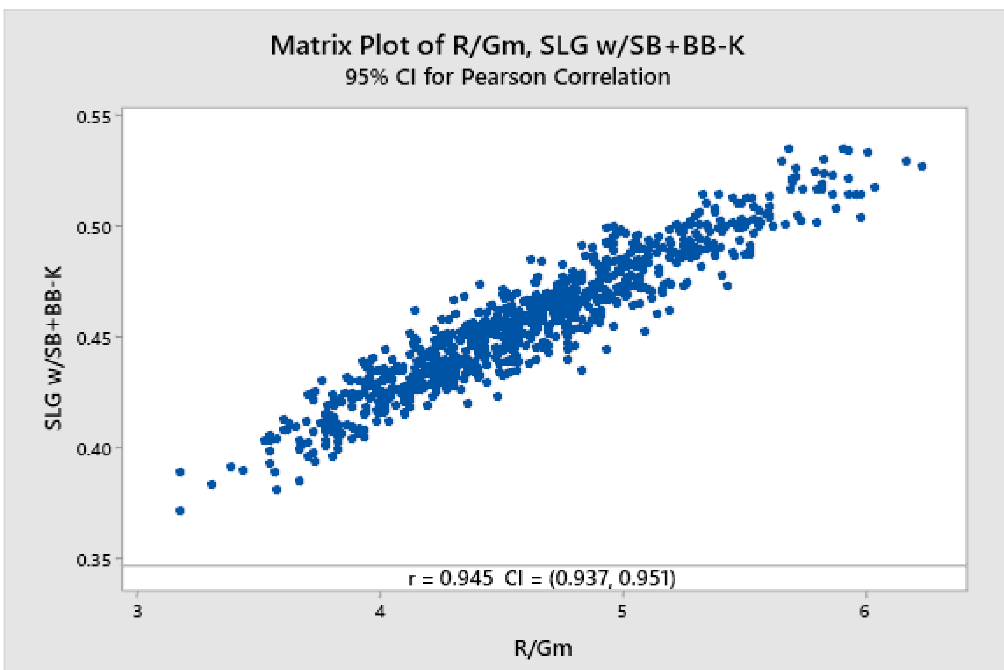

Figure 20: Correlation Plot for Runs vs. SLG w/SB + BB - K

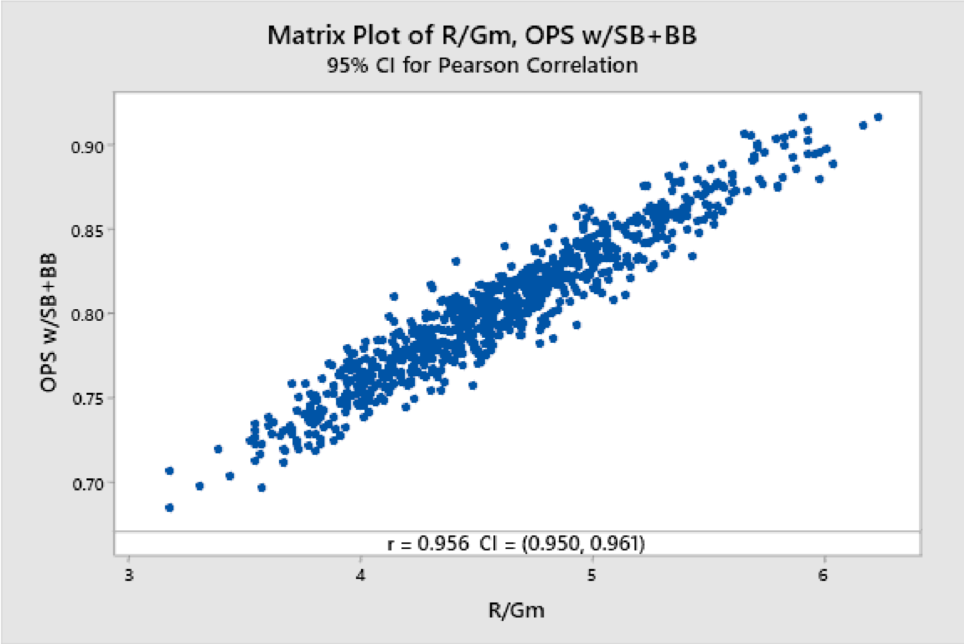

Figure 21: Correlation Plot for Runs vs. OPS w/SB + BB

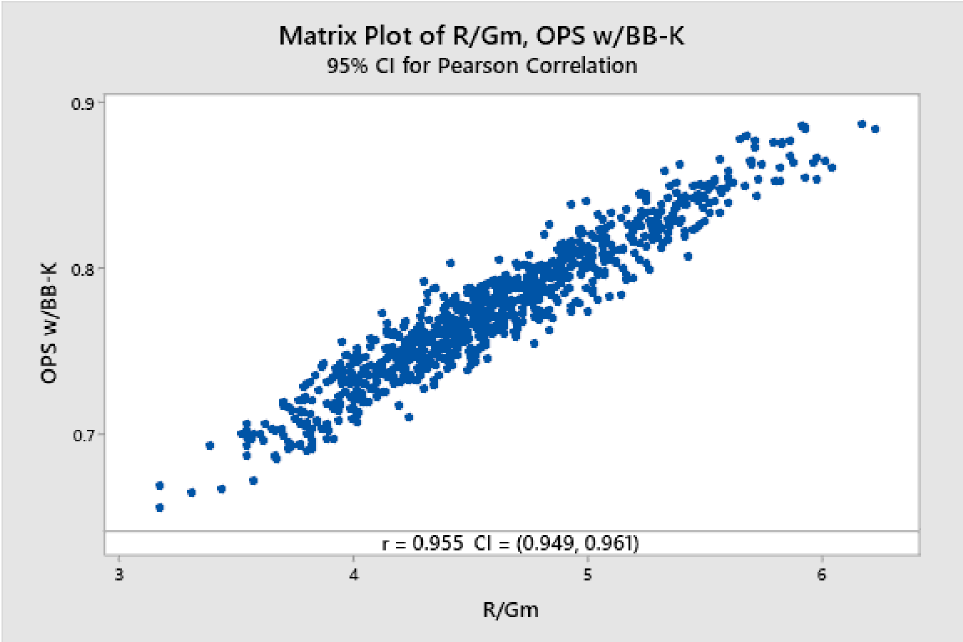

Figure 22: Correlation Plot for Runs vs. OPS w/BB - K

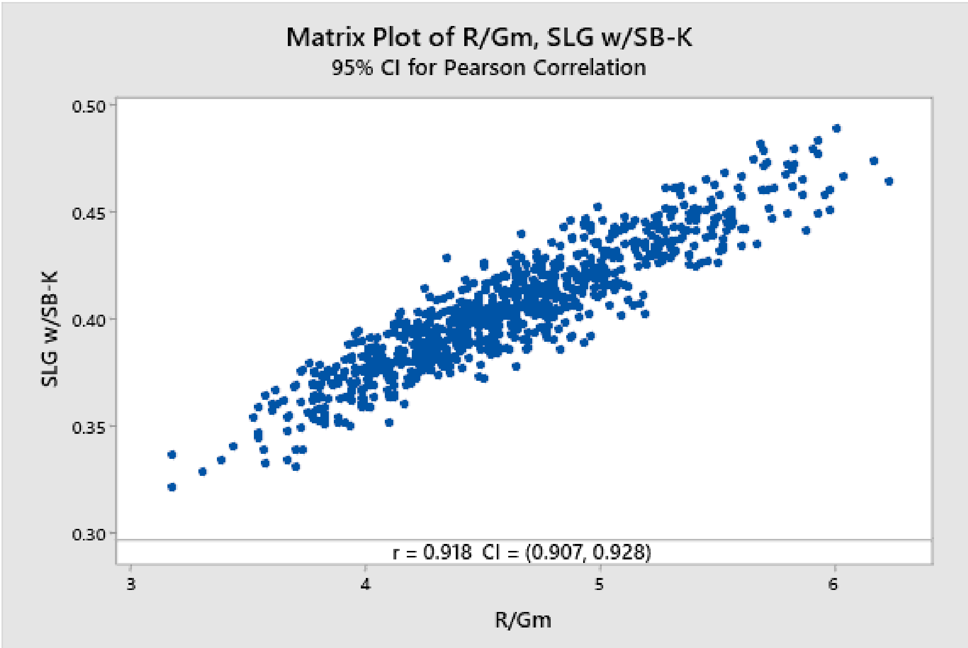

Figure 23: Correlation Plot for Runs vs. OPS w/SB – K

Table 16: 2018 IMP Leaders

Player	IMP
Alex Bregman	1.040
Mookie Betts	1.026
Xander Bogaerts	0.997
Andrew Benintendi	0.989
J.D. Martinez	0.984
Christian Yelich	0.938
Gregory Polanco	0.935
Nelson Cruz	0.920
Brian Anderson	0.893
Manny Machado	0.884

Table 17: 2017 IMP Leaders

Player	IMP
Nolan Arenado	1.042
Marwin Gonzales	1.025
Anthony Rizzo	0.989
Cody Bellinger	0.981
Mookie Better	0.976
George Springer	0.953
Mike Trout	0.945
Joe Mauer	0.933
Jake Lamb	0.924
Joey Votto	0.920

Table 18: 2016 IMP Leaders

Player	IMP
Adrian Beltre	1.003
Mike Trout	0.962
Jose Ramirez	0.957
Joey Votto	0.947
Dustin Pedroia	0.945
Bryce Harper	0.943
Charlie Blackmon	0.936
Elvis Andrus	0.910
Paul Goldschmidt	0.908
Yoenis Cespedes	0.905

Table 19: 2015 IMP Leaders

Player	IMP
Anthony Rizzo	1.028
Miguel Cabrera	1.027
Andrew McCutchen	1.016
Eric Hosmer	1.013
Matt Carpenter	0.994
Lorenzo Cain	0.991
Kris Bryant	0.987
Paul Goldschmidt	0.986
Mitch Moreland	0.957
Carlos Gonzalez	0.957

Table 20: 2019 NL MVP Race IMP Ranking

Player	IMP Ranking
Cody Bellinger	14
Christian Yelich	1
Anthony Rendon	2
Ketel Marte	21
Ronald Acuna Jr.	8
Total	46

Table 21: 2019 AL MVP IMP Ranking

Player	IMP Ranking
Mike Trout	7
Alex Bregman	14
Marcus Semien	31
DJ LeMahieu	13
Xander Bogaerts	2
Total	67

Table 22: 2018 NL MVP Race IMP Ranking

Player	IMP Ranking
Christian Yelich	1
Javier Baez	26
Nolan Arenado	12
Freddie Freeman	24
Paul Goldschmidt	5
Total	68

Table 23: 2018 AL MVP Race IMP Ranking

Player	IMP Ranking
Mookie Betts	2
Mike Trout	12
Jose Ramirez	24
J.D. Martinez	5
Alex Bregman	1
Total	44

Table 24: 2016 NL MVP Race IMP Ranking

Player	IMP Ranking
Kris Bryant	55
Daniel Murphy	20
Corey Seager	47
Anthony Rizzo	9
Nolan Arenado	6
Total	137

Table 25: 2016 AL MVP Race IMP Ranking

Player	IMP Ranking
Mike Trout	2
Mookie Betts	15
Jose Altuve	11
Josh Donaldson	9
Manny Machado	27
Total	64

Table 26: 2015 NL MVP Race IMP Ranking

Player	IMP Ranking
Bryce Harper	13
Paul Goldschmidt	4
Joey Votto	7
Anthony Rizzo	1
Andrew McCutchen	2
Total	27

Table 27: 2015 AL MVP Race IMP Ranking

Player	IMP Ranking
Josh Donaldson	10
Mike Trout	7
Lorenzo Cain	3
Manny Machado	52
Nelson Cruz	18
Total	90

Table 28: 2018 NL WAR Leaders IMP Ranking

Player	IMP Ranking
Christian Yelich	1
Trevor Story	17
Javier Baez	26
Nolan Arenado	12
Paul Goldschmidt	5
Total	61

Table 29: 2018 AL WAR Leaders IMP Ranking

Player	IMP Ranking
Mike Trout	12
Mookie Betts	2
Jose Ramirez	24
Alex Bregman	1
J.D. Martinez	5
Total	44

Table 30: 2017 NL WAR Leaders IMP Ranking

Player	IMP Ranking
Giancarlo Stanton	22
Charlie Blackmon	7
Joey Votto	5
Kris Bryant	57
Justin Turner	18
Total	109

Table 31: 2017 AL WAR Leaders IMP Ranking

Player	IMP Ranking
Jose Altuve	14
Mike Trout	4
Aaron Judge	69
Jose Ramirez	64
Carlos Correa	45
Total	196

Table 32: 2016 NL WAR Leaders IMP Ranking

Player	IMP Ranking
Kris Bryant	55
Corey Seager	47
Daniel Murphy	20
Freddie Freeman	33
Jean Segura	30
Total	185

Table 33: 2016 AL WAR Leaders IMP Ranking

Player	IMP Ranking
Mike Trout	2
Jose Altuve	11
Josh Donaldson	9
Carlos Correa	20
Mookie Betts	15
Total	57

Table 34: 2015 NL WAR Leaders IMP Ranking

Player	IMP Ranking
Bryce Harper	13
Joey Votto	7
Paul Goldschmidt	4
Andrew McCutchen	2
AJ Pollock	21
Total	47

Table 35: 2015 AL WAR Leaders IMP Ranking

Player	IMP Ranking
Mike Trout	7
Josh Donaldson	10
Nelson Cruz	18
Manny Machado	52
Adam Eaton	15
Total	102

Table 36: Yearly IMP Totals

Year	Albert Pujols	David Ortiz	Carlos Beltran
2002	0.855	0.735	0.894
2003	0.925	0.928	0.862
2004	0.963	0.889	0.980
2005	0.831	1.269	0.798
2006	1.361	1.136	1.098
2007	0.980	0.838	0.773
2008	1.036	0.765	0.981
2009	1.117	0.777	0.935
2010	0.898	0.822	0.721
2011	0.895	0.736	0.771
2012	0.894	0.948	0.831
2013	0.751	0.798	0.656
2014	0.740	0.949	0.713
2015	0.550	0.741	0.706
2016	0.815	0.888	0.739

Table 37: Yearly OPS Totals

Year	Albert Pujols	David Ortiz	Carlos Beltran
2002	0.955	0.839	0.847
2003	1.106	0.961	0.911
2004	1.072	0.983	0.915
2005	1.039	1.001	0.744
2006	1.102	1.049	0.982
2007	0.997	1.066	0.878
2008	1.114	0.877	0.876
2009	1.101	0.794	0.915
2010	1.011	0.899	0.768
2011	0.906	0.953	0.91
2012	0.859	1.026	0.842
2013	0.767	0.959	0.83
2014	0.79	0.873	0.703
2015	0.787	0.913	0.808
2016	0.78	1.021	0.85

Table 38: Yearly Clutchness Totals

Year	Albert Pujols	David Ortiz	Carlos Beltran
2002	-0.35	-0.43	0.68
2003	-1.02	0.36	-0.54
2004	-0.33	-0.18	0.65
2005	-1.64	3.31	0.8
2006	3.26	1.48	1.49
2007	0.38	-1.68	-0.79
2008	-0.17	-0.76	1.17
2009	0.67	0.27	0.37
2010	-0.69	-0.22	-0.25
2011	0.37	-1.61	-0.89
2012	0.88	-0.13	0.33
2013	0.25	-1.08	-1.08
2014	-0.01	1.23	0.47
2015	-1.87	-1.16	-0.47
2016	0.81	-0.66	-0.38