DRIVE FOR SHOW, PUTT FOR DOUGH:

USING DATA ANALYSIS TO CHALLEGE GOLF’S CONVENTIONAL WISDOM

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Abstract

For years, sports have lacked methods of objective statistical analysis. “Drive for show, putt for dough”, is an often-heard saying that embodies the belief that the ‘short game’ and putting are the most important facets of a golfer’s game. Prior literature has shown that in fact, the opposite is true: the ‘long game’ is the primary driver of scoring differences between differently skilled golfers. Panel regressions using 2015 data from the researcher’s 18-hole rounds of golf duplicate the results of previous studies, and show that the ‘long game’ is the primary driver of 18-hole score. We estimate a model to predict the researcher’s 18-hole score. These results are significant because they are scientific evaluations of golf, as opposed to the subjective evaluations that have been common for decades.

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1. **Validating a Statistical Approach**

Since the beginning of the sports analytics movement, there have been dissenters to the new ways of thinking trumpeted by statisticians and mathematicians. NBA Hall of Famer Charles Barkley has made headlines for his comments regarding analytics. “First of all, I’ve always believed analytics was crap” said Barkley. “Analytics don’t work at all,” he continued, “it’s just something that a bunch of people who were really smart made up to try and get in the game because they had no talent… The NBA is about talent. All of these guys who run these organizations who talk about analytics, they have one thing in common: they’re a bunch of guys who ain’t never played the game, and they never got the girls in high school. They just want to get in the game.”[[1]](#footnote-1)

While most doubters do not make public statements as scathing as Barkley’s, their words and actions against the analytics movement can still be strong. In 2006, the Washington Redskins hired Jeff Dominitz, a Ph.D. economist, to launch their analytics division. Dr. Dominitz’s employment with the franchise lasted barely seven weeks before he was fired. Apparently, Dr. Dominitz’s data-driven approach did not line up with organizational values: “we’re still about people here,” commented the then-head coach. The Philadelphia Phillies are one of few MLB franchises that have totally rejected statistical methods. Their General Manager, Ruben Amaro, gloated in 2010 that the team is “not a statistics-driven organization by any means”.[[2]](#footnote-2)

Given that there are many esteemed opinions against the analytics movement in sports, one might wonder whether a study utilizing analytic techniques is valuable. Benjamin Baumer and Andrew Zimbalist set out to investigate the value of sports analytics in their book *The Sabermetric Revolution: Assessing the Growth of Analytics in Baseball* (2014).[[3]](#footnote-3) The book arrives at three relevant conclusions: firstly, that traditionally adhered-to statistics are less effective evaluators of player skill than contemporary statistics; secondly, that some traditionally adhered-to game strategies have adverse effects on a team’s chances to win; and lastly, that teams who use analytics experience higher winning percentages.

Baumer and Zimbalist’s first conclusion is that traditionally adhered-to statistics are less effective evaluators of player skill than contemporary statistics. Perhaps the most well-known sabermetric insight (popularized by Michael Lewis’ *Moneyball*) is the statistical inferiority of Batting Average.[[4]](#footnote-4) The goal of offensive baseball is to score runs. For years it was believed that Batting Average was the best way to quantify a player’s contribution to scoring runs, thus measuring offensive skill. Statistical analysis has proved this approach wrong, as On-Base Percentage is more highly correlated with runs scored than Batting Average.[[5]](#footnote-5) The implications of this finding are important: although Batting Average was a serviceable way to measure offensive skill, more advanced statistics can do a better job quantifying player attributes. *Conventional wisdom, while sometimes valuable, does not always represent the best practice*. Over time, statisticians have developed even better ways to measure a hitter’s contribution to scoring runs than On Base Percentage. Two commonly used metrics are Offensive Performance Statistic, which is 94.5% correlated to runs scored, and Isolated Power, which is useful in forecasting a player’s future offensive performance. Although statisticians are in agreement that Batting Average is not as telling as other statistics, this belief has not necessarily proliferated throughout fans of baseball. For example, when one watches baseball on television, commentators seldom discuss a player’s Offensive Performance Statistic or Isolated Power. Instead, graphics are shown informing the viewer of a player’s traditional statistics, such as Batting Average, Home Runs, and Runs Batted In.

Baumer and Zimbalist’s second conclusion is that popular in-game strategies are sometimes suboptimal. An example of a popular but sometimes suboptimal strategy is sacrifice bunting. The theory behind sacrifice bunting is that advancing a runner one base at the cost of one out will maximize a team’s chances of scoring at least one run. While it may be true that this maximizes a team’s chances of scoring exactly one run, in reality, sacrifice bunting decreases a team’s expected run totals. Given an average pitcher and average batters, the expected runs scored with a runner on first base and no outs is 0.87 runs. In contrast, the expected runs scored with a runner on second base and one out is 0.67 runs.[[6]](#footnote-6) Therefore, every time a team sacrifice bunts, they are giving up one-fifth of an expected run.

Importantly, Baumer and Zimbalist note that a decrease in expected runs does not *always* make sacrifice bunting a bad idea. At the beginning and in the middle of a game, it is usually best for a team to maximize its run-scoring potential, or expected runs. However, towards the end of a game, it may be in a team’s best interest to maximize its chances of scoring at least one run. Analytic insight, combined with careful consideration of situational baseball, has given us a nuanced understanding of sacrifice bunting.

Baumer and Zimbalist’s third conclusion is that teams who utilize analytics experience high winning percentages. By computing the ratio of “new” metrics to traditional ones, the authors have developed a rough estimate of each franchise’s saber-intensity. For example, a saber-intense franchise is likely to value On Base Percentage more highly than Batting Average. Therefore, one would expect the ratio of On Base Percentage to Batting Average of a saber-intense franchise to be relatively high. Baumer and Zimbalist additionally compute metrics to quantify a team’s saber-intensity in hitting for power, pitching, fielding, base running, and sacrifice bunt frequency. After weighting each of these metrics based on their relative importance, the authors computed each team’s Sabermetric Index. When regressing a team’s Sabermetric Index against the portion of that team’s win percentage not explained by payroll, the authors conclude that Sabermetric Index explains about 37% of residual win percentage. Baumer and Zimbalist note that an increase of one percent in a team’s Sabermetric Index increases that team’s win percentage by 0.028 points, or about 4.5 games. Baseball analytics apparently possesses a very high return on investment. A statistician need only increase a franchise’s Sabermetric Index by one percent to have the same effect as a player with a Wins Above Replacement value of four and a half.[[7]](#footnote-7) Interestingly, that player would cost about $15 million on today’s market, whereas the salary of a statistician would cost substantially less.

Baumer and Zimbalist arrive at three important conclusions in *The Sabermetric Revolution*: firstly, that traditionally adhered-to statistics are less effective evaluators of player skill than contemporary statistics; secondly, that popular in-game strategies are sometimes suboptimal; lastly, that teams who use analytics experience higher winning percentages. Statistical approaches have revealed intricacies of baseball that were previously sublime. It is clearly desirable to use similar methods to study other sports. For instance, Dr. Mark Broadie has used the *strokes gained* method to better evaluate golf. *Strokes gained* measures a shot outcome against a performance benchmark based on distance. If a player makes a birdie on a par 4, how are we supposed to know which aspects of his play of the hole led to this outcome? Was it a superb drive that set him up for success? Was it a well-played approach shot? Or was it a stellar putt? The *strokes gained* statistic gives us a way to answer these questions by comparing the golfer’s actual play to average play. This system not only gives us an insight into what a golfer’s strengths and weaknesses are, but can tell us in which areas the best golfers consistently excel. We will delve into the *strokes gained* statistic more later.

1. **Using Data Analysis to Study Golf**

The objective of this section is to determine the best predictors of the subject’s golf score. Using ordinary least squares (OLS) regression tests, the researcher has been able to identify and compare the marginal effects of explanatory variables. Additionally, the researcher has used ordinary least squares regression tests to statistically examine golf’s conventional wisdom.

* 1. Data and Categorization of Data

The results of this paper are based on a study conducted by the researcher, who collected data on all 18-hole rounds of golf he played in 2015. The researcher hypothesized that his score was a function of weather, course difficulty, and personal performance;

Score = f(weather, course difficulty, personal performance)

Data was collected on a total of 79 rounds and grouped into one of four categories based on which phenomena they were meant to explain. For all regressions, *n*=79. Table 1, found in the Appendix, describes the variables measured and gives their descriptive statistics.

* 1. Variables Used

*Score in relation to par* was chosen as a better indicator of scoring than the raw score. The par rating may be different for each course; a score of 70 is better on a par-72 course than a par-70 course. While the two raw scores are identical, *score in relation to par* would capture the difference in relative performance between the two scores, with values of “-2” and “0” respectively.

*Average windspeed* was the variable chosen to gauge weather conditions. As shown in Figure 2, the first regression revealed that *average temperature* was not statistically significant. Additionally, *average temperature* had a negative coefficient when it should exhibit a positive relationship with *score in relation to par*. In the second regression, *average windspeed* is statistically significant and its coefficient exhibits the proper sign.

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| Table 2. Weather regressions | | |  |  | |  | |
| Variable | Model 1 | |  | Model 2 | | | |
| β | p-value |  | β | | p-value | |
| Average Windspeed | 0.182 | 0.003\*\*\* | |  | 0.188 | 0.002\*\*\* | |
| Average Temperature | -0.05 | 0.197 |  |  | |  |
| Adjusted R Square | 0.115 | |  | 0.107 | | | |
| \* significant at 10% | |  |  |  | |  | |
| \*\*significant at 5% | |  |  |  | |  | |
| \*\*\* significant at 1% | |  |  |  | |  | |

*Course rating* was chosen as the best variable to approximate course difficulty. As shown in Figure 3, *score in relation to par* was regressed against *yardage*, *course rating*, and *course slope*. This turned out to be a poor model, as both *yardage* and *course slope* had the incorrect sign on their coefficient. No combination of two predictors from the three produced a good model, so each predictor was regressed against *score in relation to par* individually. None of the three were statistically significant, therefore *course rating* is the best, though imperfect, proxy of course difficulty.

To best approximate personal performance, *greens in regulation*, *putts*,and *penalty strokes* were used. Many regressions were used to examine this, the final model is shown in Table 4.

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| Table 3. Course difficulty regressions | | | | | |  | |
| Variables | Model 1 | |  | Individually Regressed | | | | |
| β | p-value |  | β | | | p-value | |
| Yardage | -0.007 | 0.0195\*\*\* |  | | 0 | 0.982 | |
| Course Rating | 1.978 | 0.007\*\*\* |  | 0.298 | | | 0.286 | |
| Course Slope | -0.131 | 0.167 |  | 0.014 | | | 0.823 | |
| Adjusted R Square | 0.057 | |  |  | | | | |
| \*significant at 10% | |  |  |  | | |  | |
| \*\*significant at 5% | |  |  |  | | |  | |
| \*\*\*significant at 1% | |  |  |  | | |  | |

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| --- | --- | --- | --- | --- |
| Table 4. Personal performance regressions | | | | |
| Variables | Model 1 | |  |  |
| β | p-value |  |  |
| GIR | -1.216 | 0.000\*\*\* |  |  |
| Putts | 1.077 | 0.000\*\*\* |  |  |
| Penalty Strokes | 1.194 | 0.000\*\*\* |  |  |
| Adjusted R Square | 0.797 | |  |  |
| \*significant at 10% | |  |  |  |
| \*\*significant at 5% | |  |  |  |
| \*\*\*significant at 1% | |  |  |  |

* 1. The Model

Using the proxies constructed for weather, course difficulty, and personal performance, a model was built to predict *score in relation to par.* The results of this regression can be seen in Table 5.

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| --- | --- | --- |
| Table 5. Final model | |  |
| Variables | Model 1 | |
| β | p-value |
| Average Windspeed | 0.048 | 0.108 |
| Course Rating | 0.26 | 0.039\*\* |
| GIR | -1.147 | 0.000\*\*\* |
| Putts | 1.053 | 0.000\*\*\* |
| Penalty Strokes | 0.186 | 0.000\*\*\* |
| Adjusted R Square | 0.809 | |
| \*significant at 10% | |  |
| \*\*significant at 5% | |  |
| \*\*\*significant at 1% | |  |

* 1. Assessing the Model

With an Adjusted R Square of 0.809, the predictors explain about 81% of the variance in *score in relation to par*. Viewed differently, the average absolute value of the residuals is 1.152, as can be viewed in Table 6. This means that on average, the model’s predicted *score in relation to* par was only 1.152 strokes different than the actual *score in relation to* par. All of the predictors are statistically significant with the exception of *average windspeed*. Although the standard levels for significance are 10%, 5%, and 1%, *average windspeed’s* p-value of 0.108 is sufficiently close to significance to include it in the model.

Interestingly, *average windspeed* has a smaller marginal effect on score than a golfer may intuitively think. With a coefficient of 0.048, *average windspeed* would have to increase by about 20 mph to increase predicted *score in relation to par* by one. Similarly, with a coefficient of 0.26, *course rating* had a relatively small impact on predicted *score in relation to par*. The difference in predicted *score in relation to par* between the easiest course played (*course rating* of 67.9) and the hardest course played (*course rating* of 75.5) is only about two strokes, all else held equal.

To put this in perspective, the projected *score in relation to par* of a round on the hardest course in the study on a day when the *average windspeed* was 40 mph is only about 4 strokes higher than a round on the easiest course in the study on a day with no wind. This difference is much smaller than most golfers would guess, perhaps signifying that golfers generally overstate the impact of weather and course difficulty.

* 1. Challenging Conventional Wisdom

As discussed earlier, the mantra of “drive for show, putt for dough” (originally attributed to four time British Open champion Bobby Locke) has pervaded golf’s history. John Henry Taylor, a five time British Open champion between 1894 and 1913, wrote that “more matches are won or lost upon the green than any other portion of the course” (Broadie 3). What does this study reveal about the relative importance of putting? By comparing the marginal effect of *putts* to the marginal effect of *greens in regulation*, we can see that putting actually has a lower impact on *score in relation to par* in the final model. Moreover, this result is robust: even when other parameters are changed, putting remains the more influential predictor of *score in relation to par*, as shown in Table 7. Many legendary golfers have trumpeted the idea that putting is the key to scoring in golf, and for years it has been considered golf’s most sacred truism. However, these findings seem to imply that golf’s conventional wisdom is, in this case, incorrect.

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| Table 7. Comparing *Putts* to *GIR* | | | | |  | |  |  | | |  | | | |
| Variables | Final Model | |  | Model 2 | | |  | Model 3 | | | | | | |
| β | p-value |  | β | | p-value |  | β | | | | | | p-value |
| Average Windspeed | 0.048 | 0.108 |  | 0.04 | | 0.184 |  | 0.041 | | | | | | 0.183 |
| Course Rating | 0.26 | 0.039\*\* |  |  | |  |  |  | | | | |  | | | | |
| Yardage |  |  |  | 0.001 | | 0.187 |  | |  | | |  | | | |
| Course Slope |  |  |  |  | |  |  | | 0.031 | | | 0.278 | | | |
| GIR | -1.147 | 0.000\*\*\* |  | -1.17 | | 0.000\*\*\* |  | | -1.181 | | | 0.000\*\*\* | | | |
| Putts | 1.053 | 0.000\*\*\* |  | 1.062 | | 0.000\*\*\* |  | | 1.054 | | | 0.000\*\*\* | | | |
| Penalty Strokes | 0.186 | 0.000\*\*\* |  | 1.268 | | 0.000\*\*\* |  | | 1.191 | | | 0.000\*\*\* | | | |
| Adjusted R Square | 0.809 | |  | 0.802 | | |  | | 0.8 | | | | | | |
| \*significant at 10% | |  |  |  |  | |  | |  |  | | | | | | |
| \*\*significant at 5% | |  |  |  |  | |  | |  |  | | | | | | |
| \*\*\*significant at 1% | |  |  |  |  | |  | |  |  | | | | | | |

1. **Relative Existing Work**

In his book *Every Shot Counts*, Dr. Mark Broadie uses the *strokes gained* system to better analyze golf. “The strokes gained method allows us to analyze a player’s game as a whole,” writes Broadie, “it allows putting skill to be measured more accurately than by just counting putts. It allows driving skill to be measured better than it had been using fairways hit or driving distance. And most important, it allows putting, short game, and long-game skills to be compared directly with each other”.

The basic idea behind the *strokes* *gained* statistic is that although all shots count for the same number of strokes, not all shots are of equal distance and therefore represent different levels of skill. For example, a two-putt from 2 feet is a terrible result, while a two-putt from 60 feet is a great result. Although a simple count of putts gives two in both cases, there is clearly a difference in skill level.

*Strokes gained* measures a shot outcome against a performance benchmark based on distance. For example, the PGA Tour average number of strokes to hole out from 33 feet is two strokes. If a player makes a 33 foot putt, he gained one stroke against the field average. If a player three-putts from 33 feet, he lost one stroke against the field. From 8 feet, the PGA Tour average number of strokes to hole out is 1.5 strokes. If a player makes an 8 foot putt, he gains 0.5 strokes against the field. If a player misses an 8 foot putt, he loses 0.5 strokes against the field. *Strokes gained* is not exclusive to putting. For example, the PGA Tour average strokes to hole out from 140 yards in the fairway is 2.91 strokes. If a player hits the ball to 8 feet from 140 yards in the fairway, he will have gained 0.41 strokes on the field, because he used one stroke to get 1.41 strokes (2.91 strokes minus 1.5 strokes) “closer” to holing out.

Using PGA Tour data over millions of shots from 2004-2012, Broadie assessed how the best players gained strokes against the field. His results corroborate the findings in this paper- that putting is *not* the key to scoring in golf! Broadie found that the top 40 golfers in his study gained 40% of their scoring advantage from their approach shots, 28% from their driving, 17% from their short game, and 15% from their putting. Moreover, this result is robust, meaning that it is true across different skill levels of golfers: Broadie’s work shows that the long game accounts for about two thirds of the scoring differences in amateur golfers, while the short-game and putting accounts for the last third. While putting is important, it is, by any objective measure, less important than the long game. “It’s the closest thing to universal truth in golf…” wrote Broadie, “it’s a good long game that sets the table for good scoring in golf” (Broadie 122)

1. **Further Research**

There are several avenues of future research to consider. The first possible avenue is to continue this study as a longitudinal study. Would the research subject’s game change or improve as a result of this research? Will this study’s conclusions hold true in perpetuity? Another avenue of possible research is to expand the scope of this study to include more golfers. We cannot conclude that this research necessarily holds true for other players. Adding more golfers to the study will enable the researcher to better understand if these conclusions represent widespread themes in golf. Finally, it would be useful to have data available on a hole-by-hole basis, as opposed to a round-by-round basis. Whereas the conclusions of this research are valuable but limited in depth, better data would allow researchers to gain more nuanced insights.

1. **Reflections**

This study has taught me many things about golf, statistics, and life. My first takeaway is that one shouldn’t let a deeper understanding of a game destroy their wonderment and childlike love for that game. Golf’s conventional wisdom is certainly flawed, but that doesn’t change the feeling of a well-struck tee shot; nor does it lessen the satisfaction of a perfectly read putt; nor does it upset the peace of a warm summer morning on the course. Golf is full of legend and lore, and although I now understand its imperfections, the game is still magical to me.

I’ve learned a lot about research methods; my biggest takeaway is that one shouldn’t be both the researcher and the research subject. I often found myself wanting better data, but I was unable to collect it due to the fact that I had to actually *play golf* while collecting it. This definitely limited the scope and scale of my study.

My final takeaway is the importance of asking questions. There are many situations in life governed by “best practices” or “conventional wisdom”, and it is important to challenge underlying assumptions. In doing so, one can gain a deeper understanding of how the world works.

**Appendix**

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| --- | --- | --- | --- | --- | --- | --- |
| Table 1. Variable definitions and descriptive statistics | | |  |  |  |  |
| Variable | Category | Description | Mean | SD | Min | Max |
| 18 Hole Score | score | Total strokes | 76.67 | 3.67 | 69 | 85 |
| Score in relation to par | score | Number of strokes above or below par | 5.16 | 3.61 | -2 | 14 |
| Average Temperature | weather | Estimated in miles/hour | 72.54 | 10.37 | 46 | 92 |
| Average Windspeed | weather | Estimated in degrees Fahrenheit | 11.47 | 6.59 | 4 | 30 |
| Yardage | course difficulty | Number of yards long the course played | 6900.65 | 282.92 | 5567 | 7222 |
| Course Rating | course difficulty | Indexing number released by USGA | 73.71 | 1.47 | 67.9 | 75.5 |
| Course Slope | course difficulty | Indexing number released by USGA | 135.29 | 6.56 | 120 | 145 |
| Greens in regulation | personal performance | Number of times ball lay on green in expected number of strokes | 9.76 | 2.52 | 6 | 17 |
| Lie of approach | personal performance | Number of times ball lay in mown grass for approach shot | 12.01 | 2.22 | 7 | 16 |
| Putts | personal performance | Number of strokes on the putting green | 30.89 | 2.44 | 24 | 35 |
| Penalty strokes | personal performance | Number of penalty shots incurred | 0.96 | 1.01 | 0 | 3 |
| Birdies | personal performance | Number of birdies (one under par) made | 2.23 | 1.19 | 0 | 5 |
| Pars | personal performance | Number of pars made | 9.91 | 2.26 | 5 | 16 |
| Bogeys | personal performance | Number of bogeys (one over par) made | 4.42 | 2.16 | 0 | 9 |
| Others | personal performance | Number of scores over bogey | 1.38 | 1.18 | 0 | 5 |
| Par 3's Relative to par | personal performance | Number of strokes above or below par on Par 3's | 1.43 | 1.52 | -2 | 7 |
| Par 4's Relative to par | personal performance | Number of strokes above or below par on Par 4's | 3.7 | 2.69 | -3 | 11 |
| Par 5's Relative to par | personal performance | Number of strokes above or below par on Par 5's | 0.03 | 1.37 | -3 | 4 |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Table 6. Residual chart | |  |  |  |
| *Observation* | *Predicted Score in Relation to Par* | *Score in Relation to Par* | *Residuals* | *Residuals (Abs Value)* |
|
| 1 | 10.104 | 13 | 2.896 | 2.896 |
| 2 | 4.006 | 4 | -0.006 | 0.006 |
| 3 | 6.910 | 7 | 0.090 | 0.090 |
| 4 | 9.922 | 11 | 1.078 | 1.078 |
| 5 | 9.075 | 8 | -1.075 | 1.075 |
| 6 | 1.967 | 2 | 0.033 | 0.033 |
| 7 | 9.160 | 10 | 0.840 | 0.840 |
| 8 | 6.172 | 6 | -0.172 | 0.172 |
| 9 | 8.864 | 9 | 0.136 | 0.136 |
| 10 | 5.593 | 5 | -0.593 | 0.593 |
| 11 | 10.310 | 10 | -0.310 | 0.310 |
| 12 | 4.160 | 6 | 1.840 | 1.840 |
| 13 | 7.329 | 8 | 0.671 | 0.671 |
| 14 | 6.317 | 6 | -0.317 | 0.317 |
| 15 | 5.915 | 6 | 0.085 | 0.085 |
| 16 | 5.152 | 5 | -0.152 | 0.152 |
| 17 | 5.921 | 4 | -1.921 | 1.921 |
| 18 | 10.525 | 9 | -1.525 | 1.525 |
| 19 | 6.206 | 9 | 2.794 | 2.794 |
| 20 | 5.864 | 6 | 0.136 | 0.136 |
| 21 | 2.601 | 3 | 0.399 | 0.399 |
| 22 | 3.003 | 1 | -2.003 | 2.003 |
| 23 | 8.206 | 7 | -1.206 | 1.206 |
| 24 | 4.085 | 3 | -1.085 | 1.085 |
| 25 | 7.336 | 6 | -1.336 | 1.336 |
| 26 | 5.806 | 5 | -0.806 | 0.806 |
| 27 | 0.826 | 2 | 1.174 | 1.174 |
| 28 | 4.403 | 7 | 2.597 | 2.597 |
| 29 | 2.930 | 2 | -0.930 | 0.930 |
| 30 | -0.453 | -2 | -1.547 | 1.547 |
| 31 | 6.126 | 6 | -0.126 | 0.126 |
| 32 | 2.420 | 1 | -1.420 | 1.420 |
| 33 | -2.225 | -2 | 0.225 | 0.225 |
| 34 | 3.099 | 2 | -1.099 | 1.099 |
| 35 | 5.233 | 4 | -1.233 | 1.233 |
| 36 | 1.798 | 1 | -0.798 | 0.798 |
| 37 | 4.358 | 5 | 0.642 | 0.642 |
| 38 | 2.758 | 2 | -0.758 | 0.758 |
| 39 | 6.318 | 4 | -2.318 | 2.318 |
| 40 | 4.603 | 5 | 0.397 | 0.397 |
| 41 | 7.778 | 9 | 1.222 | 1.222 |
| 42 | 0.501 | 2 | 1.499 | 1.499 |
| 43 | 3.387 | 4 | 0.613 | 0.613 |
| 44 | 2.955 | 2 | -0.955 | 0.955 |
| 45 | 6.972 | 7 | 0.028 | 0.028 |
| 46 | 10.063 | 8 | -2.063 | 2.063 |
| 47 | 0.742 | 5 | 4.258 | 4.258 |
| 48 | 2.031 | 2 | -0.031 | 0.031 |
| 49 | 1.883 | 0 | -1.883 | 1.883 |
| 50 | 7.530 | 8 | 0.470 | 0.470 |
| 51 | 4.177 | 4 | -0.177 | 0.177 |
| 52 | 12.595 | 14 | 1.405 | 1.405 |
| 53 | 9.155 | 10 | 0.845 | 0.845 |
| 54 | 8.589 | 6 | -2.589 | 2.589 |
| 55 | 2.645 | 3 | 0.355 | 0.355 |
| 56 | 4.979 | 6 | 1.021 | 1.021 |
| 57 | 0.587 | 1 | 0.413 | 0.413 |
| 58 | 3.639 | 3 | -0.639 | 0.639 |
| 59 | 4.360 | 5 | 0.640 | 0.640 |
| 60 | 2.097 | 0 | -2.097 | 2.097 |
| 61 | 5.840 | 10 | 4.160 | 4.160 |
| 62 | 3.727 | 2 | -1.727 | 1.727 |
| 63 | 8.448 | 9 | 0.552 | 0.552 |
| 64 | 11.237 | 8 | -3.237 | 3.237 |
| 65 | 6.552 | 7 | 0.448 | 0.448 |
| 66 | -2.199 | -1 | 1.199 | 1.199 |
| 67 | 1.586 | 3 | 1.414 | 1.414 |
| 68 | 4.792 | 4 | -0.792 | 0.792 |
| 69 | 8.258 | 13 | 4.742 | 4.742 |
| 70 | 6.465 | 7 | 0.535 | 0.535 |
| 71 | 5.871 | 5 | -0.871 | 0.871 |
| 72 | 11.538 | 13 | 1.462 | 1.462 |
| 73 | -1.752 | -2 | -0.248 | 0.248 |
| 74 | 4.816 | 7 | 2.184 | 2.184 |
| 75 | 1.235 | 1 | -0.235 | 0.235 |
| 76 | 5.468 | 4 | -1.468 | 1.468 |
| 77 | 9.217 | 8 | -1.217 | 1.217 |
| 78 | 2.392 | 1 | -1.392 | 1.392 |
| 79 | 5.137 | 4 | -1.137 | 1.137 |
|  |  |  |  |  |
|  |  |  | Average Residual= | 1.152 |

Works Cited

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Lewis, Michael. *Moneyball: The Art of Winning an Unfair Game.* New York: W.W. Norton & Company, 2003.

1. Broadcast on February 10, 2015. Video can be found at: https://www.youtube.com/watch?v=NZf9NFaCQHQ [↑](#footnote-ref-1)
2. Quotes taken from ESPN’s The Great Analytics Rankings. The article can be found at: http://espn.go.com/espn/feature/story/\_/id/12331388/the-great-analytics-rankings [↑](#footnote-ref-2)
3. “sabermetric” refers to the “use of statistical methods to analyze player performance and game strategy” in baseball. [↑](#footnote-ref-3)
4. Batting Average is the average performance of a hitter, expressed as a ratio of safe hits per number of at bats. [↑](#footnote-ref-4)
5. A player’s On Base Percentage is roughly calculated as the sum of hits, walks, and hit by pitches divided by the sum of number of at bats, walks, and hit by pitches. Batting Average has an 82% correlation to runs scored, while On Base Percentage has an 88.1% correlation to runs scored. [↑](#footnote-ref-5)
6. Given that there are 8 possible configurations of baserunners (no baserunners, runner on first base, runner on second base, runner on third base, runners on first and second base, runners on first and third base, runners on second and third base, runners on first, second, and third base) and three possibilities for the number of outs left in an inning (zero, one, and two), there are 24 possible discrete scenarios in an inning. Sabermetricians have used historical data to develop a matrix that estimates the expected number of runs for each discrete scenario. [↑](#footnote-ref-6)
7. Wins Above Replacement, or WAR, is an attempt to quantify the number of additional wins a player contributes to a team over that of a replacement player. A replacement player is loosely defined as a Triple-A level player. A player with a WAR of 4.5 would generally be viewed as All-Star caliber. [↑](#footnote-ref-7)