

Data analytics effects in Baseball player's value

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Abstract

Over the past two decades, there has been a notable resurgence in the utilization of data analytics across professional sports, businesses, and governmental sectors. We can measure the value of baseball players through data analysis, which is very important to the success of the team. Therefore, this article will study how to measure the value of a player and will delve into an in-depth analysis of the myriad factors that potentially impact baseball players while they are actively engaged in the game.

1 Introduction

The surge in the availability of data, from player statistics to in-game metrics, has ushered in a new era in baseball analysis. This wealth of information has not only enriched the fan experience but has also become an invaluable tool for teams and analysts seeking a competitive edge. So how do we measure the value of players in a statistical way? Before discussing how to measure value, we need to discuss the definition of value. According to the definition in Wyers' article "How to measure a player's value"[3], we define the value of a player as "A player's value is his contributions to his team based upon his on-field performance (hitting,

running, fielding and pitching) in a neutral context. This definition excludes qualities like leadership and character, which would be horrific to see a statistical measure of performance attempt to portray! That's not to argue these things don't matter; they just aren't easily quantified. In addition, according to Wyers' approach, we need to emphasize that this is a neutral environment. First, we want to quantify a player's performance apart from his teammates' - a player is no better or worse on a good or terrible team. Besides, we aim to separate a player from his surroundings. A terrible pitcher does not become a better pitcher by pitching in Petco Park, and a poor hitter does not become a better pitcher by hitting in Coors Field.

We should realize there are some limits may effects our statistical model:

1. The data itself. Errors can occur, including transcription errors and similar inaccuracies. Additionally, certain determinations rely on borderline judgments, such as discerning whether an event constitutes a hit or an error, categorizing a hit as a fly ball or a line drive, and determining whether a pitch is a ball or a strike.
2. Critical information might be omitted from the data, necessitating inference or deliberate oversight. Questions such as the shortstop's positioning on the field or whether the coach executed a hit-and-run strategy may not be explicitly recorded and might require additional interpretation or intentional exclusion.
3. Developing a model without a grasp of the fundamental principles poses challenges. The inherent value difference between a double and a sacrifice fly in baseball may be intuitive, but expressing and capturing this nuanced understanding can be particularly challenging for a linear regression model.
4. The model overlooks certain factors, such as the quality of the opponent, platoon advantage, and other relevant considerations.

5. Neglecting to consider subtle distinctions between players, such as the influence of a ballpark on the home run rates of individuals like Barry Bonds and Juan Pierre, can lead to oversights in the analysis.

Every value indicator has an underlying baseline, whether by chance or design. As a result, it is advisable to carefully analyze the choice of a baseline and the reasoning behind it. Baselines are important since we are not interested in a single player - there is no such thing as a baseball player in isolation. We're interested in a player's contributions in the context of a team - the marginal contribution of that player in comparison to who else could have played instead. If you've ever spent a lot of time on baseball forums or message boards, you've probably seen an idea that starts with, "What could it hurt to do this?" It's the opportunity cost: playing time is a fixed commodity that cannot be transferred from one player to another. Now let's start to talk about the detail process of value baseball players.

The rest of the paper is organized as follows.

The data will be presented in Section 2.

The methods are described in Section 3.

The results are reported in Section 4.

A discussion concludes in Section 5.

2 Data

We got the 2008 season stats for 30 teams from Fangraphs website, including team name, plate appearance, average, pitches and so on. We then process the data we collect using the code mentioned in Figure 1. The data 2 and all player data is drawn from the Stats section of Fangraphs [1].

```
let url = game_day_url("mlb", "2018", "06", "10");  
let games = game_day_links(&url);  
  
dbg!(games);
```

Figure 1: code for addressing stats 2008 baseball team

3 Methods

As Wyers mentioned "A player's value is essentially an average team's runs or wins with that player, minus their runs or wins without that player." [4] We have two types of models: dynamic and linear. Dynamic models excel in assessing entire contexts, such as a team's overall performance or a pitcher's effectiveness. However, they are less effective when applied to individual hitters, as each hitter only influences a fraction of the overall context. Additionally, a hitter's performance does not interact with itself; for instance, if a hitter walks, they cannot subsequently hit a home run to drive themselves in.

On the other hand, linear models are adept at capturing the environmental context, making them well-suited for estimating a hitter's contribution to a specific context. However, they may not perform as effectively when evaluating pitchers.

Among dynamic run estimators, BaseRuns stands out as the most accurate and versatile. The formula for BaseRuns is:

$$A * B / (B + C) + D \tag{1}$$

Where A is the number of baserunners, B is the "advancement factor," C is the number of outs, and D is the number of home runs.

There are nearly too many linear weights formulas to name when it comes to linear run estimators. It's generally ideal to utilize bespoke linear weights dependent on the season for a player value system. The most important factor to consider is baseline—while all dynamic run estimators provide absolute runs, certain linear run estimators provide runs above average instead.

Measuring playing time in baseball isn't always straightforward. At the team level, the fundamental unit is the out, crucial for both offense and defense. Pitchers and fielders often use outs, games, or innings, but when it comes to batting, plate appearances or at-bats are commonly used. The challenge arises as plate appearances are not fixed, impacting a player's

contribution. Most run estimators focus on runs per out, emphasizing the importance of using the correct unit of playing time. Linear run estimators typically use plate appearances. It's crucial to recognize that comparing players should consider the same number of batting outs, not plate appearances. To make it more relatable, some analysts convert runs per out to runs per plate appearance. This simplification helps those more accustomed to plate appearances as the unit of playing time for hitters. The key is precision when comparing and evaluating player performance metrics.

In sabermetrics, it's widely accepted that a player's runs contribution should be separated from the impact of their home park. The debate revolves around using either simple, run-based park factors or more detailed component park factors.

For a value metric, the general preference is for run-based park factors. This adjustment accounts for the fact that the value of a run can vary based on the ballpark - for instance, a run in Coors is considered less valuable than a run in Petco. While there are situations where component park factors might be relevant, they don't necessarily provide a "more accurate" assessment of a player's value, especially concerning explaining team wins. The choice between the two depends on the specific analysis goals and nuances.

Fielding value is more difficult to quantify because, while there is only one hitter, the defense has nine fielders on every play. It is quite simple to determine who made a specific play, but it is frequently difficult to determine who should be liable for a ball when no play is made. Various defensive metrics attempt to determine who is responsible for a ball in play. In general, the better the outcomes, the more detailed the underlying dataset.

Table 1 are definitions we may use

$$AVG = H/AB, \tag{2}$$

which means the total number of hits divided by the total number of at-bats

$$BABIP = (H - HR)/(AB - K - HR - SF), \tag{3}$$

Table 1: Baseball Batting Statistics

| Variable | Description |
|--------------|----------------------------------|
| <i>AB</i> | At bats |
| <i>AVG</i> | Batting average |
| <i>H</i> | Hits |
| <i>K</i> | Strikeouts |
| <i>HR</i> | Home Run |
| <i>BABIP</i> | Batting Average on Balls in Play |
| <i>SF</i> | Sacrifice flies |

which states that a batter’s average for balls that are put in play (excludes strikeouts, home runs, and sacrifice flies)

4 Results

In assessing a player’s offensive value, a linear system proves to be most effective. Linear systems provide insights into the number of runs a player adds to an average team. It’s important to note that linear weights values may not necessarily sum up to team totals accurately, particularly for teams that excel or struggle significantly on the offensive front. If we’re going to use a linear run estimator, shouldn’t we also use a linear park factor? We simply take the average number of runs per plate appearance—roughly .122 in 2008—and park compensate for the difference. Simply multiply that figure by the number of plate appearances and add it to the linear weight values to get your park adjustment. And that is all there is to it. Simply put, you have a measure of a player’s offensive worth relative to the average. This gives us a linear factor to work with, as shown Table 2

Now we should consider defense value of a player. Begin using the Revised Zone Rating statistics [2] available on THT (Figure 1). We have a metric for playing time (BIZ, or balls in zone) and plays made (Plays and OOOZ, or out of zone plays). What we want to do is compare

Table 2: Park value formula and its per plate appearance in each team

| TEAM | PF | PFPA | TEAM | PF | PFPA | TEAM | PF | PFPA |
|------|------|--------|------|------|--------|------|------|--------|
| ARI | 1.05 | 0.006 | ATL | 1.00 | 0.000 | BAL | 1.01 | 0.001 |
| BOS | 1.04 | 0.005 | CHA | 1.04 | 0.005 | CHN | 1.04 | 0.005 |
| CIN | 1.02 | 0.002 | CLE | 1.00 | 0.000 | COL | 1.09 | 0.011 |
| DET | 1.00 | 0.000 | FLA | 0.98 | -0.002 | HOU | 0.99 | -0.001 |
| KC | 1.00 | 0.000 | LAA | 0.98 | -0.002 | LAN | 0.99 | -0.001 |
| MIL | 1.00 | 0.000 | MIN | 1.00 | 0.000 | NYA | 1.00 | 0.000 |
| NYN | 0.97 | -0.004 | OAK | 0.98 | -0.002 | PHI | 1.02 | 0.002 |
| PIT | 0.98 | -0.002 | SD | 0.92 | -0.010 | SEA | 0.97 | -0.004 |
| SF | 1.01 | 0.001 | STL | 0.98 | -0.002 | TB | 0.99 | -0.001 |
| TEX | 1.03 | 0.004 | TOR | 1.02 | 0.002 | WAS | 1.01 | 0.001 |

[5]

these to the average, convert the plays to runs, and then correct for position differences.

$$BIZ*(PlayerRZR - LeagueRZR) + Innings*(PlayerOOZ/PlayerInn - LeagueOOZ/LeagueInn) \quad (4)$$

Subsequently, converting plays to runs involves a straightforward application of a constant. The adjustment for position is then made by distributing the variance between positions proportionally according to playing time. This positional adjustment should be determined by assessing the relative defensive difficulty among positions, a measurement attainable by examining players who occupy multiple positions. Table 3 is the comprehensive breakdown.

Table 3: Full Nitty-Gritty

| Position | RZR (Revised Zone Rating) | OOZ_INN (Out of Zone Plays per Inning) | Run/Play | BIZ/30 (Balls in Zone per 30 Innings) | PAdj (Positional Adjustment) |
|----------|---------------------------|--|----------|---------------------------------------|------------------------------|
| 1B | 0.739422 | 0.030305 | 0.798 | 219 | -12.5 |
| 2B | 0.821831 | 0.026007 | 0.754 | 426 | 2.5 |
| 3B | 0.696536 | 0.038408 | 0.8 | 354.1333 | 2.5 |
| CF | 0.921688 | 0.067393 | 0.842 | 349.0333 | 2.5 |
| LF | 0.882837 | 0.04453 | 0.831 | 275.4 | -7.5 |
| RF | 0.899098 | 0.048531 | 0.843 | 292.0333 | -7.5 |
| SS | 0.828403 | 0.037678 | 0.753 | 424.8333 | 7.5 |

[5]

The top 10 position players, 2008

The bottom 10 position players, 2008

Table 4: Top 10 Player in 2008

| Last Name | First Name | Offesne | Bonus | Defense | Total | WAR |
|------------------|-------------------|----------------|--------------|----------------|--------------|------------|
| Pujols | Albert | 73.3 | 18.3 | 16.7 | 108.4 | 10.8 |
| Jones | Chipper | 51.5 | 15.3 | 18.1 | 84.9 | 8.5 |
| Utey | Chase | 33.6 | 20.2 | 30.0 | 83.7 | 8.4 |
| Berkman | Lance | 49.5 | 19.0 | 12.6 | 81.0 | 8.1 |
| Rodriguez | Alex | 39.0 | 21.2 | 14.3 | 74.4 | 7.4 |
| Teixeira | Mark | 45.5 | 21.2 | 7.2 | 74.0 | 7.4 |
| Ramirez | Hanley | 40.8 | 19.8 | 9.6 | 70.2 | 7.0 |
| Wright | David A | 41.0 | 21.0 | 7.3 | 69.4 | 6.9 |
| Beltran | Carlos | 30.4 | 20.2 | 16.8 | 67.4 | 6.7 |
| Sizemore | Grady | 30.1 | 26.6 | 8.1 | 64.8 | 6.5 |

Table 5: Buttom 10 Players in 2008

| Last Name | First Name | Offense | RepBonus | Defense | Total | WAR |
|------------------|-------------------|----------------|-----------------|----------------|--------------|------------|
| Wilkerson | Brad | -13.9 | 11.0 | -9.4 | -12.3 | -1.2 |
| Balentine | Wladimir R | -16.1 | 9.3 | -6.0 | -12.9 | -1.3 |
| Jacobs | Mike | 5.4 | 14.8 | -31.5 | -11.3 | -1.1 |
| Matthews Jr. | Gary | -12.6 | 17.0 | -16.4 | -11.9 | -1.2 |
| Patterson | Corey | -29.4 | 11.2 | 4.7 | -13.5 | -1.4 |
| Lamb | Mike | -15.6 | 9.6 | -8.5 | -14.4 | -1.4 |
| Francoeur | Jeff B | -26.0 | 18.7 | -4.6 | -11.9 | -1.2 |
| Pena | Tony F | -30.4 | 8.4 | 6.2 | -15.8 | -1.6 |
| Guillen | Jose | -9.7 | 22.6 | -28.3 | -15.4 | -1.5 |
| Gload | Ross | -15.4 | 14.9 | -20.1 | -20.6 | -2.1 |

5 discussion

These models are not flawless since no model is. We should constantly strive to improve these models. At THT, we use Fielding Independent Pitching, a basic but successful methodology. However, to apply linear models to pitching and thus employ a dynamic FIP based on BaseRuns. In most circumstances, the distinction is likely to be trivial, but for exceptionally good or awful pitchers, it will be significant.

Besides, some Baseball fans can be tremendously protective of their home team's players - or they can be incredibly vicious. This is heavily influenced by how good this player is and how well the team has lately performed. Fans also like to believe that their long, patient commitment to their ballclub has resulted in an unfathomable amount of knowledge about the players they follow that is not readily available to outsiders.

Analyzing player performance in baseball necessitates a holistic approach that extends beyond the confines of a single season or a limited set of matches. While the data from Fangraphs in 2008 provides valuable insights, it is crucial to recognize that a player's true quality is multifaceted. Factors such as mental acuity, strategic prowess, and long-term growth rates play pivotal roles in shaping a player's overall competence in baseball.

In order to comprehensively evaluate and understand a player's capabilities, it becomes imperative to gather a more extensive dataset spanning multiple seasons. This broader scope allows for a nuanced examination of a player's consistency, adaptability, and resilience over time. Moreover, developing more sophisticated and comprehensive analytical models can enhance our ability to unravel the intricate layers of a player's performance, going beyond mere statistical outputs to capture the intangible qualities that contribute to their success on the baseball field. By incorporating a diverse range of factors, we can build models that provide a more accurate and nuanced representation of a player's true value within the sport.

References

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