

How to Calculate Consistency in Baseball?

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Over the years, baseball has focused more and more on advanced statistics. What if we take a different view this time, focusing on the variance of baseball? The baseball world has done an incredible job of translating on-field performance into numbers. One area my colleague Samson Waisanen and I believe could still use one improvement would be analyzing the consistency of a hitter. This article will focus solely on how consistent a hitter produces his results and boiling that down to a simple number. We will call this game-by-game, or GBG for short. The goal of this exercise is to see if a hitter's consistency impacts both his production and the team's chances of winning.

Below are the parameters of this study:

1. Gathering Data

Using fangraphs.com, we gathered 2019 data on hitter last season. We focused on batting consistency initially as a focal point due to a much larger sample size and hitters typically playing every day. From there we selected the top 10 WAR contributors in each teams' batters for our research. To evaluate the players' game by game offensive production, we choose the below items:

WPA/-WPA/+WPA/RE24/REW/pLI/phLI/PH/WPA/LI/Clutch/BB%/K%/BB/K/AVG/OBP/SLG/OPS/ISO/Spd/BABIP/wRC/wRAA/wOBA/wRC+

2. Shaping the data

Using this information, we analyzed the above items with the concept of consistency. The way we found consistency was taking the standard deviation for a specific player, compared to their full season output. Using wRC+ for example, we gather the specific player's wRC+ each game and see how big the standard deviation is for the whole season. From here we found that players with higher wRC+ would typically have higher standard deviations, which makes sense as with a higher average there is a much greater opportunity to have a monster night while an occasional off night might harm his number more than average hitter. Thus we divided the standard deviation by the player's average wRC+ to not punish players for having a higher base standard deviation.

Ex. 1

As an example, let's look at Jeimer Candelario of the Detroit Tigers. Over the course of 94 games, Candelario accumulated a wRC+ of 72. This ranked 10th among Tigers hitters last season. However, taking the wRC+ from each of his games, he produced a standard deviation of 133.37. Dividing this by his average wRC+ performance you end up with a 1.96 GBG. When compared to other Tigers, this puts Candelario 5th on the team. So while he may have been only the 10th best hitter overall, he produced those results with the 5th best consistency on the team.

3. Analyze it

With this information in mind, we want to see if there is a correlation between a player's consistency and overall team success. To do this we take the player's GBG number and compare it to their WAR output for 2019. To account for playing

time, we specifically used a player's WAR/game. We use the software SPSS to analyze the correlation between the (standard deviation/average) of

WPA/- WPA/+WPA/RE24/REW/
pLI/phLI/PH/WPA/LI/Clutch/BB%/K%/BB/K/AVG/OBP/
SLG/OPS/ISO/Spd/BABIP/wRC/wRAA/wOBA/wRC+
and (WAR/Game).

Result:

| STATS | Corelation with WAR per game |
|--------|------------------------------|
| wRC+ | -0.640** |
| wRC | -0.592** |
| OBP | -0.508** |
| ISO | -0.496** |
| wOBA | -0.464** |
| OPS | -0.443** |
| AVG | -0.430** |
| SLG | -0.416** |
| Spd | -0.410** |
| -WPA | -0.355** |
| BB% | -0.369** |
| BB/K | -0.329** |
| phLI | -0.319** |
| BABIP | -0.314** |
| pLI | -0.280** |
| PH | 0.196** |
| K% | -0.151* |
| -WPA | 0.126* |
| REW | 0.096 |
| WPA | 0.008 |
| WPA/LI | 0.064 |
| RE24 | 0.064 |
| wRAA | 0.016 |
| Clutch | 0.004 |

****Indicates correlation is significant at the .01 level.**

***Indicates correlation is significant at the .05 level.**

Keep in mind that a minus correlation is not weaker than a plus correlation; they're the same strength, only in opposite directions. For example, in a +0.8 correlation, when one stat gets higher, the other also tends to; in -0.8, when one goes up, the other goes down. So it's the absolute value we care about the most. In a +1.00 correlation relationship, when one goes up, the other does go up, by a very predictable amount. But, unless you're correlating a stat with itself, you probably won't see anything like a +1.00 correlation.

We can see that from all the items we got, the consistency of wRC+ is most related to WAR per game. The correlation is quite solid at 0.639. With this in mind, we take a look at the top 50 players of our hypothesized term GBG(wRC+). It's possible that GBG(wRC+) might be a good indicator of WAR.

4. Rankings of GBG(wRC+)

| Rank | Name | GBG | Rank | Name | GBG |
|------|--------------------|-------------|------|----------------------|-------------|
| 1 | Gio Urshela | 1.013838053 | 26 | Carlos Correa | 1.288296072 |
| 2 | Mike Trout | 1.044732318 | 27 | Nicholas Castellanos | 1.289540146 |
| 3 | Cesar Puello | 1.048125375 | 28 | Freddie Freeman | 1.291018471 |
| 4 | Alex Bregman | 1.070488847 | 29 | Josh Donaldson | 1.292894586 |
| 5 | Fernando Tatis Jr. | 1.106120361 | 30 | Carlos Santana | 1.294567287 |
| 6 | Cody Bellinger | 1.14085389 | 31 | Tommy Pham | 1.296879613 |
| 7 | Christian Yelich | 1.140895199 | 32 | Mark Canha | 1.299672848 |
| 8 | Anthony Rendon | 1.154149636 | 33 | George Springer | 1.312682342 |
| 9 | Byron Buxton | 1.172048444 | 34 | Miguel Sano | 1.316825608 |
| 10 | Ketel Marte | 1.185391193 | 35 | Xander Bogaerts | 1.32201577 |
| 11 | Aaron Judge | 1.187344622 | 36 | Jose Altuve | 1.322509556 |
| 12 | Bo Bichette | 1.219025848 | 37 | Max Muncy | 1.327847771 |
| 13 | Marcus Semien | 1.221398482 | 38 | Max Kepler | 1.329520939 |
| 14 | Austin Meadows | 1.231454379 | 39 | Yasmani Grandal | 1.344453779 |
| 15 | Trey Mancini | 1.234350975 | 40 | Ronald Acuña Jr. | 1.347126709 |
| 16 | Anthony Rizzo | 1.236254033 | 41 | Rafael Devers | 1.348992093 |
| 17 | DJ LeMahieu | 1.246320997 | 42 | Michael Brantley | 1.351365479 |
| 18 | Trea Turner | 1.247042 | 43 | Tim Anderson | 1.362341266 |
| 19 | Nick Solak | 1.248332205 | 44 | Yandy Diaz | 1.365419879 |
| 20 | Kris Bryant | 1.256691602 | 45 | Keston Hiura | 1.371811328 |
| 21 | Jeff McNeil | 1.258781244 | 46 | Yoan Moncada | 1.376297148 |
| 22 | J.D. Martinez | 1.262681726 | 47 | Hunter Dozier | 1.378544796 |
| 23 | Mookie Betts | 1.262931117 | 48 | Andrew McCutchen | 1.381420659 |
| 24 | Yordan Alvarez | 1.272540412 | 49 | Trevor Story | 1.383577726 |
| 25 | Juan Soto | 1.287462586 | 50 | Luke Voit | 1.392520187 |

5. Findings:

From our findings there are a few noteworthy things to point out. The first is great players make up a majority of the members. This is a good sign as most great hitters should be relatively consistent compared to the average player. However, not every player is a current star of the MLB. Gio Urshela, the Yankees emergency option for 3rd base at the start of last season, put up the most constant numbers throughout the year. Despite ranking 115th in all of MLB with a 3.1 WAR, Urshela produced at a constant level similar to Mike Trout and Alex Bregman.

Overall we believe a players consistency does have an impact on their value along with team success. Given this was just a basic analysis, we will be looking at GBG statistics much more in-depth.