Phillies Baseball R&D
Batting Average Predictions

April 2021

1 Introduction

For years, baseball has seen batting average as a quantifiable measure of how good a player is at the plate. Although newer metrics have come along such as slugging percentage, BABIP, and on-base percentage that seek to look more into how effective a player is at the plate, batting average still seems to reign supreme over all when it comes to fans and scouts alike, and there in lies the merits of being able to predict this statistic. In the following document, the March and April batting numbers for 309 players in Major League Baseball (MLB) will be examined in order to create models that can predict their end-of-season batting average. Several methods for this prediction will be implemented, including multiple linear regression and beta distribution, and the results between predictions will be compared in order to properly understand what each is saying.

2 Approaches

There are several potential models that can be implemented that could provide a reasonable estimate of where the 309 batters will end their seasons batting average-wise. For the purposes of this study, 2 distinct modelling ideas were implemented to attempt to predict the end-of-season batting averages.

2.1 Beta Distribution

When seeking to examine the probability of an event occurring, a probability distribution naturally comes to mind as a means to understand how likely that event is. In the world of baseball statistics, David Robinson has worked on the Beta Distribution as a means of tracking/predicting a player's batting average. The following paper will utilize the work from his post from StackExchange [1] as well as the blogpost from his own personal website[2]. As defined by Wikipedia, the Beta distribution is a "family of continuous probability distributions defined on the the interval $[0, 1]$ parametrized by two shape parameters, denoted by α

and β "[3]. The exact parameters and how they will be implemented will be discussed in the Methodology Section. This model seeks to use a mean value to curve the expected batting average.

2.2 Multiple Linear Regression

The other model implemented was a multiple linear regression model, using the Regression functionality in the Data Analysis Toolpak in Microsoft Excel. A multiple linear regression model seeks to fit coefficients to relevant independent variables in order explain as much of the variation in the dependent variable (in this case, FullSeason_AVG) as possible.

3 Data

The majority of the data set was sourced from the "batting.csv" provided by the questionnaire [4]. The information for the 2015, 2016, and 2017 hits, at bats, and batting averages was sourced from Baseball Reference [5], a free, open-source baseball statistics website. Below is a list of all the independent variables in the study (with the exception of the batting averages in 2015, 2016, 2017, and March/April 2018, which are all dependent on the hits and at bats at those times).

- Playerid - player's Fangraphs ID
- Name - player's name
- Team - player's team
- MarApr_PA - player's plate appearances in March and April 2018
- MarApr_AB - player's at bats in March and April 2018
- MarApr_H - player's hits in March and April 2018
- MarApr_HR - player's home runs in March and April 2018
- MarApr_R - player's runs scored in March and April 2018
- MarApr_RBI - player's RBI in March and April 2018
- MarApr_SB - player's stolen bases in March and April 2018
- MarApr_BB% - player's walk percentage in March and April 2018
- MarApr_K% - player's strikeout percentage in March and April 2018
- MarApr_ISO - player's isolated power in March and April 2018

- MarApr_BABIP - player's BABIP in March and April 2018
- MarApr_AVG - player's batting average in March and April 2018
- MarApr_OBP - player's on-base percentage in March and April 2018
- MarApr_SLG - player's slugging percentage in March and April 2018
- MarApr_LD% - player's line drive percentage in March and April 2018
- MarApr_GB% - player's ground ball percentage in March and April 2018
- MarApr_FB% - player's fly ball percentage in March and April 2018
- MarApr_IFFB% - player's infield fly ball percentage in March and April 2018
- MarApr_HR/FB - player's home run per fly ball rate in March and April 2018
- MarApr_O-Swing% - player's out-of-zone swing-per-pitch percentage in March and April 2018
- MarApr_Z-Swing% - player's in-zone swing-per-pitch percentage in March and April 2018
- MarApr_Swing% - player's total swing-per-pitch percentage in March and April 2018
- MarApr_O-Contact% - player's out-of-zone contact-per-swing percentage and April 2018
- MarApr_Z-Contact% - player's in-zone contact-per-swing percentage in March and April 2018
- MarApr_Contact% - player's total contact-per-swing percentage in March and April 2018
- FullSeason_AVG - player's batting average for his entire 2018 season
- 2015_H - player's hits in 2015
- 2015_AB - player's at bats in 2015
- 2015_AVG - player's batting average for his entire 2015 season
- 2016_H - player's hits in 2016
- 2016_AB - player's at bats in 2016
- 2016_AVG - player's batting average for his entire 2016 season
- 2017_H - player's hits in 2017
- 2017_AB - player's at bats in 2017
- 2017_AVG - player's batting average for his entire 2017 season

4 Methodology

On examination of some of the March-April 2018 batting averages, one can make some reasonable assumptions about the end of season batting averages. Elias Diaz hitting .484 and Xander Bogaerts hitting .412 can both be expected to come down significantly, as those would represent the highest batting average for a single season ever by more than .05 for Diaz and would still be a top 5 highest batting average for a single season of all time for Bogaerts, and would both be the highest in the 21st century (the most recent entrant for top 50 highest single-season batting averages is Tony Gwynn hitting .394 in 1994), with both at least .038 more than the co-highest single season batting averages in the 21st century: .372, jointly held by Nomar Garciaparra (2000), Todd Helton (2000), and Ichiro Suzuki (2004) [5]. Conversely, there are 26 players whose batting averages would, if maintained throughout the course of the 2018 season, would be the worst single-season batting averages in Major League Baseball History. Of note, one of those 26, Chris Davis (playerid 9272) would end up setting the record in 2018 for the worst single-season batting average in Major League Baseball History at .168. But among the other players, how can their 2018 full season batting averages be properly predicted? In this section, the approaches detailed above in the Approaches section will be thoroughly examined and explained.

4.1 Beta Distribution

In regards to the problem at hand, a Beta distribution can be used to determine probabilities based off the mean. The mean of a Beta distribution is equivalent to the following: $\mu_{Beta} = \frac{\alpha}{\alpha+\beta}$, where α and β are the shape parameters mentioned in the Approaches section. A member of Beta distribution family is thus represented as Beta(α,β). From the work of David Robinson [1], we can utilize his assumptions for the sake of our study: that the average batter in the Major League has a batting average of .270, with a range between from .210 to .350. As Robinson demonstrates, the Beta distribution Beta(81,219) near perfectly maps this concept:

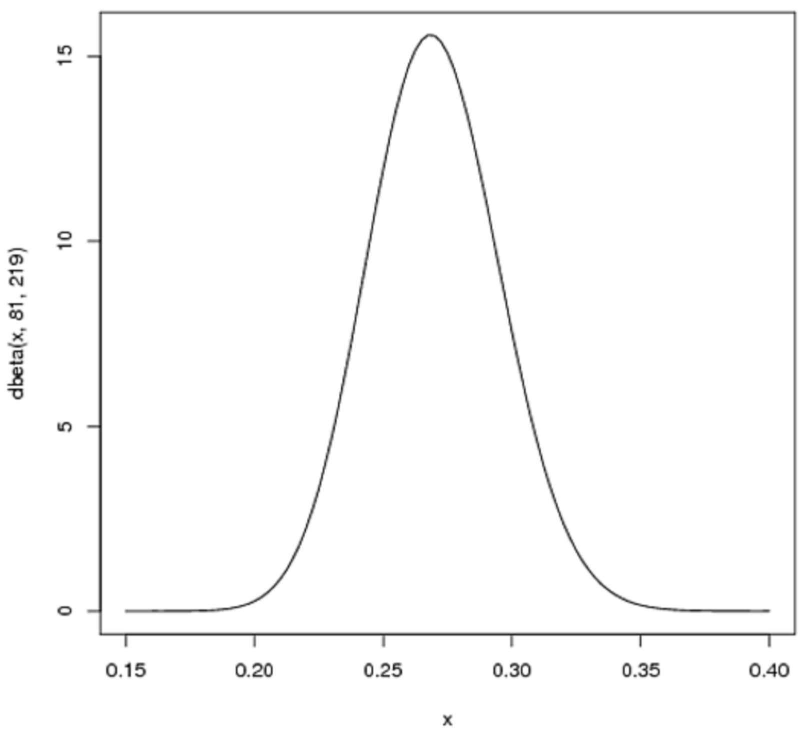

Figure 1: The Beta distribution for $\alpha = 81$ and $\beta = 219$, from David Robinson [1]

Furthermore, $\mu_{Beta} = \frac{81}{81+219} = 0.270$. Therefore, we can work off an edited Beta distribution starting with those α and β values. The idea behind using this mean is as follows: a player's batting average can be imagined as $\mu_{BA} = \frac{\alpha+\text{hits}}{\alpha+\beta+\text{at bats}}$, which means that the player's batting average can be represented by Beta(α + hits, β + misses). In other words, the player's batting average is skewed towards the average, and is given the benefit of the doubt in terms of 81 theoretical hits in 300 theoretical at bats. For the purposes of comparison, three separate methods of constructing this μ_{BA} were implemented, and are further explained below.

4.1.1 Beta Distribution - Normal

This Beta distribution was constructed purely as a baseline based on David Robinson's calculations [1] and the variables MarApr_H and MarApr_AB, with the results looking like the following: $\mu_{BDN} = \frac{81+\text{MarApr\_H}}{81+219+\text{MarApr\_AB}}$, where BDN stands for "Beta Distribution - Normal", or our normal attempt at producing a Beta distrbution mean based solely on Robinson's numbers.

4.1.2 Beta Distribution - Weighted

This alternative Beta distribution was constructed with the following concept in mind: a player goes into each season not necessarily with the league average BA, but rather their own personal average BA. Therefore, the batting average can be weighted based on the three previous years (2015, 2016, and 2017) in order to bring the mean closer to what it should be. This was done like so, with that initial assumption that in 2015 (or the year a player began their career, as some players like Shohei Ohtani (playerid 19755) began his career in 2018, and thus had no 2015, 2016, or 2017 batting data), the player begins with the established league average:

$$\mu_{2015} = \frac{81 + 2015\_\mathrm{H}}{81 + 219 + 2015\_\mathrm{AB}} \tag{1}$$

Each subsequent year undergoes a similar process for determining μ_{year}, with β being determined by $\beta_{year} = \frac{81}{\mu_{year-1}} - 81$. Thus, 2016 and 2017 looked like so:

$$\mu_{2016} = \frac{81 + 2016\_\mathrm{H}}{81 + (\frac{81}{\mu_{2015}} - 81) + 2016\_\mathrm{AB}} \tag{2}$$

$$\mu_{2017} = \frac{81 + 2017\_\mathrm{H}}{81 + (\frac{81}{\mu_{2016}} - 81) + 2017\_\mathrm{AB}} \tag{3}$$

Finally, the Beta distribution was then introduced to MarApr_H and MarApr_AB, having properly weighted the Beta distribution to the player, and not the league average. Thus, the final prediction would look like so (here, BDW stands for "Beta Distribution - Weighted":

$$\mu_{BDW} = \frac{81 + \mathrm{MarApr\_H}}{81 + (\frac{81}{\mu_{2017}} - 81) + \mathrm{MarApr\_AB}} \tag{4}$$

4.1.3 Beta Distribution - Double Weighted

This alternative carries on the concept of weighting from the Beta Distribution - Weighted, but continues one step further. Player X's batting average from March and April of 2018 are going to have a larger influence on his 2018 full season batting average than any of 2015, 2016, or 2017, so running the beta distribution weighting calculation over the March-April stats twice should allow for this to be considered properly. Thus, the additional step is as follows (here, BDDW stands for "Beta Distribution - Double Weighted":

$$\mu_{BDDW} = \frac{81 + \mathrm{MarApr\_H}}{81 + (\frac{81}{\mu_{BDW}} - 81) + \mathrm{MarApr\_AB}} \tag{5}$$

4.2 Multiple Linear Regression

Using the Regression tool in Excel's Data Analysis Toolpak, 5 separate models were created with varying numbers of variables (from 6 to 16) based on a combination of attempting to verify every statistic, the p-values of those statistics in previous iterations of the Regression tool, and examinations of the linearity relationship between the independent variable and the dependent variable (FullSeason_AVG). Below is a list of each model and the variables used.

- MLR1 ($R^2 = 0.630112121$) - MarApr_ISO, MarApr_HR, MarApr_R, MarApr_RBI, MarApr_PA, MarApr_AB, MarApr_H, MarApr_SB, MarApr_BB%, MarApr_K%, MarApr_BABIP, MarApr_AVG, MarApr_OBP, MarApr_SLG, MarApr_LD%, MarApr_GB%
- MLR2 ($R^2 = 0.643840883$) - MarApr_HR, MarApr_PA, MarApr_AB, MarApr_H, MarApr_OBP, MarApr_LD%, MarApr_GB%, MarApr_FB%, MarApr_IFFB%, MarApr_HR/FB, MarApr_O-Swing%, MarApr_Z-Swing%, MarApr_Swing%, MarApr_O-Contact%, MarApr_Z-Contact%, MarApr_Contact%
- MLR3 ($R^2 = 0.64111462$) - MarApr_HR, MarApr_PA, MarApr_AB, MarApr_H, MarApr_IFFB%, MarApr_O-Swing%, MarApr_Z-Swing%, MarApr_Swing%, MarApr_O-Contact%, MarApr_Z-Contact%, MarApr_Contact%
- MLR4 ($R^2 = 0.628850535$) - MarApr_AB, MarApr_H, MarApr_IFFB%, MarApr_O-Contact%, MarApr_Z-Contact%, MarApr_Contact%
- MLR5 ($R^2 = 0.692913308$) - MarApr_AB, MarApr_H, MarApr_IFFB%, MarApr_O-Contact%, MarApr_Z-Contact%, MarApr_Contact%, 2015_AVG, 2015_H, 2015_AB, 2016_AVG, 2016_H, 2016_AB, 2017_AVG, 2017_H, 2017_AB

5 Results

In order to properly compare each model, we first look at the absolute value of the difference between the model's predicted full season batting averages and the actual full season's batting average.

Model	Average Difference	Standard Deviation
BDN	0.02471	0.01901
BDW	0.02077	0.01604
BDDW	0.02016	0.01512
MLR1	0.01972	0.01447
MLR2	0.01922	0.01455
MLR3	0.01937	0.01445
MLR4	0.01981	0.01440
MLR5	0.01873	0.01285

Table 1: A table of the 8 separate models and their associated values

Now, it can be easily seen that each of these overlap in terms of their upper and lower bounds based on one standard deviation up or down. But that doesn't necessarily mean that all of the models are identical. We can perform an Analysis of Variance, or ANOVA, Test to test for statistically significant differences between our models. For our test, we will be using $p = 0.05$ as our standard of significance.

Anova: Single Factor						
SUMMARY						
Groups	*Count*	*Sum*	*Average*	*Variance*		*Average Variance*
BDN_Diff	309	7.63627212	0.02471285	0.00036146		0.000231204
BDW_Diff	309	6.4185494	0.020772	0.0002572		
BDDW_Diff	309	6.22841377	0.02015668	0.00022872		
MLR1_Diff	309	6.09242	0.01971657	0.00020942		
MLR2_Diff	309	5.93786283	0.01921638	0.00021157		
MLR3_Diff	309	5.98663701	0.01937423	0.00020894		
MLR4_Diff	309	6.12136019	0.01981023	0.00020729		
MLR5_Diff	309	5.78634192	0.01872603	0.00016502		
ANOVA						
rce of Variat	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Gr	0.00766464	7	0.00109495	4.73585586	2.6896E-05	2.013291924
Within Grou	0.5696863	2464	0.0002312			
Total	0.57735094	2471				

Figure 2: The ANOVA Table for our 8 models

In an ANOVA Table, we know that if our p-value is less than our standard of significance, then there exists at least 1 group with a statistically significant difference from the others. Here, we can see that the p-value = 2.6896E-05, which means that it is much much smaller than 0.05. Therefore, at least one model is statistically significantly different from the others. In order to determine which one, we can perform the Tukey-Kramer Post-Hoc Test, which involves comparing the absolute value of the difference in means between any two group to a critical Q value, which is determined by the following:

$$Q_{CRIT} = Q^* \sqrt{\frac{s^2_{pooled}}{n}} \tag{6}$$

Here, Q^* is the q-value taken from a q-table [6] using the values of number of groups (8) and the degrees of freedom between groups (since most q-tables to do not go that high, we can take a conservative estimate of 240, the largest non-infinite number most q-tables display), s^2_{pooled} is the pooled variance, which can be calculated by taking the average of all the variances (denoted as Average Variance in Figure 2), and n is the size of the groups (denoted as Count in Figure 2)). If Q_{CRIT} is smaller than the absolute value of the difference in means between any two groups, the two groups are statistically significantly different. Below is the Tukey-Kramer Post-Hoc test for all groups combinations:

Group 1	Group 2	ABS MEAN DIFF	Q Crit	Significant?
BDN_Diff	BDW_Diff	0.00394085	0.00342455	Yes
BDN_Diff	BDDW_Diff	0.004556176	0.00342455	Yes
BDN_Diff	MLR1_Diff	0.004996285	0.00342455	Yes
BDN_Diff	MLR2_Diff	0.00549647	0.00342455	Yes
BDN_Diff	MLR3_Diff	0.005338625	0.00342455	Yes
BDN_Diff	MLR4_Diff	0.004902628	0.00342455	Yes
BDN_Diff	MLR5_Diff	0.005986829	0.00342455	Yes
BDW_Diff	BDDW_Diff	0.000615326	0.00342455	No
BDW_Diff	MLR1_Diff	0.001055435	0.00342455	No
BDW_Diff	MLR2_Diff	0.00155562	0.00342455	No
BDW_Diff	MLR3_Diff	0.001397775	0.00342455	No
BDW_Diff	MLR4_Diff	0.000961777	0.00342455	No
BDW_Diff	MLR5_Diff	0.002045979	0.00342455	No
BDDW_Diff	MLR1_Diff	0.000440109	0.00342455	No
BDDW_Diff	MLR2_Diff	0.000940294	0.00342455	No
BDDW_Diff	MLR3_Diff	0.000782449	0.00342455	No
BDDW_Diff	MLR4_Diff	0.000346452	0.00342455	No
BDDW_Diff	MLR5_Diff	0.001430653	0.00342455	No
MLR1_Diff	MLR2_Diff	0.000500185	0.00342455	No
MLR1_Diff	MLR3_Diff	0.00034234	0.00342455	No
MLR1_Diff	MLR4_Diff	9.36576E-05	0.00342455	No
MLR1_Diff	MLR5_Diff	0.000990544	0.00342455	No
MLR2_Diff	MLR3_Diff	0.000157845	0.00342455	No
MLR2_Diff	MLR4_Diff	0.000593843	0.00342455	No
MLR2_Diff	MLR5_Diff	0.000490359	0.00342455	No
MLR3_Diff	MLR4_Diff	0.000435997	0.00342455	No
MLR3_Diff	MLR5_Diff	0.000648204	0.00342455	No
MLR4_Diff	MLR5_Diff	0.001084201	0.00342455	No

Figure 3: The Tukey-Kramer Post-Hoc Test for all model comparisons

The only significantly different model is the BDN model, which is different from each other model. Of note is that the test is inconclusive whether the 5 mLR models are statistically different, so even though MLR5 produces a lower average difference, it is not statistically significant.

All model results and predictions are displayed in the section below entitled: “Full Model Outputs”

6 Outliers and Examinations

In predicting player’s batting averages, inevitably there will be errors involved with the predictions. However, the outliers should be examined particularly to determine whether it was an error inherent to your model, or whether circumstances unrelated to the statistics affected your results. As an example, here are the top 5 largest deviations from the predicted to the real for MLR5 (information pulled from Baseball Reference [5]):

- Tony Wolters, playerid 11470, deviation = 0.070 - two seasons of decent batting gave way to a season of terrible batting, going from .240 to .170. That sharp of a drop is hard to predict.
- Pedro Severino, playerid 14523, deviation = 0.065 - 2018 was Pedro’s first season truly batting and so even though the model had data from 2015, 2016, and 2017, it didn’t calibrate the model enough.
- Sandy Leon, playerid 5273, deviation = 0.060 - similar reasoning to Tony Wolters. The model is especially affect by his 2016 season where he hit .310.
- Gary Sanchez, playerid 11442, deviation = 0.057 - Again, two strong seasons prior to a crash season leads to an error in predictions.
- Carlos Correa, playerid 14162, deviation = 0.051 - 3 strong preceding seasons all with a continued upward trend are succinctly followed by .076 drop in effiency, especially following a strong .315 season in 2017.

Of the 309 predicted values, 49 of the MLR5 predictions were 1 or more standard deviations away. While not every outlier prediction was due to poor hitting seasons (Mookie Betts hit .346 in 2018, an increase of 0.082 over his 2017 BA and a deviation of 0.033 from his MLR5 prediction), the majority seem to be players experiencing career worst years. Ideally, there would be something in the model that could catch this, but this study did not find it. If we remove the top 5% worst performing predicted BA’s, we improve our MLR5 by 0.00173. Therefore, a

7 Conclusion

As can be seen in the above work, several models to predict 309 player’s full 2018 season batting averages using data from their midseason form were relatively successful at approximating the full season batting averages. If this were to continue, a further step to take could be to normalize the error terms by removing the top 5% worst performing predictions, in order to get closer to the actual predictions of players who don't suffer massive career down years. As an example, by removing the top 5% worst performing predicted BA's from the MLR5 model, the model improves by a score of 0.00173. Other further steps could be to normalize the Beta distributions with not just predicted player average batting averages (the μ_{2015}, μ_{2016}, and μ_{2017}) but with their actual recorded batting averages during those years, creating a more accurate average batting average for Player X.

References

[1] David Robinson's Post on StackExchange
https://stats.stackexchange.com/questions/47771/what-is-the-intuition-behind-beta-distribution/4778247782

[2] David Robinson's Blog Post on his Website
http://varianceexplained.org/r/empirical_bayes_baseball/

[3] Beta distribution
https://en.wikipedia.org/wiki/Beta_distribution

[4] Batting 2018 Data fangraphs.com

[5] Baseball Reference
https://www.baseball-reference.com/

[6] q-table
https://www.real-statistics.com/statistics-tables/studentized-range-q-table/

8 Full Model Outputs

A	B	D	AM	AQ	AR	AY	AZ	BA	BB	BC
playerid	Name	FullSeason_AVG	Beta_D_Norm	Beta_D_W	Beta_D_DoubleW	MLR1	MLR2	MLR3	MLR4	MLR5
11680	Elias Diaz	0.286	0.290	0.269	0.289	0.292	0.278	0.271	0.271	0.273
12161	Xander Bogaerts	0.288	0.291	0.301	0.318	0.292	0.284	0.283	0.284	0.304
11342	Jesus Aguilar	0.274	0.284	0.281	0.294	0.280	0.275	0.275	0.274	0.262
10816	Jedd Gyorko	0.262	0.276	0.269	0.275	0.254	0.255	0.251	0.251	0.249
11493	Manny Machado	0.297	0.294	0.293	0.312	0.293	0.295	0.299	0.302	0.305
11739	J.T. Realmuto	0.277	0.281	0.277	0.287	0.272	0.258	0.255	0.255	0.266
13355	Luke Maile	0.248	0.279	0.233	0.244	0.261	0.259	0.257	0.258	0.249
5417	Jose Altuve	0.316	0.292	0.342	0.344	0.303	0.309	0.311	0.311	0.343
11205	Adam Eaton	0.301	0.277	0.292	0.297	0.272	0.269	0.264	0.266	0.273
13611	Mookie Betts	0.346	0.287	0.293	0.306	0.289	0.278	0.281	0.289	0.313
11476	Odubel Herrera	0.255	0.288	0.299	0.311	0.291	0.291	0.292	0.291	0.296
4106	Michael Brantley	0.309	0.284	0.304	0.312	0.286	0.297	0.298	0.288	0.280
2967	Tommy Pham	0.275	0.286	0.298	0.308	0.285	0.281	0.281	0.283	0.275
19755	Shohei Ohtani	0.285	0.279	0.279	0.287	0.266	0.278	0.273	0.275	0.272
4962	Asdrubal Cabrera	0.262	0.288	0.294	0.306	0.291	0.290	0.292	0.292	0.287
9345	Brock Holt	0.277	0.280	0.257	0.269	0.277	0.285	0.284	0.275	0.261
4418	Jed Lowrie	0.267	0.289	0.289	0.303	0.288	0.298	0.301	0.299	0.286
6184	J.D. Martinez	0.330	0.287	0.310	0.318	0.281	0.290	0.291	0.287	0.294
14145	Daniel Robertson	0.262	0.281	0.258	0.271	0.269	0.263	0.262	0.266	0.263
14162	Carlos Correa	0.239	0.285	0.307	0.314	0.292	0.287	0.288	0.289	0.290
13853	Joey Wendle	0.300	0.282	0.281	0.291	0.280	0.290	0.288	0.285	0.273
13608	Mallex Smith	0.296	0.282	0.276	0.288	0.281	0.282	0.282	0.275	0.271
7435	Ben Zobrist	0.305	0.278	0.259	0.268	0.268	0.268	0.268	0.269	0.267
8709	Elvis Andrus	0.256	0.278	0.299	0.304	0.272	0.270	0.268	0.271	0.282
6012	Didi Gregorius	0.268	0.284	0.293	0.302	0.289	0.287	0.289	0.287	0.287
12552	Eugenio Suarez	0.283	0.278	0.268	0.276	0.265	0.250	0.251	0.254	0.260
16997	Gleyber Torres	0.271	0.275	0.275	0.279	0.262	0.243	0.243	0.242	0.249
3123	Gregor Blanco	0.217	0.278	0.261	0.270	0.271	0.258	0.258	0.254	0.247
11738	Christian Villanueva	0.236	0.280	0.286	0.294	0.262	0.269	0.269	0.269	0.266
12225	Scott Schebler	0.255	0.277	0.256	0.264	0.269	0.256	0.258	0.257	0.248
5631	Matt Kemp	0.290	0.280	0.282	0.289	0.267	0.262	0.261	0.263	0.266
15191	Chad Pinder	0.258	0.276	0.259	0.266	0.246	0.257	0.254	0.253	0.254
15640	Aaron Judge	0.278	0.282	0.283	0.292	0.271	0.271	0.271	0.273	0.273
11368	Yasmani Grandal	0.241	0.280	0.258	0.271	0.276	0.267	0.267	0.271	0.253
5361	Freddie Freeman	0.309	0.281	0.315	0.314	0.284	0.287	0.289	0.282	0.300
3269	Robinson Cano	0.303	0.280	0.291	0.297	0.280	0.286	0.287	0.284	0.296
10762	Corey Dickerson	0.300	0.281	0.284	0.292	0.288	0.285	0.284	0.283	0.277
12927	Brandon Nimmo	0.263	0.274	0.271	0.275	0.243	0.252	0.252	0.250	0.252
10847	Andrelton Simmons	0.292	0.280	0.286	0.292	0.283	0.279	0.280	0.282	0.280
4579	Starlin Castro	0.278	0.281	0.294	0.299	0.288	0.285	0.288	0.287	0.285
5107	Jefry Marte	0.216	0.275	0.241	0.249	0.266	0.250	0.249	0.251	0.242
18721	Guillermo Heredia	0.236	0.274	0.261	0.265	0.256	0.257	0.257	0.252	0.253
9777	Nolan Arenado	0.297	0.279	0.305	0.306	0.273	0.277	0.275	0.272	0.290

A	B	D	AM	AQ	AR	AY	AZ	BA	BB	BC
playerid	Name	FullSeason_AVG	Beta_D_Norm	Beta_D_W	Beta_D_DoubleW	MLR1	MLR2	MLR3	MLR4	MLR5
639	Adrian Beltre	0.273	0.279	0.305	0.307	0.285	0.280	0.281	0.280	0.290
11737	Nicholas Castellanos	0.298	0.280	0.283	0.290	0.280	0.289	0.289	0.282	0.277
8203	Dee Gordon	0.268	0.280	0.304	0.305	0.289	0.296	0.294	0.294	0.303
14274	Mitch Haniger	0.285	0.280	0.281	0.288	0.268	0.267	0.270	0.276	0.272
11445	Mark Canha	0.249	0.276	0.242	0.251	0.260	0.257	0.257	0.262	0.244
5275	Francisco Cervelli	0.259	0.278	0.271	0.279	0.271	0.259	0.262	0.265	0.261
13836	Matt Duffy	0.294	0.277	0.278	0.284	0.265	0.265	0.266	0.267	0.265
13066	Teoscar Hernandez	0.239	0.276	0.268	0.275	0.266	0.261	0.260	0.259	0.257
4747	Curtis Granderson	0.242	0.276	0.238	0.249	0.258	0.256	0.253	0.259	0.248
7996	Jose Martinez	0.305	0.279	0.297	0.299	0.282	0.279	0.277	0.282	0.273
3086	Mitch Moreland	0.245	0.276	0.256	0.264	0.265	0.259	0.260	0.259	0.255
12434	Kevin Pillar	0.252	0.279	0.272	0.280	0.282	0.280	0.278	0.283	0.276
13590	Jesse Winker	0.299	0.277	0.284	0.289	0.271	0.275	0.276	0.272	0.269
14221	Jorge Soler	0.265	0.277	0.242	0.254	0.261	0.257	0.260	0.262	0.248
16472	Rhys Hoskins	0.246	0.278	0.274	0.281	0.266	0.265	0.268	0.268	0.266
4892	Mike Moustakas	0.251	0.279	0.280	0.286	0.274	0.274	0.275	0.280	0.267
10264	Brandon Belt	0.253	0.277	0.266	0.274	0.263	0.274	0.275	0.270	0.268
5930	Nick Markakis	0.297	0.278	0.282	0.287	0.283	0.287	0.285	0.279	0.284
2136	David Peralta	0.293	0.278	0.292	0.294	0.269	0.272	0.272	0.272	0.272
6153	Eduardo Escobar	0.272	0.277	0.262	0.270	0.269	0.270	0.272	0.269	0.256
10047	Wil Myers	0.253	0.274	0.255	0.260	0.259	0.249	0.247	0.258	0.256
12144	Max Kepler	0.224	0.276	0.256	0.265	0.272	0.275	0.274	0.271	0.260
10339	Scooter Gennett	0.310	0.278	0.287	0.290	0.276	0.281	0.283	0.282	0.275
5933	Jean Segura	0.304	0.278	0.299	0.299	0.286	0.279	0.278	0.280	0.291
14968	Victor Caratini	0.232	0.273	0.271	0.274	0.254	0.252	0.249	0.251	0.257
7304	Salvador Perez	0.235	0.272	0.265	0.268	0.254	0.267	0.264	0.262	0.257
16556	Ozzie Albies	0.261	0.276	0.281	0.285	0.273	0.271	0.274	0.277	0.271
1433	Wilson Ramos	0.306	0.274	0.276	0.279	0.264	0.273	0.273	0.274	0.267
10155	Mike Trout	0.312	0.275	0.302	0.299	0.265	0.271	0.273	0.276	0.292
9256	A.J. Pollock	0.257	0.275	0.280	0.283	0.267	0.269	0.270	0.276	0.269
1857	Joe Mauer	0.282	0.274	0.290	0.290	0.271	0.264	0.264	0.264	0.269
15429	Kris Bryant	0.272	0.274	0.292	0.292	0.271	0.277	0.276	0.269	0.282
11850	Tyler Austin	0.230	0.273	0.264	0.269	0.251	0.251	0.245	0.244	0.245
9077	Lorenzo Cain	0.308	0.275	0.295	0.293	0.275	0.272	0.272	0.271	0.282
3516	Eric Hosmer	0.253	0.275	0.300	0.297	0.270	0.275	0.271	0.268	0.284
8259	Kurt Suzuki	0.271	0.274	0.272	0.275	0.268	0.268	0.268	0.263	0.253
9874	DJ LeMahieu	0.276	0.275	0.308	0.303	0.274	0.276	0.276	0.283	0.309
15878	Miguel Andujar	0.297	0.274	0.280	0.282	0.268	0.265	0.266	0.265	0.260
14109	Albert Almora Jr.	0.286	0.274	0.286	0.287	0.266	0.266	0.266	0.262	0.264
11899	Joc Pederson	0.248	0.273	0.236	0.244	0.263	0.251	0.251	0.254	0.236
13593	Jose Peraza	0.288	0.275	0.275	0.279	0.283	0.287	0.287	0.286	0.275
18314	Dansby Swanson	0.238	0.275	0.259	0.266	0.269	0.273	0.273	0.274	0.265
12861	Anthony Rendon	0.308	0.272	0.289	0.288	0.257	0.259	0.260	0.263	0.270

A	B	D	AM	AQ	AR	AY	AZ	BA	BB	BC
playerid	Name	FullSeason_AVG	Beta_D_Norm	Beta_D_W	Beta_D_DoubleW	MLR1	MLR2	MLR3	MLR4	MLR5
9241	Starling Marte	0.277	0.274	0.286	0.286	0.275	0.275	0.273	0.271	0.276
10459	Adeiny Hechavarria	0.247	0.273	0.262	0.267	0.271	0.271	0.274	0.273	0.261
14553	Nomar Mazara	0.258	0.274	0.265	0.270	0.267	0.269	0.268	0.272	0.274
16252	Trea Turner	0.271	0.274	0.290	0.288	0.277	0.278	0.280	0.272	0.272
13621	Jeimer Candelario	0.224	0.273	0.273	0.276	0.266	0.273	0.273	0.277	0.267
10556	Cesar Hernandez	0.253	0.273	0.289	0.287	0.269	0.266	0.266	0.266	0.276
7859	Charlie Blackmon	0.291	0.273	0.313	0.304	0.257	0.261	0.262	0.268	0.298
15161	Mitch Garver	0.268	0.271	0.262	0.264	0.242	0.238	0.235	0.245	0.251
12979	Javier Baez	0.290	0.273	0.275	0.276	0.267	0.262	0.260	0.262	0.258
15998	Cody Bellinger	0.260	0.273	0.271	0.274	0.267	0.258	0.261	0.255	0.258
16909	Colin Moran	0.277	0.272	0.267	0.270	0.263	0.262	0.261	0.255	0.253
13367	Stephen Piscotty	0.267	0.272	0.260	0.264	0.270	0.266	0.267	0.263	0.262
5491	Austin Romine	0.244	0.271	0.245	0.247	0.242	0.240	0.241	0.240	0.245
4922	Ender Inciarte	0.265	0.272	0.293	0.288	0.278	0.280	0.279	0.276	0.288
18015	Paul DeJong	0.241	0.271	0.278	0.277	0.249	0.242	0.243	0.252	0.259
12533	Marcus Semien	0.255	0.271	0.255	0.260	0.271	0.264	0.264	0.265	0.251
2434	Nelson Cruz	0.256	0.271	0.285	0.283	0.258	0.261	0.260	0.261	0.280
14818	JaCoby Jones	0.207	0.270	0.241	0.246	0.258	0.261	0.260	0.255	0.249
16478	Kyle Schwarber	0.238	0.271	0.238	0.244	0.251	0.251	0.248	0.251	0.237
9218	Paul Goldschmidt	0.290	0.271	0.291	0.286	0.257	0.257	0.256	0.257	0.280
9166	Buster Posey	0.284	0.271	0.301	0.294	0.266	0.267	0.268	0.271	0.288
15149	Trey Mancini	0.242	0.270	0.282	0.280	0.263	0.257	0.256	0.261	0.261
4810	Brian McCann	0.212	0.270	0.247	0.251	0.249	0.255	0.255	0.257	0.243
11477	Christian Yelich	0.326	0.270	0.283	0.281	0.258	0.257	0.254	0.255	0.275
11846	Leonys Martin	0.255	0.270	0.235	0.243	0.257	0.263	0.264	0.263	0.246
10071	Jonathan Villar	0.260	0.270	0.260	0.263	0.256	0.258	0.255	0.257	0.259
9957	Steve Pearce	0.284	0.270	0.260	0.262	0.260	0.254	0.252	0.248	0.243
4314	Joey Votto	0.284	0.270	0.305	0.296	0.266	0.286	0.286	0.270	0.295
12546	C.J. Cron	0.253	0.270	0.262	0.264	0.254	0.255	0.258	0.263	0.254
16505	Matt Chapman	0.278	0.270	0.257	0.260	0.258	0.252	0.252	0.257	0.253
3376	Nick Hundley	0.241	0.270	0.260	0.261	0.249	0.249	0.250	0.249	0.249
17232	Yoan Moncada	0.235	0.269	0.256	0.259	0.247	0.248	0.249	0.252	0.248
15172	Tim Anderson	0.240	0.269	0.265	0.265	0.259	0.261	0.263	0.263	0.269
7870	Jonathan Lucroy	0.241	0.269	0.271	0.270	0.262	0.258	0.258	0.265	0.264
11936	Joe Panik	0.254	0.269	0.275	0.273	0.267	0.269	0.268	0.270	0.269
19238	Lourdes Gurriel Jr.	0.281	0.270	0.270	0.269	0.254	0.251	0.251	0.256	0.258
12856	George Springer	0.265	0.269	0.274	0.272	0.267	0.264	0.266	0.264	0.266
13510	Jose Ramirez	0.270	0.269	0.296	0.288	0.262	0.264	0.265	0.272	0.282
11281	Whit Merrifield	0.304	0.269	0.279	0.276	0.265	0.266	0.266	0.264	0.273
12179	Maikel Franco	0.270	0.269	0.246	0.249	0.262	0.261	0.261	0.256	0.251
18289	Brian Anderson	0.273	0.269	0.267	0.267	0.261	0.257	0.256	0.253	0.253
11609	Willson Contreras	0.249	0.269	0.273	0.271	0.257	0.257	0.260	0.256	0.261
9549	David Freese	0.296	0.269	0.264	0.264	0.247	0.248	0.248	0.249	0.251

A	B	D	AM	AQ	AR	AY	AZ	BA	BB	BC
playerid	Name	FullSeason_AVG	Beta_D_Norm	Beta_D_W	Beta_D_DoubleW	MLR1	MLR2	MLR3	MLR4	MLR5
11602	Yolmer Sanchez	0.242	0.268	0.255	0.257	0.265	0.264	0.264	0.264	0.244
8202	Josh Harrison	0.250	0.269	0.273	0.272	0.256	0.250	0.250	0.249	0.257
15676	Jose Abreu	0.265	0.268	0.290	0.283	0.256	0.258	0.258	0.259	0.279
5913	Leury Garcia	0.271	0.269	0.266	0.265	0.255	0.261	0.260	0.259	0.249
12147	Nick Ahmed	0.234	0.268	0.243	0.247	0.253	0.257	0.257	0.261	0.240
9393	Matt Adams	0.239	0.269	0.264	0.263	0.243	0.254	0.250	0.249	0.245
5485	Jose Pirela	0.249	0.267	0.266	0.265	0.268	0.262	0.260	0.258	0.245
7007	Yadier Molina	0.261	0.268	0.275	0.271	0.261	0.261	0.260	0.264	0.270
17678	Alex Bregman	0.286	0.267	0.273	0.269	0.265	0.266	0.266	0.261	0.263
3410	Ryan Braun	0.254	0.267	0.275	0.271	0.258	0.257	0.257	0.259	0.267
16512	Isiah Kiner-Falefa	0.261	0.268	0.268	0.266	0.250	0.253	0.252	0.258	0.258
9627	Yan Gomes	0.266	0.268	0.227	0.232	0.239	0.251	0.249	0.247	0.229
17350	Rafael Devers	0.240	0.267	0.271	0.267	0.254	0.258	0.258	0.256	0.256
14344	Matt Olson	0.247	0.267	0.258	0.258	0.246	0.243	0.243	0.247	0.244
18030	Harrison Bader	0.264	0.269	0.262	0.261	0.238	0.251	0.247	0.244	0.248
785	Todd Frazier	0.213	0.267	0.230	0.235	0.255	0.249	0.251	0.253	0.235
11379	Delino DeShields	0.216	0.268	0.257	0.257	0.248	0.247	0.246	0.251	0.246
10059	Max Stassi	0.226	0.268	0.260	0.259	0.231	0.228	0.230	0.233	0.227
4146	Gorkys Hernandez	0.234	0.268	0.259	0.259	0.244	0.244	0.243	0.236	0.242
5409	Pablo Sandoval	0.248	0.268	0.239	0.240	0.240	0.231	0.231	0.237	0.227
8347	Denard Span	0.261	0.267	0.269	0.266	0.259	0.257	0.256	0.259	0.263
9054	Justin Smoak	0.242	0.266	0.256	0.255	0.255	0.258	0.259	0.257	0.244
9368	Evan Longoria	0.244	0.266	0.262	0.261	0.249	0.250	0.252	0.254	0.260
13157	Nicky Delmonico	0.215	0.267	0.265	0.263	0.248	0.254	0.253	0.246	0.248
7226	Matt Davidson	0.228	0.266	0.244	0.246	0.243	0.246	0.242	0.249	0.240
3711	Eric Thames	0.219	0.266	0.255	0.254	0.244	0.241	0.241	0.245	0.250
9892	Jay Bruce	0.223	0.265	0.251	0.251	0.253	0.253	0.254	0.249	0.239
5352	Yangervis Solarte	0.226	0.265	0.261	0.258	0.253	0.257	0.255	0.259	0.255
5209	Alex Gordon	0.245	0.267	0.225	0.228	0.249	0.246	0.247	0.243	0.234
14106	Addison Russell	0.250	0.266	0.243	0.244	0.259	0.252	0.252	0.250	0.238
10324	Marcell Ozuna	0.280	0.265	0.283	0.274	0.255	0.261	0.260	0.260	0.266
15223	Adam Frazier	0.277	0.266	0.272	0.268	0.253	0.252	0.252	0.260	0.261
9810	Brian Dozier	0.215	0.264	0.262	0.259	0.252	0.252	0.251	0.251	0.249
1177	Albert Pujols	0.245	0.264	0.248	0.248	0.254	0.253	0.252	0.258	0.248
6609	Freddy Galvis	0.248	0.264	0.252	0.251	0.251	0.258	0.258	0.255	0.247
9744	Justin Bour	0.227	0.265	0.271	0.266	0.248	0.244	0.243	0.248	0.246
11579	Bryce Harper	0.249	0.265	0.284	0.275	0.262	0.254	0.252	0.244	0.260
6547	Jordy Mercer	0.251	0.265	0.253	0.252	0.257	0.253	0.256	0.255	0.248
4940	Jason Heyward	0.270	0.265	0.253	0.252	0.255	0.254	0.254	0.251	0.248
17919	Ian Happ	0.233	0.266	0.258	0.256	0.229	0.234	0.235	0.234	0.242
7287	Carlos Gonzalez	0.276	0.266	0.267	0.263	0.249	0.240	0.242	0.242	0.255
14523	Pedro Severino	0.168	0.266	0.262	0.260	0.242	0.243	0.242	0.244	0.233
12916	Francisco Lindor	0.277	0.263	0.271	0.264	0.255	0.256	0.256	0.258	0.273

A	B	D	AM	AQ	AR	AY	AZ	BA	BB	BC
playerid	Name	FullSeason_AVG	Beta_D_Norm	Beta_D_W	Beta_D_DoubleW	MLR1	MLR2	MLR3	MLR4	MLR5
4969	Luis Valbuena	0.199	0.264	0.228	0.231	0.241	0.238	0.239	0.244	0.226
12859	James McCann	0.220	0.265	0.247	0.246	0.256	0.253	0.252	0.249	0.239
11982	Travis Shaw	0.241	0.263	0.260	0.255	0.252	0.251	0.251	0.253	0.248
10815	Jurickson Profar	0.254	0.265	0.243	0.243	0.248	0.260	0.259	0.249	0.248
10951	Greg Garcia	0.221	0.267	0.260	0.258	0.245	0.250	0.250	0.245	0.242
5666	Devin Mesoraco	0.221	0.267	0.234	0.235	0.238	0.239	0.239	0.242	0.234
17901	Andrew Benintendi	0.290	0.263	0.265	0.260	0.262	0.262	0.262	0.256	0.257
10542	Derek Dietrich	0.265	0.262	0.254	0.251	0.248	0.253	0.252	0.252	0.244
6848	Eduardo Nunez	0.265	0.263	0.285	0.274	0.252	0.250	0.249	0.251	0.262
5038	Josh Donaldson	0.246	0.266	0.271	0.267	0.238	0.241	0.240	0.240	0.258
6368	Adam Jones	0.281	0.261	0.267	0.260	0.249	0.253	0.254	0.255	0.259
10472	Enrique Hernandez	0.256	0.264	0.232	0.233	0.244	0.238	0.238	0.239	0.228
15518	Amed Rosario	0.256	0.263	0.257	0.253	0.249	0.245	0.248	0.248	0.248
5227	Jon Jay	0.268	0.262	0.272	0.263	0.252	0.258	0.259	0.257	0.253
6310	Alcides Escobar	0.231	0.262	0.250	0.247	0.259	0.260	0.260	0.254	0.249
10348	Domingo Santana	0.265	0.262	0.262	0.256	0.246	0.250	0.250	0.244	0.242
9785	Kyle Seager	0.221	0.261	0.252	0.248	0.250	0.250	0.249	0.252	0.253
9112	Khris Davis	0.247	0.260	0.245	0.242	0.242	0.237	0.239	0.237	0.234
2530	Yonder Alonso	0.250	0.261	0.257	0.252	0.245	0.243	0.245	0.248	0.247
7802	Miguel Rojas	0.252	0.260	0.265	0.257	0.252	0.253	0.249	0.253	0.243
14320	Wilmer Difo	0.230	0.263	0.263	0.257	0.248	0.242	0.243	0.241	0.238
5760	Avisail Garcia	0.236	0.263	0.286	0.275	0.248	0.253	0.251	0.246	0.252
3892	Josh Reddick	0.242	0.262	0.284	0.272	0.244	0.240	0.240	0.243	0.254
3174	Shin-Soo Choo	0.264	0.260	0.253	0.248	0.248	0.246	0.246	0.247	0.239
5497	Marwin Gonzalez	0.247	0.261	0.273	0.263	0.246	0.245	0.245	0.249	0.251
393	Victor Martinez	0.251	0.262	0.258	0.252	0.251	0.246	0.247	0.249	0.249
13757	Chris Taylor	0.254	0.259	0.258	0.251	0.249	0.243	0.242	0.240	0.237
13145	Josh Bell	0.261	0.260	0.253	0.248	0.253	0.249	0.249	0.251	0.250
12155	Eddie Rosario	0.288	0.261	0.270	0.261	0.246	0.240	0.239	0.237	0.241
5297	Aaron Hicks	0.248	0.264	0.249	0.246	0.240	0.239	0.236	0.237	0.232
10030	Chris Owings	0.206	0.262	0.258	0.253	0.242	0.249	0.249	0.249	0.243
11265	Jonathan Schoop	0.233	0.263	0.275	0.267	0.241	0.236	0.236	0.235	0.251
12775	Brad Miller	0.248	0.263	0.226	0.226	0.239	0.243	0.245	0.243	0.234
4949	Giancarlo Stanton	0.266	0.259	0.260	0.252	0.241	0.243	0.242	0.244	0.241
2616	Zack Cozart	0.219	0.259	0.267	0.257	0.249	0.246	0.245	0.249	0.248
8392	Daniel Descalso	0.238	0.262	0.240	0.238	0.246	0.245	0.247	0.243	0.234
5222	Justin Upton	0.257	0.259	0.255	0.249	0.246	0.242	0.243	0.245	0.242
10200	Tucker Barnhart	0.248	0.261	0.258	0.252	0.246	0.246	0.245	0.242	0.240
14388	Ronald Guzman	0.235	0.265	0.265	0.260	0.236	0.238	0.240	0.241	0.246
3448	Jeff Mathis	0.200	0.266	0.232	0.232	0.224	0.233	0.235	0.238	0.233
10346	John Ryan Murphy	0.202	0.266	0.242	0.240	0.236	0.230	0.235	0.240	0.231
12564	Trevor Story	0.291	0.259	0.245	0.240	0.237	0.241	0.240	0.239	0.245
17975	Scott Kingery	0.226	0.260	0.256	0.249	0.242	0.238	0.238	0.238	0.241

A	B	D	AM	AQ	AR	AY	AZ	BA	BB	BC
playerid	Name	FullSeason_AVG	Beta_D_Norm	Beta_D_W	Beta_D_DoubleW	MLR1	MLR2	MLR3	MLR4	MLR5
19198	Yuli Gurriel	0.291	0.263	0.277	0.268	0.255	0.249	0.249	0.249	0.258
6195	Ian Kinsler	0.240	0.263	0.249	0.245	0.247	0.253	0.255	0.252	0.262
13613	Ketel Marte	0.260	0.258	0.253	0.246	0.252	0.258	0.256	0.254	0.244
10231	Jose Iglesias	0.269	0.259	0.251	0.245	0.252	0.245	0.244	0.248	0.246
11489	Michael A. Taylor	0.227	0.258	0.248	0.242	0.244	0.242	0.240	0.238	0.225
8553	Gerardo Parra	0.284	0.260	0.275	0.263	0.247	0.252	0.251	0.250	0.254
16376	Michael Conforto	0.243	0.262	0.256	0.250	0.236	0.237	0.236	0.233	0.230
5254	Robbie Grossman	0.273	0.263	0.250	0.246	0.239	0.240	0.240	0.240	0.245
4298	Matt Wieters	0.238	0.264	0.236	0.234	0.235	0.247	0.247	0.248	0.241
9848	Austin Jackson	0.245	0.260	0.275	0.264	0.235	0.239	0.240	0.239	0.239
12092	Niko Goodrum	0.245	0.263	0.253	0.249	0.232	0.244	0.245	0.240	0.245
14128	Joey Gallo	0.206	0.255	0.220	0.219	0.231	0.235	0.235	0.238	0.221
8267	Chris Iannetta	0.224	0.259	0.219	0.219	0.238	0.234	0.231	0.235	0.221
8418	Ehire Adrianza	0.251	0.264	0.250	0.246	0.233	0.238	0.238	0.235	0.229
12325	Jace Peterson	0.200	0.265	0.237	0.235	0.229	0.223	0.223	0.223	0.223
12164	Miguel Sano	0.199	0.258	0.249	0.241	0.225	0.228	0.229	0.230	0.230
5223	Cameron Maybin	0.249	0.259	0.247	0.241	0.238	0.238	0.236	0.239	0.242
12180	Jorge Alfaro	0.262	0.260	0.266	0.257	0.226	0.248	0.245	0.237	0.241
9847	Andrew McCutchen	0.255	0.256	0.259	0.247	0.240	0.234	0.232	0.230	0.244
15447	Ryon Healy	0.235	0.263	0.268	0.262	0.244	0.247	0.249	0.247	0.263
14738	Phillip Ervin	0.252	0.263	0.262	0.256	0.231	0.222	0.221	0.217	0.229
9927	Brett Gardner	0.236	0.255	0.250	0.241	0.249	0.241	0.240	0.239	0.240
2502	Lucas Duda	0.241	0.255	0.225	0.221	0.233	0.235	0.235	0.239	0.221
13301	Max Muncy	0.263	0.264	0.234	0.232	0.231	0.233	0.231	0.235	0.231
3353	Matt Joyce	0.208	0.258	0.233	0.229	0.237	0.239	0.238	0.235	0.225
12282	Rougned Odor	0.253	0.263	0.224	0.222	0.233	0.234	0.236	0.235	0.236
11472	Dixon Machado	0.206	0.254	0.246	0.237	0.246	0.230	0.231	0.235	0.228
6364	Danny Valencia	0.263	0.261	0.258	0.251	0.233	0.237	0.237	0.237	0.249
11442	Gary Sanchez	0.186	0.253	0.259	0.246	0.233	0.226	0.227	0.233	0.243
11003	Evan Gattis	0.226	0.255	0.246	0.237	0.230	0.239	0.239	0.237	0.230
15464	Hunter Renfroe	0.248	0.260	0.244	0.238	0.235	0.228	0.229	0.231	0.233
15197	Carlos Asuaje	0.196	0.253	0.251	0.239	0.234	0.235	0.236	0.233	0.235
12907	Gregory Polanco	0.254	0.252	0.243	0.232	0.232	0.228	0.227	0.230	0.230
12294	Cory Spangenberg	0.235	0.258	0.254	0.245	0.235	0.232	0.231	0.232	0.229
5827	Wilmer Flores	0.267	0.259	0.258	0.250	0.240	0.242	0.241	0.237	0.237
2829	Manny Pina	0.252	0.259	0.262	0.252	0.237	0.244	0.243	0.247	0.249
12984	Jackie Bradley Jr.	0.234	0.253	0.240	0.231	0.238	0.234	0.232	0.228	0.230
12532	Kolten Wong	0.249	0.256	0.256	0.245	0.236	0.238	0.241	0.236	0.232
14225	Yasiel Puig	0.267	0.253	0.247	0.236	0.238	0.235	0.235	0.233	0.231
11270	Aaron Altherr	0.181	0.255	0.243	0.234	0.230	0.228	0.226	0.225	0.223
14712	Manuel Margot	0.245	0.255	0.250	0.240	0.240	0.224	0.224	0.223	0.232
12158	Austin Barnes	0.205	0.260	0.259	0.251	0.224	0.243	0.242	0.238	0.233
13185	Orlando Arcia	0.236	0.253	0.250	0.238	0.232	0.232	0.232	0.232	0.238

A	B	D	AM	AQ	AR	AY	AZ	BA	BB	BC
playerid	Name	FullSeason_AVG	Beta_D_Norm	Beta_D_W	Beta_D_DoubleW	MLR1	MLR2	MLR3	MLR4	MLR5
13338	Omar Narvaez	0.275	0.261	0.263	0.255	0.226	0.245	0.245	0.245	0.252
5343	Brandon Crawford	0.254	0.251	0.243	0.232	0.227	0.223	0.221	0.219	0.227
9774	Christian Vazquez	0.207	0.253	0.255	0.242	0.236	0.242	0.243	0.240	0.244
3708	Rajai Davis	0.224	0.259	0.238	0.232	0.235	0.242	0.243	0.236	0.234
5751	Hernan Perez	0.253	0.257	0.251	0.241	0.234	0.221	0.224	0.232	0.234
14330	Nick Williams	0.256	0.257	0.264	0.252	0.227	0.239	0.239	0.233	0.244
4220	Ryan Zimmerman	0.264	0.249	0.253	0.237	0.231	0.229	0.227	0.231	0.230
15937	Aledmys Diaz	0.263	0.251	0.253	0.239	0.233	0.229	0.229	0.223	0.239
13265	Mike Zunino	0.201	0.261	0.229	0.225	0.237	0.231	0.231	0.228	0.216
3142	Robinson Chirinos	0.222	0.252	0.236	0.226	0.215	0.219	0.220	0.222	0.215
15112	Ryan McMahon	0.232	0.257	0.252	0.242	0.218	0.227	0.226	0.223	0.233
7949	Tim Beckham	0.230	0.250	0.248	0.234	0.225	0.229	0.229	0.227	0.225
12547	John Hicks	0.260	0.262	0.250	0.244	0.229	0.242	0.245	0.235	0.232
9776	Jason Kipnis	0.230	0.246	0.235	0.221	0.226	0.227	0.225	0.225	0.235
6885	Ian Desmond	0.236	0.247	0.249	0.232	0.230	0.231	0.226	0.226	0.229
10950	Adam Duvall	0.195	0.247	0.232	0.219	0.225	0.224	0.224	0.226	0.224
7476	Alex Avila	0.165	0.257	0.238	0.230	0.213	0.206	0.204	0.216	0.216
7185	Logan Forsythe	0.232	0.257	0.236	0.229	0.234	0.230	0.233	0.235	0.237
4881	Carlos Gomez	0.208	0.245	0.231	0.218	0.214	0.220	0.221	0.221	0.214
12976	Austin Hedges	0.231	0.251	0.214	0.207	0.217	0.219	0.221	0.222	0.211
11200	Kole Calhoun	0.208	0.246	0.233	0.220	0.226	0.226	0.223	0.222	0.225
8252	Hunter Pence	0.226	0.254	0.252	0.240	0.225	0.212	0.212	0.214	0.225
10199	Billy Hamilton	0.236	0.248	0.233	0.221	0.226	0.219	0.216	0.216	0.213
4062	Dexter Fowler	0.180	0.246	0.243	0.227	0.226	0.222	0.222	0.224	0.225
14942	Andrew Knapp	0.198	0.256	0.256	0.245	0.220	0.225	0.225	0.222	0.234
9272	Chris Davis	0.168	0.246	0.213	0.204	0.214	0.219	0.218	0.219	0.210
14352	Lewis Brinson	0.199	0.245	0.229	0.216	0.217	0.218	0.215	0.216	0.220
7539	Neil Walker	0.219	0.248	0.248	0.232	0.225	0.225	0.227	0.228	0.232
11038	Kevin Kiermaier	0.217	0.257	0.254	0.243	0.215	0.213	0.216	0.215	0.222
4866	Jarrod Dyson	0.189	0.249	0.241	0.227	0.231	0.218	0.219	0.221	0.221
1736	Jose Reyes	0.189	0.260	0.246	0.239	0.237	0.213	0.214	0.222	0.226
8610	Kendrys Morales	0.249	0.254	0.244	0.233	0.222	0.239	0.242	0.233	0.242
2151	Edwin Encarnacion	0.246	0.243	0.236	0.219	0.212	0.217	0.216	0.218	0.227
15082	Adam Engel	0.235	0.251	0.209	0.202	0.224	0.214	0.216	0.215	0.218
4616	Russell Martin	0.194	0.250	0.219	0.210	0.217	0.201	0.201	0.205	0.204
6887	Martin Maldonado	0.225	0.250	0.214	0.206	0.223	0.234	0.235	0.230	0.215
8090	Matt Carpenter	0.257	0.245	0.232	0.217	0.220	0.214	0.214	0.217	0.223
2396	Carlos Santana	0.229	0.241	0.233	0.215	0.224	0.218	0.220	0.218	0.216
3473	Anthony Rizzo	0.283	0.246	0.251	0.232	0.220	0.225	0.226	0.225	0.243
13862	Devon Travis	0.232	0.249	0.257	0.239	0.223	0.219	0.218	0.221	0.231
2636	Brandon Guyer	0.206	0.255	0.243	0.233	0.224	0.231	0.231	0.234	0.232
9205	Logan Morrison	0.186	0.245	0.225	0.211	0.214	0.218	0.218	0.210	0.206
11339	Jake Marisnick	0.211	0.248	0.222	0.210	0.211	0.212	0.211	0.211	0.204

A	B	D	AM	AQ	AR	AY	AZ	BA	BB	BC
playerid	Name	FullSeason_AVG	Beta_D_Norm	Beta_D_W	Beta_D_DoubleW	MLR1	MLR2	MLR3	MLR4	MLR5
11470	Tony Wolters	0.170	0.256	0.243	0.233	0.218	0.233	0.235	0.235	0.240
7087	Caleb Joseph	0.219	0.251	0.227	0.216	0.218	0.228	0.231	0.228	0.218
5273	Sandy Leon	0.177	0.257	0.240	0.231	0.220	0.230	0.237	0.241	0.237
13130	Mikie Mahtook	0.202	0.257	0.249	0.238	0.216	0.205	0.210	0.215	0.221
2900	Roberto Perez	0.168	0.255	0.214	0.206	0.203	0.187	0.192	0.197	0.199
12160	Ben Gamel	0.272	0.255	0.254	0.242	0.226	0.229	0.235	0.237	0.245
3298	Charlie Culberson	0.270	0.257	0.257	0.245	0.208	0.217	0.223	0.226	0.232
10243	Randal Grichuk	0.245	0.240	0.222	0.204	0.202	0.199	0.202	0.198	0.203