A Bayesian Approach to Quantifying Lineup Protection in Major League Baseball

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Abstract – This paper explores the concept of lineup protection in Major League Baseball (MLB) using Bayesian statistical methods. Lineup protection—the idea that the presence of a strong batter behind a player can affect the type and quality of pitches the current batter receives—has long been debated in baseball. We utilize pitch-level data from MLB's Statcast system, building hierarchical Bayesian models to stabilize expected weighted on-base average (xwOBA) metrics and to quantify the impact of the subsequent batter's ability on pitch selection.

1 Introduction

In baseball, each team consists of 9 players that form a lineup. The 9 players sequentially take their turns facing the opposing team's pitcher. Baseball lineups are strategically ordered sequences of batters designed by managers to maximize offensive productivity. Because baseball is one of the rare team sports that produces 1-on-1 matchups between the offense and the defense, conventional wisdom might suggest that each batter-pitcher matchup is an independent event. The theory of lineup protection emerges from the interaction between consecutive lineup positions, particularly in how a strong hitter batting behind another might influence pitching behavior.

Anecdotally, players and coaches frequently reference protection effects, claiming superior hitters batting behind a player compel pitchers to throw more strikes to avoid walks. Prior research on this phenomenon, however, has yielded mixed results. Juan Soto, who signed with the New York Mets in the 2024-2025 offseason, said "It's definitely different," Soto told The New York Post. "I had the best hitter in baseball [Aaron Judge] hitting behind me [in 2024 with the New York Yankees]. I was getting more attacked and more pitches in the strike zone, less intentional walks and things like that. I was pitched differently last year."[1] Past research [2][3] suggests there is a possible but small effect of protection. MLB pitchers themselves have mixed views on whether or not they change their approach based on the on-deck batter [4].

Quantifying lineup protection could significantly impact team strategy. Accurate measurement could optimize lineup constructions, improve performance projections, and more accurately assess a player's value. To address this question, we employ hierarchical Bayesian models with pitch-level Statcast data.

2 Data

Pitch-level data were collected from MLB's Statcast system using the sabRmetrics R package [5]. The dataset spans multiple seasons (2021-2024), capturing detailed pitch characteristics, batter identity, and pitcher identity. Data preprocessing ensured accuracy and completeness, eliminating incomplete pitch records, eliminating pitchers hitting in the dataset, and retaining only regular-season games.

3 Modeling Stabilized xwOBA

Expected weighted on-base average (xwOBA)[6] is a Statcast-derived metric predicting batter performance based on batted-ball characteristics (exit velocity, launch angle, and depending on the batted ball type, sprint speed). xwOBA effectively captures batter talent, minimizing randomness inherent in traditional outcomes, such as opposing defenses, ballpark dimensions, and weather. However, small-sample performances require stabilization, which we address via a hierarchical Bayesian model incorporating age curves and positional differences.

3.1 Spline Basis for Age Effects

We construct a cubic B-spline basis of dimension K = 4 on the age range (19-45) of the observed data.

$$B(A_j) = [B_1(A_j), B_2(A_j), B_3(A_j), B_4(A_j)]$$

with an intercept constraint such that

$$\sum_{b=1}^{4} B_b(A_j) = 1$$

3.2 Hierarchical Model Structure

For each player-season j = 1, …, J, let

y_j=the batter's historical xwOBA up until the given season
N_j= the batter's historical number of plate appearances up until the given season
$k_j \in \{1, \dots, 9\}$ which corresponds to the primary position (P, C, 1B, …, RF)
θ_j= "true" xwOBA to estimate.

The full hierarchical model is

$$y_j | \theta_j \sim N\left(\theta_j, \frac{\sigma}{\sqrt{N_j}}\right)$$

$$\theta_j = \mu + f_{k_j}(A_j) + \eta_j$$

$$\eta_j \sim N(0, \tau)$$

$$\mu \sim N(\mu_0, 0.05), u_0 = 0.320$$

$$\tau \sim Half - Cauchy(0, 0.05)$$

$$\sigma \sim Half - Cauchy(0, 0.05)$$

$$\gamma_{k,b} \sim N(0,1), k = 1, \dots, 9\ ;\ \ b = 1, \dots, 4$$

3.3 Fitting the Model

We use **`rstan`** to perform MCMC sampling on the model, collecting 1,000 samples on 4 chains each after 1,000 warm-up iterations.

	Mean	St Dev	2.5% CI	97.5% CI
μ	0.32	0.02	0.29	0.35
τ	0.03	0.00	0.03	0.03
σ	0.38	0.01	0.36	0.40

Table 1 above summarizes the coefficients of the hierarchical model.

Priors center on a league average μ_0=0.320 with modest variance.

Figure 2 below shows good convergence across all chains

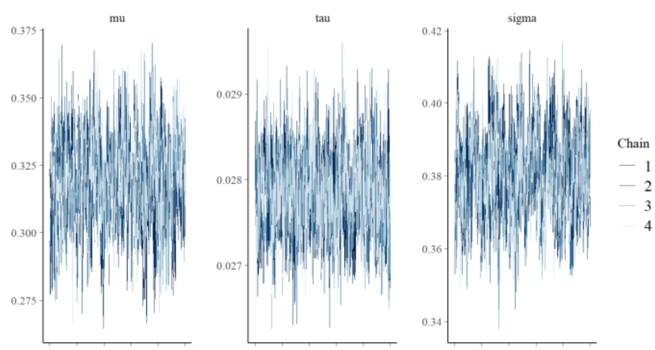
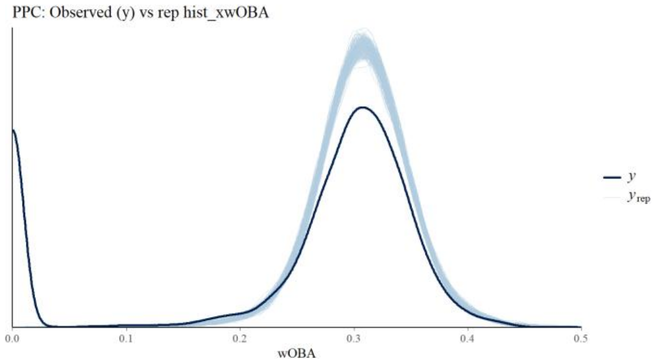
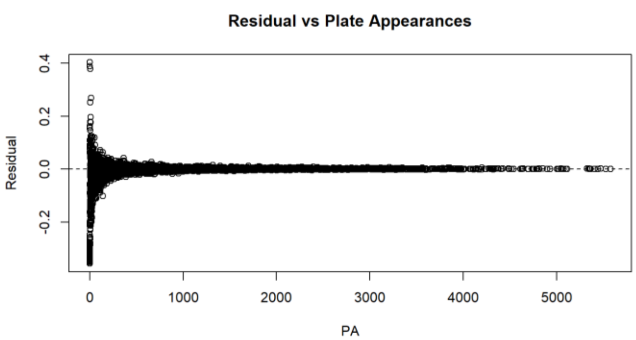


Figure 3 below shows the distribution of replicate data points drawn from the posterior predictive distribution, overlayed on the observed data.



Notably, we see a spike at 0 which represents rookies with no historical data. By design, the model shrinks those players towards the global mean of ~0.320, which explains the center of the y_{rep} curve with a higher frequency than the observed data. Essentially, this is the model saying that with limited data to no on a player, we expect that player to perform at a league-average level.

Figure 4 below shows the number of historical plate appearances (observations) vs xwOBA residuals for all player-seasons in the data set. Notably, the residual decreases as more historical data is available, meaning that the model is more confident in a player's "true xwOBA talent" as it sees more observations of that player.



4 Modeling Lineup Protection

We model the probability of a pitch being thrown inside the strike zone as a binary outcome (1 if pitch is in the zone, 0 otherwise). The model incorporates key predictors, including the current batter's stabilized xwOBA, the on-deck batter's stabilized xwOBA, and the count situation (balls and strikes). The Bayesian logistic regression framework is described by the following model:

$$\begin{aligned} logit(P[y_i = 1]) = \alpha &+ \beta_{xwOBA} * xwOBA_i \\ &+ \beta_{xwOBA\ on\ deck} * xwOBA\ on\ deck_i \\ &+ \beta_b * b_i + \beta_s * s_i + \beta_{ib} * b_i \\ &* xwOBA\ on\ deck_i + \beta_{is} * s_i \\ &* xwOBA\ on\ deck_i \end{aligned}$$

where

$\boldsymbol{y_i}$: binary indicator for whether pitch i is in strike zone

$\boldsymbol{\alpha}$: intercept term

xwOBA$_i$: stabilized xwOBA for current batter, drawn from model in Section 3

xwOBA on deck$_i$: stabilized xwOBA for the batter on deck, drawn from model in Section 3

b$_i$: balls in the count prior to pitch being thrown {0,3}

s$_i$: strikes in the count prior to pitch being thrown {0,2}

$$\alpha \sim N(0,2)$$
$$\beta_{xwOBA} \sim N(0,1)$$
$$\beta_{xwOBA\ on\ deck} \sim N(0,1)$$
$$\beta_b \sim N(0,1)$$
$$\beta_s \sim N(0,1)$$
$$\beta_{ib} \sim N(0,1)$$
$$\beta_{is} \sim N(0,1)$$

Notably, $\beta_{xwOBA\ on\ deck}$, β_{ib}, and β_{is} quantify the concept of protection. Based on conventional wisdom and previous studies, we expect these coefficients to be positive, meaning a higher xwOBA of the on deck batter leads to a higher probability of a pitch being a strike.

4.1 Fitting the Model

Prior to fitting the model, both **xwOBA$_i$** and **xwOBA on deck$_i$** were standardized. We use `rstan` to perform MCMC sampling on the model, collecting 1,000 samples on 4 chains each after 1,000 warm-up iterations.

	Mean	St Dev	2.5% CI	97.5% CI
α	-0.31	0.01	-0.33	-0.28
β_{xwOBA}	-0.01	0.00	-0.02	0.00
$\beta_{xwOBA\ on\ deck}$	0.00	0.00	-0.01	0.01
B_b	0.22	0.01	0.20	0.23
B_s	-0.33	0.01	-0.35	-0.31
B_{ib}	0.00	0.00	0.00	0.01

B_{is}	0.00	0.00	-0.01	0.01

Table 5 above summarizes the coefficients of the lineup protection model.

$\boldsymbol{\alpha}$: the log-intercept of the probability of a pitch being in the strike zone with 0 balls, 0 strikes, and a league-average hitter both at bat and on deck, which corresponds to a baseline strike probability of about 42%.

$\boldsymbol{\beta}_{xwOBA}$: all else equal, the probability of a strike decreases about 1% for each 0.010 increase in the current batter's xwOBA. This translates to pitchers being slightly more cautious when they face better hitters.

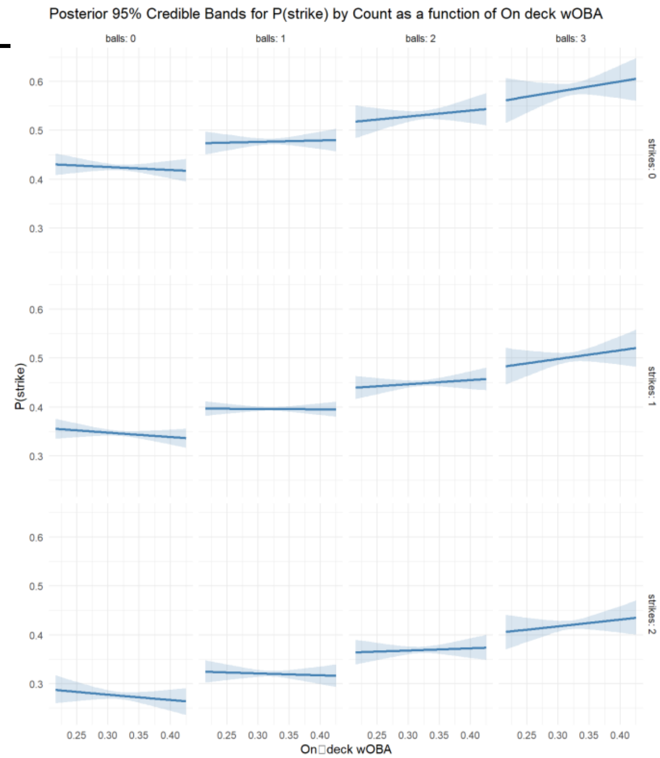
$\boldsymbol{\beta}_{xwOBA\ on\ deck}$: there is no discernable effect of the on-deck batter's xwOBA on strike probability.

$\boldsymbol{\beta}_{b}$: all else equal, the probability of a strike increases about 25% for each additional ball in the count. This aligns with conventional baseball wisdom of pitchers nearly always aiming for a strike when the count is 3 balls, 0 strikes to avoid walking the batter.

$\boldsymbol{\beta}_{s}$: all else equal, the probability of a strike decreases about 28% for each additional strike in the count. This aligns with conventional baseball wisdom of pitchers "wasting" a pitch by throwing one far outside the strike zone when the count is 0 balls, 2 strikes to get the batter to chase.

$\boldsymbol{\beta}_{ib}$, $\boldsymbol{\beta}_{is}$: there is no discernable change to the effect of the number of balls or strikes based on the on-deck batter's xwOBA.

These results are visualized below in Figure 6, which shows how the probability of a strike varies by count and on-deck batter's xwOBA, for a league-average batter currently hitting.



As seen above, the probability of a strike increases with each additional ball, and decreases with each additional strike. The blue slope represents how an increase in on-deck xwOBA affects the strike probability. Based on conventional baseball wisdom, we would expect the slope to increase as on-deck xwOBA increases. We can see this phenomenon occur as the number of balls in the count increases; however we cannot confidently say that the "protection effect" is tangible as our credible intervals (light blue bands) are wider in those situations.

5 Conclusion and Future Work

Our results reveal nuanced insights regarding the concept of lineup protection. While we observe a clear relationship between pitch location selection and situational factors such as ball and strike counts, the hypothesized protective influence of the on-deck batter's offensive ability (as measured by stabilized xwOBA) does not manifest strongly in our data. Specifically, the analysis showed that pitchers exhibit more caution against better current hitters, consistent with expectations; however, the quality of the on-deck batter has negligible direct influence.

Given these findings, the practical implications for teams are subtle yet potentially valuable. While lineup protection might not dramatically influence every at-bat, strategic lineup construction could still exploit minor situational advantages over a full season, potentially improving run production and overall offensive efficiency.

Future research should focus on refining these analyses to better capture nuanced pitcher-batter interactions. Incorporating detailed pitcher behavior might illuminate subtle decision-making processes more clearly, as individual pitchers are likely to have different location tendencies. Additionally, instead of a binary response for strike zone location, we could look at if pitchers aim for a specific hitter's "hot zones" more or less frequently depending on the strength of the on-deck hitter. Ultimately, continued refinement of Bayesian modeling techniques combined with richer contextual datasets will likely enhance our understanding of lineup protection effects and their practical implications for MLB strategy.

References

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