Analyzing the Shift Ban in Major League Baseball: A Cluster-Based Difference-in-Differences Approach

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Abstract

This paper builds on Kennedy-Shaffer's league-wide analysis of MLB's 2023 infield shift ban by examining how the policy affected specific types of hitters. To do so, batters are clustered into distinct archetypes based on their counting and performance metrics. As in Kennedy-Shaffer's study, this analysis employs a difference-in-differences (DID) approach to estimate the causal impact of the shift ban on OBP and BABIP, comparing outcomes for left-handed versus right-handed batters. The findings reveal substantial heterogeneity in the shift ban's effects across batting profiles. Specifically, *Fly-Ball Sluggers* and *Power-Contact Hitters* exhibited notable improvements in both OBP and BABIP, while *Contact & Speed Grinders* saw marginal and even negative changes. These results suggest that the shift ban indeed benefited pull-heavy hitters, those most likely to have been targeted by extreme defensive positioning, thereby achieving the MLB's stated policy goal. Moreover, the analysis highlights that league-wide DID estimates may mask important within-group variation, underscoring the value of profile-specific analysis in understanding policy impacts.

I. Introduction

In 2023, the MLB implemented a shift ban in an attempt to present a more watchable product. That is, fans were exhibiting increased frustration with the migration toward three-outcome baseball and wished to see more batted balls in play. Proceeding the shift ban in 2023, defensive shifts, a variable alignment that stacks fielders into a favorable spot on the field depending on the batters hitting tendencies, were becoming increasingly more common. This led to less balls in play, as defenses were in an optimal position to field hits from hitters, turning what could potentially be hits into outs for hitters. To combat this mounting frustration from both players and fans, the MLB decided to place a ban on extreme infield shifts now requiring two infielders on each side of second base, with both feet on the infield dirt. This change was ushered into the game with the hopes of rebalancing the playing field in favor of the offense, encouraging more balls in play.

Figure 1: Examples of infield positioning against right- and left-handed batters: regular, slight shift, and aggressive shift. Numbers represent traditional fielder positions (3 = 1B, 4 = 2B, 5 = 3B, 6 = SS).

As mentioned before, batters with different tendencies will experience different shifts. As seen in Figure 1, before the rise in popularity of the shift, teams used regular defensive alignments for all hitters. However, with the rise of analytics in baseball, teams quickly realized that they could optimize their fielding strategies by exploiting batter tendencies. For example, if a batter is an extreme pull hitter, teams could deploy aggressive shifts to capitalize on this, minimizing the chances that this player's pulled swings will drop into play.

Taking a look at league-level metrics suggests that that the 2023 ban had a tangible impact, with the MLB batting average rising from. 243 in 2022 to. 248 in 2023 and BABIP increasing from. 290 to .297. Furthermore, LHBs experienced a significant jump of 10 points in each respective category while RHBs remained unaffected, illuminating that LHBs are the main targets of these aggressive infield shifts.

However, how does this large jump in BABIP and OBP differ between hitters who exhibit different mindsets and strategies? Batters do not have the same strategies; a hitter like Aaron Judge and Brett Gardner have vastly different approaches at the plate. That is to say, how does someone who is a pull slugger, like Joey Gallo, benefit from the change in comparison to a ground ball specialist who can spray the ball to all areas of the field like Jacob Wilson? Additional steps must be taken to uncover these between-approach differences, ultimately giving a more precise picture of how this policy change impacts different players and strategies.

To address the lack of granularity and detail provided by league-wide metrics, this study utilizes unsupervised learning to naturally identify different batting profiles, which are then followed by the same DID performed at the league level. By combining clustering and DID, we can estimate the casual effect the 2023 shift ban at a much more granular level, giving a more detailed understanding of what types of players benefited the most from the policy change.

II. Literature Review

The Sabermetrics era in baseball led to a staunch rise in infield shifting throughout the 2010s, providing teams with an effective run-prevention strategy against predictable batters. Existing papers, such as Markes et al. (2024), relay that fielding shifts notably reduce expected runs, with a more pronounced negative effect on LHBs.

Upon banning shifts in 2023, Pavitt (2024) reported a five-point rise in league-wide batting average and a ten-point bump for LHBs, while RH averages were flat. Arthur (2022) predicted small effects due to defenders adapting within the new rules. The respective results from this papers reveal that LHBs experience a disproportionate bonus from the policy change.

Kennedy-Shaffer (2024) used DID and found that LHB BABIP and OBP increased by 9 points in comparison to their RH counterparts. Also within Kennedy-Shaffer (2024), the synthetic control gives a precursor to the idea of heterogeneous effects between different batting profiles, showing that some batters seem to benefit significantly more than others. Similarly, Westrick (2024) showed that pulled grounders by lefties became hits 1.5 times more often. These findings give motivation to fully explore the presence of heterogeneous effects between different batting strategies.

Additionally, other studies have utilized clustering to define batter archetypes within baseball. For instance, Carr (2025) applied K-Means clustering to identify hitter types like contact hitters, power hitters, and defensive specialists. These archetypes provide more granular detail and insight than simply analyzing BABIP and OBP differences on a single metric such as pull rates or spray charts.

This study unites these different train of thoughts by first applying unsupervised learning on pre-shift ban data to define different player archetypes and then conducting DID analyses on each resulting archetype. This methodology provides more detailed, specific casual estimates highlighting how the shift ban effects different batter profiles.

III. Data and Methodology

A. Data Sources

The methodologies found within this study make use of publicly available batting data from Statcast and FanGraphs, covering the 2015 to 2024 Major League Baseball seasons. The data used can be summarized by two major categories. First, league-wide data from FanGraphs provide annual OBP and BABIP for the entire league, with each observation representing a season-level average. Second, individual, player-level statistics from Statcast include key offensive metrics such as on-base percentage and weighted on-base average. Additionally, the 2020 season was ultimately not included due to the vast variability induced by the shortened season.

As mentioned before, shifts most commonly occur when the bases are empty, thus the analysis conducted within this survey only includes PAs with no runners on. Lastly, in order to prevent outlier data points, only players with at least 100 PAs are considered within each season.

B. Feature Engineering and Clustering

Utilizing Statcast data, a feature set of 34 performance metrics, including but not limited to BA, SLG, OBP, ISO, was clustered on. Principal Component Analysis (PCA) was then utilized to reduce the dimensionality of the data and to create interpretable PC loadings. K-Means clustering was performed on these PC loadings in conjunction with silhouette score to reveal 3 optimal clusters. These resulting clusters were then interpreted and labeled based on their respective PC means. To prevent data leakage, the clustering procedure only utilized aggregated performance metrics from 2016-2022, again not including 2020. A player's archetype should not be influenced or characterized by their respective performances from seasons after the shift ban, so these seasons were subsequently not included in the clustering data. Furthermore, only players with 100 PAs across all used seasons between 2016-2024 were included in the clustering analysis.

C. Difference-in-Differences Design

To evaluate the causal effect of the 2023 shift ban, we employed two DID models: one at the league-wide level and another at the cluster (archetype) level.

1. League-Wide DID

At the aggregate league-wide level, a DID was implemented comparing LHBs to RHBs, which in this case serve as a quasi-control group. Season-level league averages of OBP and BABIP are used from 2016-2024 (excluding 2020), restricted to PAs with no runners on.

Rather than fitting a regression, we compute year-over-year DID estimates as:

$$\mathrm{DID}_t = (\mathrm{LHB}_t - \mathrm{LHB}_{t-1}) - (\mathrm{RHB}_t - \mathrm{RHB}_{t-1})$$

where LHB_t and RHB_t represent the league-average OBP or BABIP for L and R handed batters in season t. This metric isolates the differential change for LHBs relative to RHBs in each year.

Additionally, we construct a counterfactual for LHB performance post-2022, assuming they would have followed the same trend as RHBs in the absence of the shift ban. The counterfactual is computed as:

$$\mathrm{CF\_LHB}_t = \mathrm{LHB}_{2022} + (\mathrm{RHB}_t - \mathrm{RHB}_{2022}), \quad t \in \{2023, 2024\}$$

The $\mathrm{CF\_LHB}_t$ values allow for visual comparison between actual and projected LHB outcomes, facilitating the calculation of DID estimates for the post-ban seasons.

2. Archetype-Based Cluster DID

We provide clarity regarding the shift's effect across different batter profiles through computing DID estimates across different player archetypes. The unit of analysis in this DID is each respective player cluster, again split by player handedness. We used season-level averages for OBP and BABIP from 2016–2024 (excluding 2020) for each archetype.

Again, rather than fitting a regression we construct counterfactual outcomes for left-handed hitters in each cluster based on their right-handed counterparts. Specifically, for each archetype i and year t, we define:

$$\mathrm{CF\_LHB}_{it} = \mathrm{LHB}_{i,2022} + (\mathrm{RHB}_{it} - \mathrm{RHB}_{i,2022})$$

This models the expected performance for LHBs in the absence of a shift ban by assuming their post-2022 change would have mirrored that of RHBs. We then compute the DID estimate for each cluster in the first post-ban season (2023) as:

$$\mathrm{DID}_{i,2023} = \mathrm{LHB}_{i,2023} - \mathrm{CF\_LHB}_{i,2023}$$

This framework quantifies how much each archetype of LHBs over- or under-performed relative to their counterfactual expectations. Results are presented in Section IV and visualized via time-series plots comparing actual and counterfactual values for each archetype.

IV. Data Analysis

A. League-Wide DID Estimation Results

An initial benchmark for understanding the effects of the 2023 shift ban is necessary as a comparison point. The league-wide DID is performed to achieve this baseline comparison point. Again, this approach compares LHBs, who experience significantly higher rates of shifting, to RHBs which serve as a control group.

Table 1: Year-over-Year DID Estimates (LHB vs. RHB)

Season	**DID_BABIP**	**DID_OBP**
2016	-0.0087	-0.0058
2017	0.0042	0.0043
2018	-0.0035	-0.0017
2019	0.0030	-0.0004
2021	0.0167	0.0089
2022	-0.0094	-0.0063
2023	**0.0094**	**0.0095**
2024	-0.0015	-0.0010

Table 1 reports the year-over-year DID estimates for LHBs relative to RHBs. From 2016-2022, these DID values either hover close to zero or are significantly negative. This indicates that as more teams employed shifts in conjunction with getting more efficient at employing them, BABIP and OBP for LHB continued to decrease over time in comparison to their RH counterparts. However, the ban year exhibits a 9 point jump in both BABIP and OBP, a stark jump and the most substaintial positive gain compared to pre-shift ban years. Furthermore, the DID for BABIP and OBP drop by -.001 respectively for the 2024 season, further evidence that the stark jump was a result of the shift ban.

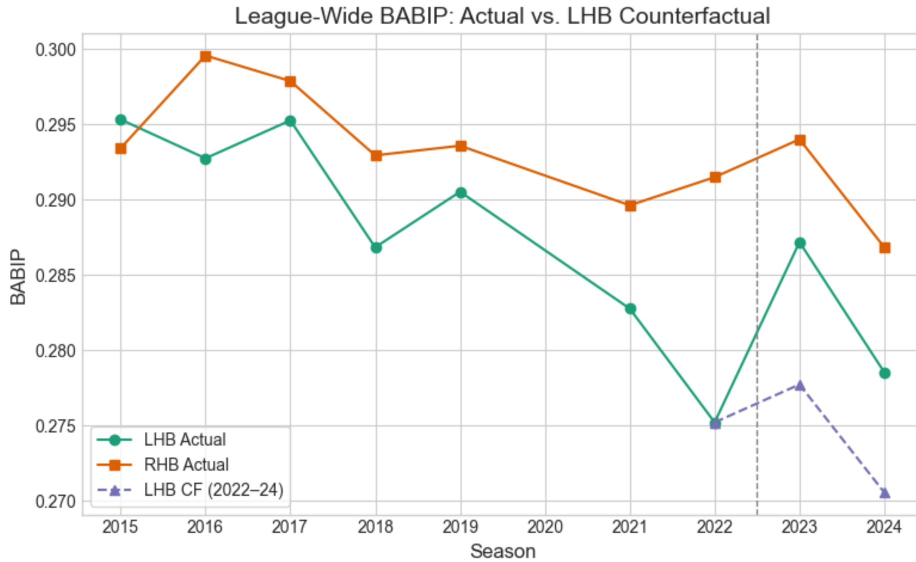

Figure 2: League-Wide BABIP: Actual vs. LHB Counterfactual

Figure 2 visually illustrates the DID effect on BABIP. The plot compares the actual BABIP values for LHBs against a counterfactual trajectory derived from RHB trends. As shown, the gap between BABIP for LH and RH batters continued to grow in magnitude as the ban year approaches. However, post ban this distinct gap significantly shrunk. When comparing to the counterfactual, it becomes clear that the increase experienced by LHBs far outpaces the expected gain, or counterfactual.

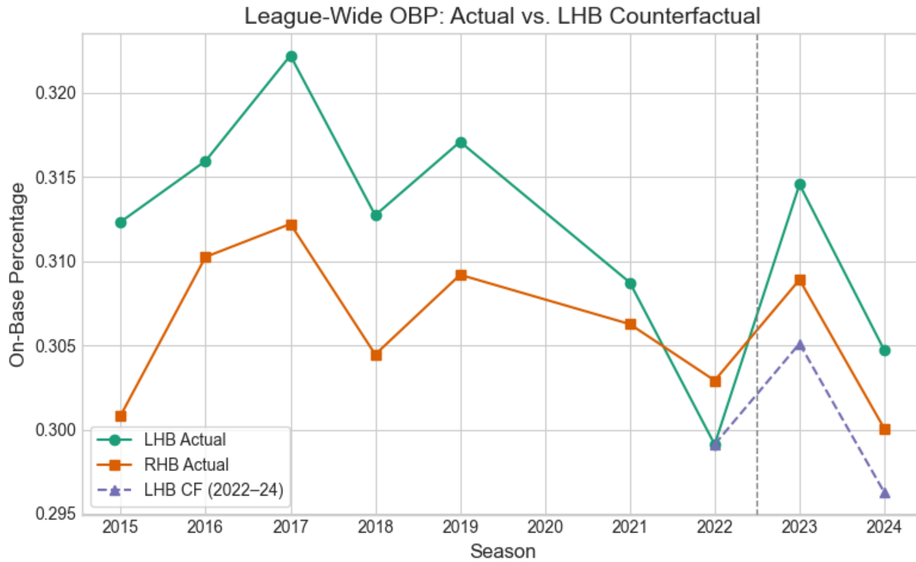

Figure 3: League-Wide OBP: Actual vs. LHB Counterfactual

Figure 3 presents a similar pattern for OBP. Again, the actual LHB far exceeds its respective counterfactual, substantiating the performance benefit tied to the shift ban.

Taking these results together offers substantial evidence that the 2023 shift ban had a meaningful, immediate impact on LHBs offensive performance. However, plenty of papers and research have verified these same results. While these results are significant, it is important to peel this discovery one layer back. Meaning, are these substantial offensive gains uniform across different hitter profiles? To discover whether this is the case, we perform K-Means clustering and DID on each respective cluster.

B. Cluster Diagnostics and Archetype Summary

1. Principal Component Analysis (PCA)

Table 2: Explained Variance by Principal Component

Principal Component	Proportion of Variance Explained
PC1	34.36%
PC2	22.28%
PC3	10.63%
PC4	6.44%
PC5	5.06%
PC6	4.40%

Prior to clustering, we applied Principal Component Analysis (PCA) to reduce the dimensionality of the data, which contained 34 features per player-season. The first three PCs explain approximately 67.3% of the total variance in the data (see Table 2). Because these PCs explain a large portion of player variance, they were chosen to visualize player clusters and inform clustering. Meaning, clustering was performed with solely the first three PCs.

Table 3: Top 5 Positive and Negative Loadings for PCs 1–3

Component	**Top 5 Positive Loadings**	**Top 5 Negative Loadings**
PC1	xISO (0.274)	Poorly Topped% (–0.173)
	xSLG (0.270)	Groundball% (–0.170)
	Isolated Power (0.263)	Poorly Weak% (–0.127)
	SLG% (0.258)	Opposite% (–0.104)
	xwOBA (0.257)	Straightaway% (–0.070)
PC2	AVG (0.292)	Poorly Under% (–0.266)
	xBA (0.280)	Launch Angle Avg (–0.258)
	BABIP (0.241)	Popup% (–0.248)
	OBP (0.226)	Pull% (–0.235)
	Groundball% (0.215)	Flyball% (–0.223)
PC3	Whiff% (0.361)	Poorly Under% (–0.300)
	K% (0.330)	Launch Angle Avg (–0.240)
	Hard Hit% (0.263)	Line Drive% (–0.237)
	Groundball% (0.241)	Flare/Burner% (–0.206)
	Exit Velocity Avg (0.234)	Sweet Spot% (–0.192)

For the respective PCs we looked at the top 5 positive and negative loadings, ideally providing insight on what each PC might represent in a baseball context. Looking at Table 3, it is clear that PC1 is focused on power metrics, with ISO and SLG as strong, dominant positive loadings. Additionally, PC2 focuses around xBA and AVG as its dominant positive loadings paired with Launch Angle Avg and Poorly Under% for its dominant negative loadings. Thus, PC2 can be interpreted as a measure of the Quality Of Contact a hitter makes, with high PC2 batters having high xBA, BABIP, while not popping up and swinging under the ball. Lastly, the PC3 has high positive loadings for Whiff% and K%, and high negative loadings for Poorly Under% and Launch Angle Avg. Meaning, PC3 relates to swing control as batters who do not strike out or whiff fall into this PC.

2. Interpreting Clusters Into Player Archetypes

Table 4: Mean Principal Component Scores by Cluster

Cluster	**Power (PC1)**	**Quality of Contact (PC2)**	**Swing Control (PC3)**
0	-3.091	1.522	-0.104
1	0.166	-2.547	-0.109
2	3.500	1.442	0.266

Table 5: Cluster Sizes by Batter Handedness and Shift Percentage

Cluster	**LHB**	**RHB**	**Total**	**% Shifted**
0 – Contact & Speed Grinders	33	38	71	2.8%
1 – Fly-Ball Sluggers	42	62	104	34.6%
2 – Power-Contact Hitters	40	53	93	65.6%

With the principal components defined, the next step was applying clustering to group players into interpretable hitting archetypes based on their scores along the first three PCs. As shown in Table 4, each cluster exhibits distinct averages on the principal component axes, indicating clear differences in batting profiles and strategies.

Cluster 0 shows high contact quality and low power, containing players who make regular contact but lack slugging ability, thus labeled *Contact & Speed Grinders*. Cluster 1 features average power but poor contact quality, suggesting players who rely heavily on fly balls and power outcomes despite lower overall consistency, earning them the name *Fly-Ball Sluggers*. Cluster 2 scores high on both power and contact, so this group is labeled *Power-Contact Hitters*.

These clusters also exhibit stark contrasts in defensive positioning tendencies. As shown in Table 5, the proportion of extremely shifted players, which corresponds to players who are shifted at a rate of over 50%, is leagues higher in Clusters 1 and 2 (34.6% & 65.6%), compared to just 2.8% in Cluster 0. This aligns with the offensive profiles, with players in Clusters 1 and 2 tending to hit for power often leading to pulling the ball which in turn typically causes extreme defensive shifts. In contrast, the contact-oriented hitters of Cluster 0 are less predictable in their batted ball distribution, leading to fewer shifts against them.

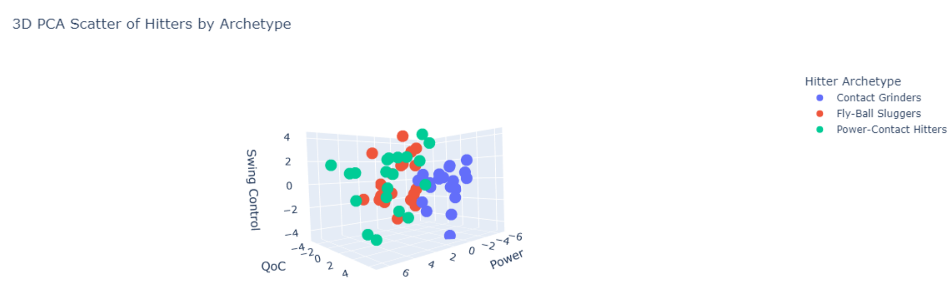

Figure 4: 3D scatter plot of hitter archetypes based on principal component scores: Power, Quality of Contact (QoC), and Swing Control.

The spacing between the three clusters in Figure 4, further supports the notion that the three principal component axes effectively distinguish the identified player archetypes. *Contact & Speed Grinders* are positioned along the lower end of the Power dimension, reflecting their emphasis on contact over slugging. *Power Contact Hitters* cluster in the upper-right quadrant, exhibiting both high power and strong quality of contact. In contrast, *Fly-Ball Sluggers* occupy the region characterized by low quality of contact but moderate power, indicating a profile focused on lift and power despite less consistent batted ball outcomes.

C. Cluster DID Estimation Results

Consider the three gathered representative clusters: *Contact & Speed Grinders*, *Fly-Ball Sluggers*, and *Power-Contact Hitters*. These groups reflect underlying differences in batted-ball profiles and batters box approaches that may alter the policy's intended impact. For each cluster, we compare the actual performance of LHBs against counterfactual trends derived from matched RHBs, allowing us to isolate the policy's effect to specifically batters within each cluster.

Contact & Speed Grinders

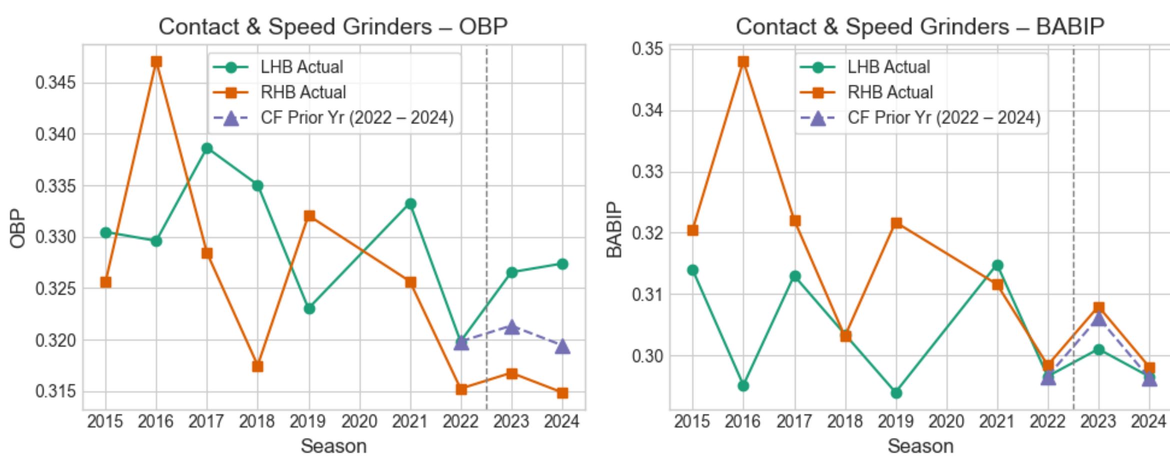

Figure 5: Contact & Speed Grinders — OBP and BABIP

For *Contact & Speed Grinders*, the OBP DID effect in 2023 remains modest and positive (+0.0052). However, the BABIP result is slightly negative, indicating that LHBs in this group underperformed relative to their counterfactuals (-0.0052). While seemingly dumbfounding at first, this adverse reaction to ban aligns with the negligible 2.8% of heavily shifted players in this cluster. Because these players already faced minimal defensive shifts due to their high contact rates and balanced spray tendencies it seems that the ban offered a small benefit or even potentially a hindrance, reinforcing the idea that this archetype was never a primary target of extreme defensive positioning.

Fly-Ball Sluggers

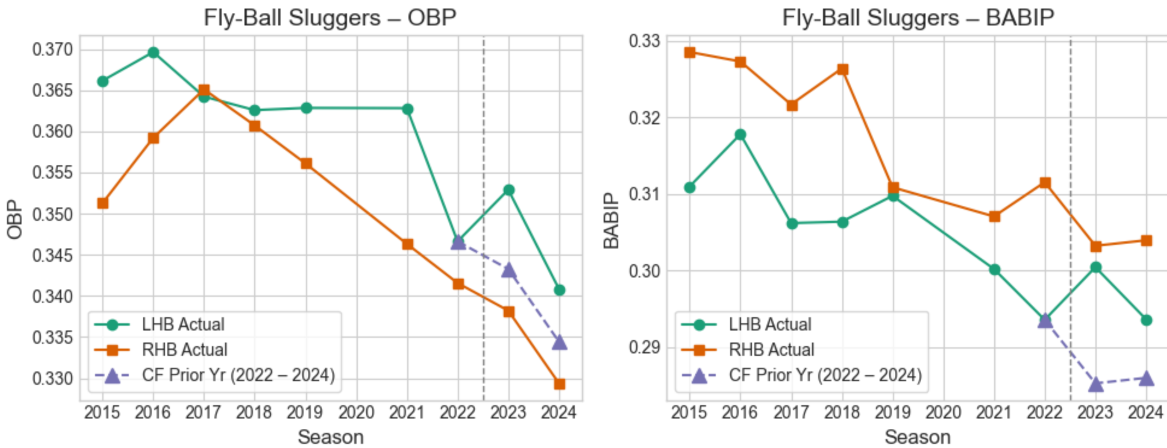

Figure 6: Fly-Ball Sluggers — OBP and BABIP

Fly-Ball Sluggers showcase clear performance gains from the shift ban, with their OBP improving by +0.0096 and their BABIP by +0.0152 relative to the RHB-based counterfactual. These effects suggest modest benefits from the rule change. While only 34.6% of players in this group were extremely shifted prior to the ban, the cluster's elevated fly ball rates may still have led to some targeted defensive positioning. The performance boost likely reflects a partial opening of outfield gaps, where balls that were once caught due to aggressive positioning are now falling for hits. However, the limited number of players facing extreme shifts within group capped the magnitude of this positive effect gained by the ban.

Power-Contact Hitters

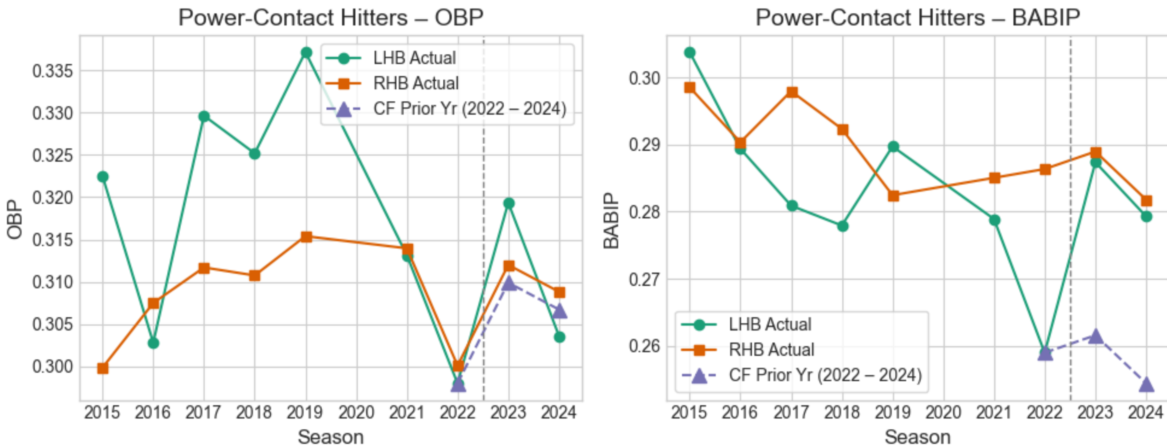

Figure 7: Power-Contact Hitters — OBP and BABIP

Among *Power-Contact Hitters*, the 2023 DID effects are even more pronounced, with a jump of +0.0094 in OBP and +0.0258 in BABIP. Following the same pattern as before, this cluster's shift % also saw a sizable jump, from 34.6% with Fly-Ball Sluggers to now 65.6%. Meaning, 65.6% of players within this cluster saw extreme rates of shifts (over 50% of PAs) prior to the ban. There are multiple factors at play as to why this cluster received the largest bump in performance. First, the jump in shift rate means that a larger portion of the batters within this cluster would be placed at an advantage post ban compared to other clusters. Secondly, this cluster of batters hit for both power and contact, meaning they take advantage of both infield and outfield shifts being banned. Thus conceptually, it makes sense that this group reaps the greatest benefit from the shift ban, as their batting style engages all of the defensive constraints that have now been removed from the game.

V. Results

Table 6: Cluster-Level Shift Ban Effects: DID Summary for 2023

Archetype	**OBP Diff (2023)**	**BABIP Diff (2023)**
Contact & Speed Grinders	0.0052	-0.0052
Fly-Ball Sluggers	0.0096	0.0152
Power-Contact Hitters	0.0094	0.0258

Table 6 summarizes the cluster-level DID estimates for 2023, quantifying how different hitter archetypes responded to MLB's shift ban. *Power-Contact Hitters* clearly benefited from the policy change the most, posting OBP & BABIP improvements of +0.0094 and +0.0258 respectively. These large increases coincide with the MLB's intent, as cluster featured by far the largest shift % at 65.6%. Because this batters are able to take advantage of both the lack of infield and outfield shifts while also facing the largest shift % this cluster having the largest jumps is logical.

Fly-Ball Sluggers were second in the boost received, at +0.0096 in OBP and +0.0152 in BABIP. Similarly, this cluster featured a shift % of 34.6%. While still boasting a high shift %, this cluster has two main conceptual reasons to explain its smaller BABIP gain to *Power-Contact Hitters.* The lower shift % means that a smaller percentage of batters in this cluster faced high shift rates, thus there are less PAs to take advantage of the new defensive lineups. Furthermore, these batters are not quality contact hitters, and thus really only take advantage of outfield shifts.

Lastly, *Contact & Speed Grinders* exhibit a seemingly counterintuitive response. Their OBP improved slightly (+0.0052), but their BABIP decreased by -0.0052, the only negative effect among all clusters. This adverse outcome is consistent with their low shift % at only 2.8%. Meaning, only 2.8% of players in this group faced shift rates over 50%. Thus, this contact grinders that can spray the ball to all areas of the field did not gain an advantage with the new policy change.

Overall, the results found do align with conceptual expectations. The shift ban most benefited players with pronounced pull tendencies and limited speed, while contact-oriented, speed-reliant hitters were relatively unaffected.

VI. Conclusion

The results found from this study provide strong evidence MLB's 2023 shift ban produced measurable offensive benefits, particularly for hitters who were heavily affected by pre-ban defensive positioning. DID estimates coincide with this, showing clusters composed of players who exhibit pull-side power and moderate speed experiencing the OBP and BABIP following the rule change.

At the archetype level, *Power-Contact Hitters* saw the greatest overall improvements, both statistically and substantively, in line with their high shift exposure rate (65.6%). In addition to benefiting from their high pre ban shift rates, these hitters also hit for power and contact. Meaning they can and ultimately do take advantage of the newfound lack of infield and outfield shifts. Furthermore, *Fly-Ball Sluggers* also benefited, although to a lesser extent, possibly due to loosened outfield positioning. *Contact & Speed Grinders*, who rarely faced extreme shifts (2.8%), saw minimal gains and even a slight decline in BABIP, confirming they were largely unaffected by the policy change.

These results support the hypothesis that the shift ban primarily helped players most constrained by traditional defensive alignments, not that the policy change introduced a blanket gain for all LHBs involved.

Future work could explore long-term adjustments by defenses and hitters, as well as assess complementary rule changes such as pitch clock implementation and larger base sizes. Integrating Statcast or biomechanical data may further clarify how hitters adapted mechanically to the shift ban. Lastly, predictive modeling could help teams proactively identify players likely to benefit from or be neutral to future regulatory changes.

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