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The Value of Strategic Unpredictability: A Natural Experiment from Baseball*

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Abstract

Strategic situations in which decision-makers need to be unpredictable are common. This paper introduces a measure of the value of strategic unpredictability for a player and shows that it determines (i) the player's incentive to follow equilibrium and (ii) the power of statistical tests of whether the player's opponent follows their equilibrium mixture. We use data from a unique natural experiment in Major League Baseball to estimate the value of strategic unpredictability for pitchers. We find that the Houston Astros gained a significant advantage by stealing opposing teams' signs, thereby reducing opposing pitchers' ability to be unpredictable.

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1 Introduction

Strategic situations in which decision makers need to be unpredictable are common: In the contest for a point in tennis, the server is unlikely to win the point if the receiver correctly anticipates the serve delivered. In a penalty kick in soccer, the kicker is less likely to score if the keeper anticipates the direction of the kick. In a hand of poker, a bettor needs to randomize the size of his bet in order to conceal the strength of his hand. Mixed-strategy Nash equilibrium is the theoretical framework for predicting behavior in such settings, and data from professional sports has established that behavior is consistent in important ways with the testable implications of the theory.

In this paper, we introduce a measure of the value of strategic unpredictability to a player and a measure of a player's exploitability in two-player zero-sum games. We use data from a unique natural experiment in Major League Baseball (MLB) to estimate the value of strategic unpredictability to pitchers in the contest between a pitcher and a batter. We show that sign stealing by the Houston Astros during the 2017 season—which reduced opposing pitchers' ability to be unpredictable—had a significant positive effect on Astros batting performance and the number of games the Astros won. Our results provide the first empirical measurement of the value of strategic unpredictability in a field setting.

There are several reasons to be interested in measuring the value of strategic unpredictability. First, players will have greater incentives to play (and learn to play) an equilibrium when the value of strategic unpredictable is greater. In particular, we prove in Theorem 1 that (i) a pitcher who departs from their equilibrium mixture is more exploitable in games where the value of strategic unpredictability to the pitcher is greater, and (ii) for any fixed game, a pitcher is more exploitable as he follows a mixture further from his equilibrium mixture.

Second, the value of strategic unpredictability is important in evaluating the power of statistical tests of equilibrium play. Theorem 2 proves that, given two games with the same equilibrium mixture and the same value, if the batter deviates from his equilibrium mixture, then the difference in the pitcher's winning probabilities is greater in the game for which the value of strategic unpredictability to the pitcher is higher. Using this result, Theorem 3 proves that empirical tests of the theory of mixed-strategy Nash equilibrium will have more statistical power when the value of strategic unpredictability is greater. This means that when comparing the results of empirical tests of equilibrium play using field data (e.g., for tennis and for soccer), the power of these tests is not merely a function of the sample size, but also depends on the features of the game that determine the value of strategic unpredictability. We are unaware of prior results of this kind, that relate strategic features of a game to the power of statistical tests of equilibrium play.

We define the value of strategic unpredictability to a player as the loss the player suffers if, while following their equilibrium strategy, their opponent learns the player's action in advance and best responds to it.[1] We estimate the value of strategic unpredictability in an at-bat in MLB using a unique natural experiment. In baseball, the catcher uses hand signals, called "signs," to secretly communicate to the pitcher the type of pitch to be thrown.[2] In 2017, the Houston Astros used a live video stream from the center field camera to observe and then transmit the catcher's signs to the dugout, where the signs were decoded, with the upcoming pitch then transmitted to the batter via bangs on trash cans or by other means. Thus the batter – unbeknown to the pitcher – obtained information about the pitch that was to be delivered. Using data from the 2014 to 2017 seasons, we estimate the value of strategic unpredictability to pitchers.

Intercepting the catcher's signs and communicating the upcoming pitch to the batter is called "sign stealing."[3] Our difference-in-difference (DID) estimates show that stealing signs enabled Astros batters to increase their on-base percentage by 0.0346, a 13% increase relative to their prior performance. This is a conservative estimate, since when we estimate the treatment effect we mix treated and untreated observations. A second commonly used measure of batter performance is slugging percentage (SLG). It is the average number of bases a batter achieves when at bat: a single counts as one base, a double is two bases, a triple is three bases, and a home round counts as four bases. The slugging percentage in MLB is, on average, 0.3769. Our DID estimates show that stealing signs enabled Astros batters to increase their slugging percentage by 0.0554, a 15.8% increase relative to their prior performance.

The benefit to the Astros of sign stealing was considerable. We estimate that the Astros won 19 additional games out of the 162 games they played in the 2017 season. Back-of-the-envelope calculations suggest that, absent sign stealing, the Astros would have had to increase their payroll by $32.3 million to achieve these 19 additional wins.

Related Literature

Walker and Wooders (2001) showed that the serve-and-return behavior of top professional tennis players is largely consistent with game-theoretic predictions. Their insight was that even though the mixed-strategy Nash equilibrium in the contest for a point between the server and receiver is unknown, theory nonetheless has several testable predictions. One is that the probability that the server wins the point when serving is the same for each type of serve in the support of the server's equilibrium mixture.[4] This hypothesis is not rejected for championship professional tennis matches. Other papers have

[1] In zero-sum games the loss of one player exactly equals the gain of his opponent.

[2] The catcher selects the pitch for several reasons: First, knowing the pitch to be delivered means that the catcher is prepared to catch it. Second, the catcher has a better view than the pitcher of the positions of the defensive players and any runners on base.

[3] Sign stealing is allowed under the rules of baseball, and catchers go to great lengths to conceal their signs. However, the use of electronics devices to steal signs is prohibited.

[4] When game payoffs are known, then one can directly test whether players follow their equilibrium mixtures, e.g., Batzilis, Jaffe, Levitt, List, and Picel (2019) test for equilibrium play using Facebook data on rock-paper-scissors matches.

used data from tennis and professional soccer to test mixed-strategy Nash equilibrium, e.g., Chiappori, Levitt, and Groseclose (2002), Palacios-Huerta (2003), Hsu, Huang, and Tang (2007), and Levitt, List, and Reiley (2010). Using a more powerful statistical test and exploiting a large data set, Gauriot, Page, and Wooders (2023) document gender differences in conformity to equilibrium, and show that even among professional tennis players, the behavior of higher-ranked players conforms more closely to equilibrium than the behavior of lower-ranked players.

The foundation of all these papers is to test whether the server's or kicker's winning probability is the same for each action in the support of the player's mixture. Our theoretical results show that if the value of strategic unpredictability to the server is low, then statistical tests will have low power to detect a departure from equilibrium play by the receiver: this follows since the difference between the server's winning probabilities will tend to be small even when the receiver departs from his equilibrium mixture.[5] While it is evident that strategic unpredictability is a crucial aspect of the game in both tennis and soccer, the present paper proposes a quantitative measure of the value of strategic unpredictability and is the first to measure it empirically in the field.

Baseball has been used to study economic decision-making in a variety of papers, including Turocy (2005), Bhattacharya and Howard (2022), and Archsmith, Heyes, Neidell, and Sampat (2025). Elmore and Matthews (2021) and Stitzel, Mattson, and Pjesky (2021) document, at a granular level, the improvement the Astros obtained in at-home batting outcomes as a result of sign stealing. Elmore and Matthews (2021) show that, following a bang, and conditional on the ball entering play, the ball leaves the bat at a higher speed and with a higher launch angle. Stitzel, Mattson, and Pjesky (2021) find that, following a bang, batters are less likely to swing at a pitch, more likely to make contact with an off-speed pitch conditional on swinging, and the ball leaves the bat at a higher speed conditional on the batter swinging and making contact. There are several substantial differences in our empirical and methodological approaches. First, we analyze the effect of sign-stealing not on batters' play but rather on their direct performance in reaching bases, and thus scoring points and winning games. Second, we do not rely directly on information on bangs.[6] This allows us to perform a broader analysis since the Astros reportedly used additional signals, including clapping, whistling, yelling, and possibly electronic devices. Third, our analysis extends to away games, where there are no recorded bangs. Finally, we link this natural experiment to the literature testing mixed-strategy Nash equilibrium, and we provide a framework for measuring the value of strategic unpredictability.

The present paper relates to a growing economic literature on forensic economics which

[5]Perhaps counterintuitively, the server's winning probabilities are equalized when the receiver follows his equilibrium mixture.

[6]The bangs data was captured by an Astros fan from recordings of Astros games, and can be found at http://signstealingscandal.com (accessed on January 15 2022). We use this data in Section 5 when defining the period during which the Astros stole signs.

uses statistical analysis of field data to uncover illicit behavior, see Zitzewitz (2012) for a survey.[7] In this respect, we provide evidence that the Astros' performance in 2017 improved at both home and away games.

The paper is organized as follows. Our theoretical results are in Section 2, with proofs in Appendix A. Sections 3 and 4 describe, respectively, the data and our empirical strategy. Section 5 reports our empirical findings. Section 6 discusses robustness checks. Section 7 reports the results of placebo tests. Section 8 concludes.

2 Theory

Our theoretical analysis applies to general two-player two-outcome zero-sum games, but for expositional ease we adopt baseball as a frame. In the contest between a pitcher and batter, the pitcher chooses the type of pitch to deliver and the batter simultaneously prepares for the pitch. We simplify the analysis by assuming that the pitcher chooses between two types of pitches – fastball (F) or offspeed (O), and the batter likewise prepares for a fastball or offspeed pitch.[8] If the batter does not swing at the ball, the pitch will be called as a ball or strike. If the batter swings, the batter may either miss (a strike) or hit the ball. If he hits the ball, it is either a foul or it goes in play. In the latter case, the batter either progresses to a base or is out (e.g., if the ball is caught). We simplify the analysis by assuming that (i) the encounter between the pitcher and batter consists of a single pitch, and (ii) there are only two possible outcomes – either the batter gets on base or not. Although highly stylized, this model serves to illustrate the value of strategic unpredictability.

We take the batter's payoff to be 1 if he gets on base and 0 otherwise. The pitcher's payoff is one minus the batter's payoff. The game is therefore constant sum. The pitcher's and batter's decisions jointly determine the probability π_{ij} that the batter gets on base when the pitch is $i \in \{F, O\}$ and the batter prepares for $j \in \{F, O\}$. Figure 1(a) is the normal form representation of a pitch for generic payoffs, Figure 1(b) provides a numerical example calibrated to our data, and Figure 1(c) is an example with the same equilibrium mixture as Figure 1(b).

We assume payoffs are such that there is a unique Nash equilibrium in mixed strategies, i.e., $\pi_{FF} > \max\{\pi_{FO}, \pi_{OF}\}$ and $\pi_{OO} > \max\{\pi_{FO}, \pi_{OF}\}$. In equilibrium the pitcher delivers a fastball with probability

$$q^* = \frac{\pi_{OO} - \pi_{OF}}{\pi_{FF} - \pi_{FO} + \pi_{OO} - \pi_{OF}}.$$

[7]Examples include uncovering teacher cheating on standardized tests (Jacob and Levitt, 2003), match rigging in Sumo wrestling (Duggan and Levitt, 2002), tax evasion (Saez, 2010), overstatement of economic growth by autocratic regimes (Martinez, 2022), election fraud (Klimek et al., 2012), racial bias in judicial decisions (Arnold et al., 2018), police stops (Goncalves and Mello, 2021), and refereeing in sports (Price and Wolfers, 2010; Parsons et al., 2011).

[8]The Astros' signals (via banging) typically only conveyed whether or not a fastball was coming.

Batter

		F	O
Pitcher	F	π_{FF}	π_{FO}
	O	π_{OF}	π_{OO}

(a) Generic payoffs: G

Batter

		F	O
Pitcher	F	.30000	.23743
	O	.22483	.30224

(b) Game 1: G_1

Batter

		F	O
Pitcher	F	.28582	.24966
	O	.24237	.28711

(c) Game 2: G_2

Figure 1: A pitch in baseball.

For games 1 and 2, in Figure 1(b) and (c), we have $q^* = .55301$, which matches the frequency of fastballs in the 2017 season. The probability that the batter gets on base is

$$v^* = \frac{\pi_{FF}\pi_{OO} - \pi_{OF}\pi_{FO}}{\pi_{FF} - \pi_{FO} + \pi_{OO} - \pi_{OF}},$$

where v^* is the *value* of the game to the batter. For games 1 and 2, $v^* = 0.2664$, which matches the Astros' on-base percentage in the 2014-2016 seasons, before they engaged in sign stealing.

We measure u_G, the value of strategic unpredictability to the pitcher in game G, as follows: Imagine that the batter learns the type of pitch to be delivered prior to choosing his own action. With probability q^* the pitcher delivers a fastball, and the (prepared) batter gets on base with probability π_{FF}. With probability $1 - q^*$ the pitcher delivers an off-speed pitch, and the (prepared) batter gets on base with probability π_{OO}. Hence a batter who learns the pitch increases his probability of getting on base by

$$u_G \equiv q^*\pi_{FF} + (1 - q^*)\pi_{OO} - v^*.$$

This difference simplifies to $q^*(\pi_{FF} - \pi_{FO})$, i.e., it is the probability that the pitcher delivers a fastball times the increase in the probability of getting on base when prepared for a fastball rather than an off-speed pitch. The difference can equivalently be written as $(1 - q^*)(\pi_{OO} - \pi_{OF})$.

The expression $q^*(\pi_{FF} - \pi_{FO})$ is intuitive: Imagine that the batter prepares for an off-speed pitch. If he learns that the pitch to be delivered is O, then he does not change his action and he obtains no benefit. If he learns the upcoming pitch is F, then he switches his action to F from O, for a gain of $\pi_{FF} - \pi_{FO}$. Since F is delivered with probability q^*, the batter's expected gain is $q^*(\pi_{FF} - \pi_{FO})$. For game G_1, the expected gain is $.553(.3 - .23743) = .03460$, which matches our estimate of the increases in the on-base percentage the Astros obtained by sign stealing. Game G_2 has the same equilibrium mixture and value as G_1, but the value of strategic unpredictability to the pitcher is only .02000.

Incentives for Equilibrium Play

Define $\pi^P(q, r)$ to be the payoff to the pitcher when the pitcher and batter choose Fastball with probability q and r, respectively. In particular,

$$\pi^P(q, r) = q\pi_F^P(r) + (1 - q)\pi_O^P(r).$$

Define $\varepsilon_G(q)$, the *exploitability of the pitcher in game G when following mixture q*, as

$$\varepsilon_G(q) = \left| \frac{\partial \pi^P(q, r)}{\partial r} \right|,$$

i.e., it is the derivative of $\pi^P(q, r)$ with respect to r. It measures the sensitivity of the pitcher's payoff to the batter's mixture, when the pitcher chooses Fastball with probability q.[9] Importantly, the pitcher is unexploitable at his equilibrium mixture, i.e., $\varepsilon_G(q)|_{q=q^*} = 0$. This is a consequence of the fact that in a mixed-strategy Nash equilibrium the batter is indifferent between his actions.

Theorem 1 shows that a pitcher who deviates from his equilibrium mixture is more exploitable in games where the value of strategic unpredictablity to the pitcher is higher. Furthermore, for any fixed game, the pitcher is more exploitable as his mixture is farther from his equilibrium mixture.

Theorem 1: Let $G = (\pi_{FF}, \pi_{FO}, \pi_{OF}, \pi_{OO})$ and $G' = (\pi'_{FF}, \pi'_{FO}, \pi'_{OF}, \pi'_{OO})$ be two constant-sum games which both have the same equilibrium mixture q^* for the pitcher. Suppose that the value of strategic unpredictability to the pitcher is higher in G than G', i.e., $u_G > u_{G'}$. Then, for $q \neq q^*$, the pitcher is more exploitable in G than G', i.e., $\varepsilon_G(q) > \varepsilon_{G'}(q)$. Further, $\varepsilon_G(q)$ is increasing in $|q^* - q|$.

Example 1, below, shows numerically that a pitcher who departs from his equilibrium mixture is more vulnerable to exploitation by the batter when the value of strategic unpredictability is greater: the pitcher has more to lose (and the batter more to gain) from exploitation. The pitcher therefore has a greater incentive to learn and adhere to his equilibrium mixture.

Example 1: Games G_1 and G_2 have the same value ($v^* = .2664$) and same equilibrium mixture for the pitcher ($q^* = .55301$). Suppose that the pitcher chooses to deviate from equilibrium, choosing F with probability $q = 0.4$ in both games. The batter's best

[9]Since the game is zero sum, it equivalently measures the responsiveness of the batter's payoff to the batter's mixture, when the pitcher chooses Fastball with probability q.

response is O. For each 0.1 increase in the batter's probability of choosing O, the pitcher's winning probability decreases by $0.1\varepsilon_{G_1}(0.4) = .13998\,|q^* - 0.4| = .00214$ in G_1 and by $0.1\varepsilon_{G_2}(0.4) = .0809\,|q^* - 0.4| = .00124$ in G_2. For the same deviation from $q = q^*$ to $q = 0.4$, the pitcher suffers a 73% greater loss in G_1 than G_2, when exploited by the batter.

Testing for Equilibrium Play

Tests of equilibrium play that exploit field data examine whether a player's payoff is the same for each action in the support of his mixture.[10] Let π_F^P and π_O^P denote the probability that the pitcher prevents the batter from getting on base with a fastball or offspeed pitch, respectively. If the batter chooses F with probability r, then

$$\pi_F^P(r) = r(1 - \pi_{FF}) + (1 - r)(1 - \pi_{FO})$$

and

$$\pi_O^P(r) = r(1 - \pi_{OF}) + (1 - r)(1 - \pi_{OO}).$$

If the batter follows his equilibrium mixture r^*, then $\pi_F^P(r^*) = \pi_O^P(r^*)$.

We are interested in how the pitcher's winning probabilities for F and O change when the batter deviates from his equilibrium mixture. Theorem 2 shows that if the batter does not follow his equilibrium mixture, then the difference of the winning probabilities of F and O is larger when the importance of strategic unpredictability is larger.

Theorem 2. Let $G = (\pi_{FF}, \pi_{FO}, \pi_{OF}, \pi_{OO})$ and $G' = (\pi'_{FF}, \pi'_{FO}, \pi'_{OF}, \pi'_{OO})$ be two constant-sum games that have the same equilibrium mixture (q^*, r^*) and the same value. Assume that the value of strategic unpredictability to the pitcher is higher in G than in G', i.e., $q^*(\pi_{FF} - \pi_{FO}) > q^*(\pi'_{FF} - \pi'_{FO})$. Then, for $r \neq r^*$, the difference between the pitcher's winning probabilities for Fastball and Offspeed is larger in G than in G'.

Figure 2 illustrates π_F^P and π_O^P as functions of r, where $G = G_1$ and $G' = G_2$. As established by Theorem 2, $|\pi_F^P(r) - \pi_O^P(r)| > |\pi'^P_F(r) - \pi'^P_O(r)|$ for all $r \neq r^*$.

If the value of strategic unpredictability to the pitcher is zero, then the functions $\pi_F^P(r)$ and $\pi_O^P(r)$ are both constant functions and equal to the value of the game.

The Power of Test of Equality of Winning Probabilities

Denote by h and l two binomial processes, with success rates p_h and p_l, respectively. Consider testing the null hypothesis that $p_h = p_l$ against the alternative hypothesis that $p_h \neq p_l$. Suppose that in the data n_{jS} and n_{jF} are the number of successes and failures in n_j trials of process $j \in \{h, l\}$. To apply the two-sample Z-test, form the test statistic

$$Z = \frac{\hat{p}_h - \hat{p}_l}{\sqrt{\hat{p}(1 - \hat{p})\left(\frac{1}{n_h} + \frac{1}{n_l}\right)}},$$

[10] For tennis, the null hypothesis is that the server's probability of winning the point is the same for each direction of serve. The null is true when the receiver follows his equilibrium mixture and is false otherwise.

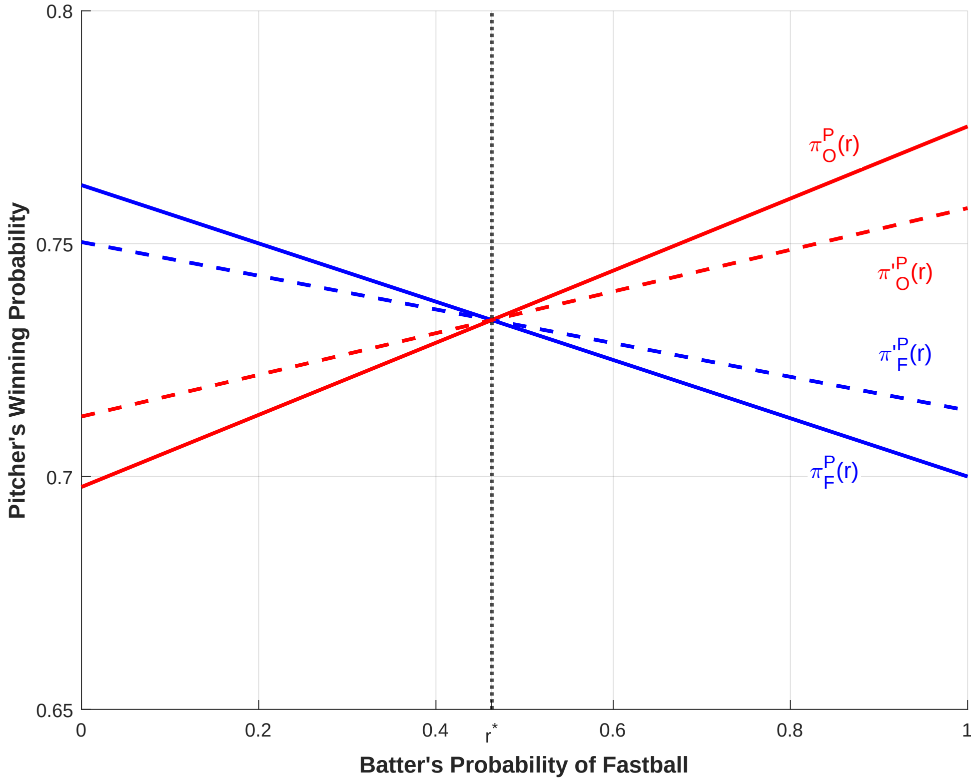


Figure 2: Pitcher's winning probabilities in $G = G_1$ and $G' = G_2$.

where $\hat{p}_j = n_{jS}/n_j$ for $j \in \{h, l\}$ and $\hat{p} = (n_{hS}+n_{lS})/(n_h+n_l)$. Under the null hypothesis, Z is approximately distributed $N(0, 1)$. Let Φ denote the *c.d.f.* of the standard normal. For significance level α, the associated critical value is $z_{\alpha/2}$, where $1-\Phi(z_{\alpha/2}) = \alpha/2$. We reject the null hypothesis if $|Z| > z_{\alpha/2}$.

The power of the test of the null hypothesis that $p_h = p_l$, when p_h and p_l are the true success rates of the h and l binomial processes, is the probability that $|Z| > z_{\alpha/2}$. The power, denoted by Θ, is given by the formula

$$\Theta(z(p_h, p_l)) \quad = \quad \Phi(z(p_h, p_l) - z_{\alpha/2}) + \Phi(-z_{\alpha/2} - z(p_h, p_l)),$$

where

$$z(p_h, p_l) = \frac{p_h - p_l}{\sqrt{\frac{p_h(1-p_h)}{n_h} + \frac{p_l(1-p_l)}{n_l}}}.$$

Suppose that the alternative hypothesis is true and $p_h \neq p_l$. Let h be the binomial process with the higher success rate, i.e., $p_h > p_l$. Lemma 1 shows that the power of the test of the null hypothesis is increasing in p_h and decreasing in p_l. In particular, the power of the test becomes smaller as the success rates move closer to each other, with p_h decreasing and p_l increasing.

Lemma 1: *Let $p_h \in (0, 1)$ and $p_l \in (0, 1)$ be such that $p_h > p_l$. Then*

$$\frac{\partial \Theta(z(p_h, p_l))}{\partial p_h} > 0,$$

and
$$\frac{\partial\Theta(z(p_h,p_l))}{\partial p_l} < 0,$$
and hence $\Theta(z(p_h,p_l)) > \Theta(z(p_h-\Delta_h, p_l+\Delta_l))$ *for* $\Delta_h > 0$ *and* $\Delta_l > 0$ *such that* $p_h - \Delta_h > p_l + \Delta_l$.

Holding the significance level and the sample size fixed, can we say anything about how the power of the test changes as the value of strategic unpredictability changes? The answer is yes. In two games with the same equilibrium mixture and the same value, the power of the test of equality of winning probabilities is larger in the game in which the value of strategic unpredictability is larger. Theorem 3 establishes this result, and follows immediately from Theorem 2 and Lemma 1.

Theorem 3. Let $G = (\pi_{FF}, \pi_{FO}, \pi_{OF}, \pi_{OO})$ and $G' = (\pi'_{FF}, \pi'_{FO}, \pi'_{OF}, \pi'_{OO})$ be two constant-sum games that have the same equilibrium mixture (q^*, r^*) and the same value. Assume that the value of strategic unpredictability to the pitcher is higher in G than in G'. The two-sample Z-test of the null hypothesis that a pitchers's winning probabilities for F and O are the same has more statistical power for G than for G'.

Example 2 illustrates Theorem 3 for the games in Figure 1.

Example 2: Recall that the value of strategic unpredictability is .03460 in G_1 and is .20000 in G_2. Consider the null hypothesis $H_0 : \pi_F^P = \pi_O^P$. The null is true for both games at the batter's equilibrium mixture. Suppose instead that the batter follows the mixture $r = .6$. For G_1, we have $\pi_F^P(.6) = .72503$ and $\pi_O^P(.6) = .74421$. For G_2, we have $\pi_F^P(.6) = .72864$ and $\pi_O^P(.6) = .73973$. Given 1000 observations of each type of pitch, the power of the two-sample Z-test is 16.54% for G_1, but it is only 8.87% for G_2.

3 Data

We use every at plate appearance in Major League Baseball in the 2014-2018 seasons. In MLB there are 30 teams divided into two leagues – the National League (NL) and the American League (AL), each with 15 teams. Each league is further divided into three divisions: East, Central, and West. Each team plays 162 games during the regular season. At the conclusion of the regular season, a post-season tournament for each league – a series of playoff games between ten teams – identifies a league champion. The two league champions then face off in the World Series, a best-of-seven tournament.

Our data was collected from www.baseball-reference.com.[11] For each game, our data has the names of the teams, and whether the team was playing at home or away. Each at plate observation identifies the batter and the pitcher, and the outcome. For computing

[11] Operated by Sports Reference LLC. Accessed on April 8, 2020.

	Season	OBP N at plate	OBP Mean	OBP Std. Dev.	SLG N at bat	SLG Mean	SLG Std. Dev.
Astros	2014	6,033	0.31	0.46	5,447	0.38	0.84
	2015	6,045	0.32	0.46	5,459	0.44	0.94
	2016	6,177	0.32	0.47	5,545	0.42	0.90
	2017	*6,260*	*0.35*	*0.48*	*5,611*	*0.48*	*0.95*
	2018	6,132	0.33	0.47	5,453	0.43	0.90
Non-Astros	2014	176,553	0.31	0.46	160,167	0.39	0.82
	2015	176,383	0.32	0.47	160,029	0.40	0.85
	2016	177,378	0.32	0.47	160,016	0.42	0.88
	2017	178,110	0.32	0.47	159,956	0.42	0.90
	2018	178,184	0.32	0.47	159,979	0.41	0.88
All MLB	Total	917,255	0.32	0.47	827,662	0.41	0.87

Table 1: Descriptive statistics for OBP and SLG. The 2017 Astros season, during which the Astros is suspected of having stolen signs, is shown in italics..

the on base percentage (OBP), the outcome is simply whether the batter gets on base or not. The slugging percentage (SLG) is based on the at-bat appearances, which is a subset of at-plate appearances.[12]

Table 1 reports descriptive statistics for OBP and SLG for the Astros and the other MLB teams, from 2014-2018. It is evident from the table that the Astros's batting performance was exceptional in the 2017 season: Their on-base percentage and slugging percentages exceeded their performance in every other season. In fact, the performance of the Astros exceeded the performance of every other team for every year in our dataset. The next highest performance was by the Boston Red Sox in 2016, a season where they were accused of stealing signs. See Table 1 in the Online Appendix for the values of OBP and SLG.

The Evidence Graphically

Figures 3 and 4 compare the batting performance of the Astros to other MLB teams in the 2014-2017 seasons. In Figure 3, the red squares and blue circles show, respectively, the weekly OBP for Astros and non-Astros batters, where week zero is the first week of the 2017 season. The solid and dashed lines show, respectively, the fitted trend lines for the Astros and the non-Astros teams, separately for the 2017 season and the prior three seasons.[13] Figure 4 shows the same, but for SLG rather than OBP.

[12] An at-plate appearance may not count as an at-bat appearance for several reasons, e.g., the batter receives a walk as a result of four balls or as a result of being hit by a pitch, the batter hits a sacrifice fly or bunt, or they are awarded first base due to interference or obstruction by the catcher.

[13] The fitted lines are weighted by the number of observations for each week (at-plates for OBP and at-bats for SLG).

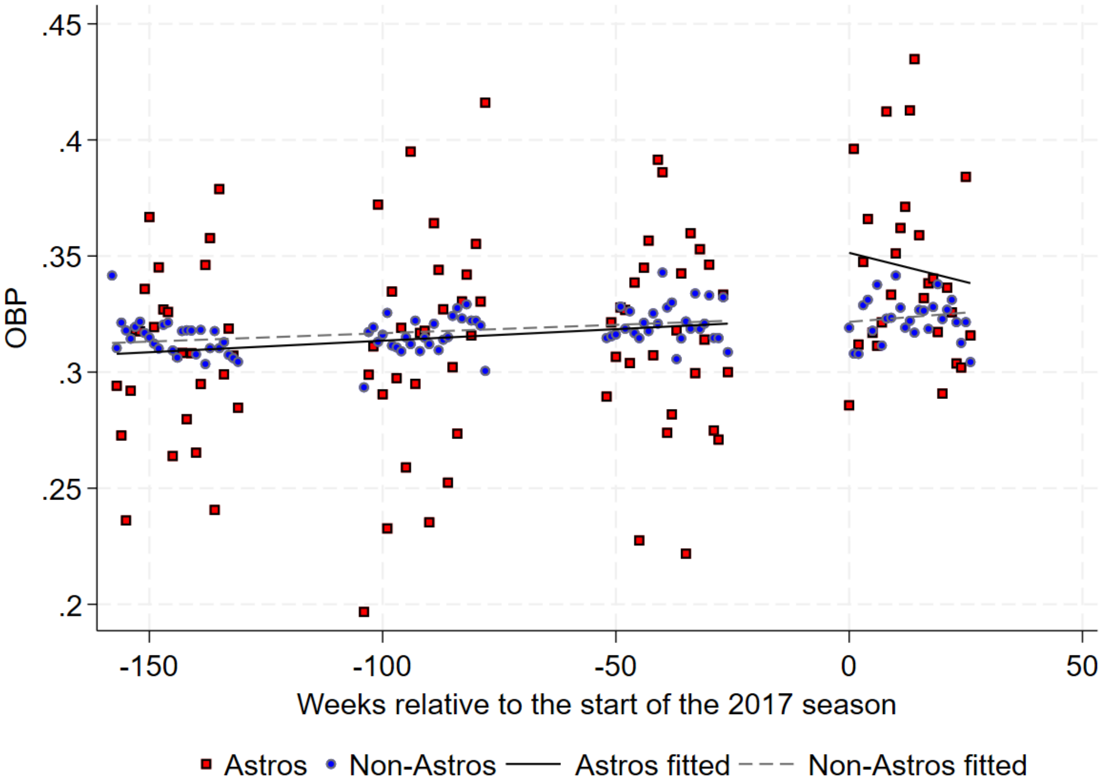


Figure 3: Weekly OBP for Astros and non-Astros batters.

The figures illustrate that the parallel trends assumption, necessary for the validity of the DID model estimated in the next section, is satisfied. Prior to the 2017 season, there was only a slight trend in improving batting performance for all teams, which continued for non-Astros batters in the 2017 season. By constrast, batting performance "jumps up" in 2017 for Astros batters.

We test the parallel trends assumption using data from the 2014-2016 seasons. We estimate the model

$$O_{iw} = \alpha + \beta_1 \times w + \beta_2 \times \mathbf{1}_i^{Astros} + \beta_3 \times \mathbf{1}_i^{Astros} \times w + \varepsilon_{iw},$$

where O_{iw} is the outcome (OBP or SLG) for team i in week w, $\mathbf{1}_i^{Astros}$ is a dummy variable for the Astros, and ε_{iw} is $i.i.d.$ noise. The parameter of interest is β_3, which captures the difference in trends for Astros and non-Astros batters. When the outcome is OBP we obtain $\hat{\beta}_3 = 0.00017$ (p-value of 0.386), and when it is SLG we obtain $\hat{\beta}_3 = -0.00017$ (p-value of 0.321). We can not reject the hypothesis of parallel trends.

4 Empirical Strategy

We identify the causal effect of sign stealing on Astros batting performance by DID estimation. We refer to the period of time where the Astros were stealing signs as the

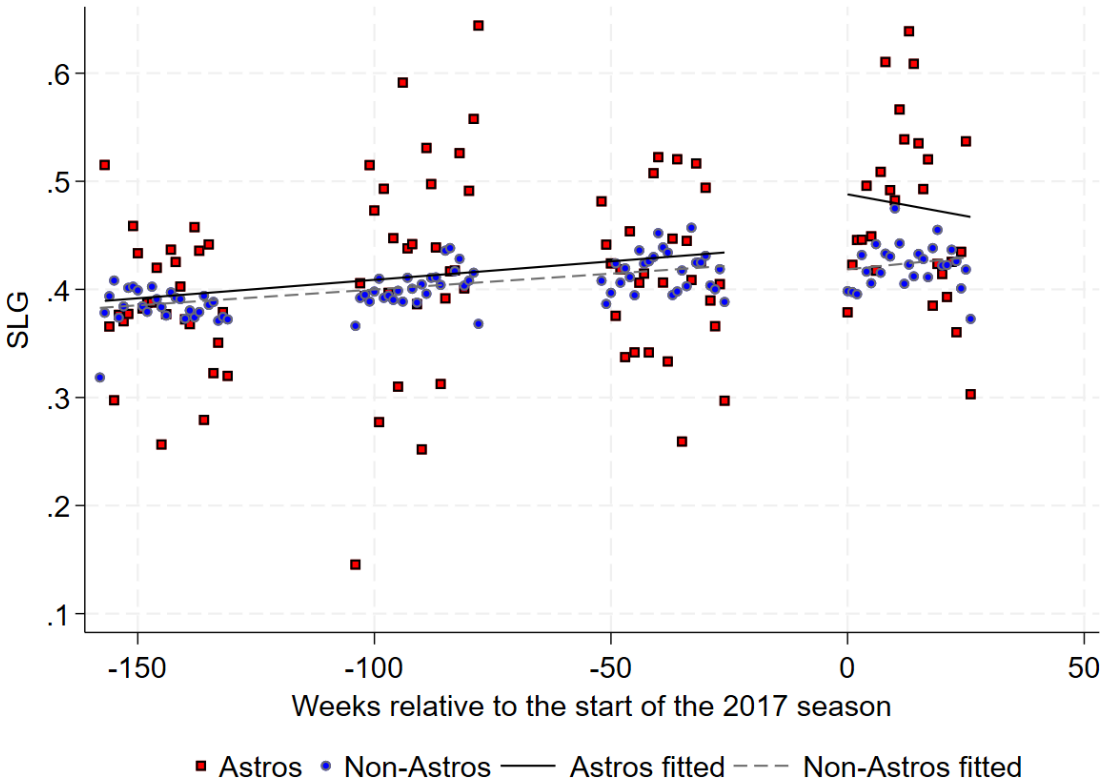


Figure 4: Weekly SLG for Astros and non-Astros batters.

Sign Stealing Period (SSP). Our estimation strategy compares the change in the Astros's batting performance between the 2014-2016 seasons and the SSP, to the change in the performance between the same two periods for non-Astros batters. Our main model takes the 2017 regular season as the sign stealing period, but we will consider several different specifications as a robustness check.[14]

Our difference in difference model is

$$O_{ibp} = \alpha + \beta \times \mathbf{1}_{ib}^{Astros} + \gamma \times \mathbf{1}_{i}^{SSP} + \delta \times \mathbf{1}_{ib}^{Astros} \times \mathbf{1}_{i}^{SSP} + \mu_{bp} + \varepsilon_{ibp},$$

where O_{ibp} is the outcome of the at-plate (for OBP) or at-bat (for SLG) appearance i with batter b and pitcher p, the dummy $\mathbf{1}_{ib}^{Astros}$ indicates whether batter b plays for the Astros, the dummy $\mathbf{1}_{i}^{SPP}$ indicates if the at plate/at bat takes place during the SSP, μ_{bp} is the fixed effect for batter b and pitcher p, and ε_{ibp} is $i.i.d.$ noise. The coefficient α measures the average performance of all batters on all teams over the 2014-2016 seasons and the SSP. The coefficient β measures the marginal effect on performance of batting for the Astros. The coefficient γ measures the marginal effect on performance, for all batters, of being in the SSP. Of primary interest is the coefficient δ, which measures the marginal effect on performance of being in the SSP for Astros batters.

[14]The exact period over which the Astros stole signs is unknown. In Section 6 we show that our results are robust to alternative definitions of the sign stealing period.

Including the dummy $\mathbf{1}_i^{SSP}$ in the model controls for changes in the performance of all batters that might result from changes in the batting "technology" between the 2014-2016 seasons and the sign stealing period.[15] Such changes might result from changes in the rules of baseball or changes in the equipment (e.g., bats and balls).[16] Likewise, including the dummy $\mathbf{1}_{ib}^{Astros}$ controls for the benefit, if any, of batting for the Astros (e.g., better coaching, stronger financial incentives) over the 2014-2016 seasons and the SSP. Changes to team rosters between the 2014-2016 seasons and the SSP are controlled for by the inclusion of pitcher and batter fixed effects.[17]

Our identification would be threaten if the start of sign stealing by the Astros coincided with other changes for the Astros' that affected batter performance, e.g., better training, coaching, or different incentives. Another identification threat would be if other teams in the league started stealing signs in the 2017 season; no evidence of such behaviour exists.

We estimate our model with four different levels of fixed effects: none, only for batters, only for pitchers, and for batter-pitcher pairs. The more granular the level of the fixed effect, the better it captures the heterogeneity in batters' and pitchers' performance. However, a more granular level of fixed effects substantially increases the number of coefficients to be estimated, thereby reducing statistical power.[18] We cluster standard errors at the level of fixed effects, following a recommendation by Cameron and Miller (2015) for cases with a large number of clusters. We therefore take a conservative approach by allowing heterogeneity in treatment effects, as discussed in Abadie et al. (2023).

5 Results

Table 2 reports results when OBP and SLG are the outcome variables, and the sign stealing period is the entire 2017 season. Columns 1 through 4 show, respectively, the results when there are (i) no fixed effects, (ii) batter fixed effects, (iii) pitcher fixed effects, and (iv) batter-pitcher fixed effects. Our preferred specification has fixed effects and clustering at the batter-pitcher level. p-values are in parentheses, and standard errors are clustered at the fixed effects level.

The estimates of α are consistent with the historical values reported for OBP and SLG in professional baseball. The effect of batting for the Astros, measured by β, is

[15]For most specifications, the coefficient γ is close to zero and statistically insignificant. This suggests that there were no changes in batting or pitching techniques, or the rules of baseball, that significantly affected the performance of all batters.

[16]The 2017 season, for example, saw the introduction of the no pitch intentional walk.

[17]At the start of the 2017 season, the Astros recruited Carlos Beltrán, Josh Reddick and Nori Aoki, but lost Colby Rasmus, Luis Valbuena and Nolan Fontana. The new players had a better batting performance in the 2016 season than did the departing players (OPB of 0.31 vs. 0.26, and SLG of 0.40 vs 0.37, respectively). Including batter fixed effects, as we do, controls for the change in the Astros roster.

[18]For example, for the OBP model, while there are $1,268$ fixed effects at the pitcher level and $1,650$ fixed effects at the batter level, there are $225,097$ fixed effects at the pitcher-batter level to be estimated.

Outcome Variable	OBP				SLG			
Model 1								
α	0.3174	0.3187	0.3168	0.3180	0.4025	0.4064	0.4016	0.4052
p-value	(< 0.001)	(< 0.001)	(< 0.001)	(< 0.001)	(< 0.001)	(< 0.001)	(< 0.001)	(< 0.001)
β	-0.0030	-0.0189	-0.0029	-0.0122	0.0095	-0.0305	0.0075	-0.0224
p-value	(0.398)	(0.011)	(0.455)	(0.369)	(0.167)	(0.016)	(0.352)	(0.435)
γ	0.0063	0.0032	0.0087	0.0050	0.0216	0.0115	0.0253	0.0147
p-value	(< 0.001)	(0.065)	(< 0.001)	(0.068)	(< 0.001)	(0.001)	(< 0.001)	(0.009)
δ	0.0244	0.0209	0.0252	0.0332	0.0442	0.0423	0.0422	0.0570
p-value	(< 0.001)	(0.009)	(0.001)	(0.031)	(0.001)	(0.006)	(0.007)	(0.081)
N obs	732, 939	732, 939	732, 939	732, 939	662, 230	662, 230	662, 230	662, 230
N clusters	.	1, 650	1, 268	225, 097	.	1, 643	1, 267	215, 892
Fixed Effect	-	Batter	Pitcher	Batter-Pitcher	-	Batter	Pitcher	Batter-Pitcher
Cluster	-	Batter	Pitcher	Batter-Pitcher	-	Batter	Pitcher	Batter-Pitcher

Table 2: DID estimates for OBP and SLG.

statistically insignificantly different from zero. The estimates of γ are small, positive, and marginally statistically significant for some specifications of fixed-effects, which suggests there might be a small overall improvement in batting performance in the 2017 season. The key result is that the estimated effect of sign stealing, measured by δ, is positive and statistically significant; the result is robust to all the specifications of fixed effects and both outcome variables.

Economic Significance

We perform several back-of-the-envelope calculations to evaluate the magnitude of the advantage gained by the Astros from stealing signs. First, we evaluate the increase in Astros batters' performance relative to average league performance. Second, we show that, absent sign stealing, the Astros would have had lower batter performance than their closest competitor. Third, using our estimates, we compute that the Astros won 19 additional games due to sign stealing. And fourth, we estimate that the Astros would have had to increase their payroll by \$32.3 million to obtain those 19 additional wins, absent sign stealing. In this analysis, we use the estimates obtained from our preferred specification, with pitcher-batter fixed effects, but our results are not sensitive to the level of fixed effects.

First, to evaluate the increase in Astros batters' performance, we consider three measures: (i) the ratio δ/α gives the increase in batting performance obtained by sign stealing relative to league average performance in the 2014-2016 seasons, (ii) the ratio $\delta/(\alpha + \beta)$ gives the increase in batting performance obtained by sign stealing relative to the Astros' average in the 2014-2016 seasons, and (iii) $\delta/(\alpha + \gamma)$ gives the increase in batting performance obtained by sign stealing relative to the league average in the 2017 season. Table 3 presents these ratios for both OBP and SLG, showing an increase in batting performance of 10% to 15%.

Estimated sign-stealing effect (δ) relative to:	OBP	SLG
League average in 2014-2016 (α)	+10%	+14%
Astros average in 2014-2016 ($\alpha + \beta$)	+11%	+15%
League average in 2017 ($\alpha + \gamma$)	+10%	+14%

Table 3: Percentage Increase in Astros Batting Performance.

Second, we compare the batting performance of the Astros to that of the New York Yankees, who finished second behind the Astros in the American League in 2017. Here, we focus on On-base Plus Slugging (OPS), a comprehensive measure of batting performance, which is the sum of OBP and SLG. Our estimates imply that the Astros gained an additional 0.09 OPS due to sign stealing, 0.033 due to OPB and 0.057 due to SLG (see Table 2). In 2017, the Astros had an OPS of 0.83 and the New York Yankees an OPS of 0.79.[19] Without the additional 0.09 OPS, the Astros would have had an OPS of only 0.74, a lower OPS than the Yankees.

Third, we compute that the Astros won 19 additional games due to sign stealing. Fox (2006) shows that, on average, an additional 0.01 OPS implies an additional 21.626 runs over a season. Hence, 0.09 OPS implies the Astros gained 194 extra runs from stealing sign over the 2017 season. Applying the commonly accepted rule of thumb that a team needs to score approximately 10 additional runs over the course of a season to turn one loss into a win, implies the Astros won 19 additional games over the 2017 season due to sign stealing.[20]

Fourth, the "cost of a win" in baseball is often computed as the total payroll divided by the number of wins. This has been estimated to be \$1.7 million for the 2019 season.[21] Following the same approach, dividing the 2017 total MLB payroll by the 2430 wins in the season, yields essentially the same result.[22] This suggests that the Astros would have had to increase their payroll by \$32.3 million to obtain the same increase in the number of wins without stealing signs.[23]

Did the Astros Steal Signs at Away Games?

The official MLB report, which documented the results of their investigation against

[19]Complete tables with OBP and SLG for all teams and years are available for comparison in the Online Appendix.

[20]See https://www.baseball-reference.com/about/war_explained_runs_to_wins.shtml for details (accessed on January 15 2026).

[21]https://www.bizjournals.com/pittsburgh/news/2019/10/08/heres-every-mlb-teams-cost-per-win-for-the-2019.html (accessed on January 15 2026).

[22]The 2017 total MLB payroll can be found here: https://legacy.baseballprospectus.com (accessed on January 15 2026).

[23]In 2017, the Astros had a payroll of \$124 million (see here: https://legacy.baseballprospectus.com/compensation).

the Astros, described the specialized equipment installed at the Astros home stadium to steal signs.[24] At home games, a monitor outside the Astros dugout displayed the view of the catcher from the center field camera. This information was used to decode the catcher's signs, which were then immediately communicated to Astros batters by banging on trash cans. These loud bangs can be heard in the replays of most home games in the 2017 season.

While it is clear that the Astros stole signs at home games, it is less clear that they did so at away games. There is no evidence that a monitor displayed catcher signs, nor was the banging of trash cans heard at away games. Nevertheless, there is reason to think that the Astros stole signs at away games. First, Diamond (2020) discusses that, at both home and away games, a group of specialists in the replay room engaged in "codebreaking," i.e., uncovering the mapping from signs to pitches. Second, according to the MLB report, the Astros had other ways to communicate stolen signs such as clapping, whistling, yelling, and the use of electronic devices. These forms of communication were available at away games.

This section explores whether the Astros stole signs at away games. In the prior analysis we pooled the data for home and away games. We now extend our analysis and distinguish between home and away games. We estimate the following difference-in-difference-in-difference (DIDID):

$$\begin{aligned} O_{ibp} \;=\; & \alpha^A + \alpha^H \times \mathbf{1}_{ib}^{Home} \\ & +\beta^A \times \mathbf{1}_{ib}^{Astros} + \beta^H \times \mathbf{1}_{ib}^{Astros} \times \mathbf{1}_{ib}^{Home} \\ & +\gamma^A \times \mathbf{1}_{i}^{SSP} + \gamma^H \times \mathbf{1}_{i}^{SSP} \times \mathbf{1}_{ib}^{Home} \\ & +\delta^A \times \mathbf{1}_{ib}^{Astros} \times \mathbf{1}_{i}^{SSP} + \delta^H \times \mathbf{1}_{ib}^{Astros} \times \mathbf{1}_{i}^{SSP} \times \mathbf{1}_{ib}^{Home} \\ & +\mu_{bp} + \varepsilon_{ibp}. \end{aligned}$$

Recall that α measures the average performance of all batters on all teams over the 2014-2016 seasons and the SSP, β measures the marginal effect on performance of batting for the Astros, γ measures the marginal effect on performance of batting during the SSP, and δ measures the marginal effect on performance of batting for the Astros during the SSP. The superscripts A and H distinguish these effects for home and away games, respectively. The dummy variable $\mathbf{1}_{ib}^{Home}$ equals one if the batter is batting at home.

Table 4 reports the estimation results for δ^A and δ^H.[25] The coefficient δ^H is not statistically significantly different from zero, which suggests that the increase in batting performance obtained by sign stealing was the same at both home and away games. These results are robust to the definition of the sign-stealing period.

[24] The report can be found here:
https://img.mlbstatic.com/mlb-images/image/upload/mlb/cglrhmlrwwbkacty27l7.pdf (accessed on January 2026).

[25] Full results are provided in Appendix B.

Outcome Variable	OBP				SLG			
δ^A	0.0315	0.0286	0.0326	0.0521	0.0617	0.0604	0.0606	0.0972
p-value	(0.001)	(0.014)	(0.002)	(0.006)	(0.001)	(0.002)	(0.006)	(0.016)
N obs	732,939	732,939	732,939	732,939	662,230	662,230	662,230	662,230
δ^H	−0.0149	−0.0161	−0.0153	−0.0394	−0.0360	−0.0374	−0.0377	−0.0823
p-value	(0.283)	(0.238)	(0.295)	(0.076)	(0.187)	(0.251)	(0.208)	(0.085)
N obs	732,939	732,939	732,939	732,939	662,230	662,230	662,230	662,230
Fixed Effect	-	Batter	Pitcher	Batter-Pitcher	-	Batter	Pitcher	Batter-Pitcher
Cluster	-	Batter	Pitcher	Batter-Pitcher	-	Batter	Pitcher	Batter-Pitcher

Table 4: DIDID estimates of sign-stealing effect, away and home.

6 Robustness to the SSP

Our analysis takes the sign-stealing period to be the entire 2017 season. However, the exact period during which the Astros stole signs is unknown. According to some sources, signs were stolen in the entire 2017 season and part of the 2018 season, while others suggest that signs were stolen in only a fraction of the 2017 season. In this section, we consider four alternative specifications of the sign-stealing period and show our results are robust: the estimates of the sign-stealing effect (δ) do not change in magnitude and remain statistically significant.

In Section 5, we use the entire 2017 season as the SSP. We refer to this period as Period 1. We consider the following alternative definitions:

Period 2: Identified by trash can bangs

At home games, Astros' players on the bench communicated stolen signs to the batter by banging on a trash can. We consider two alternative definitions of the SSP:

Period 2a consists of all games between the first and the last detected bang. This is 60 games in total, from April 3, 2017 to October 6, 2017.

Period 2b consists of the longest unbroken sequence of consecutive games with 6 or more recorded bangs. This is 34 games in total, from May 28, 2017 to September 21, 2017.

Period 3: Identified from the MLB report

The official MLB report details how the Astros stole signs. It includes information obtained from interviews with Astros players, coaches, staff, as well as information from internal Astros' correspondence.[26] We consider two more alternative definitions of the SSP:

Period 3a consists of all games from June 1, 2017 to June 1, 2018. According to the report, sign stealing started "... approximately two months into the 2017 season ..." and

[26]The report is available at https://img.mlbstatic.com/mlb-images/image/upload/mlb/cglrhmlrwwbkacty27l7.pdf (accessed on January 15 2023).

"... staff continued, at least for part of the 2018 season, to decode signs ...". The season started on April 2, 2017, and therefore we take June 1, 2017 as the start date of the SSP. We take June 1, 2018 as the end of the SSP, which includes the first two months of the 2018 season. The Astros played 182 games during this period.

Period 3b consists of all games from June 1, 2017 to September 15, 2017. The start date is the same as for Period 3a and the end date correspond to the date at which the MLB issued a press release and memorandum reminding teams that electronic sign-stealing is a violation of the rules. The Astros played 90 games during this period.

Figure 5 graphically represents the alternative definitions of the SSP.

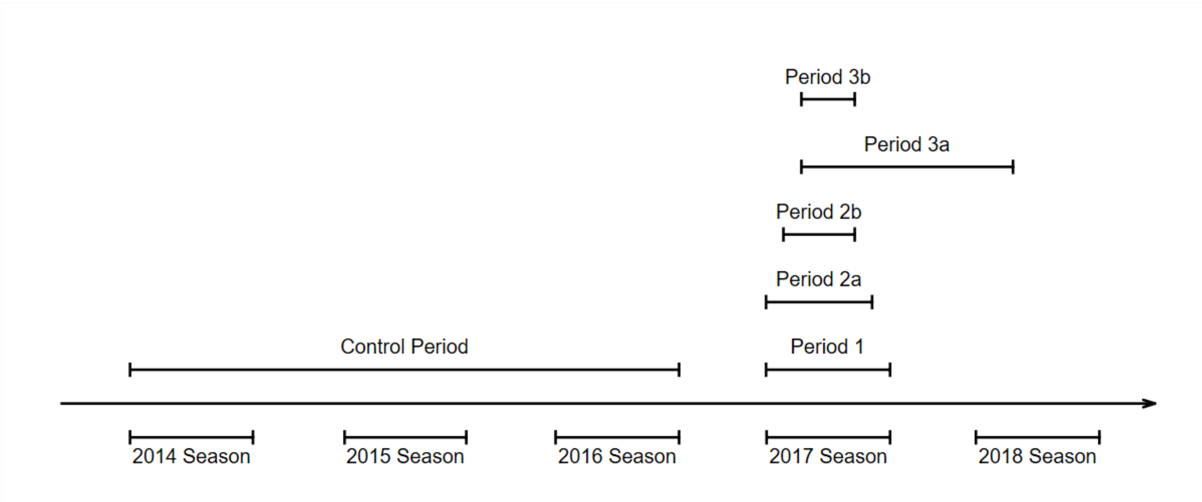


Figure 5: Definitions of the SSP.

Table 5 reports the estimates of the sign-stealing effect for the alternative definitions of the SSP. All estimates for δ are positive, most of them are statistically significant, and the magnitude is similar to those reported in Table 2.

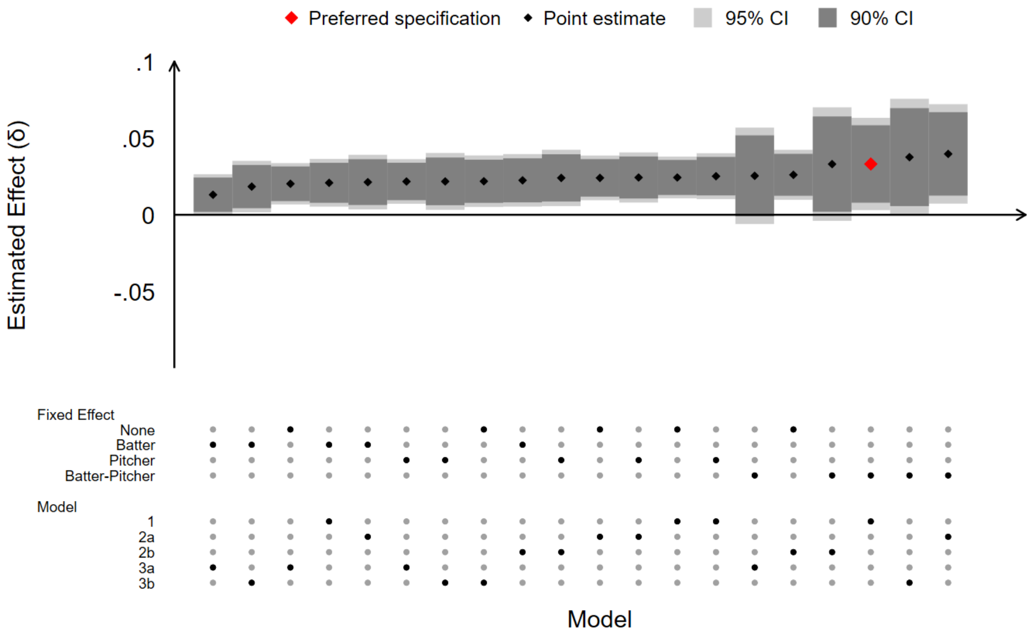
Period 2a is shorter than Period 1 and thus might include a higher proportion of games in which the Astros stole signs, which would explain the higher effect for Period 2a. Conversely, Period 3a is longer and may include some months of 2018 in which the Astros did not steal signs, thereby reducing the estimated effect.

Figure 6 gives specifications curves showing point estimates and confidence intervals for all our models.[27] Our preferred specification, depicted in red, has Period 1 as the SSP and batter-pitcher fixed effects. The specification curves show that our results are robust.

[27]See Simonsohn et al. (2020) for details.

Outcome Variable		OBP				SLG		
Model 2a								
δ	0.0241	0.0213	0.0243	0.0397	0.0507	0.0479	0.0480	0.0802
p-value	(0.001)	(0.019)	(0.004)	(0.016)	(<0.001)	(0.003)	(0.004)	(0.026)
N obs	703,078	703,078	703,078	703,078	635,435	635,435	635,435	635,435
N clusters	.	1,644	1,266	220815	.	1,637	1,265	211697
Model 2b								
δ	0.0261	0.0225	0.0241	0.0331	0.0519	0.0479	0.0455	0.0549
p-value	(0.002)	(0.010)	(0.010)	(0.080)	(0.001)	(0.003)	(0.015)	(0.169)
N obs	666,961	666,961	666,961	666,961	603,031	603,031	603,031	603,031
N clusters	.	1,622	1,262	211742	.	1,616	1,261	202911
Model 3a								
δ	0.0203	0.0131	0.0217	0.0254	0.0310	0.0225	0.0311	0.0587
p-value	(0.003)	(0.055)	(0.003)	(0.113)	(0.021)	(0.059)	(0.033)	(0.087)
N obs	737,611	737,611	737,611	737,611	666,356	666,356	666,356	666,356
N clusters	.	1,717	1,325	231113	.	1,709	1,324	221459
Model 3b								
δ	0.0219	0.0184	0.0218	0.0376	0.0459	0.0421	0.0423	0.0613
p-value	(0.011)	(0.032)	(0.021)	(0.052)	(0.006)	(0.012)	(0.029)	(0.134)
N obs	659,266	659,266	659,266	659,266	596,095	596,095	596095	596,095
N clusters	.	1,613	1,257	209632	.	1,606	1,256	200901
Fixed Effect	-	Batter	Pitcher	Batter-Pitcher	-	Batter	Pitcher	Batter-Pitcher
Cluster	-	Batter	Pitcher	Batter-Pitcher	-	Batter	Pitcher	Batter-Pitcher

Table 5: Robustness of DID estimates for OBP and SLG.



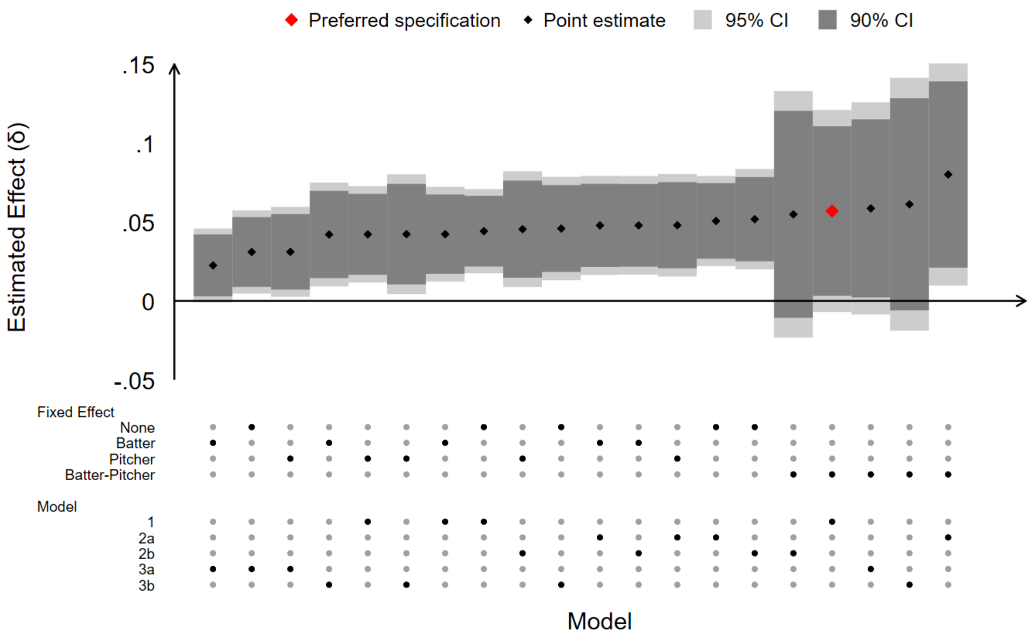


Figure 6: Specification curve for DID for OBP (Top) and SLG (Bottom).

Robustness for away games

In the previous section, we established that the increase in batting performance obtained by sign stealing was the same at both home and away games. Table 6 shows that this result is also robust to the definition of the SSP. In particular, δ^H is not statistically significant for any of the SSP specifications. Figure 7 shows the corresponding specification curves.

Outcome Variable	OBP				SLG			
Model 2a								
δ^H	-0.0076	-0.0084	-0.0073	-0.0299	-0.0355	-0.0356	-0.0380	-0.0889
p-value	(0.608)	(0.524)	(0.642)	(0.223)	(0.223)	(0.243)	(0.249)	(0.100)
N obs	703,078	703,078	703,078	703,078	635,435	635,435	635,435	635,435
Model 2b								
δ^H	0.0040	0.0042	0.0072	-0.0124	-0.0355	-0.0336	-0.0349	-0.0781
p-value	(0.810)	(0.771)	(0.674)	(0.662)	(0.275)	(0.266)	(0.323)	(0.220)
N obs	666,961	666,961	666,961	666,961	603,031	603,031	603,031	603,031
Model 3a								
δ^H	-0.0083	-0.0081	-0.0091	-0.0382	-0.0454	-0.0444	-0.0479	-0.0785
p-value	(0.547)	(0.580)	(0.521)	(0.093)	(0.093)	(0.147)	(0.082)	(0.106)
N obs	737,611	737,611	737,611	737,611	666,356	666,356	666,356	666,356
Model 3b								
δ^H	0.0147	0.0147	0.0161	0.0009	-0.0187	-0.0170	-0.0210	-0.0465
p-value	(0.393)	(0.356)	(0.356)	(0.976)	(0.578)	(0.616)	(0.558)	(0.482)
N obs	659,266	659,266	659,266	659,266	596,095	596,095	596,095	596,095
Fixed Effect	-	Batter	Pitcher	Batter-Pitcher	-	Batter	Pitcher	Batter-Pitcher
Cluster	-	Batter	Pitcher	Batter-Pitcher	-	Batter	Pitcher	Batter-Pitcher

Table 6: Robustness of DIDID estimates for OBP and SLG.

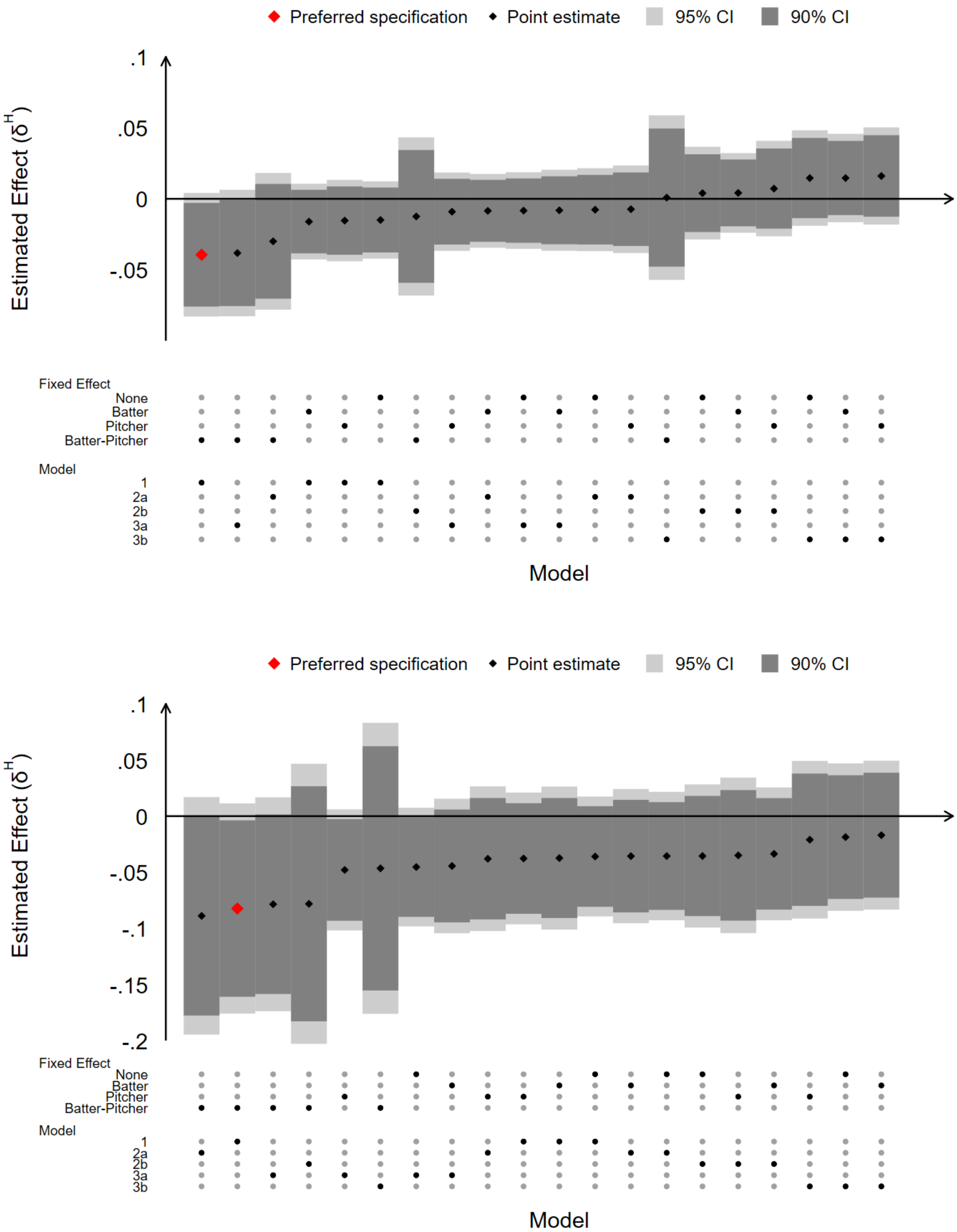


Figure 7: Specification curve for DIDID for OBP (Top) and SLG (Bottom).

7 Placebo tests

We run placebo tests to assess if our empirical approach generates false positives. We run the same regression as we did for the Astros, for teams for which we have no reason to believe they stole signs. If we find a positive effect for those teams, it will cast doubt on the validity of our approach. However, we do not find any effect for those teams, which reassures us on the validity of our approach.

A CHAMPIONS EFFECT?

We have shown that the Astros' batting performance was significantly better in 2017 than in the 2014-2016 seasons, which we attribute to sign stealing. The improvement, however, could be due to some unobserved factor not accounted for in our regressions. Perhaps league champions, for example, typically have abnormally high batting performance. To address this possibility, we repeat the analysis conducted for the Astros in 2017 for the league champions in 2016 (the Chicago Cubs and the Cleveland Indians) and in 2018 (the Boston Red Sox and the Los Angeles Dodgers).

Table 7 reports the results for the model

$$O_{ibp} = \alpha + \beta \times \mathbf{1}_{ib}^{Team} + \gamma \times \mathbf{1}_{i}^{Year} + \delta \times \mathbf{1}_{ib}^{Team} \times \mathbf{1}_{i}^{Year} + \mu_{bp} + \varepsilon_{ibp},$$

where O_{ibp} is the outcome of the at-plate (for OBP) or at-bat (for SLG) appearance i with batter b and pitcher p, the dummy $\mathbf{1}_{ib}^{Team}$ indicates whether batter b plays for the team of interest (e.g., Chicago Cubs), the dummy $\mathbf{1}_{i}^{Year}$ indicates if the at-plate/at-bat takes place during the year of interest (e.g., 2016), μ_{bp} is the fixed effect for batter b and pitcher p, and ε_{ibp} is $i.i.d.$ noise.

Outcome Variable	OBP				SLG			
Chicago Cubs (2016)								
δ	0.0274	0.0170	0.0224	0.0227	0.0160	0.0148	0.0050	0.0202
p-value	(< 0.001)	(0.053)	(0.006)	(0.192)	(0.265)	(0.320)	(0.748)	(0.564)
Cleveland Indians (2016)								
δ	0.0020	−0.0055	0.0007	−0.0018	0.0135	0.0087	0.0142	0.0210
p-value	(0.787)	(0.616)	(0.927)	(0.916)	(0.345)	(0.694)	(0.337)	(0.541)
Boston Red Sox (2018)								
δ	0.0075	0.0106	0.0044	0.0110	0.0337	0.0347	0.0302	0.0430
p-value	(0.278)	(0.430)	(0.575)	(0.441)	(0.015)	(0.145)	(0.057)	(0.153)
Los Angeles Dodgers (2018)								
δ	0.0092	0.0096	0.0111	0.0053	0.0298	0.0221	0.0326	−0.0076
p-value	(0.184)	(0.217)	(0.151)	(0.721)	(0.032)	(0.225)	(0.035)	(0.808)
Fixed Effect	-	Batter	Pitcher	Batter-Pitcher	-	Batter	Pitcher	Batter-Pitcher
Cluster	-	Batter	Pitcher	Batter-Pitcher	-	Batter	Pitcher	Batter-Pitcher

Table 7: Estimated team effect for champions in 2016 and 2018 seasons

For our preferred specification, with batter-pitcher fixed effects, δ is not statistically significant for either OBP or SLG for the league champions in either 2016 or 2018. Champions did not demonstrate any significant improvement in their batting performance.

Other teams in 2016, 2017, and 2018

We repeat the analysis above for all teams, not just the champions. In the Appendix, Tables 10, 12, and 14 report the estimates of δ for all teams in 2016, 2017, and 2018, respectively. Apart from the Houston Astros in 2017, we find no evidence of sign-stealing for any season or team, except for the Boston Red Sox, which experienced exceptionally good batting performance in 2016.

Including the Boston Red Sox in the control group when estimating the sign-stealing effect for non-Red Sox teams in 2016 may bias estimates of δ for these teams downward. Table 11 in the Appendix reports the estimates of δ for all teams in 2016, excluding the Boston Red Sox. Tables 13 and 15 report the results for the 2017 and 2018 seasons, respectively, when the Houston Astros are likewise excluded. The results reported in these tables do not reveal any evidence of sign-stealing by other teams.

8 Conclusion

Empirical studies of mixed-strategy Nash equilibria using field data test the null hypothesis that the probability of winning is identical for every action in the support of a player's equilibrium mixture. However, these tests will have low power if the serve, kick, or pitch is "not important," e.g., if the probability that the server wins a point depends only weakly on the server's and receiver's actions, and thus the value of strategic unpredictability is small. This paper exploits a unique event in professional sports to estimate the value of strategic unpredictability to the pitcher in baseball. We find that the performance of batters is significantly improved, increasing OBP and SLG by 10-15%, if batters learn the type of pitch that will be delivered. This translates into 19 extra wins for the batting team over the course of a season.

Recognising the importance of strategic unpredictability to the character of the game, in 2022 the MLB introduced an electronic system for the catcher to communicate pitches to the pitcher, thereby eliminating the possibility of sign stealing, either electronic or otherwise. In this new system, catchers use a wristband with a keypad to send an encrypted signal with a chosen pitch to the pitcher's earphone receiver. Therefore, the present study takes advantage of a unique opportunity to quantify the importance of strategic unpredictability.

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APPENDIX

A Proofs

Proof of Theorem 1. Recall that $u_G = q^*(\pi_{FF} - \pi_{FO}) = (1-q^*)(\pi_{OO} - \pi_{OF})$. We have

$$\begin{aligned}\frac{\partial \pi^P(q,r)}{\partial r} &= -q(\pi_{FF} - \pi_{FO}) + (1-q)(\pi_{OO} - \pi_{OF}) \\ &= -q\frac{u}{q^*} + (1-q)\frac{u}{1-q^*} \\ &= u_G \frac{q^* - q}{q^*(1-q^*)},\end{aligned}$$

Hence $q \neq q^*$ and $u_G > u_{G'}$ implies that

$$\varepsilon_G(q) = \left| u_G \frac{q^* - q}{q^*(1-q^*)} \right| > \left| u_{G'} \frac{q^* - q}{q^*(1-q^*)} \right| = \varepsilon_{G'}(q).$$

■

Proof of Theorem 2. For G, the pitcher's winning probabilities, given the batter's mixture r, is

$$\pi_O^P(r) = 1 - \pi_{OO} + r(\pi_{OO} - \pi_{OF})$$

and

$$\pi_F^P(r) = 1 - \pi_{FO} - r(\pi_{FF} - \pi_{FO}).$$

Differentiating with respect to r yields

$$\frac{d\pi_O^P(r)}{dr} = \pi_{OO} - \pi_{OF}$$

and

$$\frac{d\pi_F^P(r)}{dr} = -(\pi_{FF} - \pi_{FO}).$$

The value of strategic unpredictability to the pitcher for G can be written as $(1 - q^*)(\pi_{OO} - \pi_{OF})$ and for G' as $(1 - q^*)(\pi'_{OO} - \pi'_{OF})$. Since the value of strategic unpredictabily to the pitcher for G' is smaller than G, then

$$\pi'_{OO} - \pi'_{OF} < \pi_{OO} - \pi_{OF}.$$

Hence for $r > r^*$ we have

$$\pi'^P_O(r^*) < \pi'^P_O(r) < \pi^P_O(r).$$

The value of strategic unpredictability to the pitcher for G can also be written as $q^*(\pi_{FF} - \pi_{FO})$ and for G' as $q^*(\pi'_{FF} - \pi'_{FO})$. Since the value of strategic unpredictabily to the pitcher for G' is smaller than G, then

$$\pi'_{FF} - \pi'_{FO} < \pi_{FF} - \pi_{FO}.$$

Hence for $r > r^*$ we have

$$\pi_F^P(r) < \pi'^P_F(r) < \pi_F^P(r^*).$$

Since the value of G and G' is the same, then $\pi_F^P(r^*) = \pi'^P_O(r^*)$ and hence

$$\pi_F^P(r) < \pi'^P_F(r) < \pi'^P_O(r) < \pi_O^P(r).$$

It follows that

$$\pi_O^P(r) - \pi_F^P(r) > \pi'^P_O(r) - \pi'^P_F(r),$$

i.e., the difference in the winning probabilities of the pitcher's actions is greater in G than G' for $r > r^*$. A symmetric argument establishes that the difference in the winning probabilities of the pitcher's actions is greater in G than G' for $r < r^*$ as well. ∎

Proof of Lemma 1. For $r \neq r^*$, either $\pi_F^P(r) > \pi_O^P(r)$ or $\pi_F^P(r) < \pi_O^P(r)$. Let $p_h = \max(\pi_F^P(r), \pi_O^P(r))$ and $p_l = \min(\pi_F^P(r), \pi_O^P(r))$. Since $p_h > p_l$, then $z(p_h, p_l)$ is positive, where

$$z(p_h, p_l) = \frac{p_h - p_l}{\sqrt{\frac{p_h(1-p_h)}{n_h} + \frac{p_l(1-p_l)}{n_l}}}.$$

We first show that $d\Theta(z)/dz$ is positive. Differentiating Θ with respect to z yields

$$\begin{aligned} \frac{d\Theta(z)}{dz} &= \frac{d}{dz}\Phi(z - z_{\alpha/2}) + \frac{d}{dz}\Phi(-z - z_{\alpha/2}) \\ &= \phi(z - z_{\alpha/2}) - \phi(-z - z_{\alpha/2}), \end{aligned}$$

where $\phi(x) = \frac{1}{\sqrt{2\pi}}e^{-x^2/2}$ is the p.d.f. of the standard normal distribution. Since $\phi(x)$ is an even function, then $\phi(-x) = \phi(x)$ for all $x \in \mathbb{R}$. Hence

$$\frac{d\Theta(z)}{dz} = \phi(z - z_{\alpha/2}) - \phi(z + z_{\alpha/2}).$$

We show that $\phi(z - z_{\alpha/2}) > \phi(z + z_{\alpha/2})$, i.e.,

$$\frac{1}{\sqrt{2\pi}}e^{-\frac{(z-z_{\alpha/2})^2}{2}} > \frac{1}{\sqrt{2\pi}}e^{-\frac{(z+z_{\alpha/2})^2}{2}}.$$

Since e^x is an increasing function, this inequality holds if and only if

$$-\frac{(z - z_{\alpha/2})^2}{2} > -\frac{(z + z_{\alpha/2})^2}{2},$$

i.e.,

$$(z - z_{\alpha/2})^2 < (z + z_{\alpha/2})^2.$$

Simplifying yields

$$-zz_{\alpha/2} < zz_{\alpha/2}.$$

This inequality holds since z and $z_{\alpha/2}$ are positive. Hence $d\Theta(z)/dz$ is positive.

Next, we show that $\partial z(p_h, p_l)/\partial p_h > 0$ and $\partial z(p_h, p_l)/\partial p_l < 0$. We have

$$\begin{aligned}\frac{\partial z(p_h, p_l)}{\partial p_h} &= \frac{\sqrt{V(p_h, p_l)} - (p_h - p_l)\frac{1-2p_h}{2n_h\sqrt{\sigma_D^2}}}{\sigma_D^2} \\ &= \frac{2n_h\sigma_D^2 - (p_h - p_l)(1 - 2p_h)}{2n_h(\sigma_D^2)^{3/2}},\end{aligned}$$

where

$$\sigma_D^2 = \frac{p_h(1 - p_h)}{n_h} + \frac{p_l(1 - p_l)}{n_l}.$$

Since $p_h, p_l \in (0, 1)$ then $\sigma_D^2 > 0$ and hence the denominator is positive. The numerator can be written as

$$\begin{aligned}&2n_h\left(\frac{p_h(1 - p_h)}{n_h} + \frac{p_l(1 - p_l)}{n_l}\right) - (p_h - 2p_h^2 - p_l + 2p_hp_l) \\ &= 2p_h(1 - p_h) + 2\frac{n_h}{n_l}p_l(1 - p_l) - p_h + p_l + 2p_h^2 - 2p_lp_l \\ &= 2\frac{n_h}{n_l}p_l(1 - p_l) + p_h(1 - p_l) + p_l(1 - p_h).\end{aligned}$$

Since $p_h, p_l \in (0, 1)$, then the numerator is positive as well, and hence $\partial z(p_h, p_l)/\partial p_h > 0$.

We have

$$\begin{aligned}\frac{\partial z(p_h, p_l)}{\partial p_l} &= \frac{-\sqrt{\sigma_D^2} - (p_h - p_l)\frac{1-2p_l}{2n_l\sqrt{\sigma_D^2}}}{\sigma_D^2} \\ &= \frac{-2n_l\sigma_D^2 - (p_h - p_l)(1 - 2p_l)}{2n_l(\sigma_D^2)^{3/2}}.\end{aligned}$$

The denominator is positive. The numerator can be written as

$$\begin{aligned}&-2n_l\left(\frac{p_h(1 - p_h)}{n_h} + \frac{p_l(1 - p_l)}{n_l}\right) - (p_h - 2p_hp_l - p_l + 2p_l^2) \\ &= -2\frac{n_l}{n_h}p_h(1 - p_h) - p_h - p_l + 2p_lp_h \\ &= -2\frac{n_l}{n_h}p_h(1 - p_h) - p_h(1 - p_l) - p_h(1 - p_l).\end{aligned}$$

Since $p_h, p_l \in (0, 1)$, then the numerator is negative and $\partial z(p_h, p_l)/\partial p_l < 0$.

We have

$$\frac{\partial\Theta(z(p_h, p_l))}{\partial p_h} = \frac{d\Theta(z)}{dz}\frac{\partial z(p_h, p_l)}{\partial p_h} > 0,$$

and

$$\frac{\partial\Theta(z(p_h, p_l))}{\partial p_l} = \frac{d\Theta(z)}{dz}\frac{\partial z(p_h, p_l)}{\partial p_l} < 0.$$

■

B DIDID for home effect

α^A	0.3110 (1.000) 732,939	0.3126 (1.000) 732,939	0.3104 (1.000) 732,939	0.3115 (1.000) 732,939	0.3942 (1.000) 662,230	0.3986 (1.000) 662,230	0.3936 (1.000) 662,230	0.3967 (1.000) 662,230
α^H	0.0131 $(< 0.001)^{***}$ 732,939	0.0125 $(< 0.001)^{***}$ 732,939	0.0129 $(< 0.001)^{***}$ 732,939	0.0132 $(< 0.001)^{***}$ 732,939	0.0169 $(< 0.001)^{***}$ 662,230	0.0159 $(< 0.001)^{***}$ 662,230	0.0164 $(< 0.001)^{***}$ 662,230	0.0174 $(< 0.001)^{***}$ 662,230
β^A	0.0025 (0.604) 732,939	−0.0130 $(0.098)^{\dagger}$ 732,939	0.0019 (0.716) 732,939	−0.0099 (0.500) 732,939	0.0085 (0.377) 662,230	−0.0310 $(0.008)^{**}$ 662,230	0.0045 (0.656) 662,230	−0.0264 (0.390) 662,230
β^H	−0.0112 (0.110) 732,939	−0.0118 $(0.031)^{*}$ 732,939	−0.0098 (0.174) 732,939	−0.0049 (0.663) 732,939	0.0022 (0.875) 662,230	0.0014 (0.923) 662,230	0.0062 (0.667) 662,230	0.0076 (0.752) 662,230
γ^A	0.0057 $(0.001)^{**}$ 732,939	0.0025 (0.244) 732939	0.0079 $(< 0.001)^{***}$ 732,939	0.0048 (0.160) 732,939	0.0184 $(< 0.001)^{***}$ 662,230	0.0083 $(0.052)^{\dagger}$ 662,230	0.0222 $(< 0.001)^{***}$ 662,230	0.0141 $(0.045)^{*}$ 662,30
γ^H	0.0012 (0.652) 732,939	0.0014 (0.596) 732,939	0.0018 (0.501) 732,939	0.0005 (0.904) 732,939	0.0065 (0.191) 662,230	0.0066 (0.224) 662,230	0.0063 (0.248) 662,230	0.0014 (0.875) 662,230
δ^A	0.0315 $(0.001)^{**}$ 732,939	0.0286 $(0.014)^{*}$ 732,939	0.0326 $(0.002)^{**}$ 732,939	0.0521 $(0.006)^{**}$ 732,939	0.0617 $(0.001)^{**}$ 662,230	0.0604 $(0.002)^{**}$ 662,230	0.0606 $(0.006)^{**}$ 662,230	0.0972 $(0.016)^{*}$ 662,230
δ^H	−0.0149 (0.283) 732,939	−0.0161 (0.238) 732,939	−0.0153 (0.295) 732,939	−0.0394 $(0.076)^{\dagger}$ 732,939	−0.0360 (0.187) 662,230	−0.0374 (0.251) 662,230	−0.0377 (0.208) 662,230	−0.0823 $(0.085)^{\dagger}$ 662,230
Fixed Effect	-	Batter	Pitcher	Batter-Pitcher	-	Batter	Pitcher	Batter-Pitcher
Cluster	-	Batter	Pitcher	Batter-Pitcher	-	Batter	Pitcher	Batter-Pitcher

Table 8: DIDID

C Models of sign-stealing periods

Outcome Variable			OBP				SLG	
Model 2a								
α	0.3174	0.3185	0.3170	0.3179	0.4025	0.4057	0.4019	0.4047
	(0.100)	(0.008)	(0.106)	(0.121)	(0.042)	(0.005)	(0.095)	(0.132)
β	−0.0030	−0.0197	−0.0032	−0.0117	0.0095	−0.0306	0.0071	−0.0206
	(0.100)	(0.008)	(0.106)	(0.121)	(0.042)	(0.005)	(0.095)	(0.132)
γ	0.0076	0.0052	0.0094	0.0060	0.0249	0.0165	0.0279	0.0181
	(0.100)	(0.008)	(0.106)	(0.121)	(0.042)	(0.005)	(0.095)	(0.132)
δ	0.0241	0.0213	0.0243	0.0397	0.0507	0.0479	0.0480	0.0802
	(0.100)	(0.008)	(0.106)	(0.121)	(0.042)	(0.005)	(0.095)	(0.132)
N obs	703,078	703,078	703,078	703,078	635,435	635,435	635,435	635,435
N clusters	.	1,644	1,266	220,815	.	1,637	1,265	211,697
Model 2b								
α	0.3174	0.3185	0.3172	0.3182	0.4025	0.4056	0.4021	0.4047
	(0.100)	(0.009)	(0.100)	(0.160)	(0.042)	(0.005)	(0.101)	(0.175)
β	−0.0030	−0.0186	−0.0034	−0.0124	0.0095	−0.0318	0.0069	−0.0205
	(0.100)	(0.009)	(0.100)	(0.160)	(0.042)	(0.005)	(0.101)	(0.175)
γ	0.0082	0.0053	0.0096	0.0051	0.0278	0.0181	0.0305	0.0206
	(0.100)	(0.009)	(0.100)	(0.160)	(0.042)	(0.005)	(0.101)	(0.175)
δ	0.0261	0.0225	0.0241	0.0331	0.0519	0.0479	0.0455	0.0549
	(0.100)	(0.009)	(0.100)	(0.160)	(0.042)	(0.005)	(0.101)	(0.175)
N obs	666,961	666961	666,961	666,961	603,031	603,031	603,031	603,031
N clusters	.	1,622	1,262	211,742	.	1,616	1,261	202,911
Model 3a								
α	0.3174	0.3186	0.3167	0.3182	0.4025	0.4058	0.4008	0.4047
	(0.100)	(0.065)	(0.097)	(0.304)	(0.047)	(0.027)	(0.113)	(0.139)
β	−0.0030	−0.0157	−0.0034	−0.0061	0.0095	−0.0232	0.0065	−0.0233
	(0.100)	(0.065)	(0.097)	(0.304)	(0.047)	(0.027)	(0.113)	(0.139)
γ	0.0051	0.0023	0.0078	0.0023	0.0188	0.0103	0.0256	0.0135
	(0.100)	(0.065)	(0.097)	(0.304)	(0.047)	(0.027)	(0.113)	(0.139)
δ	0.0203	0.0131	0.0217	0.0254	0.0310	0.0225	0.0311	0.0587
	(0.100)	(0.065)	(0.097)	(0.304)	(0.047)	(0.027)	(0.113)	(0.139)
N obs	737,611	737,611	737,611	737,611	666,356	666,356	666,356	666,356
N clusters	.	1,717	1,325	231,113	.	1,709	1,324	221,459
Model 3b								
α	0.3174	0.3184	0.3172	0.3181	0.4025	0.4053	0.4021	0.4042
	(0.102)	(0.014)	(0.099)	(0.184)	(0.043)	(0.010)	(0.104)	(0.199)
β	−0.0030	−0.0177	−0.0035	−0.0092	0.0095	−0.0293	0.0070	−0.0144
	(0.102)	(0.014)	(0.099)	(0.184)	(0.043)	(0.010)	(0.104)	(0.199)
γ	0.0087	0.0060	0.0101	0.0054	0.0285	0.0195	0.0315	0.0225
	(0.102)	(0.014)	(0.099)	(0.184)	(0.043)	(0.010)	(0.104)	(0.199)
δ	0.0219	0.0184	0.0218	0.0376	0.0459	0.0421	0.0423	0.0613
	(0.102)	(0.014)	(0.099)	(0.184)	(0.043)	(0.010)	(0.104)	(0.199)
N obs	659,266	659,266	659,266	659,266	596,095	596,095	596,095	596,095
N clusters	.	1,613	1,257	209,632	.	1,606	1,256	200,901
Fixed Effect	-	Batter	Pitcher	Batter-Pitcher	-	Batter	Pitcher	Batter-Pitcher
Cluster	-	Batter	Pitcher	Batter-Pitcher	-	Batter	Pitcher	Batter-Pitcher

Table 9: DID model estimates with corresponding p-values in parenthesis, including the sign-stealing effect (δ) on the Astros 2017 season for periods 2a-b and 3a-b. Batting performance for OBP (Left) and SLG (Right) measures. No fixed effects (first column), Pitcher fixed effects (second column), Batter fixed effects (third column), and Batter-Pitcher fixed effects (fourth column). Standard errors are clustered at the fixed effects level.

D Teams effects in 2016

		OBP				SLG			
AL East	Baltimore Orioles	0.0015	0.0054	0.0027	−0.0000	−0.0000	0.0004	0.0045	0.0280
		(0.837)	(0.376)	(0.753)	(0.999)	(0.998)	(0.980)	(0.777)	(0.378)
	Boston Red Sox	0.0224	0.0243	0.0212	0.0268	0.0492	0.0459	0.0494	0.0498
		(0.002)	(0.002)	(0.008)	(0.071)	(0.001)	(0.002)	(0.003)	(0.101)
	New York Yankees	−0.0075	−0.0101	−0.0060	0.0064	−0.0178	−0.0255	−0.0117	−0.0108
		(0.312)	(0.292)	(0.440)	(0.687)	(0.214)	(0.211)	(0.472)	(0.754)
	Tampa Bay Rays	−0.0156	−0.0004	−0.0125	0.0090	0.0181	0.0110	0.0252	0.0285
		(0.037)	(0.961)	(0.120)	(0.585)	(0.207)	(0.588)	(0.100)	(0.390)
	Toronto Blue Jays	−0.0083	−0.0166	−0.0101	−0.0153	−0.0326	−0.0505	−0.0397	−0.0468
		(0.263)	(0.058)	(0.210)	(0.294)	(0.023)	(< 0.001)	(0.015)	(0.165)
AL Central	Chicago White Sox	0.0030	−0.0016	0.0036	−0.0103	−0.0013	−0.0095	0.0008	−0.0142
		(0.688)	(0.841)	(0.655)	(0.550)	(0.928)	(0.567)	(0.955)	(0.670)
	Cleveland Indians	0.0020	−0.0055	0.0007	−0.0018	0.0135	0.0087	0.0142	0.0210
		(0.787)	(0.616)	(0.927)	(0.916)	(0.345)	(0.694)	(0.337)	(0.541)
	Detroit Tigers	−0.0049	−0.0033	−0.0025	−0.0076	−0.0072	0.0017	−0.0021	−0.0082
		(0.512)	(0.672)	(0.748)	(0.623)	(0.612)	(0.899)	(0.897)	(0.792)
	Kansas City Royals	−0.0123	−0.0084	−0.0107	−0.0120	−0.0166	−0.0055	−0.0102	−0.0009
		(0.100)	(0.243)	(0.158)	(0.423)	(0.244)	(0.627)	(0.475)	(0.977)
	Minnesota Twins	−0.0049	−0.0024	−0.0052	−0.0084	0.0055	0.0099	0.0045	−0.0092
		(0.502)	(0.777)	(0.514)	(0.610)	(0.698)	(0.650)	(0.779)	(0.785)
AL West	Houston Astros	−0.0000	−0.0015	−0.0016	0.0038	−0.0154	−0.0286	−0.0183	−0.0191
		(0.997)	(0.872)	(0.842)	(0.811)	(0.280)	(0.164)	(0.257)	(0.571)
	Los Angeles Angels	0.0010	0.0127	0.0042	0.0118	−0.0191	−0.0107	−0.0159	−0.0228
		(0.894)	(0.189)	(0.598)	(0.479)	(0.184)	(0.222)	(0.284)	(0.518)
	Oakland Athletics	−0.0186	−0.0151	−0.0165	−0.0091	−0.0156	−0.0243	−0.0132	−0.0111
		(0.013)	(0.096)	(0.036)	(0.606)	(0.275)	(0.115)	(0.376)	(0.746)
	Seattle Mariners	0.0149	0.0001	0.0179	0.0028	0.0150	0.0274	0.0199	0.0143
		(0.043)	(0.991)	(0.023)	(0.873)	(0.294)	(0.110)	(0.195)	(0.701)
	Texas Rangers	−0.0045	−0.0059	−0.0031	0.0004	0.0176	0.0163	0.0167	0.0097
		(0.545)	(0.603)	(0.682)	(0.980)	(0.220)	(0.381)	(0.265)	(0.773)
NL East	Atlanta Braves	0.0050	0.0053	0.0073	−0.0041	0.0027	−0.0032	0.0030	−0.0204
		(0.500)	(0.595)	(0.312)	(0.823)	(0.852)	(0.875)	(0.817)	(0.561)
	Miami Marlins	0.0026	0.0026	0.0029	−0.0051	−0.0086	−0.0045	−0.0120	−0.0019
		(0.727)	(0.794)	(0.700)	(0.742)	(0.549)	(0.779)	(0.383)	(0.949)
	New York Mets	−0.0004	0.0078	−0.0021	−0.0274	0.0127	0.0129	0.0069	−0.0561
		(0.956)	(0.353)	(0.793)	(0.118)	(0.375)	(0.545)	(0.675)	(0.131)
	Philadelphia Phillies	−0.0083	−0.0101	−0.0122	−0.0087	−0.0103	−0.0047	−0.0142	−0.0269
		(0.268)	(0.259)	(0.130)	(0.637)	(0.475)	(0.769)	(0.318)	(0.436)
	Washington Senators	−0.0019	−0.0037	−0.0054	−0.0226	0.0064	−0.0039	−0.0020	−0.0558
		(0.802)	(0.778)	(0.465)	(0.187)	(0.654)	(0.874)	(0.897)	(0.088)
NL Central	Chicago Cubs	0.0274	0.0170	0.0224	0.0227	0.0160	0.0148	0.0050	0.0202
		(< 0.001)	(0.053)	(0.006)	(0.192)	(0.265)	(0.320)	(0.748)	(0.564)
	Cincinnati Reds	0.0053	0.0068	0.0050	0.0194	0.0065	0.0241	0.0051	0.0210
		(0.475)	(0.307)	(0.530)	(0.269)	(0.649)	(0.192)	(0.725)	(0.542)
	Milwaukee Brewers	0.0073	0.0252	0.0046	0.0165	−0.0107	0.0305	−0.0182	0.0341
		(0.329)	(0.009)	(0.558)	(0.421)	(0.460)	(0.059)	(0.213)	(0.389)
	Pittsburgh Pirates	−0.0004	−0.0031	−0.0007	0.0051	−0.0210	−0.0068	−0.0188	0.0033
		(0.961)	(0.799)	(0.928)	(0.754)	(0.141)	(0.742)	(0.175)	(0.909)
	St. Louis Cardinals	−0.0019	−0.0073	−0.0035	−0.0069	0.0397	0.0160	0.0355	0.0172
		(0.801)	(0.423)	(0.648)	(0.686)	(0.006)	(0.261)	(0.022)	(0.618)
NL West	Arizona Diamondbacks	0.0012	0.0122	0.0028	0.0196	0.0151	0.0262	0.0146	0.0597
		(0.867)	(0.232)	(0.734)	(0.287)	(0.285)	(0.305)	(0.325)	(0.108)
	Colorado Rockies	0.0090	0.0198	0.0075	0.0340	−0.0034	0.0141	−0.0030	0.0446
		(0.225)	(0.119)	(0.328)	(0.052)	(0.812)	(0.536)	(0.858)	(0.231)
	Los Angeles Dodgers	−0.0168	−0.0286	−0.0142	−0.0120	−0.0228	−0.0370	−0.0173	−0.0011
		(0.024)	(< 0.001)	(0.074)	(0.483)	(0.111)	(0.031)	(0.278)	(0.975)
	San Diego Padres	−0.0037	−0.0060	−0.0017	0.0065	0.0048	0.0066	0.0112	0.0485
		(0.618)	(0.554)	(0.838)	(0.740)	(0.739)	(0.744)	(0.458)	(0.202)
	San Francisco Giants	0.0047	−0.0017	0.0034	−0.0184	−0.0218	−0.0295	−0.0220	−0.0659
		(0.527)	(0.847)	(0.671)	(0.270)	(0.126)	(0.027)	(0.117)	(0.028)
	Fixed Effect	-	Batter	Pitcher	Batter-Pitcher	-	Batter	Pitcher	Batter-Pitcher
	Cluster	-	Batter	Pitcher	Batter-Pitcher	-	Batter	Pitcher	Batter-Pitcher

Table 10: Estimated team effect for all teams in 2016 season with corresponding p-values in parenthesis. Batting performance for OBP (Left) and SLG (Right) measures. No fixed effects (first column), Pitcher fixed effets (second column), Batter fixed effects (third column), and Batter-Pitcher fixed effects (fourth column). Standard errors are clustered at the fixed effects level.

		OBP				SLG			
AL East	Baltimore Orioles	0.0015	0.0054	0.0027	−0.0000	−0.0000	0.0004	0.0045	0.0280
		(0.837)	(0.376)	(0.753)	(0.999)	(0.998)	(0.980)	(0.777)	(0.378)
	New York Yankees	−0.0075	−0.0101	−0.0060	0.0064	−0.0178	−0.0255	−0.0117	−0.0108
		(0.312)	(0.292)	(0.440)	(0.687)	(0.214)	(0.211)	(0.472)	(0.754)
	Tampa Bay Rays	−0.0156	−0.0004	−0.0125	0.0090	0.0181	0.0110	0.0252	0.0285
		(0.037)	(0.961)	(0.120)	(0.585)	(0.207)	(0.588)	(0.100)	(0.390)
	Toronto Blue Jays	−0.0083	−0.0166	−0.0101	−0.0153	−0.0326	−0.0505	−0.0397	−0.0468
		(0.263)	(0.058)	(0.210)	(0.294)	(0.023)	(< 0.001)	(0.015)	(0.165)
AL Central	Chicago White Sox	0.0030	−0.0016	0.0036	−0.0103	−0.0013	−0.0095	0.0008	−0.0142
		(0.688)	(0.841)	(0.655)	(0.550)	(0.928)	(0.567)	(0.955)	(0.670)
	Cleveland Indians	0.0020	−0.0055	0.0007	−0.0018	0.0135	0.0087	0.0142	0.0210
		(0.787)	(0.616)	(0.927)	(0.916)	(0.345)	(0.694)	(0.337)	(0.541)
	Detroit Tigers	−0.0049	−0.0033	−0.0025	−0.0076	−0.0072	0.0017	−0.0021	−0.0082
		(0.512)	(0.672)	(0.748)	(0.623)	(0.612)	(0.899)	(0.897)	(0.792)
	Kansas City Royals	−0.0123	−0.0084	−0.0107	−0.0120	−0.0166	−0.0055	−0.0102	−0.0009
		(0.100)	(0.243)	(0.158)	(0.423)	(0.244)	(0.627)	(0.475)	(0.977)
	Minnesota Twins	−0.0049	−0.0024	−0.0052	−0.0084	0.0055	0.0099	0.0045	−0.0092
		(0.502)	(0.777)	(0.514)	(0.610)	(0.698)	(0.650)	(0.779)	(0.785)
AL West	Houston Astros	−0.0000	−0.0015	−0.0016	0.0038	−0.0154	−0.0286	−0.0183	−0.0191
		(0.997)	(0.872)	(0.842)	(0.811)	(0.280)	(0.164)	(0.257)	(0.571)
	Los Angeles Angels	0.0010	0.0127	0.0042	0.0118	−0.0191	−0.0107	−0.0159	−0.0228
		(0.894)	(0.189)	(0.598)	(0.479)	(0.184)	(0.222)	(0.284)	(0.518)
	Oakland Athletics	−0.0186	−0.0151	−0.0165	−0.0091	−0.0156	−0.0243	−0.0132	−0.0111
		(0.013)	(0.096)	(0.036)	(0.606)	(0.275)	(0.115)	(0.376)	(0.746)
	Seattle Mariners	0.0149	0.0001	0.0179	0.0028	0.0150	0.0274	0.0199	0.0143
		(0.043)	(0.991)	(0.023)	(0.873)	(0.294)	(0.110)	(0.195)	(0.701)
	Texas Rangers	−0.0045	−0.0059	−0.0031	0.0004	0.0176	0.0163	0.0167	0.0097
		(0.545)	(0.603)	(0.682)	(0.980)	(0.220)	(0.381)	(0.265)	(0.773)
NL East	Atlanta Braves	0.0050	0.0053	0.0073	−0.0041	0.0027	−0.0032	0.0030	−0.0204
		(0.500)	(0.595)	(0.312)	(0.823)	(0.852)	(0.875)	(0.817)	(0.561)
	Miami Marlins	0.0026	0.0026	0.0029	−0.0051	−0.0086	−0.0045	−0.0120	−0.0019
		(0.727)	(0.794)	(0.700)	(0.742)	(0.549)	(0.779)	(0.383)	(0.949)
	New York Mets	−0.0004	0.0078	−0.0021	−0.0274	0.0127	0.0129	0.0069	−0.0561
		(0.956)	(0.353)	(0.793)	(0.118)	(0.375)	(0.545)	(0.675)	(0.131)
	Philadelphia Phillies	−0.0083	−0.0101	−0.0122	−0.0087	−0.0103	−0.0047	−0.0142	−0.0269
		(0.268)	(0.259)	(0.130)	(0.637)	(0.475)	(0.769)	(0.318)	(0.436)
	Washington Senators	−0.0019	−0.0037	−0.0054	−0.0226	0.0064	−0.0039	−0.0020	−0.0558
		(0.802)	(0.778)	(0.465)	(0.187)	(0.654)	(0.874)	(0.897)	(0.088)
NL Central	Chicago Cubs	0.0274	0.0170	0.0224	0.0227	0.0160	0.0148	0.0050	0.0202
		(< 0.001)	(0.053)	(0.006)	(0.192)	(0.265)	(0.320)	(0.748)	(0.564)
	Cincinnati Reds	0.0053	0.0068	0.0050	0.0194	0.0065	0.0241	0.0051	0.0210
		(0.475)	(0.307)	(0.530)	(0.269)	(0.649)	(0.192)	(0.725)	(0.542)
	Milwaukee Brewers	0.0073	0.0252	0.0046	0.0165	−0.0107	0.0305	−0.0182	0.0341
		(0.329)	(0.009)	(0.558)	(0.421)	(0.460)	(0.059)	(0.213)	(0.389)
	Pittsburgh Pirates	−0.0004	−0.0031	−0.0007	0.0051	−0.0210	−0.0068	−0.0188	0.0033
		(0.961)	(0.799)	(0.928)	(0.754)	(0.141)	(0.742)	(0.175)	(0.909)
	St. Louis Cardinals	−0.0019	−0.0073	−0.0035	−0.0069	0.0397	0.0160	0.0355	0.0172
		(0.801)	(0.423)	(0.648)	(0.686)	(0.006)	(0.261)	(0.022)	(0.618)
NL West	Arizona Diamondbacks	0.0012	0.0122	0.0028	0.0196	0.0151	0.0262	0.0146	0.0597
		(0.867)	(0.232)	(0.734)	(0.287)	(0.285)	(0.305)	(0.325)	(0.108)
	Colorado Rockies	0.0090	0.0198	0.0075	0.0340	−0.0034	0.0141	−0.0030	0.0446
		(0.225)	(0.119)	(0.328)	(0.052)	(0.812)	(0.536)	(0.858)	(0.231)
	Los Angeles Dodgers	−0.0168	−0.0286	−0.0142	−0.0120	−0.0228	−0.0370	−0.0173	−0.0011
		(0.024)	(< 0.001)	(0.074)	(0.483)	(0.111)	(0.031)	(0.278)	(0.975)
	San Diego Padres	−0.0037	−0.0060	−0.0017	0.0065	0.0048	0.0066	0.0112	0.0485
		(0.618)	(0.554)	(0.838)	(0.740)	(0.739)	(0.744)	(0.458)	(0.202)
	San Francisco Giants	0.0047	−0.0017	0.0034	−0.0184	−0.0218	−0.0295	−0.0220	−0.0659
		(0.527)	(0.847)	(0.671)	(0.270)	(0.126)	(0.027)	(0.117)	(0.028)
	Fixed Effect	-	Batter	Pitcher	Batter-Pitcher	-	Batter	Pitcher	Batter-Pitcher
	Cluster	-	Batter	Pitcher	Batter-Pitcher	-	Batter	Pitcher	Batter-Pitcher

Table 11: Estimated team effect for all teams excluding Red Sox in 2016 season with corresponding p-values in parenthesis. Batting performance for OBP (Left) and SLG (Right) measures. No fixed effects (first column), Pitcher fixed effets (second column), Batter fixed effects (third column), and Batter-Pitcher fixed effects (fourth column). Standard errors are clustered at the fixed effects level.

E Teams effects in 2017

		OBP				SLG			
AL East	Baltimore Orioles	−0.0074	−0.0066	−0.0054	0.0022	−0.0174	−0.0228	−0.0114	0.0126
		(0.290)	(0.535)	(0.487)	(0.880)	(0.200)	(0.230)	(0.481)	(0.691)
	Boston Red Sox	−0.0077	−0.0044	−0.0083	−0.0246	−0.0328	−0.0265	−0.0324	−0.0496
		(0.262)	(0.375)	(0.254)	(0.093)	(0.015)	(0.032)	(0.021)	(0.083)
	New York Yankees	0.0173	0.0093	0.0188	0.0203	0.0220	−0.0003	0.0245	0.0156
		(0.013)	(0.276)	(0.013)	(0.165)	(0.106)	(0.986)	(0.085)	(0.610)
	Tampa Bay Rays	−0.0037	0.0076	−0.0015	0.0319	−0.0001	−0.0054	0.0061	0.0192
		(0.599)	(0.310)	(0.850)	(0.031)	(0.997)	(0.771)	(0.704)	(0.543)
	Toronto Blue Jays	−0.0264	−0.0222	−0.0251	−0.0113	−0.0449	−0.0355	−0.0409	−0.0213
		(< 0.001)	(0.058)	(< 0.001)	(0.445)	(0.001)	(0.108)	(0.005)	(0.489)
AL Central	Chicago White Sox	−0.0048	0.0167	−0.0036	−0.0037	−0.0021	0.0220	−0.0023	−0.0093
		(0.495)	(0.199)	(0.648)	(0.822)	(0.876)	(0.344)	(0.872)	(0.772)
	Cleveland Indians	0.0083	0.0024	0.0048	0.0075	0.0206	0.0158	0.0142	0.0360
		(0.235)	(0.803)	(0.494)	(0.617)	(0.133)	(0.475)	(0.317)	(0.239)
	Detroit Tigers	−0.0132	−0.0026	−0.0134	−0.0047	−0.0283	−0.0009	−0.0280	0.0083
		(0.059)	(0.813)	(0.067)	(0.735)	(0.038)	(0.969)	(0.057)	(0.771)
	Kansas City Royals	−0.0120	−0.0149	−0.0135	−0.0187	0.0004	−0.0063	−0.0038	−0.0403
		(0.090)	(0.170)	(0.075)	(0.171)	(0.977)	(0.750)	(0.797)	(0.107)
	Minnesota Twins	0.0123	0.0163	0.0068	−0.0145	0.0076	0.0165	−0.0058	−0.0505
		(0.078)	(0.004)	(0.374)	(0.316)	(0.580)	(0.041)	(0.687)	(0.101)
AL West	Houston Astros	0.0244	0.0209	0.0252	0.0332	0.0442	0.0423	0.0422	0.0570
		(< 0.001)	(0.009)	(0.001)	(0.031)	(0.001)	(0.006)	(0.007)	(0.081)
	Los Angeles Angels	−0.0093	−0.0047	−0.0103	−0.0090	−0.0290	−0.0183	−0.0280	−0.0143
		(0.184)	(0.564)	(0.151)	(0.530)	(0.035)	(0.298)	(0.056)	(0.623)
	Oakland Athletics	0.0004	0.0065	0.0003	0.0102	0.0233	0.0135	0.0236	0.0161
		(0.957)	(0.497)	(0.969)	(0.547)	(0.090)	(0.545)	(0.095)	(0.666)
	Seattle Mariners	0.0058	0.0080	0.0046	−0.0100	−0.0055	0.0111	−0.0079	−0.0181
		(0.408)	(0.465)	(0.540)	(0.530)	(0.686)	(0.538)	(0.563)	(0.590)
	Texas Rangers	−0.0074	−0.0122	−0.0098	−0.0078	−0.0008	−0.0065	−0.0061	−0.0064
		(0.288)	(0.226)	(0.195)	(0.577)	(0.956)	(0.750)	(0.707)	(0.827)
NL East	Atlanta Braves	0.0058	−0.0020	0.0047	−0.0036	0.0220	0.0140	0.0212	0.0019
		(0.406)	(0.751)	(0.501)	(0.813)	(0.107)	(0.406)	(0.106)	(0.949)
	Miami Marlins	0.0077	0.0068	0.0055	0.0006	0.0230	0.0256	0.0230	0.0174
		(0.271)	(0.425)	(0.469)	(0.968)	(0.091)	(0.087)	(0.122)	(0.561)
	New York Mets	0.0014	0.0095	0.0010	0.0028	0.0181	0.0245	0.0157	−0.0110
		(0.846)	(0.186)	(0.888)	(0.863)	(0.187)	(0.070)	(0.298)	(0.750)
	Philadelphia Phillies	0.0061	−0.0081	0.0057	−0.0133	0.0097	−0.0023	0.0107	−0.0054
		(0.388)	(0.431)	(0.455)	(0.375)	(0.479)	(0.896)	(0.494)	(0.851)
	Washington Senators	0.0027	0.0031	0.0012	0.0070	0.0197	0.0152	0.0166	0.0278
		(0.700)	(0.774)	(0.879)	(0.658)	(0.149)	(0.512)	(0.304)	(0.411)
NL Central	Chicago Cubs	0.0093	−0.0017	0.0092	0.0069	0.0107	−0.0022	0.0069	−0.0348
		(0.182)	(0.852)	(0.180)	(0.660)	(0.436)	(0.865)	(0.620)	(0.305)
	Cincinnati Reds	0.0140	0.0179	0.0173	0.0217	0.0211	0.0292	0.0264	0.0585
		(0.045)	(0.102)	(0.015)	(0.151)	(0.125)	(0.146)	(0.065)	(0.062)
	Milwaukee Brewers	0.0020	0.0033	0.0045	0.0182	0.0073	0.0136	0.0137	0.0413
		(0.776)	(0.796)	(0.522)	(0.359)	(0.598)	(0.450)	(0.319)	(0.306)
	Pittsburgh Pirates	−0.0182	−0.0159	−0.0186	−0.0097	−0.0393	−0.0267	−0.0368	−0.0148
		(0.009)	(0.033)	(0.022)	(0.539)	(0.004)	(0.024)	(0.012)	(0.630)
	St. Louis Cardinals	0.0047	−0.0017	0.0100	−0.0109	0.0007	−0.0158	0.0048	−0.0041
		(0.497)	(0.874)	(0.185)	(0.471)	(0.961)	(0.337)	(0.749)	(0.894)
NL West	Arizona Diamondbacks	0.0071	−0.0005	0.0069	0.0024	0.0146	0.0090	0.0146	0.0137
		(0.309)	(0.945)	(0.363)	(0.877)	(0.286)	(0.535)	(0.334)	(0.688)
	Colorado Rockies	0.0045	0.0078	0.0043	0.0111	−0.0254	−0.0221	−0.0239	−0.0155
		(0.515)	(0.338)	(0.591)	(0.485)	(0.063)	(0.371)	(0.142)	(0.634)
	Los Angeles Dodgers	0.0014	−0.0072	0.0015	−0.0238	0.0047	−0.0174	0.0051	−0.0229
		(0.837)	(0.459)	(0.834)	(0.139)	(0.734)	(0.324)	(0.720)	(0.494)
	San Diego Padres	−0.0053	0.0009	−0.0030	0.0094	−0.0024	0.0042	0.0010	0.0094
		(0.456)	(0.921)	(0.686)	(0.628)	(0.862)	(0.813)	(0.944)	(0.813)
	San Francisco Giants	−0.0212	−0.0200	−0.0213	−0.0076	−0.0415	−0.0378	−0.0429	−0.0037
		(0.002)	(0.012)	(0.003)	(0.617)	(0.002)	(0.001)	(0.001)	(0.903)
	Fixed Effect	-	Batter	Pitcher	Batter-Pitcher	-	Batter	Pitcher	Batter-Pitcher
	Cluster	-	Batter	Pitcher	Batter-Pitcher	-	Batter	Pitcher	Batter-Pitcher

Table 12: Estimated team effect for all teams in 2017 season with corresponding p-values in parenthesis. Batting performance for OBP (Left) and SLG (Right) measures. No fixed effects (first column), Pitcher fixed effets (second column), Batter fixed effects (third column), and Batter-Pitcher fixed effects (fourth column). Standard errors are clustered at the fixed effects level.

		OBP				SLG			
AL East	Baltimore Orioles	−0.0067	−0.0060	−0.0048	0.0034	−0.0155	−0.0217	−0.0093	0.0147
		(0.340)	(0.569)	(0.542)	(0.813)	(0.253)	(0.255)	(0.566)	(0.642)
	Boston Red Sox	−0.0070	−0.0039	−0.0074	−0.0234	−0.0309	−0.0254	−0.0304	−0.0475
		(0.312)	(0.435)	(0.306)	(0.111)	(0.022)	(0.041)	(0.030)	(0.096)
	New York Yankees	0.0180	0.0111	0.0195	0.0229	0.0239	0.0028	0.0262	0.0186
		(0.009)	(0.187)	(0.010)	(0.120)	(0.079)	(0.867)	(0.066)	(0.545)
	Tampa Bay Rays	−0.0029	0.0082	−0.0008	0.0332	0.0018	−0.0041	0.0078	0.0214
		(0.674)	(0.274)	(0.923)	(0.024)	(0.894)	(0.824)	(0.627)	(0.498)
	Toronto Blue Jays	−0.0257	−0.0217	−0.0241	−0.0104	−0.0430	−0.0344	−0.0388	−0.0196
		(< 0.001)	(0.064)	(< 0.001)	(0.483)	(0.002)	(0.119)	(0.008)	(0.525)
AL Central	Chicago White Sox	−0.0041	0.0172	−0.0028	−0.0025	−0.0003	0.0231	−0.0005	−0.0073
		(0.563)	(0.185)	(0.725)	(0.878)	(0.985)	(0.321)	(0.969)	(0.820)
	Cleveland Indians	0.0090	0.0029	0.0055	0.0087	0.0225	0.0170	0.0157	0.0382
		(0.194)	(0.759)	(0.432)	(0.560)	(0.100)	(0.443)	(0.269)	(0.212)
	Detroit Tigers	−0.0125	−0.0020	−0.0128	−0.0035	−0.0264	0.0002	−0.0271	0.0105
		(0.075)	(0.856)	(0.081)	(0.803)	(0.053)	(0.994)	(0.068)	(0.715)
	Kansas City Royals	−0.0112	−0.0143	−0.0129	−0.0178	0.0023	−0.0051	−0.0028	−0.0388
		(0.111)	(0.188)	(0.090)	(0.193)	(0.868)	(0.798)	(0.849)	(0.121)
	Minnesota Twins	0.0130	0.0169	0.0076	−0.0133	0.0095	0.0177	−0.0041	−0.0484
		(0.061)	(0.003)	(0.318)	(0.358)	(0.488)	(0.028)	(0.779)	(0.117)
AL West	Los Angeles Angels	−0.0086	−0.0045	−0.0092	−0.0080	−0.0272	−0.0170	−0.0263	−0.0129
		(0.221)	(0.583)	(0.198)	(0.577)	(0.049)	(0.336)	(0.073)	(0.658)
	Oakland Athletics	0.0011	0.0066	0.0012	0.0120	0.0252	0.0139	0.0256	0.0183
		(0.873)	(0.498)	(0.859)	(0.477)	(0.067)	(0.534)	(0.069)	(0.623)
	Seattle Mariners	0.0065	0.0087	0.0055	−0.0087	−0.0036	0.0125	−0.0060	−0.0165
		(0.350)	(0.425)	(0.464)	(0.584)	(0.789)	(0.488)	(0.661)	(0.623)
	Texas Rangers	−0.0067	−0.0116	−0.0088	−0.0062	0.0011	−0.0050	−0.0043	−0.0032
		(0.339)	(0.252)	(0.240)	(0.660)	(0.934)	(0.806)	(0.791)	(0.913)
NL East	Atlanta Braves	0.0066	−0.0013	0.0054	−0.0022	0.0239	0.0153	0.0227	0.0047
		(0.348)	(0.839)	(0.442)	(0.888)	(0.080)	(0.363)	(0.083)	(0.874)
	Miami Marlins	0.0084	0.0073	0.0066	0.0018	0.0249	0.0267	0.0253	0.0195
		(0.226)	(0.391)	(0.390)	(0.902)	(0.067)	(0.075)	(0.090)	(0.515)
	New York Mets	0.0021	0.0099	0.0018	0.0037	0.0200	0.0256	0.0174	−0.0097
		(0.763)	(0.165)	(0.804)	(0.819)	(0.144)	(0.058)	(0.249)	(0.779)
	Philadelphia Phillies	0.0068	−0.0076	0.0066	−0.0121	0.0115	−0.0011	0.0123	−0.0034
		(0.333)	(0.461)	(0.394)	(0.420)	(0.399)	(0.948)	(0.431)	(0.907)
	Washington Senators	0.0034	0.0036	0.0022	0.0083	0.0216	0.0164	0.0188	0.0300
		(0.621)	(0.733)	(0.784)	(0.601)	(0.113)	(0.478)	(0.246)	(0.375)
NL Central	Chicago Cubs	0.0100	−0.0011	0.0099	0.0081	0.0126	−0.0010	0.0086	−0.0327
		(0.148)	(0.900)	(0.152)	(0.604)	(0.359)	(0.937)	(0.535)	(0.335)
	Cincinnati Reds	0.0147	0.0185	0.0181	0.0230	0.0229	0.0304	0.0285	0.0608
		(0.035)	(0.092)	(0.011)	(0.129)	(0.095)	(0.130)	(0.046)	(0.053)
	Milwaukee Brewers	0.0028	0.0039	0.0052	0.0194	0.0092	0.0149	0.0153	0.0435
		(0.695)	(0.761)	(0.461)	(0.328)	(0.506)	(0.409)	(0.266)	(0.281)
	Pittsburgh Pirates	−0.0174	−0.0154	−0.0179	−0.0085	−0.0375	−0.0256	−0.0352	−0.0128
		(0.013)	(0.039)	(0.027)	(0.590)	(0.006)	(0.031)	(0.016)	(0.679)
	St. Louis Cardinals	0.0055	−0.0011	0.0106	−0.0097	0.0026	−0.0146	0.0063	−0.0019
		(0.430)	(0.915)	(0.159)	(0.523)	(0.852)	(0.374)	(0.677)	(0.950)
NL West	Arizona Diamondbacks	0.0078	0.0001	0.0075	0.0037	0.0165	0.0102	0.0163	0.0159
		(0.261)	(0.989)	(0.322)	(0.815)	(0.228)	(0.481)	(0.283)	(0.643)
	Colorado Rockies	0.0053	0.0084	0.0051	0.0124	−0.0235	−0.0210	−0.0223	−0.0133
		(0.447)	(0.304)	(0.529)	(0.436)	(0.086)	(0.396)	(0.172)	(0.683)
	Los Angeles Dodgers	0.0022	−0.0067	0.0022	−0.0231	0.0066	−0.0164	0.0068	−0.0215
		(0.752)	(0.489)	(0.757)	(0.150)	(0.633)	(0.355)	(0.634)	(0.521)
	San Diego Padres	−0.0046	0.0016	−0.0023	0.0107	−0.0006	0.0053	0.0026	0.0117
		(0.519)	(0.867)	(0.754)	(0.583)	(0.967)	(0.762)	(0.855)	(0.771)
	San Francisco Giants	−0.0204	−0.0193	−0.0204	−0.0066	−0.0397	−0.0366	−0.0409	−0.0019
		(0.004)	(0.015)	(0.004)	(0.664)	(0.004)	(0.002)	(0.001)	(0.950)
	Fixed Effect	-	Batter	Pitcher	Batter-Pitcher	-	Batter	Pitcher	Batter-Pitcher
	Cluster	-	Batter	Pitcher	Batter-Pitcher	-	Batter	Pitcher	Batter-Pitcher

Table 13: Estimated team effect for all teams excluding Astros in 2017 season with corresponding p-values in parenthesis. Batting performance for OBP (Left) and SLG (Right) measures. No fixed effects (first column), Pitcher fixed effets (second column), Batter fixed effects (third column), and Batter-Pitcher fixed effects (fourth column). Standard errors are clustered at the fixed effects level.

F Teams effects in 2018

		OBP				SLG			
AL East	Baltimore Orioles	−0.0113	−0.0116	−0.0116	−0.0140	−0.0368	−0.0321	−0.0347	−0.0450
		(0.110)	(0.355)	(0.092)	(0.324)	(0.008)	(0.150)	(0.016)	(0.151)
	Boston Red Sox	0.0075	0.0106	0.0044	0.0110	0.0337	0.0347	0.0302	0.0430
		(0.278)	(0.430)	(0.575)	(0.441)	(0.015)	(0.145)	(0.057)	(0.153)
	New York Yankees	0.0072	−0.0007	0.0050	−0.0072	0.0348	−0.0101	0.0304	−0.0192
		(0.300)	(0.945)	(0.459)	(0.670)	(0.012)	(0.665)	(0.041)	(0.613)
	Tampa Bay Rays	0.0243	0.0284	0.0213	0.0285	−0.0052	0.0088	−0.0157	0.0157
		(< 0.001)	(0.009)	(0.001)	(0.146)	(0.710)	(0.649)	(0.217)	(0.689)
	Toronto Blue Jays	−0.0129	0.0008	−0.0122	−0.0078	0.0021	−0.0111	0.0047	−0.0439
		(0.066)	(0.931)	(0.083)	(0.650)	(0.883)	(0.475)	(0.744)	(0.233)
AL Central	Chicago White Sox	−0.0084	0.0014	−0.0131	−0.0124	0.0058	0.0110	0.0018	−0.0117
		(0.234)	(0.896)	(0.071)	(0.438)	(0.679)	(0.394)	(0.905)	(0.717)
	Cleveland Indians	0.0038	−0.0017	−0.0019	−0.0038	0.0148	0.0123	0.0127	0.0272
		(0.581)	(0.853)	(0.783)	(0.796)	(0.288)	(0.460)	(0.396)	(0.377)
	Detroit Tigers	−0.0253	0.0039	−0.0284	0.0077	−0.0427	0.0134	−0.0478	0.0316
		(< 0.001)	(0.701)	(< 0.001)	(0.649)	(0.002)	(0.437)	(0.001)	(0.328)
	Kansas City Royals	−0.0072	0.0041	−0.0117	0.0004	−0.0128	−0.0042	−0.0163	−0.0017
		(0.310)	(0.634)	(0.095)	(0.978)	(0.357)	(0.764)	(0.253)	(0.956)
	Minnesota Twins	0.0020	−0.0005	0.0000	0.0044	−0.0068	−0.0036	−0.0093	0.0130
		(0.772)	(0.949)	(0.994)	(0.753)	(0.623)	(0.834)	(0.493)	(0.647)
AL West	Houston Astros	0.0053	0.0016	0.0087	−0.0101	−0.0124	−0.0099	−0.0098	−0.0198
		(0.446)	(0.840)	(0.255)	(0.481)	(0.375)	(0.484)	(0.519)	(0.531)
	Los Angeles Angels	0.0016	0.0007	0.0015	0.0104	0.0211	0.0011	0.0220	0.0156
		(0.824)	(0.946)	(0.843)	(0.483)	(0.133)	(0.934)	(0.162)	(0.639)
	Oakland Athletics	0.0169	0.0082	0.0177	0.0060	0.0386	0.0127	0.0415	−0.0147
		(0.015)	(0.272)	(0.008)	(0.694)	(0.005)	(0.479)	(0.003)	(0.660)
	Seattle Mariners	−0.0041	−0.0037	−0.0046	0.0027	−0.0071	0.0062	−0.0053	0.0249
		(0.555)	(0.712)	(0.519)	(0.852)	(0.611)	(0.587)	(0.719)	(0.432)
	Texas Rangers	−0.0012	−0.0016	0.0022	0.0215	−0.0153	−0.0080	−0.0082	0.0435
		(0.860)	(0.849)	(0.761)	(0.165)	(0.276)	(0.599)	(0.547)	(0.165)
NL East	Atlanta Braves	0.0067	−0.0034	0.0069	−0.0015	0.0396	0.0133	0.0383	0.0187
		(0.335)	(0.560)	(0.327)	(0.927)	(0.004)	(0.360)	(0.005)	(0.536)
	Miami Marlins	−0.0162	0.0045	−0.0113	0.0224	−0.0412	0.0040	−0.0383	0.0250
		(0.021)	(0.579)	(0.158)	(0.249)	(0.003)	(0.813)	(0.003)	(0.483)
	New York Mets	−0.0009	−0.0024	−0.0005	0.0025	−0.0225	−0.0205	−0.0232	−0.0179
		(0.902)	(0.725)	(0.948)	(0.880)	(0.107)	(0.202)	(0.121)	(0.604)
	Philadelphia Phillies	0.0111	−0.0128	0.0091	0.0038	0.0076	−0.0126	0.0016	0.0219
		(0.114)	(0.062)	(0.220)	(0.828)	(0.586)	(0.325)	(0.906)	(0.550)
	Washington Senators	0.0118	0.0025	0.0124	−0.0040	−0.0010	−0.0037	0.0002	0.0008
		(0.089)	(0.714)	(0.097)	(0.807)	(0.940)	(0.831)	(0.988)	(0.982)
NL Central	Chicago Cubs	0.0015	0.0047	0.0042	0.0157	−0.0046	−0.0132	−0.0058	−0.0105
		(0.823)	(0.356)	(0.557)	(0.275)	(0.742)	(0.493)	(0.682)	(0.735)
	Cincinnati Reds	0.0117	0.0133	0.0086	−0.0049	−0.0034	0.0052	−0.0091	−0.0306
		(0.093)	(0.075)	(0.209)	(0.751)	(0.807)	(0.820)	(0.467)	(0.318)
	Milwaukee Brewers	0.0085	−0.0046	0.0101	0.0047	0.0220	0.0050	0.0237	0.0312
		(0.224)	(0.612)	(0.157)	(0.763)	(0.115)	(0.800)	(0.107)	(0.347)
	Pittsburgh Pirates	−0.0049	0.0071	−0.0040	0.0111	0.0200	0.0364	0.0218	0.0262
		(0.489)	(0.279)	(0.545)	(0.500)	(0.152)	(0.011)	(0.111)	(0.403)
	St. Louis Cardinals	−0.0032	−0.0141	−0.0016	−0.0249	−0.0053	−0.0134	−0.0036	−0.0294
		(0.651)	(0.103)	(0.844)	(0.118)	(0.704)	(0.468)	(0.808)	(0.388)
NL West	Arizona Diamondbacks	−0.0124	−0.0148	−0.0097	0.0014	−0.0271	−0.0109	−0.0247	0.0170
		(0.076)	(0.031)	(0.170)	(0.930)	(0.052)	(0.538)	(0.075)	(0.585)
	Colorado Rockies	−0.0051	−0.0027	−0.0008	−0.0103	−0.0027	0.0009	0.0029	−0.0064
		(0.465)	(0.775)	(0.912)	(0.486)	(0.843)	(0.943)	(0.837)	(0.837)
	Los Angeles Dodgers	0.0092	0.0096	0.0111	0.0053	0.0298	0.0221	0.0326	−0.0076
		(0.184)	(0.217)	(0.151)	(0.721)	(0.032)	(0.225)	(0.035)	(0.808)
	San Diego Padres	0.0009	−0.0038	0.0031	−0.0088	−0.0030	−0.0096	0.0010	0.0023
		(0.893)	(0.629)	(0.644)	(0.613)	(0.831)	(0.524)	(0.941)	(0.947)
	San Francisco Giants	−0.0198	−0.0177	−0.0165	−0.0274	−0.0212	−0.0253	−0.0141	−0.0685
		(0.005)	(0.016)	(0.044)	(0.075)	(0.127)	(0.031)	(0.289)	(0.020)
	Fixed Effect	-	Batter	Pitcher	Batter-Pitcher	-	Batter	Pitcher	Batter-Pitcher
	Cluster	-	Batter	Pitcher	Batter-Pitcher	-	Batter	Pitcher	Batter-Pitcher

Table 14: Estimated team effect for all teams in 2018 season with corresponding p-values in parenthesis. Batting performance for OBP (Left) and SLG (Right) measures. No fixed effects (first column), Pitcher fixed effets (second column), Batter fixed effects (third column), and Batter-Pitcher fixed effects (fourth column). Standard errors are clustered at the fixed effects level.

		OBP				SLG			
AL East	Baltimore Orioles	−0.0113	−0.0116	−0.0116	−0.0140	−0.0368	−0.0321	−0.0347	−0.0450
		(0.110)	(0.355)	(0.092)	(0.324)	(0.008)	(0.150)	(0.016)	(0.151)
	Boston Red Sox	0.0075	0.0106	0.0044	0.0110	0.0337	0.0347	0.0302	0.0430
		(0.278)	(0.430)	(0.575)	(0.441)	(0.015)	(0.145)	(0.057)	(0.153)
	New York Yankees	0.0072	−0.0007	0.0050	−0.0072	0.0348	−0.0101	0.0304	−0.0192
		(0.300)	(0.945)	(0.459)	(0.670)	(0.012)	(0.665)	(0.041)	(0.613)
	Tampa Bay Rays	0.0243	0.0284	0.0213	0.0285	−0.0052	0.0088	−0.0157	0.0157
		(< 0.001)	(0.009)	(0.001)	(0.146)	(0.710)	(0.649)	(0.217)	(0.689)
	Toronto Blue Jays	−0.0129	0.0008	−0.0122	−0.0078	0.0021	−0.0111	0.0047	−0.0439
		(0.066)	(0.931)	(0.083)	(0.650)	(0.883)	(0.475)	(0.744)	(0.233)
AL Central	Chicago White Sox	−0.0084	0.0014	−0.0131	−0.0124	0.0058	0.0110	0.0018	−0.0117
		(0.234)	(0.896)	(0.071)	(0.438)	(0.679)	(0.394)	(0.905)	(0.717)
	Cleveland Indians	0.0038	−0.0017	−0.0019	−0.0038	0.0148	0.0123	0.0127	0.0272
		(0.581)	(0.853)	(0.783)	(0.796)	(0.288)	(0.460)	(0.396)	(0.377)
	Detroit Tigers	−0.0253	0.0039	−0.0284	0.0077	−0.0427	0.0134	−0.0478	0.0316
		(< 0.001)	(0.701)	(< 0.001)	(0.649)	(0.002)	(0.437)	(0.001)	(0.328)
	Kansas City Royals	−0.0072	0.0041	−0.0117	0.0004	−0.0128	−0.0042	−0.0163	−0.0017
		(0.310)	(0.634)	(0.095)	(0.978)	(0.357)	(0.764)	(0.253)	(0.956)
	Minnesota Twins	0.0020	−0.0005	0.0000	0.0044	−0.0068	−0.0036	−0.0093	0.0130
		(0.772)	(0.949)	(0.994)	(0.753)	(0.623)	(0.834)	(0.493)	(0.647)
AL West	Los Angeles Angels	0.0016	0.0007	0.0015	0.0104	0.0211	0.0011	0.0220	0.0156
		(0.824)	(0.946)	(0.843)	(0.483)	(0.133)	(0.934)	(0.162)	(0.639)
	Oakland Athletics	0.0169	0.0082	0.0177	0.0060	0.0386	0.0127	0.0415	−0.0147
		(0.015)	(0.272)	(0.008)	(0.694)	(0.005)	(0.479)	(0.003)	(0.660)
	Seattle Mariners	−0.0041	−0.0037	−0.0046	0.0027	−0.0071	0.0062	−0.0053	0.0249
		(0.555)	(0.712)	(0.519)	(0.852)	(0.611)	(0.587)	(0.719)	(0.432)
	Texas Rangers	−0.0012	−0.0016	0.0022	0.0215	−0.0153	−0.0080	−0.0082	0.0435
		(0.860)	(0.849)	(0.761)	(0.165)	(0.276)	(0.599)	(0.547)	(0.165)
NL East	Atlanta Braves	0.0067	−0.0034	0.0069	−0.0015	0.0396	0.0133	0.0383	0.0187
		(0.335)	(0.560)	(0.327)	(0.927)	(0.004)	(0.360)	(0.005)	(0.536)
	Miami Marlins	−0.0162	0.0045	−0.0113	0.0224	−0.0412	0.0040	−0.0383	0.0250
		(0.021)	(0.579)	(0.158)	(0.249)	(0.003)	(0.813)	(0.003)	(0.483)
	New York Mets	−0.0009	−0.0024	−0.0005	0.0025	−0.0225	−0.0205	−0.0232	−0.0179
		(0.902)	(0.725)	(0.948)	(0.880)	(0.107)	(0.202)	(0.121)	(0.604)
	Philadelphia Phillies	0.0111	−0.0128	0.0091	0.0038	0.0076	−0.0126	0.0016	0.0219
		(0.114)	(0.062)	(0.220)	(0.828)	(0.586)	(0.325)	(0.906)	(0.550)
	Washington Senators	0.0118	0.0025	0.0124	−0.0040	−0.0010	−0.0037	0.0002	0.0008
		(0.089)	(0.714)	(0.097)	(0.807)	(0.940)	(0.831)	(0.988)	(0.982)
NL Central	Chicago Cubs	0.0015	0.0047	0.0042	0.0157	−0.0046	−0.0132	−0.0058	−0.0105
		(0.823)	(0.356)	(0.557)	(0.275)	(0.742)	(0.493)	(0.682)	(0.735)
	Cincinnati Reds	0.0117	0.0133	0.0086	−0.0049	−0.0034	0.0052	−0.0091	−0.0306
		(0.093)	(0.075)	(0.209)	(0.751)	(0.807)	(0.820)	(0.467)	(0.318)
	Milwaukee Brewers	0.0085	−0.0046	0.0101	0.0047	0.0220	0.0050	0.0237	0.0312
		(0.224)	(0.612)	(0.157)	(0.763)	(0.115)	(0.800)	(0.107)	(0.347)
	Pittsburgh Pirates	−0.0049	0.0071	−0.0040	0.0111	0.0200	0.0364	0.0218	0.0262
		(0.489)	(0.279)	(0.545)	(0.500)	(0.152)	(0.011)	(0.111)	(0.403)
	St. Louis Cardinals	−0.0032	−0.0141	−0.0016	−0.0249	−0.0053	−0.0134	−0.0036	−0.0294
		(0.651)	(0.103)	(0.844)	(0.118)	(0.704)	(0.468)	(0.808)	(0.388)
NL West	Arizona Diamondbacks	−0.0124	−0.0148	−0.0097	0.0014	−0.0271	−0.0109	−0.0247	0.0170
		(0.076)	(0.031)	(0.170)	(0.930)	(0.052)	(0.538)	(0.075)	(0.585)
	Colorado Rockies	−0.0051	−0.0027	−0.0008	−0.0103	−0.0027	0.0009	0.0029	−0.0064
		(0.465)	(0.775)	(0.912)	(0.486)	(0.843)	(0.943)	(0.837)	(0.837)
	Los Angeles Dodgers	0.0092	0.0096	0.0111	0.0053	0.0298	0.0221	0.0326	−0.0076
		(0.184)	(0.217)	(0.151)	(0.721)	(0.032)	(0.225)	(0.035)	(0.808)
	San Diego Padres	0.0009	−0.0038	0.0031	−0.0088	−0.0030	−0.0096	0.0010	0.0023
		(0.893)	(0.629)	(0.644)	(0.613)	(0.831)	(0.524)	(0.941)	(0.947)
	San Francisco Giants	−0.0198	−0.0177	−0.0165	−0.0274	−0.0212	−0.0253	−0.0141	−0.0685
		(0.005)	(0.016)	(0.044)	(0.075)	(0.127)	(0.031)	(0.289)	(0.020)
	Fixed Effect	-	Batter	Pitcher	Batter-Pitcher	-	Batter	Pitcher	Batter-Pitcher
	Cluster	-	Batter	Pitcher	Batter-Pitcher	-	Batter	Pitcher	Batter-Pitcher

Table 15: Estimated team effect for all teams excluding Astros in 2018 season with corresponding p-values in parenthesis.