ESRI Discussion Paper Series No.354

To Swing or Not to Swing? Reference Point and Professional Baseball Players

Koji Yashiki

Yoshiyuki Nakazono

July 2020

Economic and Social Research Institute
Cabinet Office
Tokyo, Japan

To Swing or Not to Swing? Reference Point and Professional Baseball Players *

Koji Yashiki† and Yoshiyuki Nakazono‡

July 2020

Abstract

Does the batting average influence players' decision on whether or not to swing? We examine if the decision on whether to swing is influenced by the batting average of Japanese professional baseball players using pitch-by-pitch data. We show that when the batting average is just .300, the probability of swinging becomes significantly lower than when the average is well above or below .300. This suggests that a .300 batting average is considered as a reference point, which plays a central role in behavioral economics, for professional baseball players and influences their attitudes toward risk at every plate appearance throughout the season. This is likely to reflect in the behavior of loss aversion among professional baseball players.

JEL Classification: D91; L83; Z21; Z22

Keywords: behavioral economics; decision making; judgment; loss aversion; reference point

---

*This paper was formerly circulated as "Loss Aversion: Conservative Baseball Players with Batting Average Just Above .300." We thank Nippon Professional Baseball (NPB) and DataStadium Inc. for providing us data from NPB's Baseball-Data Innovation Platform. We also thank the discussant, Fumio Ohtake, for invaluable inputs and Rui Ota and Qing-Yuan Sui, as well as participants at the Japanese Economic Association 2020 Spring Meeting and the seminar at The Institute of Statistical Mathematics for their comments and suggestions. This research is supported by the Research Organization of Information and Systems.

†Yokohama City University

‡Cabinet Office, Government of Japan; Yokohama City University

1 Introduction

The reference point is one of the most important topics in behavioral economics, although very little literature examines whether a reference point influences decision-making among professional athletes. Pope and Simonsohn (2011) is one of the few exceptions. They show that a batting average, for example, is a reference point for Major League Baseball players, and professional baseball players modify their behavior such that they finish with a batting average just above rather than below .300 as the season is about to end. In this case, a batting average of .300 functions as a reference point and may be a criterion for managers to evaluate outcomes.

There is evidence that a .300 batting average acts as a reference point even in Japan.[1] Figure 1 shows the distribution of batting averages in the Japanese professional league from 1995 to 2018, approximately three weeks before the end of the season. Figure 2 shows the distribution of batting averages at the end of the season from 1995 to 2018. Although the histogram in Figure 1 follows normal distribution, Figure 2 shows a peak and a trough at the averages of .300 and .299, respectively. The break around .300 in Figure 2 strongly suggest that the behavior of professional players is manipulated; this is because it is likely that a batting average of .300 is used as a reference point in the wage-setting process.

In this study, we examine whether a reference point influences the decision on whether or not to swing using pitch-by-pitch data on the performance of Japanese professional baseball players. We test whether a batter with a batting average of just .300 or slightly above .300 is less likely to swing compared with one with an average well above or below .300. We find that a .300 batting average influences the players' decision on whether or not to swing. In fact, we show that the probability to swing becomes significantly low when the batting average is

[1]There are very few studies on professional athletes in Japan. A few exceptions are Ohtake and Ohkusa (1994), Ohkusa and Ohtake (1996), and Yamamura and Shin (2009).

just .300 or slightly above .300. This suggests that a player may hesitate to swing when the batting average is likely to fall below .300 if the player is forced out.

Our results imply that a .300 batting average is considered as a reference point for Japanese professional baseball players. The evidence also implies that the reference point influences the attitudes toward the risks professional baseball players face. A batter may become a risk-averter when the batting average is at the risk of falling below .300 depending on the result at-bat. This result reflects the loss aversion of professional baseball players. Although the batting average constantly changes throughout the season, our result indicates that the players' decisions are influenced by the .300 batting average as a reference point at every plate appearance.

Our study sheds light on the behavior of loss aversion as well as the reference point of professional baseball players. Loss aversion, as proposed by Kahneman and Tversky (1979), means that decisions among risky prospects are more sensitive to losses than profits of the same scale. A growing amount of literature has examined how the behavior of loss aversion influences the agent's decision-making, including experimental research using lotteries (Kachelmeier and Shehata, 1992; Sasaki et al., 2008) and field research in medical (Tom et al., 2007; Tanaka et al., 2014; Tanaka et al., 2017). Studies on loss aversion have also been conducted in professional sports. For example, Elmore and Urbaczewski (2019) investigate loss aversion using data on professional golfers. Riedl et al. (2015) examine the case of a team playing for a draw instead of a win in soccer. Our finding contributes to the existing literature by showing that a batter with the batting average of .300 or slightly above .300 may prefer the "wait-and-see" approach instead of swinging aggressively to mitigate the risk of dipping below the .300 batting average plateau.

The structure of this paper is as follows. Section 2 explains our approach to examine a change in the decision making of baseball players. Section 3 describes the pitch-by-pitch data we use. Section 4 describes the results, and Section 5 concludes.

2 Identification strategy for the reference point

When is a batter more likely to swing? Does a batting average influence the batter's decision whether or not to swing? To examine whether a reference point influences players' decision-making, we focus on two indicators, the probability to swing and batting average. The probability to swing is the probability that the batter swings the bat out of all pitches thrown. Using this, we investigate whether the probability to swing depends on the player's batting average. The batter's decision whether or not to swing for each pitch may change conditional on the skills of the opponent's pitcher and the situation at the plate appearance. Thus, it would be unlikely that the probability to swing is influenced by the player's batting average at that time. Thus, the probability should be constant at any batting average.

However, if a batting average of .300 is considered as a reference point, it may influence the batter's decision-making. When the batting average is above .300 and there is a possibility that it could fall below .300, the batter who wishes it to remain above .300 may be less likely to swing. Here, the wait-and-see approach makes sense because it will raise the probability to draw a walk.[2] In fact, drawing a walk does not change a players' batting average according to baseball rules. Thus, this approach can mitigate the risk of dipping below the .300 batting average plateau.

Using pitch-by-pitch data, we test if a batting average of .300 influences the decision on whether or not to swing. We conduct a Fisher exact probability test to verify the difference between the probability to swing among batters whose batting average is just .300, above .300, and below .300. When a batter does not

[2]In baseball, a batter receiving four pitches outside the strike zone draws a walk. According to our database, approximately half of the pitches are outside the strike zone. Thus, rather than aggressively swinging, the wait-and-see approach will raise the probability of drawing a walk.

consider a batting average of .300 as a reference point, that batter's probability to swing is not different from that of each plate appearance. On the other hand, if the batting average functions as a reference point, we expect that a player with a batting average of just above .300 is less likely to swing; that is, the probability to swing becomes lower than when the batting average is well above or below .300. That player is then treated as a risk averter.

We classify players with batting averages of just .300 or above as the "Down" group. On the other hand, we classify players whose batting averages are slightly below .300 as the "Up" group. If the batting average is considered as a reference point and the batter's attitude toward risk changes at the .300 batting average, the probability to swing conditional on the batting average around .300 is expected to be as follows:

$$P\{swing|up\} > P\{swing|control\} > P\{swing|Down\},$$

where $P\{swing|up\}$ and $P\{swing|down\}$ refer to the probability to swing, which is calculated using the samples from the Up and Down groups, respectively. $P\{swing|control\}$ is computed as the probability to swing using samples other than the Up and Down groups.

More precisely, we divide the data into three groups. The first is the Up group, which includes samples from the situation wherein if a player gets a hit, the batting average reaches .300 or over. For example, data from a batter with 120-for-401 and a batting average of .299 are classified as the Up group. In this case, the batting average reaches .300 when the player gets a hit at that plate appearance. The second is the Down group, which includes samples from the situation wherein if a player strikes out, the batting average falls below .300. For example, data from a batter with 120-for-400 and a .300 batting average are classified as being in the Down group. In this case, the batting average falls below .300 when the player is forced out at that plate appearance. Further, the samples of the Down group are drawn from the situation wherein if a batter makes out, the batting average falls below .300. The third is the "Control" group, which includes samples other than those in the Up and Down groups. For example, data from a batter with 121-for-410 and a batting average of .295 are classified as the Control group. In this case, the batting average remains under .300 even when the player gets a hit. Similarly, data from a batter with 125-for-415 and a batting average of .301 are classified as the Control group. In this case, the batting average remains above .300 even when the player is forced out.

3 Data

The pitch-by-pitch data we use are collected by Data Stadium.[3] These data cover the time period from 2016 to 2018 and provide the performance indicators and covariates of all players in Nippon Professional Baseball (NPB). The performance indicators can be calculated on a real-time basis. Furthermore, the data recode each player's decision on whether or not to swing for every pitch. The sample sizes of the all pitch records reach approximately 800,000.[4]

We focus on the decision-making of players with at least 400 plate appearances at the end of the seasons from 2016 to 2018.[5] Moreover, we use pitch-by-pitch data approximately three weeks before the end of every season, which is on September 20 for every season, to control the change in the behavior of batting, as shown in Figure 2. As discussed before, the break around .300 in Figure 2 strongly suggest that the behavior of professional players is manipulated, possibly to obtain a higher salary. If so, just before the end of the seasons, the probability to swing of a batter with a batting average of .300 is definitely influenced by the wage contract. Because we focus on whether a .300 batting average influences the decision on whether or not to swing even during "normal" time, we omit the data for the last three weeks before the end of the seasons.

[3] See details in https://www.datastadium.co.jp/.

[4] The basic statistics is shown in Table 1.

[5] The official NPB rules set approximately 400 as the minimum required plate appearances for acquiring batting titles.

4 Result

Table 2 reports the estimation results upon comparing the probability to swing using the whole sample and shows that the probability is significantly different between the two groups. Batters in the Up group swing with a probability of 46.1%, while those in the Down group swing with a probability of 41.0%. The difference in the probability is 5.1% and significant. This result suggests that the probability becomes significantly low when the batting average falls below .300 depending on the result of at-bat. The result is robust using the sample from the Control group. Batters in the control group swing with a probability of 44.2%. The Down group batters' probability to swing is significantly lower than that of Control group batters: the difference is 3.2%. On the other hand, Up group batters' probability to swing is not significantly different from that of Control group batters: the difference is only 1.9%. This result suggests that only batters in the Down group are less likely to swing; they may hesitate to swing if the batting average would fall below .300 if they are forced out.

The probability to swing may also depend on the ball count. As a robustness check, we further examine whether only batters in the Down group is less likely to swing by dividing the sample into four subsamples,[6] namely, the samples

(I) from a first pitch to the batter,

(II) excluding a pitch from a two-strike count,[7]

(III) from a pitch inside the strike zone, and

(IV) from a pitch outside the strike zone.

Table 3 presents results of the robustness check using the four subsamples. The table shows that the probability to swing is consistently lower in the Down group than in the Up group in all four cases; the difference between them is significant in three out of the four cases. The results are similar when we use

[6]Data Stadium (https://www.datastadium.co.jp/) has data on the pitch area in a coordinate format and defines whether each pitch is strike or ball.

[7]This subsample covers a "hitter's count."

the samples from the Down and Control groups. The probability to swing is always lower in the Down group than in the Control group in all four cases; the difference between them is significant in three out of the four cases. On the other hand, there are no statistical differences between the Up and Control groups. The table suggests that our baseline results are robust: only a batter in the Down group is less likely to swing.

We further conduct a robustness check by estimating a probit model. In the model, a dummy variable (D^{Swing})— which takes one when a batter swings and otherwise zero— is regressed on D^{Up}— which takes one when a batter is from the Up group.[8] In addition, we include batter fixed effects and pitch characteristics as the control variables.[9] Table 4 shows that the above results are robust: the coefficient of D^{Up} is significantly positive in all cases. The probability to swing by an Up group batter is significantly larger than that of a Down group batter. The evidence suggests that a .300 batting average influences whether a batter swings or not and is considered as a reference point. The result of the probit analysis supports our benchmark result.

In sum, these results suggest that a .300 batting average is considered as a reference point and influences the players' decision on whether or not to swing. The wait-and-see approach makes sense to mitigate the risk of dipping below the .300 batting average plateau. This evidence implies that attitude toward the risks of professional baseball players may be asymmetric at the .300 batting average, which is considered as a reference point. Batters may become risk-averters when their batting averages fall below .300 depending on the result of at-bat.

[8]Because we omit D^{Down} as an independent variable, the coefficient on D^{Up} represents the difference between the probability to swing among the Up and Down groups.

[9]Pitch characteristics cover four variables: (1) distance from the center of the strike zone, (2) pitch speed, (3) dummies for the pitches [(a) fastball, (b) slider, (c) curve, (d) cutter, (e) two seam fastball, (f) change-up, and (g) split finger fastball], and (4) dummies for the ball count.

5 Conclusion

We examine whether Japanese professional baseball players' decision on whether or not to swing is influenced by their batting averages using pitch-by-pitch data. We show that when the batting average is just .300, the probability to swing becomes significantly lower than that when the average is well above or below .300. In fact, batters seem to become risk-averters when their batting averages fall below .300 depending on the result of at-bat. This result suggests that a .300 batting average is considered as a reference point for professional baseball players and influences their attitudes toward risk. Although a batting average is constantly changing throughout the season, our result indicates that players' decisions are influenced by a .300 batting average at every plate appearance. This is likely to reflect in the behavior of loss aversion among professional baseball players.

References

Benjamini, Y., and Hochberg, Y., (1995), “Controlling the False Discovery Rate: a Practical and Powerful Approach to Multiple Testing”, *Journal of the Royal Statistical Society* 57, pp.289-300.

Elmore, R., and Urbaczewski, A., (2019), “Loss Aversion in Professional Golf”, *SSRN Electronic Journal*.

Kachelmeier, S. J., and Shehata, M., (1992), “Examining Risk Preference under High Monetary Incentives: Experimental Evidence from the People’s Republic of China”, *American Economic Review* 82, pp.1120-1141.

Kahneman, D., and Tversky, A., (1979), “Prospect Theory: An Analysis of Decision under Risk”, *Econometrica* 47, pp.263-292.

Ohkusa, Y., and Ohtake, F., (1996), “The Relationship between Supervisor and Workers — The Case of Professional Baseball in Japan”, *Japan and the World Economy* 8, pp.475-488.

Ohtake, F., and Ohkusa, Y., (1994), “ Testing the Matching Hypothesis: The Case of Professional Baseball in Japan with Comparisons to the United States”, *Journal of the Japanese & International Economies* 8, pp.204–219.

Pope, D., and Simonsohn, U., (2011), “Round Numbers as Goals: Evidence from Baseball, SAT Takers, and the Lab”, *Psychological Science* 22, pp.71–79.

Riedl, D., Heuer, A., and Strauss, B., (2015), “Why the Three-Point Rule Failed to Sufficiently Reduce the Number of Draws in Soccer: An Application of Prospect Theory”, *Journal of Sport & Exercise Psychology* 37, pp.316–326.

Sasaki, S., Xie, S., Ohtake, F., Qin, J., and Tsutsui, Y., (2008), “Experiments on Risk Attitude: The Case of Chinese Students”, *China Economic Review* 19, pp.245–259.

Tanaka, S. C., Yahata, N., Todokoro, A., Kawakubo, Y., Kano, Y., Nishimura, Y., Ishii-Takahashi, A., Ohtake, F., and Kasai, K., (2017), “Preliminary Evidence of Altered Neural Response during Intertemporal Choice of Losses in Adult Attention-Deficit Hyperactivity Disorder”, *Scientific Reports* 8, p.6703.

Tanaka, S. C., Yamada, K., Yoneda, H., and Ohtake, F., (2014), “Neural Mechanisms of Gain–Loss Asymmetry in Temporal Discounting”, *The Journal of Neuroscience* 34, pp.5595–5602.

Tom, S, M., Fox, C. R., Trepel, C., and Poldrack, R.A., (2017), “The Neural Basis of Loss Aversion in Decision-Making under Risk”, *Science* 315, pp.515–518.

Yamamura, E., and Shin, I., (2009), “Convergence, Clustering and their Effects on Attendance in the Japan Professional Baseball League”, *Applied Economics* 41, pp.3257–3265.

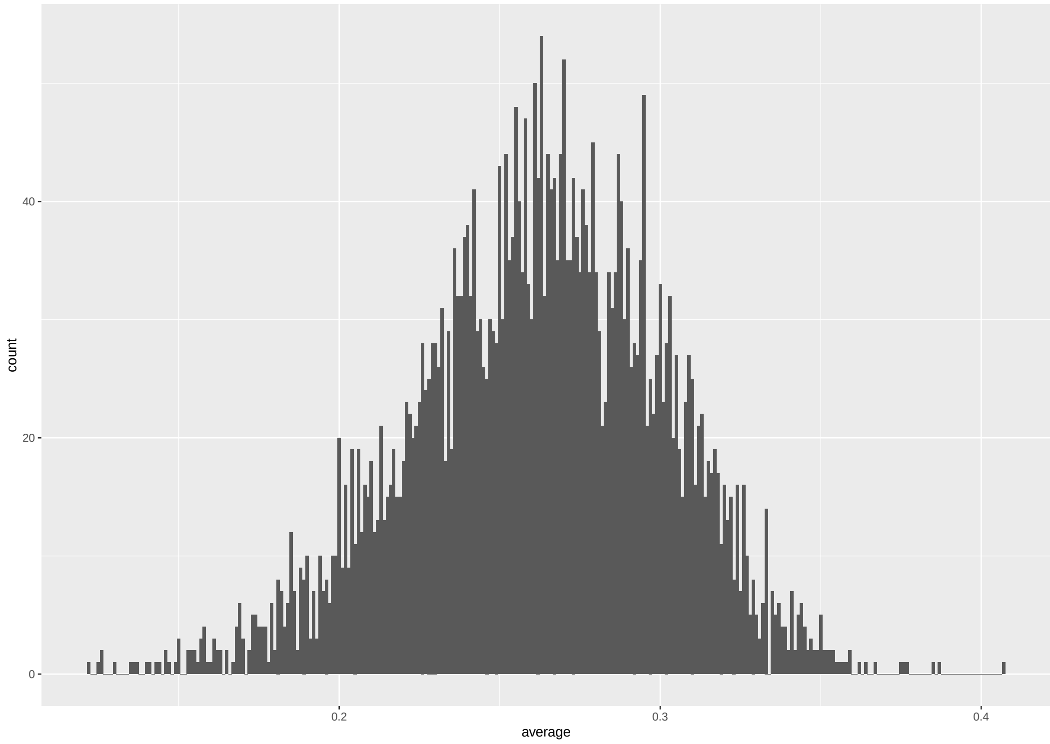

Figure 1: Distribution of batting averages in the NPB, as of September 20 for every season from 1995 to 2018. The histogram includes the sample only from the batters with the minimum requirement plate appearances. The data is from the BIP platform.

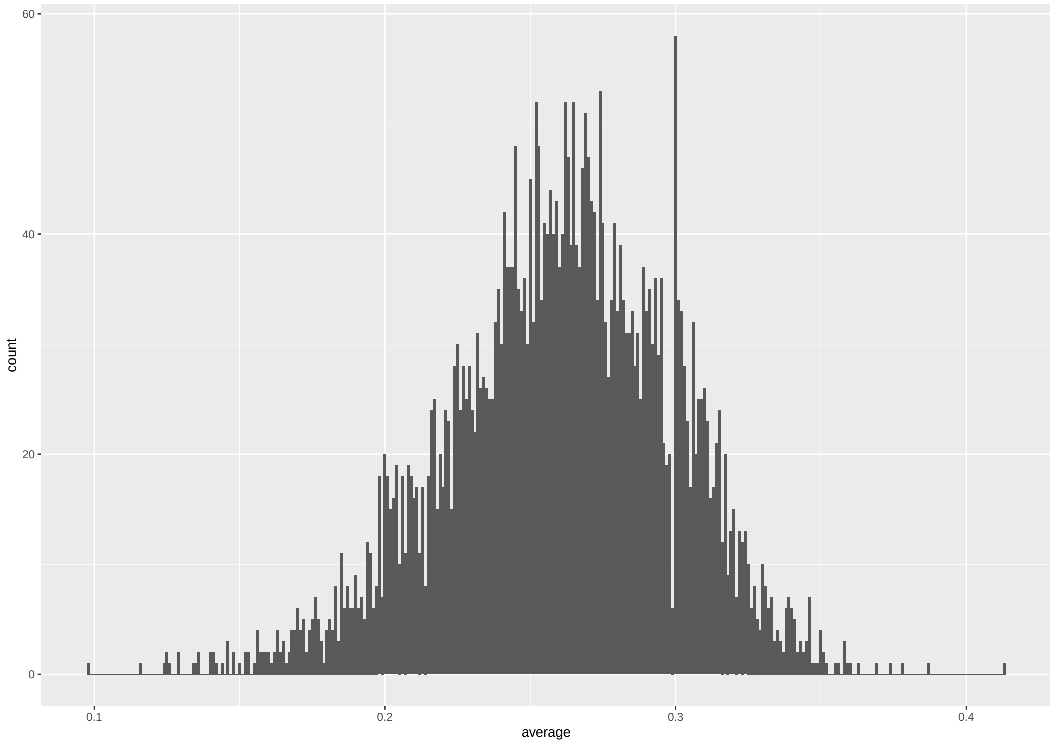

Figure 2: Distribution of batting averages at the end of the seasons from 1995 to 2018. The histogram includes the sample only from the batters with the minimum requirement plate appearances. The data is from the BIP platform.

Table 1: Classification of sample

	Up group	Down group	Control group	All
Pitch	1,727	766	15,779	776,528
Plate apperance	319	129	2,875	140,756
Pitches to strike zone	858	365	7,507	369,836
Pitches outside the strike zone	869	401	8,272	406,692

Table 2: Comparison of the probability of swinging from the whole sample

	Up	Down	Control	diff	p-value	q-value
Up − Down	0.461	0.410	−	$0.051**^{+}$	0.018	0.054
	(1,727)	(766)				
Up − Control	0.461	−	0.442	0.019	0.132	0.132
	(1,727)		(15,779)			
Down − Control	−	0.410	0.442	$-0.032*$	0.087	0.131
		(776)	(15,779)			

Note: Sample size is in parentheses. ** indicates 5% significance. The q-value indicates False Discovery Rate (FDR) following the approach by Benjamini and Hochberg (1995). Based on the q-value, $^{+}$ indicates 10% significance.

Table 3: Comparison of the probabilities of swinging from the four subsamples

		Up	Down	Control	Difference	p-value	q-value
	Up-Down	0.286	0.213	–	0.073*	0.069	0.150
		(423)	(178)				
Pitchers first pitch	Up-Control	0.286	–	0.270	0.016	0.490	0.490
		(423)		(3,883)			
	Down-Control	–	0.213	0.270	−0.057*	0.100	0.150
			(178)	(3,883)			
	Up-Down	0.363	0.297	–	$0.066{*}{*}^{++}$	0.013	0.038
		(1,007)	(465)				
Except for 2-strike count	Up-Control	0.363	–	0.348	0.015	0.331	0.331
		(1,007)		(9,510)			
	Down-Control	–	0.297	0.348	$-0.051{*}{*}^{++}$	0.025	0.038
			(465)	(9,510)			
	Up-Down	0.662	0.630	–	0.032	0.294	0.441
		(858)	(365)				
Pitches to strike zone	Up-Control	0.662	–	0.641	0.021	0.229	0.441
		(858)		(7,507)			
	Down-Control	–	0.630	0.641	−0.011	0.696	0.696
			(365)	(7,507)			
	Up-Down	0.262	0.209	–	$0.053{*}{*}^{+}$	0.042	0.063
		(869)	(401)				
Pitches outside the strike zone	Up-Control	0.262	–	0.261	0.001	0.903	0.903
		(869)		(8,272)			
	Down-Control	–	0.209	0.261	$-0.052{*}{*}^{+}$	0.023	0.063
			(401)	(8,272)			

Note: Sample size is in parentheses. ***, **, and * indicate 5% and 10% significance, respectively. The q-value indicates False Discovery Rate (FDR) following the approach by Benjamini and Hochberg (1995). Based on the q-value, $^{++}$ and $^{+}$ indicate 5% and 10% significance, respectively.

Table 4: Robustness check: A Probit analysis

Dependent variable: Dummy variable (D^{Swing})			
	Model		
Independent variable	1	2	3
D^{Up}	0.107*	0.108**	0.129**
	(1.629)	(1.960)	(2.034)
$D^{Control}$	0.043	0.052	0.095*
	(0.772)	(1.101)	(1.753)
Batter fixed effect	✓	✓	
Pitch characteristics	✓		✓
Observation	$17,514$	$18,272$	$17,514$

Note: D^{Up} ($D^{Control}$) takes one when a batter is from the Up (Control) group; otherwise zero. D^{Swing} takes one when a batter swings; otherwise zero. Standard errors are in parentheses. ** and * indicate 5% and 10% significance, respectively.