

Reference Dependence and Monetary Incentive

-Evidence from Major League Baseball-

Reio TANJI²

Osaka University, Graduate School of Economics

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²ot.shunie.rt@gmail.com

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Abstract

- This paper explored the relationship between observed reference dependent behavior and monetary incentives.
- Specifically, this paper used performance stats and contract design of Major League Baseball (MLB) players, and identified their salary determination procedure.
- MLB players have round-number reference dependence about their performance indexes, which is not caused by their monetary incentives.

Research Question

- How observed reference dependence is related to the monetary incentives?
- What factor lead individuals to recognize a reference point and make effort to achieve it?

Background

- Reference dependence is one of the two main characteristics of the prospect theory:
Individuals evaluate outcomes by the relative value to their internal benchmarks, or reference point, not by their absolute ones
- There are a lot of subsequent researches that shows the evidence for the reference dependence in field and laboratory settings.

Literature

- There are also some researches that use cases from athletes' decision making.

Reference Dependence of Athletes

- Pope and Schweizer (2011, AER) pointed out that for the professional golf players regard “par” as a reference point, which results in the different probability of success in their putts.
- Allen et al. (2016) identified existence of reference point dependence of marathon runners, using data about the finish time of enormous number of races in the United States.
⇒ Runners try to goal before the round numbers, and it results in observed excess mass, or “bunching” around 4 hours.

Literature

- Pope and Simonsohn (2011) picked up the case of Major League Baseball (MLB) players about the observed attitude to their performance indexes.
- MLB position players make effort to manipulate their batting-average (AVG), in order to meet their internal goals: .300
- As a result, there is observed excess mass, or “bunching” around .300 of AVG.

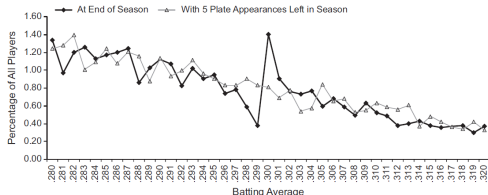


Fig. 1. Relative frequency of batting averages among Major League Baseball players between 1975 and 2008. Batting averages at the end of the baseball season and with five plate appearances left in the season are shown. The graph includes only player-seasons with at least 200 at bats.

Figure: Excess Mass Around .300 (quoted from Pope and Simonsohn (2011))

Contribution

- The case of MLB is different from that of marathon in that players are professional, and receive salary, or monetary rewards.
- There may exist an economically reasonable factor that leads them to bunching:
The fact that a player achieves round-number of a performance index (such as .300 of batting-average) itself is to be rewarded
- The contribution of our research is to explore this: examine if there exists any monetary incentives that make players make effort to the cutoff point.

Benefit of Better Performance

This paper assume two ways of specification of players benefit of better number of indexes.

- 1 Players yield internal benefits that depend on their performance index X , $b(X, Z)$. Z is other observed player-specific characteristics, such as age, position, and so on.
- 2 Players receive monetary reward determined by $f(X, Z)$, and they regard this as their benefit for better performance.

The second case corresponds to the assumption that monetary incentive leads them to bunching.

Effort Cost for Better Performance

- On the other hand, getting better performance requires them to make some additional effort:
 X is determined by the players' effort level e .
- Then, effort cost $c(\cdot)$ is defined with $c'(\cdot) > 0$ and $c''(\cdot) < 0$.
 Note that $c(\cdot)$ differs from player to player.
 \Rightarrow Player i at season t 's objective function of the maximization problem is:

$$① \quad U_{it} = b(X(e_{it}), Z_{it}) - c_{it}(e_{it})$$

$$② \quad U_{it} = f(X(e)_{it}, Z_{it}) - c_{it}(e)$$

This specification way follows that of Allen et al (2016).

Assumptions for Excess Mass

- There are two possible assumptions about functional form of $b(., .)$ and $f(., .)$, which leads to bunching around a reference point r .

Functional Features of Bunching

- 1 “Notch” at r .

$$\lim_{\epsilon \rightarrow 0} b_r(r + \epsilon) \neq \lim_{\epsilon \rightarrow 0} b_r(r - \epsilon)$$

$$\lim_{\epsilon \rightarrow 0} f_r(r + \epsilon) \neq \lim_{\epsilon \rightarrow 0} f_r(r - \epsilon)$$

- 2 “Kink” at r .

$$\lim_{\epsilon \rightarrow 0} b'_r(r + \epsilon) \neq \lim_{\epsilon \rightarrow 0} b'_r(r - \epsilon)$$

$$\lim_{\epsilon \rightarrow 0} f'_r(r + \epsilon) \neq \lim_{\epsilon \rightarrow 0} f'_r(r - \epsilon)$$

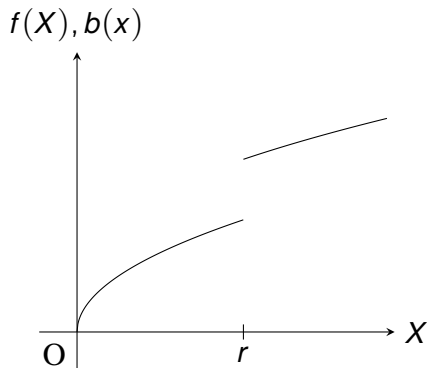


Figure: "Notch" at the reference point

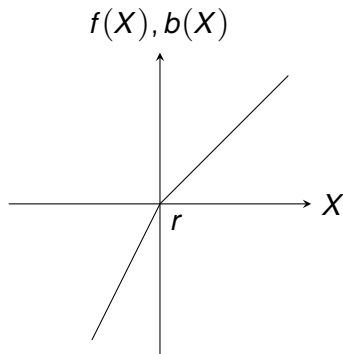


Figure: "Kink" at the reference point

- Suppose there exists bunching around a possible reference point such as .300 of batting-average, b or f should have functional forms mentioned above.
- This paper test if f has such features or not:
If the players' salary jump or kink at the reference point, then it works as the cause that lead them to bunching.

Flow of Identification

- ① First, we follow Pope and Simonsohn (2011):
identify bunching around round-numbers of various indexes.
 - We test not only batting-average, but also other indexes of position player.
- ② Then, we test if there exists additional monetary bonus where bunching was observed.

Identification of Bunching

- We exploit the McCrary (2007)'s manipulation test, which is used in regression discontinuity design.
- Make local approximation of the histogram of the variable of interest, and calculate the predicted values of $f(r)$ at the cutoff point, from both above and below there.

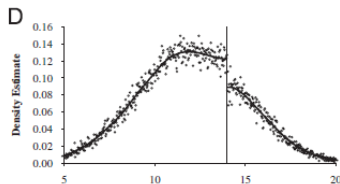


Figure: Discontinuous frequency (quoted from McCrary(2007))

Identification of Reward Function

- Notch of the contract design is tested by local-linear regression:

$$w_{it} = \beta_0 + \beta_1 \text{PERF}_{it} + \beta_2 \text{ABOVE}_{it}$$

where

w_{it} : log salary of the next season

PERF_{it} : performance index

ABOVE_{it} : indicator for achievement

- Also, kink is examined by introducing the interaction term of PERF_{it} and ABOVE_{it}

$$w_{it} = \beta_0 + \beta_1 \text{PERF}_{it} + \beta_2 \text{ABOVE}_{it} + \beta_3 \text{PERF}_{it} \times \text{ABOVE}_{it}$$

We also conduct analysis including other performance and other player specific characteristics.

Data Description

We obtain information about the players' stats (indexes) and annual salary.

- Stats Data
 - From *FanGraphs*
 - Play stats from 1957 to 2018
 - We restrict the sample to the players with at least 200 plate-appearances $N = 18143$ (62 seasons \times players)
- Salary Data
 - From *USA TODAY* and *Baseball References*
 - Contract information from 1987 to 2017 $N = 8915$ (31 seasons \times players)
 - Fixed part of the salary of each player
 - Information about possession of free agency, the right to negotiate any team in MLB.

Results

To be written...

Bunching: McCrary's Test

Figure: Histogram of Batting-Average

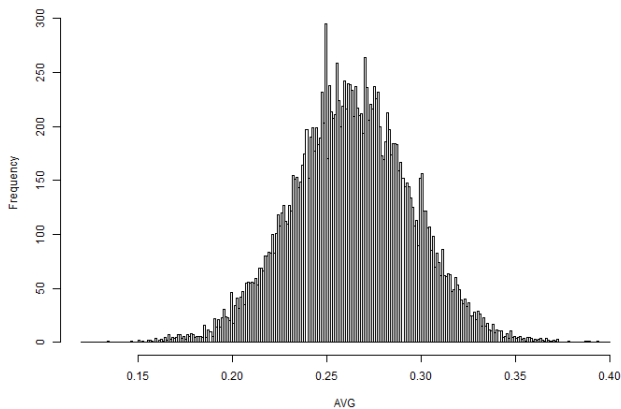


Figure: Discontinuity at .300 of AVG

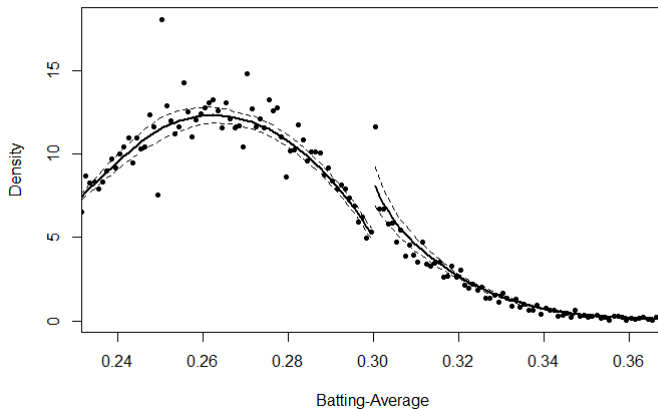


Table: Test for Bunching, leastPA = 200

index	type	cutpoint	binsize	bandwidth	θ	z
AVG	rate	.300	.001	.019	.499 (.067)	7.442***
		.250	.001	.024	.212 (.042)	5.061***
OBP	rate	.350	.001	.024	.139 (.049)	2.854**
HR	cumulative	20	1	5.309	.259 (.075)	3.465***
RBI	cumulative	100	4	15.423	.311 (.094)	3.295***
SB	cumulative	30	1	10.000	.529 (.124)	4.274***
		40	1	11.505	.481 (.174)	2.764**
PA	cumulative	500	1	.003	.160 (.063)	2.515*
H	cumulative	200	1	18.922	.453 (.178)	2.547 *

Note

***: $p < 0.1\%$, **: $p < 1\%$, *: $p < 5\%$.

Bandwidth is optimized following the method of McCrary(2008).

Monetary Reward: Notch

Monetary Reward: Kink

Robustness

Piece-Rate Rewards

Contract Length

By-Time Analysis

Bunching

Monetary Reward

Conclusion

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