

Reference Dependence and Monetary Incentive

-Evidence from Major League Baseball-

Reio TANJI²

Osaka University, Graduate School of Economics

Mar. 5th, 2019

²ot.shunie.rt@gmail.com

Contents

- 1 Introduction
- 2 Theoretical Framework
- 3 Methodology and Data
- 4 Results
- 5 Alternative Interpretation and Discussion
- 6 Extention
- 7 Conclusion

Abstract

- This paper explored the relationship between observed ("apparent") reference dependent behavior and monetary incentives, using Major League Baseball (MLB) position players.
- Specifically, this paper obtained performance stats and contract design of MLB players, and estimated their salary determination procedure.
- MLB players regard some of round-numbers of performance indexes as reference points, 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
- Values of the previous periods, well-known benchmarks or round-numbers are likely to be set as the reference points.
- 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.

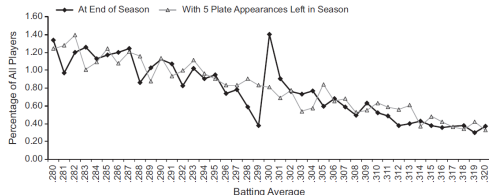


Fig. 1. Relative frequency of batting averages among Major League Baseball players between 1975 and 2008. Batting averages at the end of the baseball season and with five plate appearances left in the season are shown. The graph includes only player-seasons with at least 200 at bats.

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 $c(.)$ is defined with $c'() > 0$ and $c''(.) > 0$.
 Note that $c(.)$ differs from player to player.
 \Rightarrow Player i at season t 's objective function of the maximization problem is:

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

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

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 .

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

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

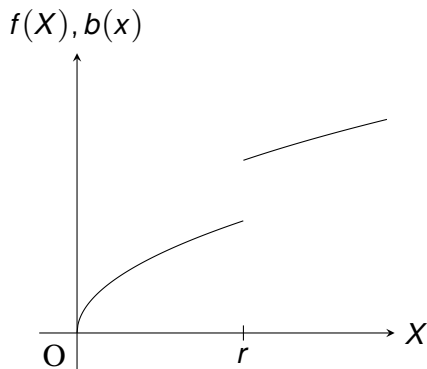


Figure: "Notch" at the reference point

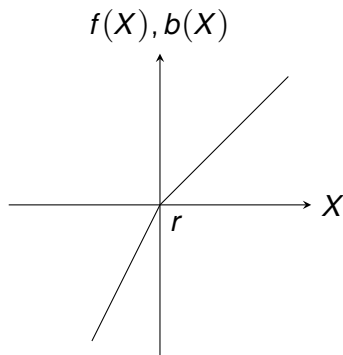
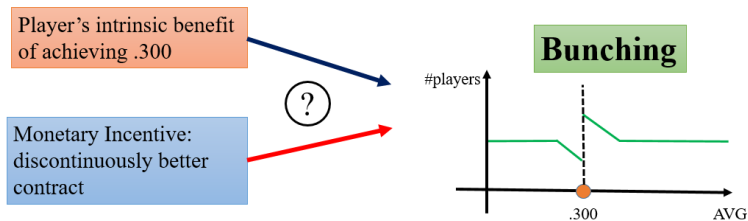


Figure: "Kink" at the reference point

- Suppose there exists bunching around a possible reference point such as .300 of batting-average, b or f should have at least one of the 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.

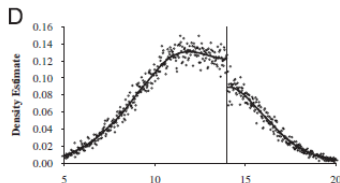


Figure: Discontinuous frequency (quoted from McCrary(2007))

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)

FANGRAPHS

Player & Blog Search

Membership

Games

Blogs

Projections

Scores

Standings

Leaders

Teams

Glossary

Sign In

Dashboard

Standard

Advanced

Batted Ball

Win Probability

Pitch Type

Pitch Value

Plate Discipline

Value

Pitch Info

Show Filters | Custom Reports

Export Data

H

1

2

3

4

5

6

7

8

9

10

...

Page size: 30

2861 items in 96 pages

#	Season Name	Team	G	PA	HR	R	RBI	SB	BB%	K%	ISO	BA	AVG	OBP	SLG	wOBA	wRC+	Bat	OF	Def	WAR
1	2000 Todd Helton	Rockies	160	697	42	138	147	5	14.8%	8.8%	.326	.357	.372	.463	.698	.476	162	-0.3	58.1	6.4	8.3
2	2000 Nomar Garciaparra	Red Sox	140	599	21	104	96	5	10.2%	8.3%	.227	.378	.372	.434	.599	.432	154	0.2	44.4	15.0	7.6
3	2004 Ichiro Suzuki	Mariners	161	762	8	101	60	36	6.4%	8.3%	.082	.399	.372	.414	.455	.375	131	3.5	33.9	12.9	7.1
4	2002 Barry Bonds	Giants	143	612	46	117	110	9	32.4%	7.7%	.429	.330	.370	.582	.799	.544	244	-1.2	108.9	-2.0	12.7
5	2009 Joe Mauer	Twins	138	606	28	94	96	4	12.5%	10.4%	.222	.373	.365	.444	.587	.438	170	-2.1	50.8	4.6	7.6
6	2008 Chipper Jones	Braves	128	534	22	82	75	4	16.9%	11.4%	.210	.383	.364	.470	.574	.445	174	-0.4	49.5	4.6	7.1
7	2007 Magglio Ordonez	Tigers	157	679	26	117	139	4	11.2%	11.6%	.232	.381	.363	.434	.595	.438	169	-1.4	57.8	1.1	8.0
8	2004 Barry Bonds	Giants	147	617	45	129	101	6	37.6%	6.6%	.450	.310	.362	.609	.812	.537	233	-0.3	105.7	-4.4	11.9
9	2010 Josh Hamilton	Rangers	133	571	32	95	100	8	7.5%	16.6%	.274	.390	.359	.411	.633	.445	175	4.9	55.3	5.9	8.4
10	2003 Albert Pujols	Cardinals	157	685	43	137	124	5	11.5%	9.5%	.308	.346	.359	.439	.667	.461	184	5.6	79.8	-5.4	9.5
11	2003 Todd Helton	Rockies	160	703	33	135	117	0	15.8%	10.2%	.271	.363	.358	.458	.630	.453	163	0.3	56.9	-13.2	6.6
12	2008 Albert Pujols	Cardinals	148	641	37	100	116	7	16.2%	8.4%	.296	.340	.357	.462	.653	.459	184	-0.2	67.7	-1.0	8.7
13	2000 Darin Erstad	Angels	157	747	25	121	100	28	8.6%	11.0%	.186	.375	.355	.409	.541	.408	140	2.0	42.2	22.2	8.7
14	2000 Moises Alou	Astros	126	517	30	82	114	3	10.1%	8.7%	.269	.338	.355	.416	.623	.436	154	-0.7	37.2	-19.3	3.2
15	2009 Ichiro Suzuki	Mariners	146	678	11	88	46	26	4.7%	10.5%	.113	.384	.352	.386	.465	.367	125	7.6	29.1	2.1	5.4

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.

USA TODAY NEWS SPORTS LIFE MONEY TECH TRAVEL OPINION 33° CROSSWORDS MORE Subscribe Sign In							
PLAYER SALARIES							
RANK	NAME	TEAM	POS	SALARY	YEARS	TOTAL VALUE	AVG ANNUAL
1	Max Scherzer	WSH	SP	\$42,142,857	7 (2015-21)	\$210,000,000	\$30,000,000
2	Stephen Strasburg	WSH	SP	\$36,428,571	7 (2017-23)	\$175,000,000	\$25,000,000
3	Mike Trout	LAA	OF	\$34,083,333	6 (2015-20)	\$144,500,000	\$24,083,333
4	Zack Greinke	ARI	SP	\$32,421,884	6 (2016-21)	\$206,500,000	\$34,416,667
5	David Price	BOS	SP	\$31,000,000	7 (2016-22)	\$217,000,000	\$31,000,000
5	Clayton Kershaw	LAD	SP	\$31,000,000	3 (2019-21)	\$93,000,000	\$31,000,000
7	Miguel Cabrera	DET	1B	\$30,000,000	10 (2014-23)	\$292,000,000	\$29,200,000
8	Yoenis Cespedes	NYM	OF	\$29,000,000	4 (2017-20)	\$110,000,000	\$27,500,000
9	Albert Pujols	LAA	1B	\$28,000,000	10 (2012-21)	\$240,000,000	\$24,000,000
9	Justin Verlander	HOU	SP	\$28,000,000	7 (2013-19)	\$180,000,000	\$25,714,286
11	Felix Hernandez	SEA	SP	\$27,857,143	7 (2013-19)	\$175,000,000	\$25,000,000
12	Jon Lester	CHC	SP	\$27,500,000	6 (2015-20)	\$155,000,000	\$25,833,333
13	Giancarlo Stanton	NYY	OF	\$26,000,000	13 (2015-27)	\$325,000,000	\$25,000,000
13	Nolan Arenado	COL	3B	\$26,000,000	1 (2019)	\$26,000,000	\$26,000,000
15	Jake Arrieta	PHI	SP	\$25,000,000	3 (2018-20)	\$75,000,000	\$25,000,000
15	Joey Votto	CIN	1B	\$25,000,000	10 (2014-23)	\$225,000,000	\$22,500,000
15	Jordan Zimmermann	DET	SP	\$25,000,000	5 (2016-20)	\$110,000,000	\$22,000,000
18	Robinson Cano	NYM	2B	\$24,000,000	10 (2014-23)	\$240,000,000	\$24,000,000
19	J.D. Martinez	BOS	OF	\$23,750,000	5 (2018-22)	\$110,000,000	\$22,000,000

Results

Step 1. Bunching

Bunching: McCrary's Test

Figure: Histogram of Batting-Average

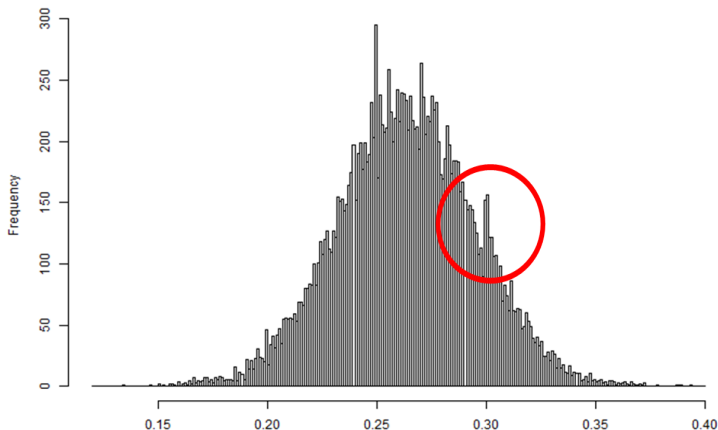


Figure: Discontinuity at .300 of AVG

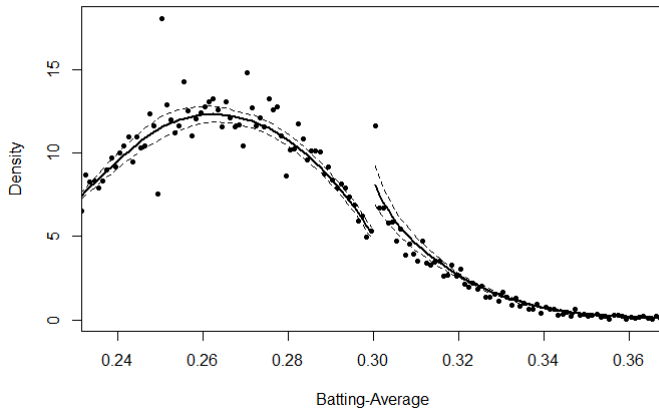


Table: Test for Bunching, leastPA = 200

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).

Results

Step 2. Monetary Incentive

Table: Local-Linear Regression for Monetary Incentives

index,cutpoint	Other Control	bw type	bandwidth	Observations	Estimate	Std. Error	z
AVG, .300	No	LATE	.084	8514	.047	.061	.773
		Half-BW	.042	5599	.088	.075	1.174
		Double-BW	.170	8915	.067	.056	1.184
	Yes	LATE	.045	5930	.034	.056	.615
		Half-BW	.023	3005	.061	.077	.788
		Double-BW	.090	8605	.016	.045	.354
AVG, .250	No	LATE	.036	6110	.019	.068	.286
		Half-BW	.018	3496	.015	.092	.161
		Double-BW	.072	8539	.034	.054	.636
	Yes	LATE	.048	7271	.070	.052	1.340
		Half-BW	.024	4402	.066	.069	.953
		Double-BW	.096	8810	.075	.044	1.713
HR, 20	No	LATE	3.32	1315	.071	.175	.406
		Half-BW	1.66	562	.073	.127	.576
		Double-BW	6.64	2582	-.004	.109	-.034
	Yes	LATE	3.30	1307	-.002	.141	-.015
		Half-BW	1.65	560	.030	.102	.299
		Double-BW	6.61	2558	-.032	.088	-.364
OBP, .350	No	LATE	.044	6440	-.038	.065	-.592
		Half-BW	.021	3542	-.076	.089	-.849
		Double-BW	.087	8656	-.029	.051	-.570
	Yes	LATE	.045	6525	-.013	.049	-.272
		Half-BW	.022	3673	-.055	.069	-.807
		Double-BW	.089	8637	.004	.039	.107

Note:

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

Bandwidth is optimized following the method of Imbens and Kalyanaraman (2009).

“Half” and “Double” stands for using a half and twice of bandwidths, respectively.

“Yes” in “Other Control” shows including players’ age (quadratic), FLD, BsR, FA dummy, Season and Position dummies.

Table: Regression on Log-Salary, Including Interaction Term: around .300

<i>Dependent variable:</i> Logarithm of Salary Next Year						
	<i>OLS</i>			<i>feIm</i>		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	11.166*** (.423)	-6.616*** (.665)	-5.203*** (.671)	-5.319*** (.667)		
AVG	11.513*** (1.537)	11.620*** (1.209)	4.361*** (1.209)	4.221*** (1.201)	3.774** (1.194)	3.808** (1.189)
AVG_300	-.169 (1.050)	-.413 (.821)	-.191 (.785)	-.142 (.780)	-.287 (.775)	-.069 (.706)
AVG:AVG_300	.663 (3.429)	1.428 (2.681)	.681 (2.566)	.540 (2.549)	.996 (2.532)	.160 (2.312)
FLD		.006*** (.002)	.008*** (.002)	.007*** (.002)	.007*** (.002)	.008*** (.002)
BsR		.009* (.005)	.002 (.005)	.003 (.005)	.004 (.004)	.020*** (.005)
Season dummies		X	X	X	X	X
WPA			X	X	X	X
AGE (quadratic)		X	X	X	X	
FA dummy				X	X	X
Position dummies			X	X		
Fixed effects					Team	Individual
Observations	5,960	5,930	5,930	5,930	5,930	5,930
R ²	.035	.420	.470	.478	.488	.744
Adjusted R ²	.035	.416	.466	.473	.482	.660
Residual Std. Error	1.286 (df = 5956)	1.001 (df = 5892)	.957 (df = 5881)	.950 (df = 5880)	.943 (df = 5860)	.764 (df = 4459)
F Statistic	71.983*** (df = 3; 5956)	15.152*** (df = 37; 5892)	208.865*** (df = 48; 5881)	109.753*** (df = 49; 5880)		

Note:

*p<0.05; **p<0.01; ***p<0.001

The bandwidth is same as RDD for .300 of AVG.

FLD and BsR stands for the contribution of the player to the team, expressed by the runs they earned.

WPA is "win-percentage added."

FA dummy indicates the possession of the free agency.

": " stands for the interaction term of the two elements.

Downward Biases

- Players can “manipulate” their batting-average by stopping to appear to the plate after reaching .300 of batting-average (Pope and Simonsohn, 2011).
- If team managers can detect such players, then managers offer them contracts that is offered to the players with .299.
⇒ the estimated size of notch or kink were likely to be underestimated.
- To deal with this problem, we remove the samples around .300, and made the same regression.

Table: Without Players around the Cutoff

	<i>Dependent variable:</i>					
	Logarithm of Salary Next Year					
	<i>OLS</i>			<i>feim</i>		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	11.457*** (.465)	-6.672*** (.709)	-5.567*** (.716)	-5.734*** (.711)		
AVG	10.428*** (1.697)	11.419*** (1.328)	4.782*** (1.325)	4.643*** (1.315)	4.346*** (1.306)	4.393*** (1.333)
AVG_300	-1.277 (1.440)	-.032 (1.122)	.274 (1.076)	.320 (1.068)	.136 (1.062)	.190 (.968)
AVG:AVG_300	4.263 (4.600)	.309 (3.582)	-.757 (3.438)	-.897 (3.412)	-.333 (3.393)	-.657 (3.103)
FLD		.007*** (.002)	.008*** (.002)	.008*** (.002)	.008*** (.002)	.009*** (.002)
BsR		.006 (.005)	-.0003 (.005)	-.0003 (.005)	.0004 (.005)	.018** (.006)
Season dummies		X	X	X	X	X
WPA			X	X	X	X
AGE (quadratic)		X	X	X	X	
FA dummy				X	X	X
Position dummies			X	X		
Fixed effects					Team	Individual
Observations	5,259	5,232	5,232	5,232	5,232	5,232
R ²	.034	.425	.473	.481	.492	.752
Adjusted R ²	.034	.421	.468	.476	.485	.657
Residual Std. Error	1.286 (df = 5255)	.996 (df = 5194)	.955 (df = 5183)	.947 (df = 5182)	.939 (df = 5162)	.767 (df = 3787)
F Statistic	62.260*** (df = 3; 5255)	5303.758*** (df = 37; 5194)	46.869*** (df = 48; 5183)	37.991*** (df = 49; 5182)		

Note:

*p<0.05; **p<0.01; ***p<0.001

The bandwidth is same as RDD for .300 of AVG.

FLD and BsR stands for the contribution of the player to the team, expressed by the runs they earned.

WPA is "win-percentage added."

FA dummy indicates the possession of the free agency.

"." stands for the interaction term of the two elements.

Plural-Year Contract

- If players agree plural-year contracts, then achieving the reference points are not reflected to their rewards immediately.
- We restrict the samples to those who have the right of free agency: those who agreed a new contract with their team.

Table: Regression on Log-Salary: around .300, Including Only FA Players

	Dependent variable:					
	Logarithm of Salary Next Year					
	OLS			felm		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	7.033** (2.374)	7.339* (3.225)	7.114* (3.243)	7.524* (3.062)		
AVG	26.614** (8.308)	26.230*** (7.245)	22.624** (7.355)	14.443* (6.851)	16.909* (6.961)	13.286 (10.076)
AVG_300	6.740 (4.231)	2.770 (3.707)	1.883 (3.749)	.969 (3.453)	1.636 (3.468)	2.727 (4.444)
AVG:AVG_300	-23.155 (14.071)	-10.065 (12.333)	-6.893 (12.474)	-4.015 (11.489)	-6.451 (11.540)	-9.953 (14.911)
FLD		.005 (.006)	.006 (.006)	.007 (.005)	.004 (.005)	.001 (.007)
BsR		.027 (.014)	.025 (.015)	.019 (.014)	.016 (.014)	-.013 (.025)
Season dummies		X	X	X	X	X
WPA				X	X	X
AGE (quadratic)		X	X	X	X	
Position dummies			X	X		
Fixed effects					Team	Individual
Observations	503	493	493	493	493	493
R ²	.028	.388	.406	.502	.529	.937
Adjusted R ²	.022	.339	.345	.448	.453	.735
Residual Std. Error	1.052 (df = 499)	.870 (df = 455)	.866 (df = 446)	.795 (df = 444)	.791 (df = 424)	.551 (df = 117)
F Statistic	4.824** (df = 3; 499)	30.808*** (df = 37; 455)	31.630*** (df = 46; 446)	60.328*** (df = 48; 444)		

Note:

* p<0.05; ** p<0.01; *** p<0.001

The bandwidth is same as RDD for .300 of AVG.

WPA is "win-percentage added."

FLD and BsR stands for the contribution of the player to the team, expressed by the runs they earned.

":" stands for the interaction term of the two elements.

Piece-Rate Rewards

- Some players receive additional payments by reaching reference points, such as .300 of batting-average.
- From *Cot's Baseball Contracts*, we obtained specific contents of players' contracts.
- Players receive additional performance-dependent rewards: Award bonus and index-dependent bonus.
- Few position players sign the contract with index-dependent bonus, and all of them are related to the number of attendance: Plate-appearances, games-attended

Contracts

- Ichiro Suzuki, Outfielder, 4-year contract with Seattle Mariners (2004-'07)
 - signing bonus- \$6M
 - fixed payment- 04:\$5M, 05:\$11M, 06:\$11M, 07:\$11M
 - performance bonuses- \$1.25M in performance bonuses for plate appearances
 - \$50,000 each for 400 PAs, 2004-06
 - \$0.1M each for 500 & 600 PAs, 2004-06
 - \$0.1M for 400 PAs, 2007
 - \$0.2M each for 500 & 600 PAs, 2007
 - award bonuses: \$50,000 each for Gold Glove, All Star selection
 - trade-Protection (Veto for moving the team without his acceptance): limited no-trade clause (may block deals to 10 clubs)
 - Other
 - housing allowance: \$28,000 in 2004, \$29,000 in 2005, \$30,000 in 2006, \$31,000 in 2007
 - interpreter, trainer, transportation for spring & regular season
 - 4 annual round-trip airline tickets from Seattle to Japan

Contract Length

- Krautmann and Oppenheimer (2002) pointed out that the longer the contract duration extend, the lower return to their performance is obtained: Players show the risk-aversion.

$$\ln(SAL_{it}) = \beta_1 + \beta_2 PERF_{it} + \beta_3 (PERF_{it} * LENGTH_{it}) + \beta_4 LENGTH_{it}$$

* The model is quoted from Krautmann and Oppenheimer (2006).

Estimated value of β_3 was negative.

Further research considering the contract length to be required.

By-Time Analysis

- By-Time analysis
 - Replicate the same examination, but now we divide the sample by historical terms:
 - ① Before the system of free agency regulated (-1975)
 - ② Before the Strike of Players Association (-1994)
 - ③ Before *Moneyball* (Lewis) was published (-2003)
 - ④ Afterward (2004-)

* Note that because we obtain the sample of contract design only after '87, we cannot conduct the second analysis for before '86.
 - Hakes and Sauer (2006) argued that after the publication of *Moneyball*, team managers regard on-base percentage as more important index to measure the players' contribution to the team they belong to.

Table: Bunching Test for the Grouped Sample by Time

index, cutpoint		'57-'75	'76-'94	'95-2003	2004-	full sample
AVG, .300	bw	.023	.020	.022	.019	.019
	θ	.573 (.146)	.566 (.120)	.310 (.130)	.403 (.120)	.499 (.067)
	z	3.934***	4.732***	2.393*	3.376***	7.442***
AVG, .250	bw	.028	.028	.032	.027	.024
	θ	.250 (.080)	.151 (.069)	.306 (.094)	.121 (.076)	.212 (.042)
	z	3.149**	2.188*	3.242**	1.595	5.061***
OBP, .350	bw	.031	.030	.036	.030	.024
	θ	.137 (.089)	.149 (.081)	-.035 (.093)	.137 (.082)	.139 (.049)
	z	1.538	1.846	-.380	1.672	2.854**
HR, 20	bw	6.313	6.677	10.165	7.273	5.309
	θ	.222 (.150)	.214 (.123)	.145 (.129)	.315 (.112)	.259 (.075)
	z	1.479	1.751	1.117	2.819**	3.465***

Note

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

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

Table: Local-Linear Regression for the Grouped Sample by Time

index, cutpoint	bw, type		'87-'94	'95-2003	2004-	full sample
AVG, .300	LATE	bw	.024	.042	.030	.045
		Obs.	697	1806	1872	5930
		estimate	-.034 (.137)	.064 (.092)	.066 (.103)	.034 (.056)
		z	-.250	.697	.637	.615
AVG, .250	LATE	bw	.036	.043	.075	.048
		Obs.	1482	1806	3991	7271
		estimate	.154 (.084)	.064 (.092)	.076 (.060)	.070 (.052)
		z	1.825	.697	1.277	1.340
HR, 20	LATE	bw	4.183	3.685	2.46	3.30
		Obs.	341	371	475	1307
		estimate	-.255 (.228)	-.348 (.218)	.343 (.264)	-.002 (.141)
		z	-1.122	-1.600	1.300	-.015
OBP, .350	LATE	bw	.031	.025	.027	.045
		Obs.	1098	1281	2042	6525
		estimate	.109 (.106)	-.151 (.120)	-.030 (.093)	-.013 (.049)
		z	1.031	-1.262	-.323	-.272

Note:

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

Bandwidth is optimized following the method of Imbens-Kalyanaraman.

Conclusion

Main Findings

- 1 Bunching is observed in their performance indexes, caused by the players' adjustment of their effort level to meet them with some round numbers.
- 2 There exist no monetary incentives in their contracts that makes players to do so.
- 3 Tendency of the bunching changes through the history of baseball.
 - Among them, especially, .300 of AVG shows consistent results, which shows it is solid benchmarks for the players.

Note that some indexes require following research, obtaining information that makes limitation of our analysis.

References



Pope and Simonsohn. 2011. Round Numbers as Goals: Evidence From Baseball, SAT Takers, and the Lab *Psychological Science* 22(1) 7179



Hakes and Sauer. 2006. An Economic Evaluation of the Moneyball Hypothesis *Journal of Economic Perspectives* Volume 20, Number 3 - Summer 2006 - Pages 173185



Allen, Dechow, Pope and Wu. 2016. Reference-Dependent Preferences: Evidence from Marathon Runners *Management Science* 63(6):1657-1672.



Pope and Schweizer. 2011. Is Tiger Woods Loss Averse? Persistent Bias in the Face of Experience, Competition, and High Stakes *American Economic Review* 101 (February 2011): 129157



Kahneman and Tversky. 1979. Prospect Theory: An Analysis of Decision under Risk. *Econometrica* Journal of the Econometric Society 47 (2):263291.



McCrary. 2007. Manipulation of the running variable in the regression discontinuity design: A density test *Journal of Econometrics* 142 (2008) 698 - 714



Krautmann and Oppenheimer. 2002. Contract Length and the Return to Performance in Major League Baseball *Journal of Sports Economics* February 2002



Tversky and Kahneman. 1992. Advances in Prospect Theory: Cumulative Representation of Uncertainty *Journal of Risk and Uncertainty*, 5:297 - 323 (1992)



Imbens and Kalyanaraman. 2009. *NBER Working Paper Series*. 14726



Alex Rees-Jones. 2018. Quantifying Loss-Averse Tax Manipulation *Review of Economic Studies* (2018) 85, 1251 - 1278

Data

- *Fangraphs Baseball*
<https://www.fangraphs.com/>
- *Baseball Reference*
<https://www.baseball-reference.com>
- *USA TODAY*
<https://www.usatoday.com/sports/mlb/>
- *Baseball Prospectus: Cot's Baseball Contracts*
<https://www.baseballprospectus.com/>