Reference Dependence and Monetary Incentive -Evidence from Major League Baseball-

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Many empircal studies have revealed the existance of reference-point dependent preference in field settings, including cases from professional sports players' decision making, whose performance is observed by the manager and evaluated. If there is some incentives that leads the individuals take "apparent" reference point dependent behaviror, then we should rather think it is reference dependence of the managers that evaluates the players.. In this paper, I picked up the case of Major League Baseball players, which Pope and Simonsohn (2011) reported have reference-point dependent tastes about the number of their batting-average. I first confirmed the evidences that supports reference point dependent manipulation of batting-average and other performance indexes. Then I tested if there exist any monetary incentives that encourage the players to do so. My results are against this assumption: no overestimation of achieving the possible reference point was observed, which confirms that players adjust their aspiration level to reach their internal goal, even though there is no additional bonus that rewards their achievement.

1 Introduction

Reference-point dependence is one of the most important concepts to evaluate outcomes, and it affects agents' following economic behavior. Classical economic models assume that economic agents evaluate their choices/prospects according to the abolute value of (expected) return. On the other hand, Tversky and Kahneman (1992) introduced the behavioral assumption: reference-point dependent preference sets some target value of the outcomes and then subjects regard the possible outcome as gain or loss from the target. For example, workers feel happy if her/his wage goes up to \$15 per hour, but vice versa if it goes down to \$15, although the absolute value of \$15 is actually the same. In this case, s/he evaluates their new wage with the reference point of the previous one. In this paper, we picked up an empirical instance that this reference dependence occurs in nonmonetary outcomes, and tested if there exists any monetary incentives.

Prospect theory consists of two main charactaristics: one is the probability weighting function, and the other isreference dependence, mentioned above. It enabled us to interpret phenomena that seem inconsistent with the traditional economic theory, and made it possible to understand them with some additional assumptions. Thus, a lot of following researches have been conducted in field and laboratory settings.

Reference dependence is also observed in the behavior of athletes. Pope and Schweizer (2011) found that professional golf players regard "per," the standard number of shots determined according to the difficuly of each hole, as reference points. Also, Pope and Simonsohn (2011) tested the existance of the reference dependence in the Major League Baseball, a professional baseball league of America. When dealing with the case of the professional athletes, however, we must pay attention to how their salary contract is designed.

Suppose the case of the professional golf player. Golf is essentialy competition of the total number of shots they needed to finish the whole tour, regardless of that of each single hole, or whether s/he saves per or not in the hole. Rank of order is determined according to the number of shots, and those with better scores are rewarded. Then, there appears a question that what if there is some monetary incentive to make effort to save per. Or it considers the following situation: when every time s/he saves per in each hole, then s/he can get some additional bonus separated from their total score. In this case, then, making effort to save per can be interpreted as sufficiently "rational" choice for the player, although the observed behavior itself appears to be evidence of the reference dependence.

Dealing with reference dependence that occurs as some nonmanetary outcomes, therefore, we have to check if there exists any monetary incentives that modifies the benefit function of the individuals discontinuous, which leads to the behavior as if they have reference point dependent utility function. What we show in this paper is one of the empirical instances to be specified. We picked up the evidence from Major League Baseball (MLB) position players' behavior and considered the questions above.

MLB position players seems to have some reference points, about their batting performance indexes: .300 of batting average is one of the possible ones. Pope and Simonsohn (2011) have shown, that there exists bunching just above .300 of the distribution of this index. However, it might not be sufficient to prove that this is caused by reference point dependent utility function about their performance indexes: team managers may assign some monetary incentives for the players to adjust their aspiration level to meet those points, as we described in the example above.

Our most important contribution is this: to conduct analysis that reveals the observed behavior to be in fact reference dependence. First, we tested if there is any evidence for the manipulation around the round numbers, by using McCrary (2008)'s method to test manipulation. not only .300 of batting average, both for other points of batting-average and other indexes, such as homerun or stolen-bases. Confirming this, then we made examinations to answer the question, "Is this observed manipulation truly driven by the reference dependence of the players?" We applied regression analysis using the data of the players' salary.

Our paper found three important results. First, our examination for manipulation supported the previous study. There observed evidence to show there in fact exists seemingly reference point dependent behavior, where .300 of batting-average works as a reference point. Similar results were obtained about other round number of batting-average, and other batting indexes such as on-base percentage or homerun. Second, we found that as a whole, there does not exists any monetary incentive for them: for their fixed part of the salary contract, they does not receive any additional payment by achieving their internal goals. This results confirmed that observed behavior is actually caused by the reference dependence of the players. Furthermore, we complement our results, discussing some alternative interpretation about the form of monetary incentives: the part of incentivesed contract, and relation with contract length. And the third is that the indexes where players' reference dependence occurs vary through the history of the MLB: events that rotates how to design the contracts or evaluation about the importance of each performance index are likely to affects the behavior of the players.

This paper proceed as follows. In the Section 2, we review some literature and verify the standpoint of my paper. Section 3 describes the data we availed. Section 4 presents theoretial framework and empirical way to specification, and make some conjecture. Section 5 show the results of the analysis. Discussion about some alternative interpretation and non-statistical data are included in Section 6. Finally, Section 7 concludes the paper.

2 Literature Review

Tversky and Kahneman (1992) mentioned reference point dependence as one of the two distinct respects of their prospect theory. The most primitive form of reference dependent utility function is:

$$u(x|r) = \begin{cases} x - r & \text{if } x \geq r \\ \lambda(x - r) & \text{if } x < r \end{cases}$$

where x denotes a certain outcome, and r is one of the reference points. This agent evaluates the outcome by the difference from the reference point. In adiition, they assume "loss-aversion" of the individual, or $\lambda > 1$. Those who have this type of utility function, than they regard same absolute amount of outcome in different way, depending on s/he faces gain or loss situation. "Diminishing sensitivity," which is concave in facing gain and convex in facing loss is an advanced form of this specification.

Diecidue and Van de Ven (2008)'s "aspiration level" model added discontinuity assumption: that is, a utility function that "jumps" at the reference point. When ther exists jump in their utility function, then individuals try to manipulate outcome level, paying addtional cost which was not accepted in the standard "smooth" form of utility function. As mentioned below, I exploit this assumption to my model in this paper.

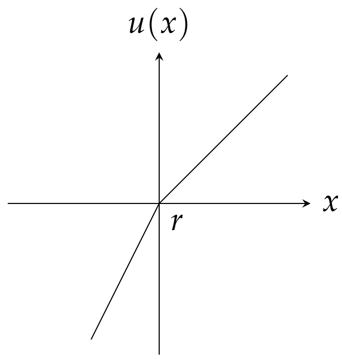

Figure 1: primitive gain-loss function

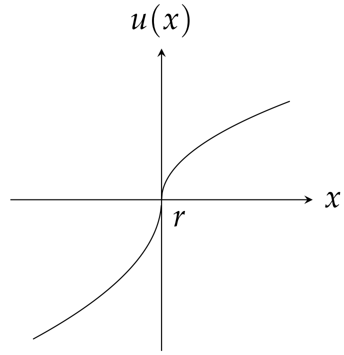

Figure 2: diminishing sensitivity

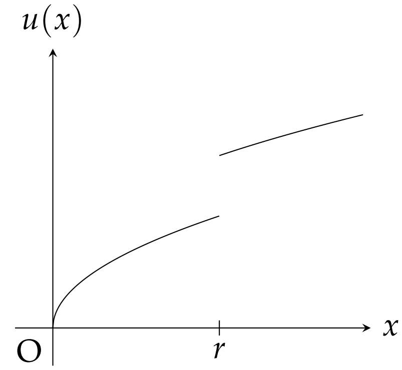

Figure 3: jump at the reference point

Individuals with such reference-point dependent utility try to adjust their effort level so as to achieve their internal target, or reference point. There is a number of empirical literature that specifies the existence of reference dependence in the field or lab studies. Farber(2008) applied this model to the labor supply of New York cab drivers to show that as soon as they reached daily target sales, they considers to quit, even when they reached it early in each day. Jones(2018) made analysis on the system of American tax payment. He showed that individuals try to manipulate their real payment by substituting it by donation or other charitable action, and that especially when facing losses, they make more effort. This observation is also caused loss-aversion, with the reference point of zero-payment threshold.

Reference dependence also occurs in the cases of sports. One of the most well-known papers amoung them is Pope and Schweizer (2011). They obtained the data of professional golf players, to point out that in each hole, players behave as they take "per" as the reference point: Specifically, they scceeed their putts, significantly better when the putt was one to save per than when it was one to get "eagle" or "birdie." Similarly, Allen *et al* (2016) specified the existance of reference point dependence of marathon runners, using data about the finish time of enormous number of race in the United States. In this case, the distribution of finishing time has excess mass around evry hour and 30 minutes. Note that these cases are common in that even if they achieve their internal goals, they do not receive any monetary reward for their success. Professional golf players are awarded according to the total number of shots through the whole tour, not to the number of pers they saved.

Pope and Simonsohn (2011) mention a seemingly similar case. They picked up three empirical evidence of round number as reference points: SAT (a standardized test for college admission in the United States) scores, laboratory experiment, and baseball. In their section of baseball, they picked up the evidence of Major League Baseball (MLB) players to claim that they suggest their reference depenent preference by the distribution of their perfonmance index: batting-average (AVG). According to their paper, the position players (batters) pay attention to their batting-average (AVG), especially to finish each season with their batting average of just above .300. They obatined MLB season individual AVG data from 1975 to 2008 and observed position players (= players except for pitchers) with at least 200 at-bats in each season. Then, they found that their distribution of the batting-average has excess mass just above .300, which reveals the existance of manipulation there.Furthermore, they found that players with batting-average of just below .300 are more likely to hit a base-hit and less likely to get a base-on-balls. Both base-hits and base-on-balls avoid the batter from being gotten out, so for the team he belongs to, base-on-balls also have important value to win the game. However, batting-average does not count base-on-balls as the element to raise the number (For the definition of performance statistics, see Appendix), so they prefer getting hit to base-on-balls. Thus, observed behavior they claims is sufficient evidence that shows the existance of round-number reference point dependent preference of the MLB players.

It is true that there is observed behavior similar to the cases of Pope and Schweizer (2011) or Allen *et al* (2016). However, one important thing we have to take care of is there exists procedure of contract between the player and the team manager: those who evaluate the player. In other words, it may owe to their monetary value function, not by the preference of themselves. This is the main contribution of my research.

Pope and Simonsohn stated in their own paper that they conducted analysis only for batting-average, and following research is to be made. So I first follow this: "Is batting-average unique case?" Then, I test if there exists monetary incentive for the player. If the team managaers they belong to adopt a system of salary that discontinuously "jump" by a certain performance index reaching to the point where manpulation is observed, then for the players it can be interpreted as rational choice, given the contract design. In general, players with their performance index just above these cutoff point and those just below the point have almost same ability as a baseball player. At least, it is natural to think there is no reason to treat players discontinuously better, only because he achieve the cutoff. Then, it is interpreted that it is rather the team manager than the players themselves who have the reference-point dependent preference, which makes the players encouraged to meet their goals.

On the other hand, if there exists no evidence that team managers evaluate the players by the achievement of the cutoff, then we can say that the observed behavior is truly drawn by their own reference dependence. In addition, the consistency is so strong that even there exists no rational reason, they try to reach there. Analysing this and verify which hypothesis is my main contribution of this paper.

3 Data Description

In order to make empirical research, I need information about players' performance, contracts and other details. Then, I generated panel data that contains these specific information from some open data-source. Each sample is obtained by unit of a single season, but due to lack of open source of information about countracts, time range of the data used in each analysis is unbalanced.

Performance are obtained obtained from baseball fan website: *fangraphs* and *Baseball*

Reference. Since the regulation of "qualified plate-appearances," the cutoff number to get batting title such as batting-average, was introduced in 1957, I collected dataset from this year. Stats in each season contains that of only during the regular season, not that of Spring-Training or postseason games. The full-sample is $N = 54469$.

Salary data are obtained from American media site: *USA TODAY*. I collected salary data of the position players who are registered in MLB Roaster at the beginning of each season, and merged with the play stats in the previous year, because salary is as usually determined based on the performance of the previous season. Data was available only that since 1987, and as I need data of the next year about the salary, latast season is 2017. The aggregated number of the panel is $N = 13226$.

Then, for precise research, I made some sample-restriction. First of all, I have to distinguish the data with both play stats and contract, with that with only play stats. In section of specifying excess mass, I utilize the latter one (I call this Sample A), and in analyzing the monetary incentive, I use the former one (Sample B).

In considering rate indexes, we have to restrict the sample to the batters with a certain number of attendances, since these indexes of those with too little at-bats are enormously affected by the result of every single plate-appearances, and so team managers might not see them in evaluating performance. At Pope and Simonsohn (2011), the threshold was set at 200 at-bats, but in my research, I substitute at-bats with plate-appearances, since at-bats exclude the plate appearances with base-on-balls and hit-by-pitch, even though they attended the game and appear to the plate. Restricting the sample to the players with at least 200 plate-appearances yields $N = 18143$ for Sample A and $N = 8915$ for Sample B.

Play stats are tagged by players' ID and season, including batting indexes tested bunching: batting-average, on-base percentage, base-hits, stolen-base, homerun, runs-batted-in, and plate appearances. Moreover, for the analysis of monetary incentives, I collected other indexes that control the performance: slugging-average, OPS, fWAR, BATTING, FIELDING, BaseRun, and WPA. Salary data includes annual salary at the year: for the players with plural-year contract, it is calculated by deviding total payment of the contract by the years. It also contains the player-specific charactaristics: age, position (catcher, firstbaseman, ... right fielder), team they signed, and possession of the right of free agency.

The summery statistics are descripted in Table 1 and Table 2.

4 Theoretical Frameworks and Way of Specification

4.1 Frameworks

MLB position players try to maximize their performance, for two main goals: one is to contribute to their team winning more games, and the other is to improve their living standard. That is, getting better contract and playing as long as possible is one of the most important object to play for the team. Performance index is clear and valid benchmarks to signal their ability to the team managers. Baseball is so rich in such indexes, so we can say these are good reliable proxy for their ability as a player. We assume a utility function of the player/manager as $u(x)$ for the value of a certain index x. Players' self-evaluation

Table 1: Summary Statistics for Sample A

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
PA	18,143	456.477	152.836	200	320	591	778
HR	18,143	11.811	9.747	0	4	17	73
RBI	18,143	51.882	26.912	4	31	69	165
SB	18,143	7.846	10.869	0	1	10	130
AVG	18,143	.264	.032	.135	.242	.285	.394
OBP	18,143	.331	.039	.174	.305	.356	.609
Age	18,143	28.506	4.042	18	25	31	46
H	18,143	108.941	42.933	29	72	143	262
OPS	18,143	.738	.106	.382	.665	.805	1.422

Table 2: Summary Statistics for Sample B

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
+WPA	8,915	8.715	3.471	2.030	5.820	11.430	19.160
-WPA	8,915	−8.270	2.610	−15.050	−10.420	−6.060	−2.740
AB	8,915	419.820	133.528	162	305	537	716
AVG	8,915	.268	.031	.146	.248	.289	.394
Salary	8,915	3,487,838	4,487,344	62,500	512,750	4,658,334	29,200,000
Age	8,915	28.714	3.901	19	26	31	46
Bat	8,915	3.257	16.139	−44.200	−7.300	11.100	116.800
BsR	8,915	.092	2.712	−12.600	−1.200	1.200	14.300
FA	8,915	.168	.374	0	0	0	1
Fld	8,870	.304	7.482	−36.100	−4.000	4.400	37.000
H	8,915	114.232	42.481	30	78	148	262
HR	8,915	13.446	10.213	0	6	19	73
OBP	8,915	.337	.038	.174	.311	.360	.609
OPS	8,915	.761	.104	.382	.691	.825	1.422
PA	8,915	471.946	150.890	200	342	605.5	778
RBI	8,915	56.339	27.621	5	35	74	165
SB	8,915	8.534	10.851	0	1	11	109
SLG	8,915	.425	.075	.208	.372	.472	.863
fWAR	8,915	1.860	1.950	−3.100	.500	2.900	12.700

and his salary for the next season reflects this value.

Then, here I describe the nature of the indexes. Baseball batting indexes are roughly divided into two types. One is that simply indicates the number of a ceratain plays, and another is calculated using these numbers. Here I call the former “cumulative index,” and the latter “rate statistics.” Cumulative index are for example “base-hit” or “homerun,” or “stolen-bases.” They are irreversible and so once they reach a certain number then it cannot be decrease. On the other hand, rate indexes can be fluctuate, so in order to keep this kind of indexes above their goal, they have to continue to make effort or stop attending game and wait for the end of the season. Batting-average is sorted of this type, and On-base percentage or OPS are also kind of them. Note that even though I call this for “rate” index for simplisity, it contains all the index that can both go up and down according to the player’s performance, such as OPS or slugging-average. See Appendix for specific definition of each index.

Anyway, the important assumption is that players evaluate their performance index using referene-dependent utility function of themselves or the team manager, and manipulate it in order to maximize their utility. This aspiration results in odd distribution of the index at the end of the season: excess mass around the possible referene point. In this paper, following Allen *et al* (2016), I exploit the assumption of the utility function of Diecidue and Van De Ven (2008)‘s “aspiration level” model. The model presents the form of the utility function with “notch,”

$$\lim_{\epsilon \to 0} v_r(r+\epsilon) \neq \lim_{\epsilon \to 0} v_r(r-\epsilon)$$

This form of utility function is discontinuous at the reference point r.

In my paper, it is not determined who has such a utility function. At least one of the these two agents: players and managers has reference dependent feature in their utility. Players pay attention to if each index are above the reference points.In Allen *et al* (2016), it is assumed that discontinuous utility function occurs as excess mass around the reference points. In my paper, I suppose there may be another story. That is, discontinuous utility function of the managers emerges as discontinuous evaluation of the players: salary scheme jumps, depending on whether a ceatain performance index is above or below the reference point. Then, it modifies the income function of the players discontinuous, which results in bunching as the best response of them.

4.2 Empirical Method

4.2.1 Test for Bunching

First, we test if there is observed any behavior that seems to be related to reference dependent preference. As we explained in the previous chpaters, the existance is verified by the observation of bunching, or excess mass around the possible reference point. To specify the excess mass, we apply the method of regression discontinuity design (RDD).

RDD is a way to measure the effect of a treatment, such that whether the treatment is assigned or not depends on the threshold of a certain variable (called “running variable”).

Then, comparing the samples just above and just below the threshold is sufficient examination of the treatment, since they are in almost same states except for the existance of the treatment.

However, there is an important assumption for this specification to be valid (Lee and Lemieux, 2010): continuity of the running variable around the threshold. In other words, individuals must not be able to manipulate the running variable so as to be above the cutpoint. This is because if there exists manipulation, then there occurs selection bias problem, that those who try to be assigned the treatment can adjust their running variable. Therefore, there are some empirical way to test the manipulation of a variable, which is the very method I apply in our analysis.

One of the frequently applied methods for this specification is McCrary(2008)'s local linear density estimation. We avail this to our specification of bunching.

This estimation of the manipulation at the cutoff point c, proceeds in two steps: undersmoothing histograms and local linear smoothing. Undersmoothing means to determine the binsize b of the running variable: in this paper, the index argued.

$$g(R_i) = \left\lfloor \frac{R_i - c}{b} \right\rfloor b + \frac{b}{2} + c \in \left\{ \ldots, c - 5\frac{b}{2}, c - 3\frac{b}{2}, c - \frac{b}{2}, c + \frac{b}{2}, c + 3\frac{b}{2}, c + 5\frac{b}{2}, \ldots \right\}$$

where $\lfloor a \rfloor$ denotes the greatest integer less than a, and $g(R_i)$ stands for the height, or frequency of each bin. Then, we make local approximation above and below c, the possible value of reference dependence point. Bandwidth is calculated to minimize the estimation error. Then, we estimate the frequency at the cutoff point, $\hat{f}(r)$, by fitting the estimated density function below and above the cutoff, $\hat{f}^+$ and $\hat{f}^-$, respectively. Finally, we take the difference between $\ln \hat{f}^+$ and $\ln \hat{f}^-$ to calculate the statistics θ. With θ and its estimator of standard deviation, t-tests can be condtructed to specifying manipulation.

4.2.2 Monetary Incentive

Then, We examine the existance of the monetary incentive. We employ the method of sharp regression discontinuity design (RDD): local linear regression around the possible reference point as the cutoff.

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

For each player i in the season t, w_{it} is loggarithm of their annual salary in next season $t+1$. X_{it} are the value of performance index (batting-average, on-base percentage,...). ABOVE_{it} is an indicator of the achievement of their goals for the index. That is, if he finished his season with a certain index with above the possible reference point, it takes 1, and otherwise 0, so this is the variable of interest. The bandiwidths in each analysis were selected according to the optimization of Imbens, Guido and Kalyanaraman (2009), using polynominal approximation.

Estimation was conducted in two ways: one only includes the index term and the dummy for achieving their goals in the model, while the other includes term Z_{it}, which consists other elements to affect their annual salary. Concretely, it includes player-specific characters (age, team he signed, position,…), and other performance indexes that controls the aspects that covers the players' residual skill, where the performance index X_{it} does not argues. For further explanation, please see Appendix.

As we mentioned above, usually this method is not applied in this kind of analysis, since RDD can be invalid when individuals can manipulate the running variable, because if they can intentionally control this variable, then anyone who know or want to receive treatment are to manipulate it and so observed sample can be biased. In this research, however, we are interested in the existance itself of the treatment: monetary incentive, so it does not matter if the players did know the (possible) reward or not. Therefore, we regard this way to specification appropreate one to our interests.

As well as OLS, team, position, or individual fixed effect model estimation was also conducted.

5 Result

5.1 Excess Mass Around The Reference Point

In this section, we present our main results of analysis. First, we show the results that verifies bunching. Table 3 includes the summary of McCrary (2008)'s manipulation tests about the performance indexes that say there is some manipulation occurs. Consistent with Pope and Simonsohn (2011), there actually occurs excess mass around .300, and in addition .250 of batting-average. Also, manipulation were also observed in some of other numbers of other indexes: .350 of on-base percentage, 20 of homeruns, 100 of runs-batted-in, 30 and 40 of stolen-bases, and 200 of base-hits.

Table 3 shows parts of results that denies the existance of excess mass. For precise estimation of bunching, we set the binsizes of undersmoothing artificially: .001 for batting-average and on-base percentage, 1 for homerun (HR), stolen-base (SB), plate-apparance (PA), and base-hit (H), and 4 for runs-batted-in (RBI). Batting-average (AVG) and on-base percentage (OBP) are usually shown by three decimal digits, rounding the fourth decimal digit, so strictly batters with .2995 of batting-average are taken as .300. Homerun, stolen-base, plate-appearance, and base-hit are indexes that takes integer and they earn one for each plate appearances or such a chance to manipulate. Runs-batted-in is also an integer-index, but they can get at most 4 at one plate-appearance, so we set it 4. To confirm the robustness of our results, we repeated this test with various binsize, but we yield essentialy same results. Bandwidths are optimized by calculation, followin

For batting-average, extending sample size from Pope and Simonsohn (2011) yields similar results: Players manipulate their batting-average. The difference between the estimated frequency according to the approximation below .300 and that of above .300 was significant at .1% ($z = 7.442$) level.

In addition, bunching occurs also in .250 ($z = 5.061$, p ¡ 0.1%). It was not reported in Pope and Simonsohn (2011): for their sample, there was no bunching observed in any other round numbers of batting-average, so it can be related to that the sample size is ex-

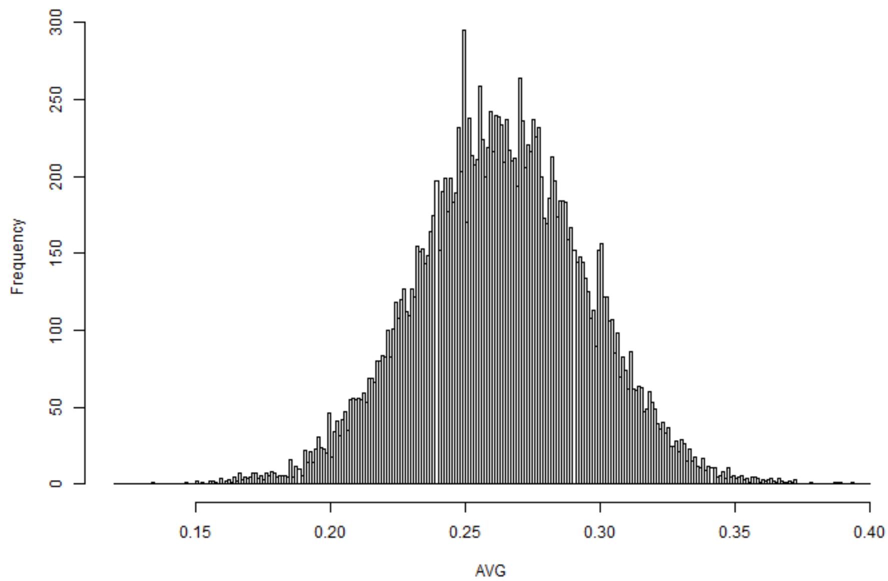

Figure 4: Histgram of Batting-Average

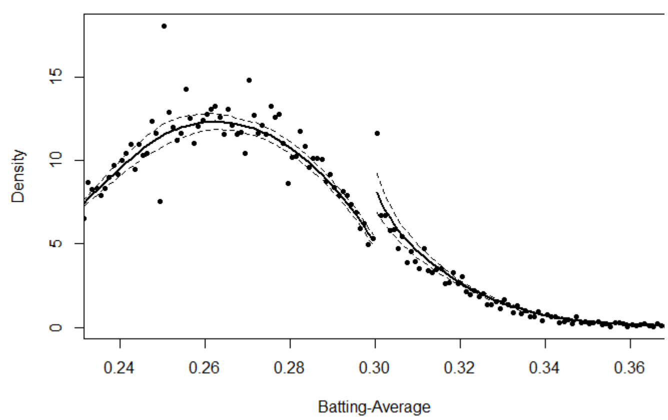

Figure 5: Discontinuity at .300 of AVG

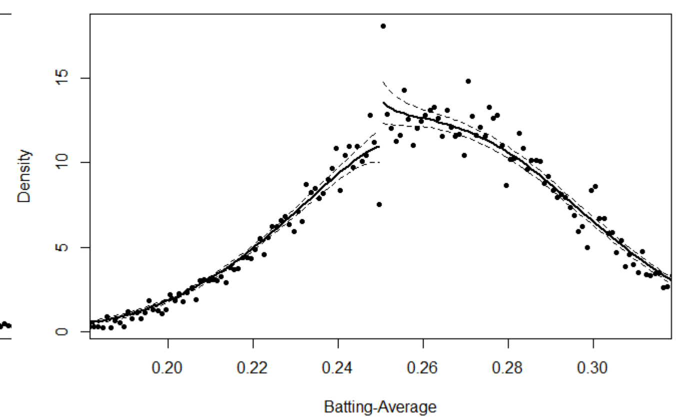

Figure 6: Discontinuity at .250 of AVG

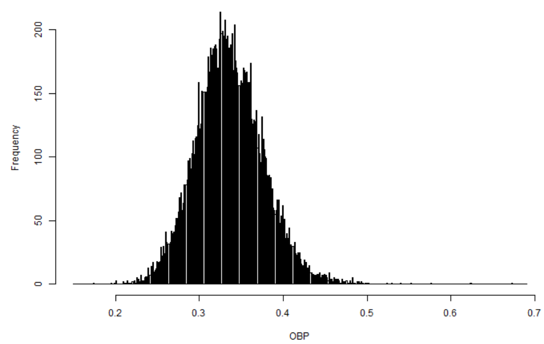

Figure 7: Histgram of On-Base Percentage

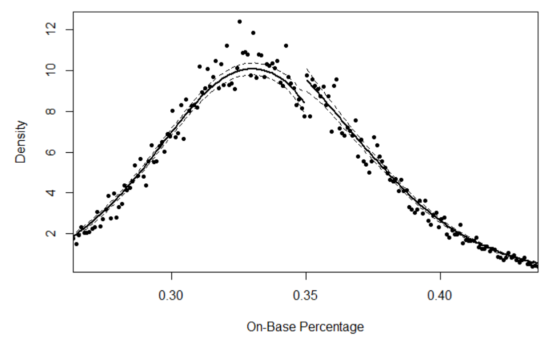

Figure 8: Discontinuity at .350 of OBP

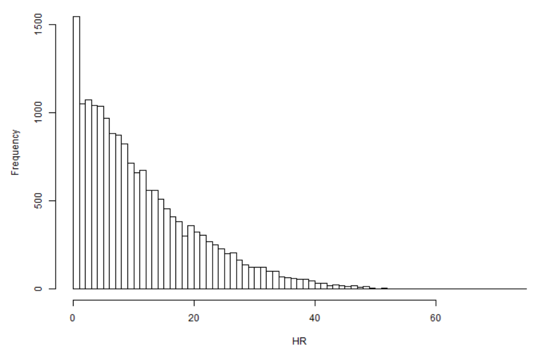

Figure 9: Histgram of Homerun

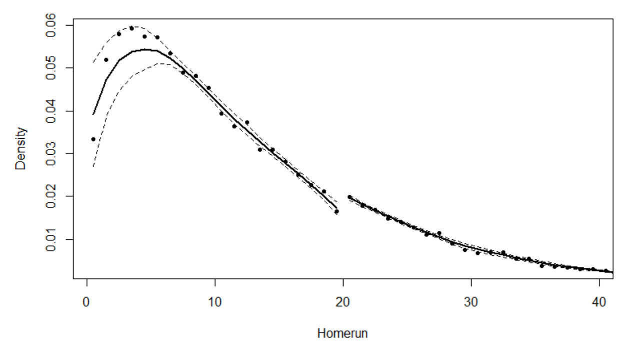

Figure 10: Discontinuity at 20 of HR

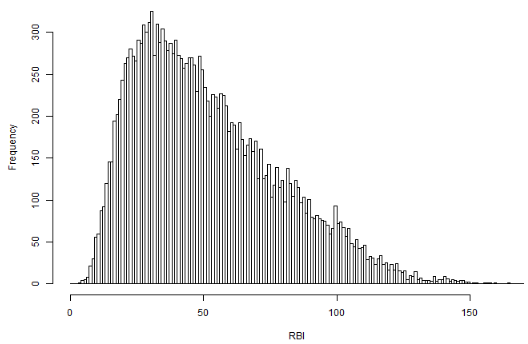

Figure 11: Histgram of Runs-Batted-In

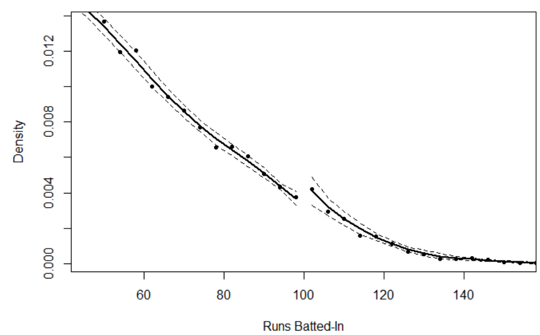

Figure 12: Discontinuity at 100 of RBI

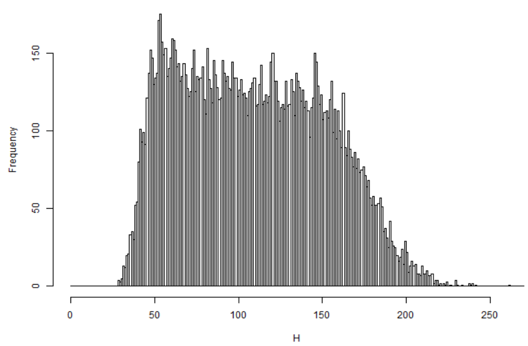

Figure 13: Histgram of Base-Hit

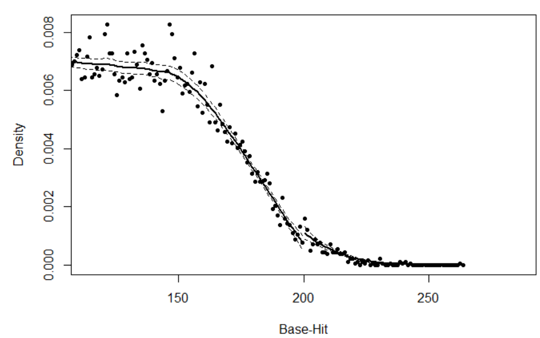

Figure 14: Discontinuity at 200 of Base-Hit

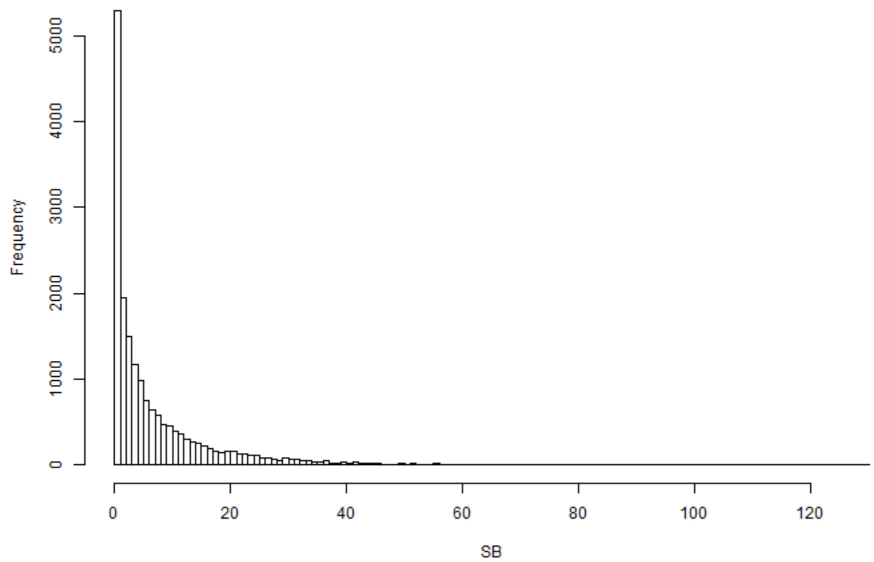

Figure 15: Histgram of Stolen-Base

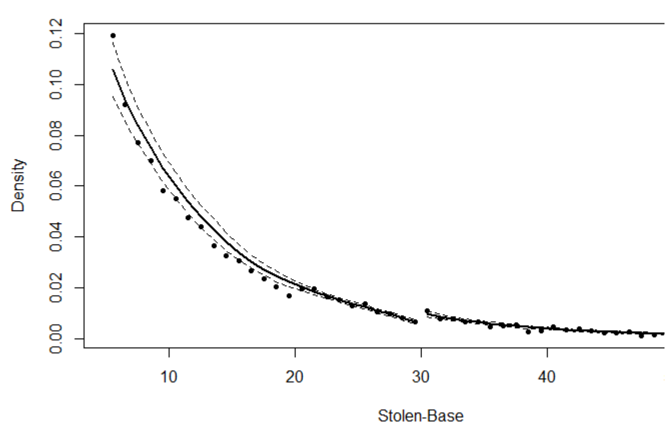

Figure 16: Discontinuity at .300 of AVG

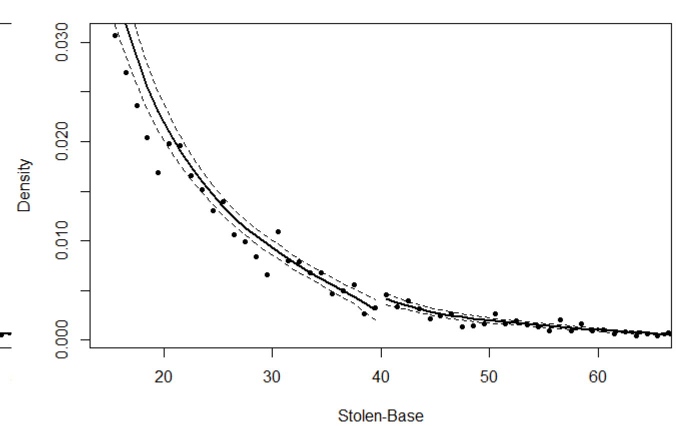

Figure 17: Discontinuity at .250 of AVG

index	type	cutpoint	binsize	bandwidth	θ	z
AVG	rate	.300	.001	.019	.499	7.442***
					(.067)	
		.250	.001	.024	.212	5.061***
					(.042)	
OBP	rate	.350	.001	.024	.139	2.854**
					(.049)	
HR	cumulative	20	1	5.309	.259	3.465***
					(.075)	
RBI	cumulative	100	4	15.423	.311	3.295***
					(.094)	
SB	cumulative	30	1	10.000	.529	4.274***
					(.124)	
		40	1	11.505	.481	2.764**
					(.174)	
PA	cumulative	500	1	.003	.160	2.515*
					(.063)	
H	cumulative	200	1	18.922	.453	2.547 *
					(.178)	
Note	***: $p < 0.1\%$, **: $p < 1\%$, *: $p < 5\%$. Bandwidth is optimized following the method of McCrary(2008).					

Table 3: Test for Manipulation, leastPA = 200

tended to further old ages. We specifically analyzed this in Section 6.4. Changing binsize to .002 or .005 also yields similar results.

On-base percentage, on the other hand, showed similar tendency in .350, although the significance level was $z = 2.854$ (significant at 5% level). Pope and Simonsohn (2011) reported that they are less likely to get base-on-balls when facing marginal range of batting-average and so they feel of more importance in batting-average than on-base percentage. However, when they face marginal point of on-base percentage, they may try to get more base-on-balls in order to achieve .350.

Bunching also occurs in cumulative indexes. Cumulative ones are irreversible, and so players may feel these indexes are easier to manipulate. As same as batting-average and on-base percentages, however, such manipulation was observed in only limited numbers: not in all the round numbers. For Homerun, bunching occurred only in 20 ($z = 3.465, p < 0.1\%$): there may be diminishing sensitivity: 20 is located on above the 75 percentiles of the whole Sample A. Also, stolen-base and base-hit have shown bunching, at 30 ($z = 4.274, p < 0.1\%$) and 40 ($z = 2.764, p < 1\%$) of stolen-base and 200 in base-hit ($z = 2.547, p < 5\%$). Stealing-bases are skill that are talented to limited number of the players, but succeeds with the prpbability of 60% to alomost 100%, so those who are evaluated by their number of stolen-bases, it may certain be relatively accessible number to manipulate. 30 and 40 of stolen-bases are also far above the 75 percentiles of all the players.

Base-hit is also manipulated, but the confidence level of the discontinuity was lower than that of batting-average (z = 2.547, $p < 5\%$). Base-hit is a close index to batting-average, for both indexes increase by getting base-hits. It may because the number of base-hit is not regarded as important as batting-average (In most TV live on baseball, they introduce player with his batting-average, not the number of base-hits.) Furtheremore, it can be related that for cumulative indexes, it is not worth "keeping" indexes.

And surprisingly such manipulation occurs also in runs-batted-in (z=3.295, p¡0.1%). Compared to other indexes, runs-batted-in is harder to manipulate, since the number of that depends on the performance of his teammates, and the number they can earn at a single plate-appearance varies from 1 to 4. As in Table 3, the test said that there occurs the evidence in plate-appearances. However, it may insufficient because the optimized bandwidth was smaller than one, even though the number of PAs takes only integers. Setting bandwidth larger than 1, then the result went insignificant.

Summarizing the results, there in fact exists manipulation of the batting indexes and they are possible reference point of the players. However, it occurs in only some parts of round numbers. In the case of marathon runners, Allen et al. (2016), there occured bunching in every round numbers of the goal time, although the size of discontinuity monotonically decreased. That is, it should be considered that the reference points are not determined only because they are round numbers as Pope and Simonsohn (2011) argued. That is, the nature of the reference points are likely to be close to "per" in Pope and Schweizer (2011) rather than round numbers; or well, these numbers are monetarily incentivised goals by the team managers. So next, I examine whether there is any monetary bonus in their contract.

5.2 Existance of Monetary Incentive

In Section 5.1, we found that there actually exits the player's manipulation for some of the representative indexes. Then in this section, we show whther they are led to aim these goals by their reference dependence, or by their design of the contracts with monetary incentive.

Table 4 describes the results of RDD analysis on loggarithm of their salary next year, with the cutpoint of each possible reference point. Column "Other Control" indicates if the model includes other varivales (other performance indexes, player's age, WPA and dummy for possession of the right of free agency). "bw type" indicates the bandwidths used in the model: "LATE" includes the sample that are in the optimal bandwidth calculated by Imbens and Kalyyanaraman (), while "Half-BW" and "Double-BW" are using a half and a twice of the LATE bandwidth, respectively. As a whole, there is no evidence that suports the existance of monetary incenive to make effort for their observed goals. There is no essential difference between the cumulative indexes and rate indexes.

Also, to confirm the robustness of our analysis, we made regression analysis with an interaction term of X_{it} and ABOVE$_{it}$, which considers the change in average return of the index in argument to their annual salary when the value of the index is above the cutoff point. Each model includes the players that are included in RDD analysis, or those who are located within the optimal bandwidths in RDD. Table 5 to 10 show the results of this analysis for each possible reference points. Consistent with RDD, they give us no evidence of jump of their fixed rewards, except for stolen-bases.

Table 4: RDD Test 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
RBI, 100	No	LATE	4.08	393	.072	.289	.250
		Half-BW	2.04	228	.282	.400	.707
		Double-BW	8.16	714	.008	.185	.043
	Yes	LATE	4.04	390	.018	.209	.086
		Half-BW	2.02	227	-.042	.324	.130
		Double-BW	8.07	708	.056	.127	.435
H, 200	No	LATE	3.173	75	-.786	.396	-1.985*
		Half-BW	1.587	35	.386	.271	-1.421
		Double-BW	6.347	137	-.061	.309	-.199
	Yes	LATE	3.175	75	-.420	1.042	-.403
		Half-BW	1.587	35	-4.779	.576	-8.288**
		Double-BW	6.349	137	-.109	.413	-.265
SB, 30	No	LATE	3.39	282	.962	.372	2.585**
		Half-BW	1.70	134	.920	.263	3.492***
		Double-BW	8.16	714	.008	.185	2.941**
	Yes	LATE	3.40	282	.379	.297	1.271
		Half-BW	1.70	134	.290	.249	1.163
		Double-BW	6.79	533	.408	.180	2.260*
SB, 40	No	LATE	3.16	134	-1.276	.453	-2.818**
		Half-BW	1.58	56	-.736	.383	-1.924
		Double-BW	6.32	245	-.712	.313	-2.274*
	Yes	LATE	3.16	134	-.346	.396	-.875
		Half-BW	1.58	56	-.313	.429	-.730
		Double-BW	6.33	245	-.115	.244	-.472

Note: ***: $p < 0.1\%$, **: $p < 1\%$, *: $p < 5\%$.
Bandwidth is optimized following the method of Imbens-Kalyanaraman.

Table 5: Regression on Log-Salary, Including Interaction Term: around .300

	Dependent variable:							
	Sal							
			OLS				*felm*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	11.166***	9.728***	−6.616***	−5.049***	−5.161***			
	(.423)	(.399)	(.665)	(.673)	(.669)			
AVG	11.513***	11.604***	11.620***	4.232***	4.083***	4.221***	3.808**	3.752**
	(1.537)	(1.405)	(1.209)	(1.212)	(1.204)	(1.201)	(1.189)	(1.412)
AVG_300	−.169	−.455	−.413	−.261	−.213	−.142	−.069	−.279
	(1.050)	(.954)	(.821)	(.789)	(.784)	(.780)	(.706)	(.918)
FLD		.004	.006***	.007***	.007***	.007***	.008***	.005**
		(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)
BsR		−.014**	.009*	.003	.003	.003	.020***	−.018**
		(.005)	(.005)	(.004)	(.004)	(.005)	(.005)	(.005)
AGE			1.005***	.983***	.984***	.997***		
			(.039)	(.037)	(.037)	(.037)		
AGE_sq			−.015***	−.014***	−.014***	−.014***		
			(.001)	(.001)	(.001)	(.001)		
AVG:AVG_300	.663	1.689	1.428	.930	.791	.540	.160	1.077
	(3.429)	(3.118)	(2.681)	(2.577)	(2.560)	(2.549)	(2.312)	(3.000)
WPA				X	X	X	X	X
FA dummy					X	X	X	X
Season dummies		X	X	X	X	X	X	X
Fixed effects						Position	Individual	Position
Observations	5,960	5,930	5,930	5,930	5,930	5,930	5,930	5,930
R^2	.035	.215	.420	.464	.471	.478	.744	.276
Adjusted R^2	.035	.210	.416	.461	.468	.473	.660	.271
Residual Std. Error	1.286 (df = 5956)	1.164 (df = 5894)	1.001 (df = 5892)	.962 (df = 5890)	.956 (df = 5889)	.950 (df = 5880)	.764 (df = 4459)	1.119 (df = 5882)
F Statistic	71.983*** (df = 3; 5956)	46.134*** (df = 35; 5894)	115.152*** (df = 37; 5892)	130.803*** (df = 39; 5890)	131.204*** (df = 40; 5889)			

Note: *p<0.05; **p<0.01; ***p<0.001

Table 6: Regression on Log-Salary, Including Interaction Term: around .250

	Dependent variable:							
	Sal							
	OLS						*felm*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	12.039***	10.292***	−6.061***	−5.288***	−5.513***			
	(.501)	(.457)	(.632)	(.632)	(.624)			
AVG	8.003***	9.795***	8.623***	2.156	1.906	1.554	1.960	2.722
	(2.145)	(1.926)	(1.636)	(1.621)	(1.599)	(1.592)	(1.557)	(1.909)
AVG_250	−.684	−.250	−.597	−.771	−.783	−.923*	−.492	−.488
	(.618)	(.555)	(.471)	(.459)	(.452)	(.450)	(.432)	(.539)
FLD		.003	.004**	.006***	.005***	.006***	.007***	.006***
		(.002)	(.002)	(.002)	(.001)	(.001)	(.002)	(.002)
BsR		−.027***	−.001	−.006	−.006	−.006	.014**	−.027***
		(.005)	(.004)	(.004)	(.004)	(.005)	(.005)	(.005)
AGE			1.021***	1.013***	1.019***	1.030***		
			(.034)	(.033)	(.033)	(.033)		
AGE_sq			−.015***	−.015***	−.015***	−.015***		
			(.001)	(.001)	(.001)	(.001)		
AVG:AVG_250	2.836	1.098	2.591	3.383	3.409	3.957*	2.297	2.161
	(2.520)	(2.262)	(1.922)	(1.871)	(1.845)	(1.836)	(1.763)	(2.201)
WPA				X	X	X	X	X
FA dummy					X	X	X	X
Season dummies		X	X	X	X	X	X	X
Fixed effects						Position	Individual	Position
Observations	7,307	7,271	7,271	7,271	7,271	7,271	7,271	7,271
R^2	.032	.231	.445	.476	.490	.497	.735	.277
Adjusted R^2	.031	.227	.442	.473	.487	.494	.655	.273
Residual Std. Error	1.271 (df = 7303)	1.135 (df = 7235)	.964 (df = 7233)	.937 (df = 7231)	.924 (df = 7230)	.918 (df = 7221)	.758 (df = 5590)	1.101 (df = 7223)
F Statistic	79.391*** (df = 3; 7303)	62.031*** (df = 35; 7235)	156.664*** (df = 37; 7233)	168.232*** (df = 39; 7231)	173.678*** (df = 40; 7230)			

Note: *p<0.05; **p<0.01; ***p<0.001

Table 7: Regression on Log-Salary, Including Interaction Term: around .350

	Dependent variable:							
	Sal							
	OLS					*felm*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	10.793***	9.117***	−7.002***	−6.993***	−7.081***			
	(.516)	(.472)	(.666)	(.689)	(.683)			
OBP	10.357***	11.155***	10.183***	5.580***	5.445***	5.346***	6.739***	7.368***
	(1.574)	(1.421)	(1.228)	(1.258)	(1.248)	(1.242)	(1.212)	(1.467)
OBP_350	−.132	−.625	.103	.080	.103	.130	−.832	−.625
	(.888)	(.801)	(.691)	(.676)	(.670)	(.667)	(.620)	(.788)
FLD		.006**	.007***	.008***	.007***	.008***	.007***	.007***
		(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)
BsR		−.022***	.002	.001	.001	−.0003	.022***	−.020***
		(.005)	(.004)	(.004)	(.004)	(.005)	(.005)	(.005)
AGE			1.016***	1.021***	1.021***	1.037***		
			(.036)	(.035)	(.035)	(.035)		
AGE_sq			−.015***	−.015***	−.015***	−.015***		
			(.001)	(.001)	(.001)	(.001)		
OBP:OBP_350	.356	1.783	−.237	−.188	−.274	−.321	2.166	1.790
	(2.516)	(2.269)	(1.960)	(1.915)	(1.898)	(1.889)	(1.760)	(2.232)
WPA				X	X	X	X	X
FA dummy					X	X	X	X
Season dummies		X	X	X	X	X	X	X
Fixed effects						Position	Individual	Position
Observations	6,656	6,620	6,620	6,620	6,620	6,620	6,620	6,620
R^2	.036	.231	.427	.453	.462	.470	.733	.260
Adjusted R^2	.035	.227	.424	.450	.459	.466	.650	.255
Residual Std. Error	1.267 (df = 6652)	1.135 (df = 6584)	.980 (df = 6582)	.957 (df = 6580)	.949 (df = 6579)	.943 (df = 6570)	.764 (df = 5042)	1.114 (df = 6572)
F Statistic	81.971*** (df = 3; 6652)	56.520*** (df = 35; 6584)	132.495*** (df = 37; 6582)	139.690*** (df = 39; 6580)	141.515*** (df = 40; 6579)			

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table 8: Regression on Log-Salary, Including Interaction Term: around 20 HR

	Dependent variable:							
	Sal							
	OLS						*felm*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	14.429***	12.592***	−6.385***	−5.374***	−5.750***			
	(1.092)	(1.045)	(1.381)	(1.425)	(1.409)			
HR	.014	.036	.076	.076	.074	.083	.070	.036
	(.061)	(.057)	(.046)	(.045)	(.045)	(.045)	(.054)	(.056)
HR_20	−1.154	−.474	.008	−.142	−.051	−.003	.993	−.847
	(1.393)	(1.313)	(1.055)	(1.035)	(1.022)	(1.025)	(1.248)	(1.295)
FLD		.005	.010***	.010**	.010***	.010***	.006	.004
		(.004)	(.003)	(.003)	(.003)	(.003)	(.004)	(.004)
BsR		−.032**	.001	−.011	−.012	−.022*	−.007	−.053***
		(.011)	(.009)	(.009)	(.009)	(.010)	(.015)	(.012)
AGE			1.109***	1.107***	1.123***	1.127***		
			(.073)	(.072)	(.071)	(.071)		
AGE_sq			−.016***	−.016***	−.016***	−.016***		
			(.001)	(.001)	(.001)	(.001)		
HR:HR_20	.061	.025	−.005	.0004	−.003	−.007	−.052	.040
	(.073)	(.069)	(.055)	(.054)	(.054)	(.054)	(.065)	(.068)
WPA				X	X	X	X	X
FA dummy					X	X	X	X
Season dummies		X	X	X	X	X	X	X
Fixed effects						Position	Individual	Position
Observations	1,315	1,307	1,307	1,307	1,307	1,307	1,307	1,307
R^2	.009	.172	.467	.488	.501	.508	.806	.212
Adjusted R^2	.007	.149	.452	.473	.485	.489	.610	.183
Residual Std. Error	1.203 (df = 1311)	1.114 (df = 1271)	.894 (df = 1269)	.877 (df = 1267)	.867 (df = 1266)	.864 (df = 1257)	.755 (df = 650)	1.092 (df = 1259)
F Statistic	3.882** (df = 3; 1311)	7.543*** (df = 35; 1271)	30.087*** (df = 37; 1269)	31.023*** (df = 39; 1267)	31.805*** (df = 40; 1266)			
Note:								$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table 9: Regression on Log-Salary, Including Interaction Term: around 30 SB

	Dependent variable:							
	Sal							
			OLS				*felm*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	13.466***	8.006*	−4.126	−3.729	−2.949			
	(3.672)	(3.191)	(3.586)	(3.651)	(3.675)			
SB	.029	.167	−.036	−.041	−.052	−.067	.075	.145
	(.132)	(.114)	(.099)	(.099)	(.099)	(.096)	(.185)	(.113)
SB_30	12.468**	13.567***	2.544	2.234	1.579	.816	7.200	12.144**
	(4.569)	(3.972)	(3.531)	(3.526)	(3.541)	(3.464)	(6.586)	(3.947)
FLD		.003	.007	.007	.007	.008	.013	.005
		(.007)	(.006)	(.006)	(.005)	(.005)	(.011)	(.006)
BAT		.028***	.023***	.015**	.014*	.017**	.019	.021**
		(.003)	(.003)	(.006)	(.006)	(.006)	(.010)	(.007)
AGE			1.142***	1.150***	1.105***	1.132***		
			(.174)	(.174)	(.176)	(.172)		
AGE_sq			−.018***	−.018***	−.017***	−.017***		
			(.003)	(.003)	(.003)	(.003)		
SB:SB_30	−.391*	−.444**	−.071	−.061	−.039	−.013	−.230	−.397**
	(.158)	(.137)	(.122)	(.122)	(.122)	(.119)	(.229)	(.136)
WPA				X	X	X	X	X
FA dummy					X	X	X	X
Season dummies		X	X	X	X	X	X	X
Fixed effects						Position	Individual	Position
Observations	282	282	282	282	282	282	282	282
R^2	.075	.472	.628	.633	.636	.675	.915	.523
Adjusted R^2	.065	.397	.571	.573	.576	.608	.651	.430
Residual Std. Error	1.229 (df = 278)	.988 (df = 246)	.833 (df = 244)	.830 (df = 242)	.828 (df = 241)	.796 (df = 233)	.751 (df = 68)	.960 (df = 235)
F Statistic	7.559*** (df = 3; 278)	6.276*** (df = 35; 246)	11.110*** (df = 37; 244)	10.684*** (df = 39; 242)	10.537*** (df = 40; 241)			

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table 10: Regression on Log-Salary, Including Interaction Term: around 40 SB

	Dependent variable:							
	Sal							
	OLS						*felm*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	.097	2.795	−6.186	−5.258	−3.914			
	(6.865)	(6.575)	(6.345)	(6.781)	(6.974)			
SB	.392*	.287	.191	.183	.148	.148	.679*	.187
	(.182)	(.174)	(.155)	(.158)	(.163)	(.163)	(.265)	(.182)
SB_40	20.483*	7.339	5.634	5.543	5.082	7.669	37.152**	7.632
	(8.497)	(8.171)	(7.281)	(7.430)	(7.461)	(7.511)	(12.783)	(8.367)
FLD		.003	.005	.005	.005	.008	.021	.005
		(.009)	(.008)	(.008)	(.008)	(.009)	(.020)	(.009)
BAT		.025***	.023***	.020*	.020*	.021*	−.001	.017
		(.005)	(.004)	(.009)	(.009)	(.009)	(.020)	(.010)
AGE			.763**	.751**	.751**	.745**		
			(.239)	(.242)	(.243)	(.245)		
AGE_sq			−.011**	−.011**	−.011**	−.011*		
			(.004)	(.004)	(.004)	(.004)		
SB:SB_40	−.537*	−.205	−.152	−.149	−.134	−.198	−.956**	−.203
	(.218)	(.210)	(.187)	(.191)	(.192)	(.194)	(.328)	(.215)
WPA				X	X	X	X	X
FA dummy					X	X	X	X
Season dummies		X	X	X	X	X	X	X
Fixed effects						Position	Individual	Position
Observations	134	134	134	134	134	134	134	134
R^2	.062	.519	.634	.636	.638	.665	.949	.559
Adjusted R^2	.041	.353	.499	.490	.488	.494	.645	.348
Residual Std. Error	1.158 (df = 130)	.951 (df = 99)	.837 (df = 97)	.845 (df = 95)	.846 (df = 94)	.841 (df = 88)	.705 (df = 19)	.955 (df = 90)
F Statistic	2.875* (df = 3; 130)	3.137*** (df = 34; 99)	4.674*** (df = 36; 97)	4.363*** (df = 38; 95)	4.257*** (df = 39; 94)			

Note: *p<0.05; **p<0.01; ***p<0.001

Table 11: Regression on Log-Salary, Including Interaction Term: around 100 RBI

	Dependent variable:							
	Sal							
	OLS						*felm*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	17.552*	13.364*	−3.577	−3.767	−3.797			
	(7.013)	(6.189)	(5.256)	(5.174)	(5.183)			
RBI	−.023	.001	−.017	−.007	−.007	−.011	.049	.007
	(.072)	(.063)	(.052)	(.051)	(.051)	(.050)	(.078)	(.061)
RBI_100	−11.458	−3.512	−2.428	−1.810	−1.692	−2.447	.582	−4.377
	(8.459)	(7.492)	(6.115)	(5.971)	(6.001)	(5.966)	(8.865)	(7.250)
FLD		−.0002	.004	.004	.004	.007	−.004	.003
		(.005)	(.004)	(.004)	(.004)	(.004)	(.007)	(.005)
BsR		−.035*	.001	−.008	−.008	−.016	.034	−.046**
		(.014)	(.012)	(.012)	(.012)	(.013)	(.023)	(.015)
AGE			1.185***	1.195***	1.195***	1.187***		
			(.127)	(.125)	(.125)	(.126)		
AGE_sq			−.018***	−.018***	−.018***	−.018***		
			(.002)	(.002)	(.002)	(.002)		
RBI:RBI_100	.115	.036	.026	.019	.018	.026	−.007	.044
	(.086)	(.076)	(.062)	(.060)	(.061)	(.060)	(.090)	(.073)
WPA				X	X	X	X	X
FA dummy					X	X	X	X
Season dummies		X	X	X	X	X	X	X
Fixed effects						Position	Individual	Position
Observations	393	390	390	390	390	390	390	390
R^2	.015	.345	.569	.592	.592	.614	.895	.422
Adjusted R^2	.007	.281	.523	.546	.545	.559	.670	.343
Residual Std. Error	1.033 (df = 389)	.880 (df = 354)	.717 (df = 352)	.699 (df = 350)	.700 (df = 349)	.690 (df = 340)	.596 (df = 124)	.841 (df = 342)
F Statistic	1.984 (df = 3; 389)	5.333*** (df = 35; 354)	12.547*** (df = 37; 352)	13.012*** (df = 39; 350)	12.654*** (df = 40; 349)			

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Here we consider each indexes respectively.

First, for batting-average, RDD analysis denied the existance of any additional monetary bonus for achieving either .300 or .250. Although estimated jump at each cutoff points were positive, but their standard errors are large and so the difference were insignificant. The same results were obtained in the model with interaction terms: dummies for achieving their internal goals are all insignificant. That is, players with their batting-average around .250 and .300 make effort to meet them just above these numbers, even though there is no monetary reward to do so. These findings support the assumption that preferences of the players are reference dependent, even when evaluating nonmonetary outcomes.

On-base percentage shows similar tendency. For this index, the estimated jump takes negative, although the estimator is insignificant. As is mentioned in Section 6, on-base percentage is considered as more important index: it is closer correlation with the winning-average of the team than batting-average. Thus, it can be the case that team managers evaluate on-base percentage more than batting-average and think of paying players with higher number more. However, our results are against this hypothesis.

For the cumulative indexes, observed results are almost the same: 20 of homerun, 100 of runs-batted-in, and 200 base-hits does not discontinuously raise the players' salary. Homeruns produce at least one score to the team, and are take one of the most "attractive" aspects of baseball, so there may exists additional positive effect for the team: it may bring a lot of audience, which profits them by stadium fees. Nevertheless, discontinuous scheme of the salary was not observed. Regressions with the interaction term reported the same results.

Stolen-base, however, shows different results. In RDD for the cutpoint of 30, including no other controls yields significant discontinuity in every bandwidth. Also, the results are consistent in some models of the interaction term. Compared to the other indexes, there were observed evidence that are for the monetary incentives. However, we do not regard them as sufficient support. First, for RDD, controling other player-specific charactarisitcs, their significancy level drastically goes down. Also, in interaction-term analysis, the estimated values are mixture of significant ones and not significant ones, and they fluctuate from .816 to 13.567. And finally, for 40 stolen-bases, the results of RDD estimation showed negative jump, inconsistent with that of 30, even though these results argue the same index. Thus, we conclude these results cannot support the counter hypothesis that denies discontinuity of the salary contracts, but either vice versa.

One possible alternative interpretation is that there exits the players that sign the contracts that includes plural-year service. Such a player plays receive fixed salary regardless of their single-year performance. Thus, we conducted a supplimental analysis that restricts the sample to those who have the free-agency, which enables them to negotiate with any MLB or other professional baseball teams. These players cannot play for the MLB without signing a new contract, which always reflects his performance of the previous year. In the analysis above, we consider the possession of the right of free agency by adding the dummy variable that indicates whether he holds the right or not.

Table 12 shows the results of RDD, with the restricted sample to free-agent players. This is consistent with the main results: there does not exist evidence that supports the

Table 12: RDD Test for Discontinuity, Only Including FA Players

index,cutpoint	Other Control	bw type	bandwidth	Observations	Estimate	Std. Error	z
AVG, .300	No	LATE	.025	503	-.175	.197	-.888
		Half-BW	.013	252	-.307	.302	-1.016
		Double-BW	.052	1043	-.180	.141	-1.271
	Yes	LATE	.026	509	-.253	.138	-1.832
		Half-BW	.013	266	-.209	.212	-.986
		Double-BW	.052	1038	.199	.102	-1.938
AVG, .250	No	LATE	.056	1366	.074	.102	.721
		Half-BW	.028	910	.147	.133	1.099
		Double-BW	.114	1501	.067	.090	.735
	Yes	LATE	.058	1367	.084	.082	1.020
		Half-BW	.029	923	.149	.107	.398
		Double-BW	.117	1480	.070	.072	.964
HR, 20	No	LATE	3.48	211	-.302	.300	-1.007
		Half-BW	1.74	96	-.123	.226	-.543
		Double-BW	6.96	387	.045	.203	.224
	Yes	LATE	3.50	206	-.273	.296	-.924
		Half-BW	1.75	95	-.156	.278	-.560
		Double-BW	7.00	439	-.098	.174	-.565
OBP, .350	No	LATE	.045	1103	.034	.129	.262
		Half-BW	.023	597	-.106	.172	-.620
		Double-BW	.092	1469	.024	.105	.225
	Yes	LATE	.043	1044	.021	.107	.196
		Half-BW	.021	566	-.085	.153	-.558
		Double-BW	.086	1435	.016	.084	.194
RBI, 100	No	LATE	4.90	50	-.100	.559	-.179
		Half-BW	2.45	30	-.095	.949	-.101
		Double-BW	9.80	102	.256	.333	.770
	Yes	LATE	4.93	49	.195	.433	.449
		Half-BW	2.46	30	-1.360	1.295	-1.050
		Double-BW	9.86	100	.398	.160	2.481*
H, 200	No	LATE	4.498	107	-.070	.447	-.156
		Half-BW	2.249	61	-.439	.726	-.605
		Double-BW	8.996	218	-.025	.293	-.086
	Yes	LATE	4.512	106	.649	.355	1.824
		Half-BW	2.256	61	1.084	.963	1.125
		Double-BW	9.024	240	.264	.243	1.087

Note: ***: $p < 0.1\%$, **: $p < 1\%$, *: $p < 5\%$.
Bandwidth is optimized following the method of Imbens-Kalyanaraman.
For stolen-bases, it cannot be calculated because of lack of samples.

additional reward at each cutoff points.

In summary, we find that players does not have monetary incentives at their observed internal goals. That is, they adjust their effort level to make their performance indexes just above the reference points, because of their reference point dependent: discontinuous at the reference point preferences. In the next section, we consider other alternative explanations by conducting additional analysis, and empirical evidences.

6 Alternative Interpretation and Some Evidence

In section 5, our analysis presented that there in fact exists manipulation in some of the batting indexes, but no evidence observed in their contracts, which supports the assumption these observations are driven by the reference dependence of the players themselves. Here we consider some possible alternative and additional discussion about our results.

6.1 Incentivised Contract

One most possible explanation that may interpret our result is the incentivised design of the contract. So far, I checked monetary incentive for the player, analyzing only the fixed parts of the contract. However, players often sign contracts with additional bonus according to their performances. Even though the results in Section 5.2 did not support the existance of incentives in fixed salary, it may occurs as this additional rewards. Here I present that this story is hard to be applied, showing the specific contracts of the some players.

Table 13 shows the specific contents of the MLB position players' contracts, quated by *Cot's Baseball Contracts* from *Baseball Prospectus*, a fan's website that discloses information about that. In addition to signing bonus, fixed payment (we made analysis for this part), and other optional bonus or service, players receive some monetary incentives according to their performance. They are roughly grouped into two: award bonus and bonus for reaching certain number of their indexes. While the former includes winning Gold Glove or All-Star Game selection (a match between the two big leagues of MLB, each of which is composed by players selected by the manager and the fan's vote), the latter consists of only round numbers with plate appearances, not batting-average, on-base percentage or homeruns. Therefore, we can conclude that in the additional bonus parts of their contracts, there are no incentives that leads them to manipulating their batting-average, on-base percentage or other batting-indexes.

6.2 Contract Length

Skilled players often sign contracts with plural-year duration. This is related to why we supplied analysis with the sample of players who had the right of free agency. Furthermore, we should also take care of their contract length, that is, until when the players are insured to play for the team they signed, because it can be some substitution for the additional monetary bonus.

Table 13: Descriptions of the Contract of the Specific Players

- Ichiro Suzuki, 4-year contract with Seattle Marinars (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

Krautmann & Oppenheimer(2002) conducted research about this point. They used the salary dataset of MLB from 1990 to 1994 seasons, and regressed log salary on an interaction term of the performance proxy and the contract years they signed.

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

The model is quated from Krautmann & Oppenheimer(2002). According to their results, the coefficient of the interaction term, β_3, was estimated to be negative. In other words, the longer the contract years at once stretched, the less the return to their performance goes. This is caused, they claimed, by the player's risk-aversive preference that dislikes the risk of being fired. Introducing this to our model, it can be the case that those who achieved their goals are in fact receive additional bonus, but instead of getting higher basesalary, they choose to sign the contract with longer duration. For the team manager, it is profitable to propose such contracts, which may enable them to hold highly skilled players with relatively reasonable costs. These days, it is usual that players sign the plural-year package contracts with the right to opt-out: the player or the manager nullify the contract while it is under duration, for the players to get some better contract, or for the manager to modify the contract or release the player. So it might require more complicate model to describe this situation, but it helps us to consider these nonmonetary bonus.

6.3 By-Time Analysis

Our research used data from wide range of time: 62 years for bunching, 31 years for monetary incentives. Through such a long time, techniques of the players or the quality of instruments must have evolved, which leads to change in mean or the standard value of the indexes: that is, unlike the reference point "per" of golf, the reference point of baseball might move through its history. Also, it is natural to think there may have been a lot of change in the design of the contract they agreed. Here we consider time-variable elements in our analysis. specifically, there are two main possible effect that changes the contract design: one is the relative market power of the players, and another is change in relative importance of each performance index.

Relative market power has direct relation to the contract. Before the system of free agency was introduced, players are forbidden to move to other teams without permission by the team they belong to. '94 strike by the Players Association of Major League Baseball, against the team owners to request improvement of their treatment, also may have great influence on their contracts (See Appendix about the specific information about free agency and Strike).

Relative importance captures the change in evaluation of each index. Through the history of baseball, there have been invented a lot of indexes that measures the performance/ability of the player, and it has been argued which index is the most efficient one to evaluate them. One of the most important revoution was the publication of *'Moneyball'*(2003), written by Michael Lewis, a financial reporter. In this book, he described that batting-average is not as approprate measure: there is more close correlation with total runs the team earns in the season in on-base percentage. In practice, Oakland Athletics applied strategy to form the menber of the team, and won the playoff. This story was widely spread and changed the sense of view about the baseball index.

The impact of this publication was such a great one that it was evaluated in an economic article. Hakes and Sauer (2006) tested the Lewis's claim in econometric specification. They stated that on-base percentage was gives us the better explain about the winning-percentage of the team than batting-average, but team managers had been take batting-average of more importance when evaluating players. After *Moneyball* published, however, their evaluation revolved. In 2004, a year after its publication, the estimated return to on-base percentage for the players increased, compared to the previous 4 years.

Then, one possible question occurs: "Does the tendency of manipulation/discoutinuous contract design also change through the history of baseball?"

In this section, we replicate the methodologies conducted in the previous sections, but sorting the sample into periods below:

1. Before Free Agency (1957 - 1975)
2. After Free Agency and Before Strike (1986 - 1994)
3. After Strike and Before *Moneyball* (1995 - 2003)
4. After *Moneyball* (2004 - 2017)

Sample B does not include data from 1957 to 1986, so in the section of mondetary incentive, We conducted tests for only three parts except for "Before Free Agency." From here, we mention the three important batting indexes: batting-average, on-base percentage, and homerun.

6.3.1 Bunching

Table 14 shows the results of the McCrary (2008)'s manipulation tests, for each grouped samples. Compared to the full-sample analysis conducted in Section 5.1, we observed partly different results for each index.

First, .300 of batting-average, was the most solid benchmarks of the players. Each subsamples show the significant discontinuity at the cutoff point. On the other hand, .250, seems not to be regarded not as important after *Moneyball*, as other previous days. In this term, the discontinuity at .250 becomes no more insignificant one. This may be related to that the mean of the batting-average are going up until 1994-2003.

6.3.2 Monetary Incentive

Then, we

Table 14: Manipulation Test for the Grouped Sample by Time

index, cutpoint		'57-'75	'75-'93	'94-2003	2004-	full sample
AVG, .300	bw	.023	.020	.022	.019	.019
	θ	.573	.566	.310	.403	.499
		(.146)	(.120)	(.130)	(.120)	(.067)
	z	3.934***	4.732***	2.393*	3.376***	7.442***
AVG, .250	bw	.028	.028	.032	.027	.024
	θ	.250	.151	.306	.121	.212
		(.080)	(.069)	(.094)	(.076)	(.042)
	z	3.149**	2.188*	3.242**	1.595	5.061***
OBP, .350	bw	.031	.030	.036	.030	.024
	θ	.137	.149	-.035	.137	.139
		(.089)	(.081)	(.093)	(.082)	(.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	.214	.145	.315	.259
		(.150)	(.123)	(.129)	(.112)	(.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 15: RDD 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	.064	.066	.034
			(.137)	(.092)	(.103)	(.056)
		z	-.250	.697	.637	.615
AVG, .250	LATE	bw	.036	.043	.075	.048
		Obs.	1482	1806	3991	7271
		estimate	.154	.064	.076	.070
			(.084)	(.092)	(.060)	(.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	-.348	.343	-.002
			(.228)	(.218)	(.264)	(.141)
		z	-1.122	-1.600	1.300	-.015
OBP, .350	LATE	bw	.031	.025	.027	.045
		Obs.	1098	1281	2042	6525
		estimate	.109	-.151	-.030	-.013
			(.106)	(.120)	(.093)	(.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.

Table 16: RDD for the Grouped Sample by Time, Only Including FA Players

index, cutpoint	bw, type		'87-'94	'95-2003	2004-	full sample
AVG, .300	LATE	bw	.060	.032	.039	.026
		Obs.	218	229	354	509
		estimate	-.026	-.309	-.186	-.253
			(.247)	(.182)	(.182)	(.138)
		z	-.108	-1.700	-1.020	-1.832
AVG, .250	LATE	bw	.018	.023	.078	.058
		Obs.	123	227	716	1367
		estimate	.425	.293	.047	.084
			(.281)	(.230)	(.103)	(.082)
		z	1.512	1.272	-.448	1.020
HR, 20	LATE	bw	5.35	3.504	3.566	3.50
		Obs.	47	70	102	206
		estimate	.004	-.701	-.337	-.273
			(.284)	(.492)	(.513)	(.296)
		z	-1.600	-1.423	-.657	-.924
OBP, .350	LATE	bw	.034	.042	.031	.043
		Obs.	154	344	395	1044
		estimate	.080	-.174	.115	.021
			(.291)	(.179)	(.188)	(.107)
		z	.276	-.971	.616	.196

Note: ***: $p < 0.1\%$, **: $p < 1\%$, *: $p < 5\%$.
Bandwidth is optimized following the method of Imbens-Kalyanaraman.

Table 17: Regression on Log-Salary, Including Interaction Term: around .300

	Dependent variable:							
	Sal							
			OLS				*felm*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	12.194***	11.645***	−1.113	.922	.917			
	(2.026)	(1.919)	(2.322)	(2.306)	(2.305)			
AVG	5.130	4.726	9.079	.891	.530	−.404	5.004	−4.048
	(7.089)	(6.702)	(5.977)	(5.839)	(5.841)	(5.837)	(5.919)	(6.589)
AVG_300	−3.292	−2.067	−1.271	−1.856	−2.054	−1.456	−2.129	−1.695
	(3.601)	(3.398)	(3.023)	(2.910)	(2.911)	(2.906)	(2.879)	(3.290)
FLD		.0005	.001	.002	.002	.002	.001	.002
		(.005)	(.004)	(.004)	(.004)	(.004)	(.005)	(.005)
BsR		.077***	.083***	.062***	.063***	.062***	.041	.054**
		(.019)	(.017)	(.017)	(.017)	(.017)	(.021)	(.020)
AGE			.699***	.690***	.695***	.692***		
			(.099)	(.096)	(.096)	(.096)		
AGE_sq			−.010***	−.010***	−.010***	−.010***		
			(.002)	(.002)	(.002)	(.002)		
AVG:AVG_300	11.428	7.355	4.333	6.289	6.955	5.047	6.977	6.200
	(11.958)	(11.288)	(10.043)	(9.665)	(9.670)	(9.653)	(9.588)	(10.927)
WPA				X	X	X	X	X
FA dummy					X	X	X	X
Season dummies		X	X	X	X	X	X	X
Fixed effects						Position	Individual	Position
Observations	703	697	697	697	697	697	697	697
R^2	.031	.174	.348	.400	.402	.413	.849	.246
Adjusted R^2	.027	.159	.335	.386	.387	.393	.697	.223
Residual Std. Error	1.026 (df = 699)	.955 (df = 684)	.850 (df = 682)	.816 (df = 680)	.816 (df = 679)	.812 (df = 673)	.573 (df = 348)	.919 (df = 675)
F Statistic	7.539*** (df = 3; 699)	11.988*** (df = 12; 684)	26.031*** (df = 14; 682)	28.385*** (df = 16; 680)	26.867*** (df = 17; 679)			

Note: *p<0.05; **p<0.01; ***p<0.001

Table 18: Regression on Log-Salary, Including Interaction Term: around .300

	Dependent variable:							
	Sal							
	OLS						*felm*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	10.414***	9.677***	−8.332***	−5.706***	−5.673***			
	(.717)	(.718)	(1.250)	(1.242)	(1.227)			
AVG	13.708***	14.833***	13.943***	4.183	3.672	3.604	.837	3.979
	(2.594)	(2.583)	(2.280)	(2.269)	(2.242)	(2.238)	(2.182)	(2.569)
AVG_300	−1.285	−1.084	−.554	−.969	−1.009	−1.241	−.816	−1.631
	(1.696)	(1.679)	(1.482)	(1.407)	(1.390)	(1.387)	(1.226)	(1.593)
FLD		.002	.005	.006*	.006*	.006*	.007*	.004
		(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
BsR		.020	.040***	.031**	.031**	.033**	.029*	.018
		(.013)	(.011)	(.011)	(.011)	(.011)	(.012)	(.013)
AGE			1.142***	1.092***	1.088***	1.107***		
			(.073)	(.069)	(.068)	(.069)		
AGE_sq			−.017***	−.017***	−.016***	−.017***		
			(.001)	(.001)	(.001)	(.001)		
AVG:AVG_300	4.259	3.544	1.861	3.258	3.470	4.216	2.874	5.344
	(5.555)	(5.497)	(4.852)	(4.607)	(4.551)	(4.544)	(4.023)	(5.218)
WPA				X	X	X	X	X
FA dummy					X	X	X	X
Season dummies		X	X	X	X	X	X	X
Fixed effects						Position	Individual	Position
Observations	1,878	1,867	1,867	1,867	1,867	1,867	1,867	1,867
R^2	.062	.099	.299	.370	.385	.392	.766	.197
Adjusted R^2	.060	.093	.294	.364	.379	.384	.657	.187
Residual Std. Error	1.166 (df = 1874)	1.148 (df = 1853)	1.014 (df = 1851)	.962 (df = 1849)	.950 (df = 1848)	.947 (df = 1842)	.707 (df = 1271)	1.087 (df = 1844)
F Statistic	41.081*** (df = 3; 1874)	15.715*** (df = 13; 1853)	52.680*** (df = 15; 1851)	63.750*** (df = 17; 1849)	64.330*** (df = 18; 1848)			

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table 19: Regression on Log-Salary, Including Interaction Term: around .300

	Dependent variable:							
	Sal							
			OLS				*felm*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	14.252***	13.060***	−4.948***	−3.925**	−3.852**			
	(1.163)	(1.155)	(1.392)	(1.415)	(1.409)			
AVG	2.257	5.079	7.693*	1.969	2.193	1.946	.332	−1.304
	(4.111)	(4.067)	(3.399)	(3.333)	(3.320)	(3.312)	(3.374)	(4.010)
AVG_300	−.732	−.034	−1.023	−.166	.129	.275	−1.570	.395
	(2.357)	(2.327)	(1.945)	(1.880)	(1.874)	(1.869)	(1.757)	(2.264)
FLD		.0001	.006	.007*	.007*	.008*	.002	.003
		(.004)	(.003)	(.003)	(.003)	(.003)	(.004)	(.004)
BsR		−.031***	−.0001	−.005	−.004	−.006	.013	−.037***
		(.008)	(.006)	(.006)	(.006)	(.007)	(.009)	(.008)
AGE			1.034***	1.026***	1.013***	1.032***		
			(.067)	(.065)	(.065)	(.065)		
AGE_sq			−.015***	−.015***	−.014***	−.015***		
			(.001)	(.001)	(.001)	(.001)		
AVG:AVG_300	3.198	.745	3.577	.711	−.269	−.759	5.210	−.736
	(7.782)	(7.683)	(6.421)	(6.209)	(6.187)	(6.169)	(5.813)	(7.473)
WPA				X	X	X	X	X
FA dummy					X	X	X	X
Season dummies		X	X	X	X	X	X	X
Fixed effects						Position	Individual	Position
Observations	1,880	1,872	1,872	1,872	1,872	1,872	1,872	1,872
R^2	.013	.056	.342	.387	.392	.403	.776	.124
Adjusted R^2	.011	.047	.335	.379	.384	.393	.640	.109
Residual Std. Error	1.273 (df = 1876)	1.250 (df = 1853)	1.044 (df = 1851)	1.009 (df = 1849)	1.005 (df = 1848)	.998 (df = 1839)	.769 (df = 1165)	1.209 (df = 1841)
F Statistic	8.204*** (df = 3; 1876)	6.103*** (df = 18; 1853)	48.083*** (df = 20; 1851)	52.968*** (df = 22; 1849)	51.809*** (df = 23; 1848)			
Note:								*p<0.05; **p<0.01; ***p<0.001

Table 20: Regression on Log-Salary, Including Interaction Term: around .250

	Dependent variable:							
	Sal							
			OLS				*felm*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	11.622***	11.080***	−1.923	−1.853	−2.264			
	(1.047)	(1.022)	(1.306)	(1.315)	(1.314)			
AVG	6.412	6.379	4.973	−.329	−.057	−.302	3.633	.208
	(4.422)	(4.298)	(3.690)	(3.640)	(3.625)	(3.615)	(3.479)	(4.244)
AVG_250	−.743	−.662	−.601	−.790	−.677	−.681	−.281	−.872
	(1.333)	(1.293)	(1.110)	(1.081)	(1.076)	(1.074)	(1.016)	(1.261)
FLD		.004	.003	.005*	.005	.005	.006*	.007*
		(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
BsR		.027	.031*	.015	.015	.012	.002	.010
		(.017)	(.015)	(.014)	(.014)	(.015)	(.017)	(.017)
AGE			.811***	.815***	.834***	.836***		
			(.067)	(.065)	(.065)	(.065)		
AGE_sq			−.012***	−.012***	−.012***	−.012***		
			(.001)	(.001)	(.001)	(.001)		
AVG:AVG_250	3.425	3.103	2.981	3.770	3.306	3.323	1.649	4.007
	(5.390)	(5.233)	(4.491)	(4.371)	(4.355)	(4.343)	(4.120)	(5.100)
WPA				X	X	X	X	X
FA dummy					X	X	X	X
Season dummies		X	X	X	X	X	X	X
Fixed effects						Position	Individual	Position
Observations	1,521	1,510	1,510	1,510	1,510	1,510	1,510	1,510
R^2	.038	.112	.347	.383	.389	.396	.770	.166
Adjusted R^2	.036	.105	.340	.377	.382	.387	.642	.154
Residual Std. Error	1.004 (df = 1517)	.969 (df = 1497)	.832 (df = 1495)	.809 (df = 1493)	.805 (df = 1492)	.802 (df = 1486)	.613 (df = 972)	.942 (df = 1488)
F Statistic	19.883*** (df = 3; 1517)	15.715*** (df = 12; 1497)	56.641*** (df = 14; 1495)	57.955*** (df = 16; 1493)	55.828*** (df = 17; 1492)			

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table 21: Regression on Log-Salary, Including Interaction Term: around .250

	Dependent variable:							
	Sal							
			OLS				*felm*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	10.767^{***}	10.285^{***}	-7.056^{***}	-5.992^{***}	-6.050^{***}			
	(1.070)	(1.057)	(1.403)	(1.384)	(1.347)			
AVG	12.553^{**}	12.610^{**}	10.263^{**}	2.621	2.395	1.963	5.558	4.376
	(4.553)	(4.498)	(3.905)	(3.818)	(3.717)	(3.705)	(3.607)	(4.415)
AVG_250	.703	.448	−.148	−.289	−.183	−.322	1.007	.359
	(1.270)	(1.253)	(1.088)	(1.049)	(1.021)	(1.018)	(.965)	(1.213)
FLD		.006	$.006^{*}$	$.007^{**}$	$.006^{*}$	$.006^{*}$	$.007^{*}$	$.007^{*}$
		(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
BsR		−.016	.011	.0003	.004	.004	.019	−.020
		(.014)	(.012)	(.012)	(.012)	(.012)	(.012)	(.014)
AGE			1.117^{***}	1.119^{***}	1.107^{***}	1.135^{***}		
			(.073)	(.071)	(.069)	(.069)		
AGE_sq			$-.017^{***}$	$-.017^{***}$	$-.016^{***}$	$-.017^{***}$		
			(.001)	(.001)	(.001)	(.001)		
AVG:AVG_250	−2.668	−1.685	.700	1.339	.980	1.537	−3.777	−1.228
	(5.206)	(5.136)	(4.459)	(4.299)	(4.185)	(4.171)	(3.963)	(4.970)
WPA				X	X	X	X	X
FA dummy					X	X	X	X
Season dummies		X	X	X	X	X	X	X
Fixed effects						Position	Individual	Position
Observations	1,934	1,927	1,927	1,927	1,927	1,927	1,927	1,927
R^2	.038	.079	.307	.357	.391	.398	.764	.144
Adjusted R^2	.036	.073	.302	.351	.385	.391	.646	.134
Residual Std. Error	1.174 (df = 1930)	1.151 (df = 1913)	.999 (df = 1911)	.963 (df = 1909)	.938 (df = 1908)	.933 (df = 1902)	.712 (df = 1282)	1.112 (df = 1904)
F Statistic	25.188^{***} (df = 3; 1930)	12.648^{***} (df = 13; 1913)	56.445^{***} (df = 15; 1911)	62.241^{***} (df = 17; 1909)	67.973^{***} (df = 18; 1908)			

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table 22: Regression on Log-Salary, Including Interaction Term: around .250

	Dependent variable:							
	Sal							
	OLS					*felm*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	13.563***	12.692***	−5.106***	−4.164***	−4.177***			
	(.550)	(.553)	(.846)	(.850)	(.841)			
AVG	3.865	5.769*	5.847**	−.646	−1.249	−2.190	−3.109	−1.573
	(2.379)	(2.359)	(1.971)	(1.961)	(1.941)	(1.941)	(1.853)	(2.358)
AVG_250	−1.645*	−1.423*	−1.371*	−1.575**	−1.717***	−1.979***	−1.574**	−1.772**
	(.652)	(.645)	(.539)	(.526)	(.520)	(.518)	(.484)	(.630)
FLD		.001	.004	.006**	.006*	.006**	.005*	.005
		(.003)	(.002)	(.002)	(.002)	(.002)	(.002)	(.003)
BsR		−.036***	−.006	−.009	−.008	−.010	.017**	−.037***
		(.006)	(.005)	(.005)	(.005)	(.005)	(.006)	(.006)
AGE			1.068***	1.053***	1.056***	1.072***		
			(.048)	(.046)	(.046)	(.046)		
AGE_sq			−.016***	−.015***	−.015***	−.015***		
			(.001)	(.001)	(.001)	(.001)		
AVG:AVG_250	6.660*	5.787*	5.801**	6.738**	7.256***	8.315***	6.612***	7.361**
	(2.688)	(2.659)	(2.222)	(2.166)	(2.144)	(2.135)	(1.993)	(2.595)
WPA				X	X	X	X	X
FA dummy					X	X	X	X
Season dummies		X	X	X	X	X	X	X
Fixed effects						Position	Individual	Position
Observations	4,008	3,991	3,991	3,991	3,991	3,991	3,991	3,991
R^2	.039	.079	.358	.394	.407	.418	.733	.139
Adjusted R^2	.038	.075	.355	.391	.404	.413	.644	.133
Residual Std. Error	1.233 (df = 4004)	1.209 (df = 3972)	1.010 (df = 3970)	.981 (df = 3968)	.971 (df = 3967)	.963 (df = 3958)	.750 (df = 2995)	1.171 (df = 3960)
F Statistic	53.575*** (df = 3; 4004)	19.000*** (df = 18; 3972)	110.623*** (df = 20; 3970)	117.455*** (df = 22; 3968)	118.457*** (df = 23; 3967)			

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table 23: Regression on Log-Salary, Including Interaction Term: around .350

	Dependent variable:							
	Sal							
	OLS						*felm*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	9.531***	9.212***	−1.887	−1.753	−1.986			
	(1.440)	(1.377)	(1.643)	(1.676)	(1.672)			
OBP	11.761**	10.736**	10.050**	4.791	4.747	4.464	8.332*	5.986
	(4.320)	(4.125)	(3.743)	(3.708)	(3.695)	(3.695)	(3.756)	(4.149)
OBP_350	2.549	.982	1.389	1.382	1.492	1.407	.372	.809
	(2.347)	(2.246)	(2.039)	(1.971)	(1.964)	(1.966)	(1.851)	(2.207)
FLD		.006	.004	.006	.006	.005	.006	.007
		(.004)	(.003)	(.003)	(.003)	(.003)	(.003)	(.004)
BsR		.046**	.054***	.035*	.036*	.033*	.041*	.031
		(.017)	(.016)	(.015)	(.015)	(.016)	(.018)	(.018)
AGE			.693***	.712***	.724***	.725***		
			(.077)	(.074)	(.074)	(.074)		
AGE_sq			−.010***	−.010***	−.010***	−.010***		
			(.001)	(.001)	(.001)	(.001)		
OBP:OBP_350	−7.008	−2.664	−3.751	−3.731	−4.036	−3.781	−1.182	−2.166
	(6.683)	(6.393)	(5.803)	(5.608)	(5.589)	(5.594)	(5.285)	(6.279)
WPA				X	X	X	X	X
FA dummy					X	X	X	X
Season dummies		X	X	X	X	X	X	X
Fixed effects						Position	Individual	Position
Observations	1,108	1,098	1,098	1,098	1,098	1,098	1,098	1,098
R^2	.037	.146	.300	.348	.354	.359	.791	.188
Adjusted R^2	.035	.137	.291	.339	.343	.345	.646	.172
Residual Std. Error	1.000 (df = 1104)	.949 (df = 1085)	.860 (df = 1083)	.831 (df = 1081)	.828 (df = 1080)	.827 (df = 1074)	.608 (df = 646)	.929 (df = 1076)
F Statistic	14.308*** (df = 3; 1104)	15.464*** (df = 12; 1085)	33.159*** (df = 14; 1083)	36.120*** (df = 16; 1081)	34.756*** (df = 17; 1080)			

Note: *p<0.05; **p<0.01; ***p<0.001

Table 24: Regression on Log-Salary, Including Interaction Term: around .350

	Dependent variable:							
	Sal							
	OLS						*felm*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	5.281*	4.395*	−10.795***	−10.617***	−10.635***			
	(2.095)	(2.066)	(2.189)	(2.185)	(2.151)			
OBP	26.125***	27.294***	21.250***	15.192**	15.684**	15.472**	8.583	22.958***
	(6.221)	(6.122)	(5.482)	(5.390)	(5.306)	(5.317)	(5.469)	(6.097)
OBP_350	2.589	3.439	4.426	4.651	4.763	4.693	−1.519	3.863
	(3.080)	(3.036)	(2.714)	(2.627)	(2.585)	(2.598)	(2.561)	(2.986)
FLD		.005	.009**	.007*	.008*	.008*	.007	.004
		(.004)	(.003)	(.003)	(.003)	(.003)	(.004)	(.004)
BsR		−.0002	.021	.019	.020	.021	.042**	.003
		(.015)	(.014)	(.013)	(.013)	(.014)	(.015)	(.016)
AGE			1.078***	1.079***	1.055***	1.077***		
			(.084)	(.082)	(.080)	(.081)		
AGE_sq			−.016***	−.016***	−.016***	−.016***		
			(.001)	(.001)	(.001)	(.001)		
OBP:OBP_350	−8.245	−10.629	−12.975	−13.572	−13.929	−13.714	3.634	−11.835
	(8.815)	(8.688)	(7.766)	(7.516)	(7.398)	(7.434)	(7.347)	(8.545)
WPA				X	X	X	X	X
FA dummy					X	X	X	X
Season dummies		X	X	X	X	X	X	X
Fixed effects						Position	Individual	Position
Observations	1,285	1,281	1,281	1,281	1,281	1,281	1,281	1,281
R^2	.031	.084	.269	.317	.339	.342	.781	.129
Adjusted R^2	.029	.074	.261	.308	.330	.329	.622	.113
Residual Std. Error	1.165 (df = 1281)	1.139 (df = 1267)	1.018 (df = 1265)	.985 (df = 1263)	.969 (df = 1262)	.970 (df = 1256)	.728 (df = 743)	1.115 (df = 1258)
F Statistic	13.839*** (df = 3; 1281)	8.922*** (df = 13; 1267)	31.083*** (df = 15; 1265)	34.517*** (df = 17; 1263)	35.987*** (df = 18; 1262)			
Note:								*p<0.05; **p<0.01; ***p<0.001

Table 25: Regression on Log-Salary, Including Interaction Term: around .350

	Dependent variable:							
	Sal							
	OLS						*felm*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	13.575***	12.636***	−6.244***	−6.180***	−6.325***			
	(1.653)	(1.622)	(1.687)	(1.741)	(1.728)			
OBP	3.505	5.128	9.240*	5.879	6.451	7.316	6.127	2.449
	(4.914)	(4.806)	(4.004)	(4.020)	(3.990)	(3.961)	(3.983)	(4.826)
OBP_350	−2.396	−1.247	.506	.985	1.377	1.736	−2.266	−.593
	(2.526)	(2.468)	(2.056)	(2.027)	(2.013)	(1.999)	(1.961)	(2.436)
FLD		.010*	.012***	.012***	.012***	.011***	.007*	.010**
		(.004)	(.003)	(.003)	(.003)	(.003)	(.003)	(.004)
BsR		−.030***	.001	.001	.002	.004	.023**	−.027**
		(.007)	(.006)	(.006)	(.006)	(.007)	(.009)	(.008)
AGE			1.052***	1.047***	1.039***	1.067***		
			(.066)	(.065)	(.064)	(.064)		
AGE_sq			−.015***	−.015***	−.015***	−.015***		
			(.001)	(.001)	(.001)	(.001)		
OBP:OBP_350	7.097	3.920	−1.321	−2.730	−3.892	−4.923	6.108	2.030
	(7.210)	(7.045)	(5.868)	(5.787)	(5.746)	(5.709)	(5.607)	(6.954)
WPA				X	X	X	X	X
FA dummy					X	X	X	X
Season dummies		X	X	X	X	X	X	X
Fixed effects						Position	Individual	Position
Observations	2,075	2,063	2,063	2,063	2,063	2,063	2,063	2,063
R^2	.013	.077	.361	.381	.391	.404	.772	.113
Adjusted R^2	.011	.069	.355	.375	.384	.395	.639	.100
Residual Std. Error	1.258 (df = 2071)	1.221 (df = 2044)	1.016 (df = 2042)	1.001 (df = 2040)	.993 (df = 2039)	.985 (df = 2030)	.761 (df = 1300)	1.201 (df = 2032)
F Statistic	8.919*** (df = 3; 2071)	9.436*** (df = 18; 2044)	57.728*** (df = 20; 2042)	57.141*** (df = 22; 2040)	56.931*** (df = 23; 2039)			

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table 26: Regression on Log-Salary, Including Interaction Term: around 20 HR

	Dependent variable:							
	Sal							
	OLS					*felm*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	11.805***	11.894***	−.144	.298	.303			
	(1.091)	(.993)	(1.697)	(1.819)	(1.824)			
HR	.125*	.076	.040	.044	.044	.035	.050	.075
	(.063)	(.057)	(.048)	(.048)	(.048)	(.048)	(.061)	(.057)
HR_20	2.620	.239	−.242	.007	.005	−.376	−.019	.237
	(1.547)	(1.409)	(1.193)	(1.182)	(1.184)	(1.196)	(1.384)	(1.411)
FLD		.0004	.003	.003	.003	.003	.004	−.001
		(.005)	(.004)	(.004)	(.004)	(.004)	(.006)	(.005)
BsR		.108***	.110***	.092***	.092***	.087**	−.003	.086**
		(.031)	(.026)	(.026)	(.027)	(.027)	(.046)	(.032)
AGE			.774***	.759***	.758***	.753***		
			(.100)	(.100)	(.100)	(.101)		
AGE_sq			−.011***	−.011***	−.011***	−.011***		
			(.002)	(.002)	(.002)	(.002)		
HR:HR_20	−.141	−.019	.009	−.005	−.005	.014	−.010	−.021
	(.080)	(.073)	(.062)	(.061)	(.061)	(.062)	(.073)	(.073)
WPA				X	X	X	X	X
FA dummy					X	X	X	X
Season dummies		X	X	X	X	X	X	X
Fixed effects						Position	Individual	Position
Observations	348	341	341	341	341	341	341	341
R^2	.015	.261	.475	.490	.490	.500	.830	.297
Adjusted R^2	.006	.234	.452	.465	.463	.464	.617	.250
Residual Std. Error	.948 (df = 344)	.837 (df = 328)	.707 (df = 326)	.699 (df = 324)	.700 (df = 323)	.700 (df = 317)	.591 (df = 151)	.828 (df = 319)
F Statistic	1.727 (df = 3; 344)	9.641*** (df = 12; 328)	21.051*** (df = 14; 326)	19.443*** (df = 16; 324)	18.243*** (df = 17; 323)			

Note: *p<0.05; **p<0.01; ***p<0.001

Table 27: Regression on Log-Salary, Including Interaction Term: around 20 HR

	Dependent variable:							
	Sal							
	OLS					*felm*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	13.328***	12.700***	−10.122***	−9.386**	−9.889***			
	(1.798)	(1.836)	(2.908)	(2.990)	(2.921)			
HR	.071	.085	.180*	.182*	.182*	.191*	.132	.082
	(.100)	(.102)	(.086)	(.084)	(.082)	(.083)	(.099)	(.102)
HR_20	.324	.046	1.417	1.419	1.535	1.684	6.165**	−.303
	(2.340)	(2.400)	(2.014)	(1.984)	(1.937)	(1.967)	(2.361)	(2.409)
FLD		.004	.010*	.011*	.013*	.013**	−.002	.005
		(.006)	(.005)	(.005)	(.005)	(.005)	(.006)	(.006)
BsR		.035	.053*	.029	.022	.005	−.034	−.011
		(.030)	(.025)	(.026)	(.025)	(.026)	(.033)	(.032)
AGE			1.323***	1.318***	1.338***	1.328***		
			(.159)	(.156)	(.152)	(.155)		
AGE_sq			−.020***	−.020***	−.020***	−.020***		
			(.003)	(.003)	(.003)	(.003)		
HR:HR_20	−.021	−.009	−.089	−.091	−.097	−.106	−.307*	.007
	(.122)	(.125)	(.105)	(.104)	(.101)	(.103)	(.123)	(.126)
WPA				X	X	X	X	X
FA dummy					X	X	X	X
Season dummies		X	X	X	X	X	X	X
Fixed effects						Position	Individual	Position
Observations	374	371	371	371	371	371	371	371
R^2	.006	.046	.336	.365	.397	.409	.873	.102
Adjusted R^2	−.002	.011	.308	.334	.366	.368	.663	.045
Residual Std. Error	1.071 (df = 370)	1.066 (df = 357)	.892 (df = 355)	.875 (df = 353)	.854 (df = 352)	.852 (df = 346)	.622 (df = 140)	1.047 (df = 348)
F Statistic	.744 (df = 3; 370)	1.327 (df = 13; 357)	11.971*** (df = 15; 355)	11.929*** (df = 17; 353)	12.849*** (df = 18; 352)			

Note: *p<0.05; **p<0.01; ***p<0.001

Table 28: Regression on Log-Salary, Including Interaction Term: around 20 HR

	Dependent variable:							
	Sal							
	OLS						*felm*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	19.239***	18.618***	−1.330	−1.373	−2.020			
	(3.381)	(3.382)	(3.119)	(3.159)	(3.139)			
HR	−.229	−.198	−.182	−.141	−.123	−.125	−.103	−.151
	(.184)	(.184)	(.135)	(.133)	(.132)	(.132)	(.190)	(.181)
HR_20	−5.545	−4.512	−4.699	−4.220	−3.460	−3.979	−3.839	−4.799
	(3.871)	(3.877)	(2.840)	(2.798)	(2.785)	(2.788)	(3.955)	(3.840)
FLD		.005	.014*	.013*	.013*	.012*	−.0005	.002
		(.008)	(.006)	(.006)	(.006)	(.006)	(.010)	(.008)
BsR		−.042**	.002	−.007	−.008	−.016	−.006	−.062***
		(.016)	(.012)	(.012)	(.012)	(.014)	(.025)	(.018)
AGE			1.144***	1.182***	1.195***	1.200***		
			(.123)	(.121)	(.120)	(.121)		
AGE_sq			−.016***	−.017***	−.017***	−.017***		
			(.002)	(.002)	(.002)	(.002)		
HR:HR_20	.301	.248	.254	.224	.187	.211	.204	.253
	(.204)	(.205)	(.150)	(.148)	(.147)	(.147)	(.209)	(.203)
WPA				X	X	X	X	X
FA dummy					X	X	X	X
Season dummies		X	X	X	X	X	X	X
Fixed effects						Position	Individual	Position
Observations	475	475	475	475	475	475	475	475
R^2	.009	.052	.494	.513	.522	.535	.894	.112
Adjusted R^2	.003	.015	.472	.489	.498	.501	.665	.052
Residual Std. Error	1.247 (df = 471)	1.240 (df = 456)	.908 (df = 454)	.893 (df = 452)	.885 (df = 451)	.882 (df = 442)	.723 (df = 150)	1.216 (df = 444)
F Statistic	1.491 (df = 3; 471)	1.388 (df = 18; 456)	22.182*** (df = 20; 454)	21.625*** (df = 22; 452)	21.436*** (df = 23; 451)			

Note: *p<0.05; **p<0.01; ***p<0.001

7 Conclusion

So far, we have considered monetary incentives that exists behind the behavior that appears to be related to reference dependent preference. For the case of MLB, we conclude that there are not observed clear results that supports the the existance of monetary incentives, at least in the fixed part of their contracts. On the contrary in recent years, although the effects are limited to .250 of batting-average and 30 of stolen-bases, there turns up some possible evidences that supports the existance of monetary incentives. So to make better analysis in these indexes, we will require some following research. As we mentioned in Section 5 and 6, there are a lot of room for discussion.

But as a whole, Players manipulate their own performance indexes to achieve their internal goals, even though they cannot receive any additional bonus by doing so. Our results indicate that professional sports players seem to have preferences that yield utility not only by the monetary rewards, but also by their own performance situationally. In many articles of analysis on professional sports, we have considered that the players' benefit consists only of the contract package itself, so it may support interpreting their decision making more prescicely by inroducing additional assumptions. For the team managers, on the other hand, our analyses help make better contract packages that attract the skilled players more, or search the player relatively underestimated, to get the players more "efficiently."Also, we had better pay attention to the oppsite-side approach: whether there exists discontinuous design of the contracts that does not affect the players manipulation behavior.

Analyzing professional sports yields some important knowledge. Professional sports can generate outcomes both monetary ones, salary, and nonmonetary ones, performance. They can be appropreate empirical samples to compare the same situation with monetary reward and that with nonmonetary ones.In particular, when it comes to MLB, the performance indexes, nonmonetary outcomes, have been recorded for alomost 150 years, and thanks to the community of the fans, we can fairly compare players played in the different generations. As we used in this paper, rich information about their contracts is published. Also, there exists room for international comparision: Many countries around the world, Japan, Germany, Italy or Australia and so on, have their own professional leagues. Of course, there are a number of amateur players, those who does not receive any reward for their plays.

To conclude our paper, we state that it is worth continuing analysis about baseball, both for the sports itself and economics.

8 Appendix

8.1 Proxies for Performance: BATTING, FIELDING, and BaseRun

Baseball position players' skill is divided into three groups: batting, fielding and base-running.

8.2 Important Events Related to Section 6.4

9 References

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