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"Peak-End Effect in Salary Determination:
The Case of Japanese Professional Baseball"

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Peak-End Effect in Salary Determination:

The Case of Japanese Professional Baseball[1]

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1. Introduction

Because Hideo Nomo, a famous Japanese baseball player, joined Los Angeles Dodgers in 1995, many Japanese baseball players have gone to the United States to play Major League Baseball (MLB). Some people assert that "Baseball" in the United States differs from "Yakyu" (Japanese baseball) in Japan, although both sports have common rules. For instance, generally, those playing the game of "Baseball" are more powerful than those playing "Yakyu" because the American baseball players have greater physical capabilities than Japanese players have. However, Japanese baseball is more detailed than that of the United States. These differences between "Baseball" and "Yakyu" are attributable to

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the national traits of the respective countries. Although talented players will be developed as fourth batters and pitchers in Japan, such players will be developed as third batters and shortstops in the United States. Because these differences depend on the culture of baseball in each country and have a strong influence on baseball game progression, the head coaches of each country respectively select different strategies to win games. Japanese baseball players also played baseball in high school. In high school baseball, the game includes much sacrificial batting in the game. The view of baseball in Japan has found a high value for a player's sacrifice for the team. Although Japanese head coaches might choose a sacrifice bunt as strategy, we rarely watch it in the game of MLB. These differences are brought about by the quality of this different baseball culture.

Scully (1974) showed that one factor to increase team revenue is a high winning percentage because a higher winning percentage of a team engenders increased attendance and sales of team-related products. Fundamentally, players' performance is an important factor in raising the winning percentage of the team. Hakes and Sauer (2006) reported that the contributive performance for team winning is the "On-base percentage (OB)" rather than the "Slugging percentage (SL)", which supports the hypothesis of "*Moneyball*". Moreover, Demmink (2010) described with MLB data that a stolen base contributes to increasing the winning percentage. These results suggest that a higher on-base percentage or stolen base is more important than the slugging percentage for winning, although spectators prefer the showy performance of MLB. Consequently, a first purpose of this paper is to verify whether Japanese baseball holds to the *Moneyball* hypothesis or not.

However, regarding player salaries, Hakes and Sauer (2006) showed that sluggers with a high slugging percentage get a higher salary than players with a high on-base percentage. They emphasized that an inefficiency prevails in the MLB labor market. The possibility exists that high salaries tend to be paid for sluggers, who attract many baseball fans, rather than the players playing a devoted performance. Healy (2008), using the data of free agent players for 1985–2004, analyzed which performance affects player salaries, presenting results showing that player salary depends on the latest results of performance. The possibility exists that some general managers of a team tend to determine the salary of players based not on a comprehensive investigation of player performance in several years, but only the latest results of performance, based on which they get an impression of players. He proves the availability heuristic possibility as to memory. Apparently, it is easy for sluggers to obtain a higher salary rather than that of a player with a high on-base percentage in the contract in MLB because general managers are impressed by sluggers rather than high on-base percentage players because of the availability heuristic possibility.

Consequently, the possibility exists that the determination of a player's salary is not estimated by a player's exact performance such as the on-base percentage and slugging percentage, which describe productivity but affected by other factors which are psychological factors particularly. Moreover, we analyze the determination of a player's salary in terms of behavioral economics, which specifically examine mental action in human decision-making.

The Peak-End Effect is that by which the most impressive and final parts are assigned greater important when people make a decision based on past memory. Redelmeier and Kahneman (1993) study the Peak-End Rule by estimating pain that occurs with the colonoscopic inspection. We examine whether the Peak-End Effect holds for the estimation of professional sports players. Following the Peak-End Rule, a player's salary depends on performance at the peak of the season and final results. Moreover, we analyze whether the determinacy of a player's salary depends on a score in peak activity and final activity using data of Nippon (Japanese) Professional Baseball (NPB), or not, which is a second purpose of this paper.

The organization of this paper is the following. The next section outlines the dataset, which we use in our analysis, and constructs a regression model to analyze which aspect of performance contributes to the winning percentage. Section 3 presents the salary determination mechanism. Section 4 describes our examination of whether the Peak-End Effect holds in the case of NPB. Finally, we conclude our report.

2. Model of contribution to winning

This study collected data released by the NPB of all 12 Japan professional baseball teams during 2005–2012. The NPB introduced Interleague Play between the Central League and the Pacific League from 2005. Each team thereafter played games with teams of the other league during the regular season. Hakes and Sauer (2006) conducted a panel data analysis of Major League Baseball (MLB) data obtained during 1998–2003.

In this section, we use panel data of the team's winning percentage, a team's own on-base percentage, the on-base percentage of its opponent, a team's own slugging percentage, the slugging percentage of its opponent to examine the relation between each team's winning percentage and its performance. The on-base percentage is defined as the fraction of plate appearances at which the player reached first base after either a hit or a walk. The slugging percentage is the total bases (= singles×1+doubles×2+triples×3+home runs×4) divided by at-bats. The descriptive statistics of respective variables are shown in Table 1.

Table 1 Descriptive statistics of Winning percentage and Performance

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Win	96	0.500	0.078	0.281	0.667
On-base	96	0.322	0.013	0.296	0.352
On-base against	96	0.322	0.009	0.302	0.336
Slugging	96	0.385	0.034	0.316	0.458
Slugging against	96	0.385	0.027	0.332	0.419

The winning percentage, which is the dependent variable, is the product of division of the number of winning games by the number of total games from which the number of tied games is subtracted. The mean winning percentage is 0.500. The minimum value is 0.281 of Tohoku Rakuten Eagles in 2005. The maximum value is 0.667 of the Tokyo Yomiuri Giants in 2012. The independent variable is a team's own on-base percentage (On-base), the on-base percentage of its opponent (On-base against), a team's own slugging percentage (Slugging), and the slugging percentage of its opponent (Slugging against). The mean of the On-base percentage is 0.322. The minimum value is 0.296 of Yokohama Baystars. The maximum value is 0.352 of Chiba Lotte Marines. The mean of the On-base against is the same 0.322 as that of the On-base. The mean of Slugging is 0.385. The minimum value is 0.316 of Hanshin Tigers. The maximum value is 0.458 of Tokyo Yomiuri Giants. The mean of Slugging against is the same 0.385 as that of Slugging.

Following Hakes and Sauer (2006), we use a logarithmic linear regression analysis to confirm the effect of the on-base percentage and the opponent's on-base percentage on winning percentage:

$$\ln(\text{win})_{it} = \beta_0 + \beta_1 \ln(\text{OB})_{it} + \beta_2 \ln(\text{OBA})_{it} + \varepsilon, \qquad (1)$$

where win, OB, OBA, and ε respectively denote the winning percentage, on-base percentage, opponent's on-base percentage, and an error term. Therein, i is the name of team; t is time. Regarding OBA, we weighted the ratio of the game to each team for the number of all games in a season. Using official data of NPB during 2005–2012, we estimated the relation between the winning percentage and on-base percentage using logarithmic linear regression analysis. As a result of model (1) in Table 2 shows, an increase by one percentage point of the own team's on-base percentage brings an increase of about three percentage points of the team's winning percentage. However, we know that the correlation between the team's winning percentage and the opposing team's on-base percentage is negative. Baseball is a game in which teams scramble for points. The number of runners who come back to home base becomes the score of baseball. Consequently, as the number of one's own team's runners increases, the team has increased opportunities to score runs in the game. However, it is difficult for one's own team to win the game when the opposing team scores many runs because one's own team must score more runs than the opposing team does. Moreover, this model shows that the team's own on-base percentage and the opponent's on-base percentage explain 38.0 percent of the variation in winning percentage. Comparison of our results with those of Hakes and Sauer (2006) shows that our results are similar to theirs. However, although the team's own on-base percentage and the opposing team's on-base percentage in the United States can explain 82.5 percent of the variation in the winning percentage, those in Japan can explain 38 percent of the variation in winning percentage.

Next we consider the impact of the slugging percentage of either one's own or an opposing team on one's own team's winning percentage. Next we specify the following logarithmic linear regression model to ascertain the effect of the slugging percentage and the opponent's slugging percentage on the winning percentage.

$$\ln(\text{win})_{it} = \beta_0 + \beta_1 \ln(\text{SL})_{it} + \beta_2 \ln(\text{SLA})_{it} + \varepsilon, \tag{2}$$

Therein, SL and SLA respectively denote one's own team's slugging rate and the opponents' slugging rate. Regression results shown that the own team's slugging rate engenders an increased winning percentage of one's own team. Moreover, the relation between the slugging percentage of opponents and the winning percentage of one's own team has a negative coefficient. Comparing the coefficient of

Table 2 Effect of on-base and slugging percentage on winning

win	Model 1	Model 2	Model 3
Constant	-0.831	-0.744 (-3.029)	-0.680 (-0.588)
On-base	3.052 (7.120)***		2.575 (5.101)***
On-base against	-3.164 (-4.956)***		-2.477 (-1.722)*
Slugging		1.195 (4.648)***	0.534 (2.009)**
Slugging against		-1.237 (-3.631)***	-0.627
Number of observation	96	96	96
R^2	0.38	0.20	0.40

Notes: Numbers in the upper row are coefficients. The number in parentheses is *t*-statistic. Coefficients were obtained using ordinary least squares. ***, ** and * respectively indicate statistical significance at the 1%, 5%, and 10% levels.

determination of model (2) with that of model (1) reveals that the coefficient of determination of model (1) is larger than that of model (2). Although the on-base percentage of one's own and opposing teams can explain the variation in winning percentage, the slugging percentage of one's own team and opposing teams can explain only 20.0 percent of the variation in the winning percentage. The on-base percentage of one's own team can contribute more to the winning percentage than the slugging percentage can.

Here we combine these measures and consider the impact of on-base percentage and the slugging percentage of either one's own team or opposing teams on one's own team's winning percentage. We specify the logarithmic linear regression model as

$$\ln(\text{win})_{it} = \beta_0 + \beta_1 \ln(\text{OB})_{it} + \beta_2 \ln(\text{OBA})_{it} + \beta_3 \ln(\text{SL})_{it} + \beta_4 \ln(\text{SLA})_{it} + \varepsilon, \quad (3)$$

from which we know that the coefficient of one's own team's on-base percentage is larger than that of the slugging percentage. However, the slugging percentage of opposing teams was not statistically significant. The coefficients in model (3) for on-base percentage are more than five times as large as the coefficient for slugging. Consequently, the on-base percentage represents a more important contribution to winning games than the slugging percentage. By the analysis of Hakes and Sauer (2006), the coefficients in similar regression for on-base percentage are more than twice as large as the coefficients for slugging. Therefore, a method that does not include slugging affects the winning percentage for Japanese professional baseball teams.

Therefore, we know that the effect of the On-base percentage in NPB on the winning percentage is higher than the effect of the On-base percentage in MLB on winning percentage. We can interpret that this difference of results between NPB and MLB are that baseball in NPB assigns value to *smaller* baseball, which entails sacrifice hitting or bunting more than in MLB.

3. Model of Salary Determination

In the previous section, we analyzed player performance effects on the team winning percentage. We showed that the On-base percentage contributed to the team's winning percentage more than the Slugging percentage in NPB as well as MLB. The effect level of the winning percentage of the On-base percentage was about five times that of the Slugging percentage in NPB. Moreover, the effect level on the winning percentage of the On-base percentage was about twice that of the Slugging percentage in MLB according to Hakes and Sauer (2006). We consider which factor affects a player's salary in this section. Most baseball players in Japanese professional baseball negotiate an annual salary after the season ends with teams for which they play. In the process, the player's salary is always determined in light of the results that a player posted during the season. In actuality, it is difficult to determine the player's salary with a uniform standard because the characteristics of each player differ, as do the needs of teams. This section assesses which aspects of player performance affect a player's salary.

We use the data of performance (on-base or slugging) and the annual salary of each player derived from the homepage of NPB and *Professional Baseball Players Who's Who* during 2006–2012[4]. The descriptive statistics of respective variables are shown in Table 3.

Table 3 Descriptive statistics of Salary and Performance

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Salary	398	157.023	119.502	5.000	650.000
On-base	398	0.347	0.033	0.263	0.453
Slugging	398	0.427	0.079	0.271	0.665

The salaries (million yen), which are dependent variables, are data obtained from the *Professional Baseball Players Who's Who*. We use panel data of all players with regulation at bats during 2006–2012. The mean of salaries is 157.023 million yen. The minimum value is 5 million yen. The maximum value is 650 million yen. The mean of the On-base percentage is 0.347. The mean of the Slugging percentage is 0.427 on all players with regulation at bats.

We consider the relation between the salary in t year and the performance in t-1 year because the player's salary is invariably determined in light of the results that a player posted during the prior season. Here we specify the following model (4), used to estimate the relation between the player's salary and the on-base percentage. We use a logarithmic linear regression analysis.

4 We excluded data in 2005 by the restriction of used data although we used data from 2005–2012 for analyses explained in the previous section.

$$\ln\left(\text{Salary}_t\right) = \beta_0 + \beta_1 \ln\left(\text{OB}_{t-1}\right) + \varepsilon. \tag{4}$$

The datasets used in our estimation are the data of a batter attaining the number of regulation at bats and the data of their on-base percentages in NPB during 2006–2012. Next we specify the following model (5) to estimate the relation between the player's salary and the Slugging rate. We use a logarithmic linear regression analysis.

$$\ln\left(\text{Salary}_t\right) = \beta_0 + \beta_1 \ln\left(\text{SL}_{t-1}\right) + \varepsilon. \tag{5}$$

Table 4 Effects of On-base and Slugging percentage on salary

Win	Model 4	Model 5	Model 6
Constant	8.359	6.401	7.937
On-base	3.365 (9.092)***		1.908 (4.379)***
Slugging		1.864 (9.965)***	1.298 (5.794)***
Number of observations	398	398	398
R^2	0.17	0.20	0.23

Notes: Numbers in the upper row are coefficients; numbers in parentheses is t-statistic.
Coefficients were obtained using ordinary least squares. ***, ** and * respectively indicate statistical significance at the 1%, 5%, and 10% levels.

Next we combine these measures to assess the impact of On-base percentage and Slugging percentage of players on the salary (model (6)).

$$\ln(\text{Salary}_t) = \beta_0 + \beta_1 \ln(OB_{t-1}) + \beta_2 \ln(\text{SL}_{t-1}) + \varepsilon. \quad (6)$$

Table 4 shows that the player's salary in NPB has a positive correlation with the on-base and slugging percentage. From Model (6), the coefficients of the On-base percentage and Slugging percentage are 1.908 and 1.298 respectively; both are significant. A 1 percentage point increase of the On-base percentage in the season increases a salary by 1.908 percent. A 1 percentage point increase of the Slugging percentage in the season increases a salary by 1.298 percent. According to Hakes and Sauer (2006), the respective coefficients of the On-base percentage and Slugging percentage were 1.360 and 2.392 in MLB during 2000–2004. Consequently, the salaries in MLB are evaluated by the slugging percentage rather than the on-base percentage. However, regarding the salaries of NPB players, the on-base percentage valued more highly than the slugging percentage was. A high salary tends to be paid for the players with a high on-base percentage, which contributes to a team's winning in the Japanese labor market of professional baseball players rather than in the case of MLB. Consequently, the Japanese professional baseball teams conduct management following the "*Moneyball Hypothesis*".

5. Peak-End Effect in Salary Determination

We know that players with a high "On-base percentage" receive a high salary. We next consider how the temporary activity of the highest "On-base percentage" during a season or the last stage activity of the "On-base percentage" at the end of a season affect player's salary. The "Peak-End Effect" is the effect on a person's evaluation of great emotional pain or financial loss in the immediately preceding stage. Although a player does not contribute to winning games on average, it is possible that a player who achieved remarkable results and made a strong impression over the short term tends to be paid a high salary. Moreover, when the annual salary of baseball players is determined, general managers tend to have a strong impression of results achieved in September and October, which is nearest the time of contract renewal. We analyze whether this peak-end effect prevails for salaries of professional sports players, or not.

Here we divide the data of On-base percentage to ascertain the performance every month. We analyze how the highest on-base percentage (Peak Effect) or final on-base percentage (End Effect) affects the determination of a player's salary. We obtained panel data of the on-base percentages of all players with regulation at-bats every month (March and April, May, June, July, August, September and October) during 2006–2012 from *Professional Baseball Nul Date Okiba*, <http://lcom.sakura.ne.jp/NulData/index.html>. Table 5 presents descriptive statistics of the highest values in monthly on-base percentage and the values of the final month (September and October) in monthly on-base percentages of all players with regulation at-bats during 2006–2012.

The mean of the highest value in monthly on-base percentage, 0.413, is larger than the mean of on-base percentage "throughout the year" in Table 2. Moreover, the means of on-base percentage of the final month and the on-base percentage "throughout the year" is almost identical.

We construct a salary determination model and conduct regression analysis using data of Highest Value in Monthly On-base and Final Value in Monthly On-base. First, we construct the

Table 5 Descriptive statistics of Highest Value and Final Value of On-base

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Highest Value in Monthly On-base	398	0.413	0.043	0.293	0.525
On-base of Final Month	398	0.344	0.063	0.149	0.525

following logarithmic linear regression model to analyze the "Peak Effect":

$$\ln\left(\text{Salary}_t\right) = \beta_0 + \beta_1 \ln\left(POB_{t-1}\right) + \varepsilon, \tag{7}$$

where POB is the highest value in monthly On-base percentage of players in t-1 year. If we obtain a coefficient derived by the regression of model (7) that is larger than the coefficient of OB in model (4), then we can infer a "Peak Effect". Although a player does not contribute to winning games on average, it is possible that a player who posts remarkable results and makes a strong impression in the short term tends to be paid a high salary. For example, although Takashi Toritani, who played for Hanshin Tigers in 2010, had an On-base percentage of 0.373 during the whole 2010 season, his On-base percentage was 0.504 on August in 2010. Consequently, his salary was changed to 260 million yen from 160 million yen.

Next we construct the following model to analyze the "End Effect":

Table 6 Effect of on-base, Peak on-base and End on-base in salary determination

Win	Model 4	Model 7 (Peak Effect)	Model 8 (End Effect)
Constant	8.359	7.058	6.150
On-base Peak On-base End On-base	3.365 (9.092)***	2.555 (7.339)***	1.256 (6.796)***
Number of observations	398	398	398
R^2	0.17	0.12	0.10

Notes: Numbers in the upper row are coefficients. Numbers in parentheses are *t*-statistics.
The coefficients were obtained using ordinary least squares. ***, ** and * respectively indicate statistical significance at the 1%, 5%, and 10% levels.

$$\ln\left(\text{Salary}_t\right) = \beta_0 + \beta_1 \ln\left(EOB_{t-1}\right) + \varepsilon, \tag{8}$$

where EOB is the final value in monthly On-base percentage (on September and October) in *t*-1 year. Similar to the analysis of model (7), if the coefficient derived from model 8 is larger than the coefficient in model (4), then we can recognize an “End Effect”.

When the annual salary of baseball players is determined, the General Manager tends to have a strong impression of results in September and October, which is the time nearest to contract renewal. Moreover, September and October is the end of the season. They are the months during which play is particularly important for a team competing for a championship. Therefore, we can consider that it is natural to increase the assessment of players who made the greatest impact during that time. Presuming that we consider two players posting the same average on-base percentage during the season, the player who did not show good results in the first half and showed them in the second half will tend to receive a higher assessment than the player who shows good results in the first half and did not show them in the second half.[5] We estimate model (7) and model (8) using each month's On-base percentage data of the On-base percentage and annual salary which 398 players in NPB who established regulation at-bats during 2006–2012. We compared those estimations with that of the model (4) in Table 4. For POB, the coefficient is 2.555 and is significant. Namely, a 1 percentage point increase of the On-base percentage on peak month in the season increases a player's salary by 2.555 percent. The coefficient of EOB is 1.256 and significant. Consequently, a 1 percentage point increase of the On-base percentage on September and October in the season increases a salary by 1.256 percent. Comparing these coefficients, we know that the "Peak Effect" on the player's annual salary is about

[5] Tomotaka Sakaguchi of the ORIX Buffaloes posted a total On-base percentage 0.371 in 2010. This result was lower than the total On-base percentage of 0.371 in 2009. However, his salary in 2011 increased from 65 million yen to 100 million yen because his September On-base percentage in 2010 was 0.478, which was extremely high.

twice as large as the effect of "End effect". Moreover, comparing the coefficients in model (4), we know that the effect of OB on the player's annual salary is greater than the effect of either POB or EOB on it. Here we add an economic interpretation to these results. There is little effect of both Peak Effect and End Effect on the assessment of baseball players in NPB. Therefore, NPB general managers assess the results of the whole season rather than temporary results in particular months under the annual salary determination system in NPB. Although most previous studies of Peak-End Effect evaluated the degree of pain, the value assessment of professional baseball players is based on an objective index such as the On-base percentage. Consequently, it is difficult to show any bias such as a "Peak-End Effect".

We analyzed all players in the aggregate. However, it will be necessary to do grouping with annual salaries in NPB and to analyze every group because the annual salary extends from a minimum 5 million yen to 650 million yen, as shown in Table 3. Now we define the groups as follows. Players earning over one hundred million yen are categorized in group 1. The other players are categorized in group 2. The numbers of samples of group 1 and group 2 are, respectively, 249 and 149. The average annual salary of group 1 is 215.868 million yen; that of group 2 is 58.685 million yen, as shown in Table 8. Consequently, the difference of the average annual salary between the two groups is greater than 150 million yen.

First, we analyze whether the effect of the On-base percentage on annual salary of players in group 1 differs from that in group 2 or not. Next we assess the existence of a Peak-End Effect. We try to apply either group 1 or group 2 to model (4), model (7) and model (8). From estimation, we present those results in Table 8 and Table 9. Here all coefficients of model (4), model (8), and model (9) for both groups are significant. Comparing the coefficient of the On-base percentage in group 1 with that in group 2, we understand that the coefficient 1.730 for group 1 is larger than that 1.169 for group 2 from Columns 1 of Table 5 and Table 6. Consequently, the effect from 1% increase of the On-base percentage of players in group 1 is larger than that in group 2. This result means that an increase of

Table 7 Descriptive statistics across Salary Groups

Sample Means	Obs.	Salary (million yen)	On-base percentage	Highest Value in Monthly On-base	Final Value in Monthly On-base
Group 1 (Salary $\geq$ 100 million yen)	249	215.868	0.355	0.421	0.356
Group 2 (Salary < 100 million yen)	149	58.685	0.334	0.399	0.322

that the increase of 1 percentage point of the On-base percentage is reflected in the annual salaries of famous players rather than the annual salary of a lower than average players because the value of one hit is extremely high for famous players earning a high annual salary.

Does a Peak-End Effect apply for each group? Table 8 shows that, although the coefficient of the On-base percentage of group 1 in the whole season is 1.730, the coefficients of the On-base percentage in peak month and in final month are 1.033 and 0.593, respectively.

Therefore, the On-base percentage of group 1 in the whole season affects the annual salary determination most. Similar to results obtained without grouping data, we infer no Peak-End Effect

Table 8 Peak-End Effect in Group 1

Win	Model 4 (Group 1)	Model 7 (Group 1)	Model 8 (Group 1)
Constant	7.062	6.160	5.884
On-base Peak On-base End On-base	1.730 (6.174)***	1.033 (3.798)***	0.593 (3.796)***
Number of observations	249	249	249
R^2	0.13	0.05	0.05

Table 9 Peak-End Effect in Group 2

Win	Model 4 (Group 2)	Model 7 (Group 2)	Model 8 (Group 2)
Constant	5.274	5.143	4.418
On-base Peak On-base End On-base	1.169 (2.558)**	1.248 (3.303)***	0.373 (2.118)**
Number of observations	149	149	149
R^2	0.04	0.06	0.02

for annual salary determination in group 1. However, from Table 9, although the coefficient of the On-base percentage of group 2 in the whole season is 1.169, the coefficient of the On-base percentage in final month is 0.373. Consequently, no End Effect is detected in this estimation. However, the On-base percentage in peak month affects the annual salary in group 2 strongly because the coefficients of the On-base percentage in peak month are 1.248, which is larger than 1.169 for the whole season. A Peak Effect is inferred in this case. We can add the following economic interpretation to this result. Because professional baseball general managers have some prejudice that players earning an annual salary over one million yen show good results naturally, a good result in a particular month does not impress them much. However, if players who do not earn over one million yen show splendid results in a particular month, then their results strongly impress general managers. Consequently, that impression affects the annual salary of those players.

When general managers assess a player's annual salary, they do so based on an objective index such as the On-base percentage or Slugging percentage. Consequently, it is easy for them to exclude Peak-End Effect bias. However, general managers have no prejudice for players without actual results and are affected by temporary results shown by those players. In this case, it is difficult for them to exclude Peak-End Effect bias.

6. Concluding Remarks

Following Hakes and Sauer (2006), we analyzed the effect of on-base percentage and slugging percentage on the winning percentage in Japanese professional baseball. We constructed a regression model to analyze which performance contributes for determining the player's salary. Moreover, we considered how the temporary results affect a player's salary: the highest "On-base percentage" in the season or the last stage activity which is the "On-base percentage" in the end of season. We examined the Peak-End Effect in salary determination. The result is the following.

As explained in section 2, we found that the on-base percentage makes a more important contribution to winning games than the slugging percentage. Results show that the effect of the on-base percentage in Japanese Baseball League on the winning percentage is greater than the effect of the on-base percentage in MLB on the winning percentage. Section 3 describes that a player's salary in

NPB has a positive correlation with on-base and slugging percentage. In the salary determination of NPB players, results show that the on-base percentage was assigned a greater value than the slugging percentage. That characteristic differs from MLB, which evaluates players by the slugging percentage rather than on-base percentage according to Hakes and Sauer (2006). Section 5 described the stronger effects on the player's salary determination of a long-term activity, the “On-base percentage”, throughout the season is greater than the effect of temporary activity, the highest "On-base percentage", in the season, or the last stage activity, which is the “On-base percentage" in the end of season. However, results show that a temporary activity, the highest "On-base percentage" in the season, has a larger effect than the long-term activity, the “On-base percentage” throughout the season, when general managers evaluate no famous player earning a salary below 100 million yen. Therefore, it is difficult for them to exclude Peak-End Effect bias.

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