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Apply Production Efficiency to Assess the Pay Equity of Chinese Professional Baseball Pitchers

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Abstract — People perceive inequity whenever they sense that the ratios between the outcomes they have obtained and their inputs do not equal the ratios for their counterparts. This argument represents the same logic that data envelopment analysis (DEA) applies to measure the relative efficiency using several inputs to produce a single output or a set of outputs. This study applies DEA to performance data in year 2007 for 43 pitchers of the Chinese professional baseball league (CPBL) and to estimate the proportion of pitchers who perceived their signed salaries for the next year were paid with inequity. Each pitcher is treated as a decision-making unit. The input variables include the numbers of innings pitched, the pitchers' earned run averages, and walks plus hits per inning pitched, while the single and most important output is the pitcher's salary for the next year (2008). The results show that approximately 91% CPBL pitchers (39 out of 43) perceived that they received relatively low salaries. Moreover, underpayment inequities were prevailing for both starting pitchers and relief ones without significant differences.

Keywords — data envelopment analysis (DEA), pay equity, pitcher's performance, Chinese professional baseball league (CPBL)

1. INTRODUCTION

Baseball is considered a national sport in Taiwan. As of this year 2011, the Chinese professional baseball league (CPBL) has been operating, though with ups and downs, for twenty-two years. To improve the standards of baseball in Taiwan, reviews must be made regarding the abilities of professional baseball players in the country, in which salaries play a deciding role. A good payment system strengthens the structure of the organization and its business culture; in other words, giving appropriate remuneration to workers who perform exceptionally helps motivate them to continue contributing to the organization. Pay equity refers to the equality between the ratio of a person's efforts and pay, compared with those of other people. Adams (1963) stated "…people perceive inequity whenever they perceive that the ratios between the outcomes they have attained and their inputs do not equal the ratios for social referents…" This argument represents the same logic that data envelopment analysis (DEA) applies to objective data.

DEA is a mathematical programming approach for measuring the technical efficiency of units, such as the branches of a bank and schools or hospitals under some controlling body, performing the same function. Such units are referred to as decision-making units (DMUs). DEA works by estimating a piecewise linear envelopment surface, or the "best-practice frontier." This journal IJOR recently published two articles related to DEA. Amin and Emrouznejad (2007) applied the inverse linear programming into DEA field to provide an alternative approach which is capable to determine all the efficient DMUs and speed up the computations of the so-called "additive" model; Gupta *et al.* (2008) analyzed the performance of the Indian banking sector through the construct of productive efficiency. Besides the pre-mentioned, Bowlin *et al.* (1985) compared DEA with regression in accessing the performance of 15 hypothetical hospitals and found DEA provides the advantage of being able to identify the sources of inefficiency. Thanassoulis (1993) restricted the comparison to DMUs which either use a single resource or produce a single output; the comparison revealed that DEA offers more accurate estimates of relative efficiency because it is a boundary method basing estimates on efficient rather than average performance, and the estimates are not affected by correlations and multi-collinearity between inputs and outputs. Though DEA can be alternatively interpreted as nonparametric least-squares regression subject to shape constraints on the frontier, Kuosmanen and Johnson (2010) concluded DEA outperforms regression in general; this is because DEA is the approach producing a maximizing or minimizing solution, whereas regression is based on central or average tendencies. Most recently, Krivonozhko *et al.* (2011) showed that using ratio analysis implies a one multi-dimensional space is projected onto other subspaces many times, and this causes significant distortion of the performance assessment of units; their computational experiments on the financial data validated that DEA outperforms other techniques such as ratio analysis and regression

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approaches as alternative methods in performance assessments. Therefore, this article will utilize DEA to produce efficiency metric indicating the degree to which compensation is proportional to the performance variables for each of the baseball pitchers.

Baseball is a bat-and-ball sport played between two teams of nine players each (from Wikipedia, http://www.wikipedia.org/). Baseball players are characterized by positions, and the pitchers are naturally the most important because their performance criteria are essentially different from those of fielders. According to the CPBL website (http://www.cpbl.com.tw/) reporting the annual salary for pitchers from 2005 to 2010 (accessed on July 15, 2010), the highest-paid pitchers earn six million new Taiwan dollars (NTD) a year, which is approximately a mere of 5~10% of the pay received by new recruits of major league baseball (MLB, http://www.mlb.com/) teams in the US. However, to our best knowledge, there is not yet any performance evaluation research on pitchers in MLB and other teams; in literature there is even a lack of discussion regarding pay equity among professional baseball pitchers. Analyzing the pay and performance relationships is a difficult issue, but without any doubt, pay equity is important to peer's perception and much influential to any one's performance.

This article contributes to assessing the pay equity of Chinese professional baseball pitchers by demonstrating that DEA shows the promise for generating objective estimates for this purpose. Using the performance data in season 2007 for 43 pitchers of the CPBL and their next-year salaries signed by their teams at the end of year 2007, this study is to estimate the proportion of these pitchers who perceived inequity that their signed salaries were under-paid. To the best of our knowledge, this would be the first article in operations research (O.R.) applying production efficiency on pitchers' salaries. The remainder of this paper is structured as the follows. Section 2 outlines literature review. Section 3 describes the methods employed, including DEA, in the current study. Section 4 reports the empirical results and the final section offers concluding remarks.

2. LITERATURE REVIEW

Even in the O.R. literature, e.g., Sherman and Zhu (2006), DEA has been proved to be useful in evaluating service performance. Studies that have applied DEA in sports is rich, however, the relevant literature to this research can be divided into two categories as follows.

2.1 DEA in Baseball Player's Performance

DEA provides more objective and fairer results than other methods in assessing baseball player's performance. Anderson and Sharp (1997) used DEA to create an alternative measure called the Composite Batter Index (CBI). Advantages of CBI over traditional statistics include the fact that players are judged on the basis of what they accomplish relative to other players and that it automatically accounts for changing conditions of the game that raise or lower batting statistics. Sueyoshi *et al.* (1999) proposed a new analytical approach for baseball evaluation by combining DEA with offensive earned-run average. An important feature of the proposed approach is that it can select a best performer among many baseball players and their ranking scores. Sexton and Lewis (2003) applied a two-stage DEA to performance evaluation of thirty teams from the MLB in 1999. Their model detects inefficiencies that standard DEA models miss, and it can allow for resource consumption that the standard DEA model counts towards inefficiency. Lewis and Sexton (2004) further extended their model with a network of intervening steps between the entering inputs and exiting outputs, and proved some theoretical properties of the network DEA model. Lin *et al.* (2005) demonstrated the usefulness of the two-stage DEA in assessing the aggregated performance of six professional baseball teams in Taiwan. Lin (2007) applied DEA as a relatively efficient measurement for obtaining the decreasing rankings of the Chinese Taipei's participating in the last five Asian Games; time series analysis was then utilized to exam the productivity changes of Chinese Taipei Olympic Committee since its return from Beijing 1990 to Doha 2006. More recently, Lin and Chang (2008) utilized the fuzzy analytic hierarchy process to classify the performance evaluation indices; they also analyzed the data from the 17th program of CPBL with technique for order preference by similarity to ideal solution and examined professional baseball catchers' performance.

2.2 DEA in Player's Pay to Performance

There are many articles studying the relationship between pay and performance. To name a few, Ferris (1982) indicated that there is little relationship between educational background and subsequent on-the-job performance of professional accountants; no relationship was found between academic performance and public accounting compensation. Dharmapala *et al.* (2007) used goal programming to investigate pay equality of faculty among different colleges in universities, in order to inspire the equalization of salary levels between colleges. Fung (2009) suggested that innovativeness and executive pay-performance sensitivity are inversely related from the pooled sample by econometric time series. However, methodology in the above mentioned is not based on the applications of production efficiency. Mohan and Ruggiero (2003) was the first to apply DEA to investigate whether there were differences in salary levels between male and female CEOs; results showed that male CEOs receive higher salaries than female CEOs.

In the literature, there is a lack of discussion regarding pay equity among professional baseball pitchers and only few articles relate baseball players' salary to their performance. Mazur (1995) used DEA to assess the relative efficiency values and showed that there exists a correlation between the efficiency value rankings and the individual baseball player's performance. Depken (2000) used panel data approach to test the effect of wage disparity on MLB team performance and concluded that greater wage disparity reduces overall team productivity. Hadley and Ruggiero (2006) used nonparametric statistics to calculate the relative efficiency of MLB players to assist teams in salary arbitration for pitchers and other players as well. Stiroh (2007) examined contract-related incentive effects on individual performance using a dataset from professional basketball players in the 1980s and 1990s; the results showed that individual performance improves significantly in the year before signing a multi-year contract but declines after the contract is signed.

3. METHODOLOGY

This article intends to apply DEA to estimate the proportion of the underpayment among CPBL pitchers and to determine whether there exist differences in pay inequity between two groups of starting pitchers and relief pitchers by using non-parametric statistical tests.

3.1 DEA models

Based on earlier work initiated by Farell (1957), Charnes *et al.* (1978) formulated the DEA model as a fractional linear program, also called the CCR (Charnes-Cooper-Rhodes) model, where each operating unit of a group of DMUs transforms multiple inputs into a single output or a set of multiple outputs. This efficiency measure is constrained so that the weights selected must be feasible and cannot result in an efficiency ratio greater than 1.0, which is the one observed for the most "relatively efficient" units. Those relatively efficient DMUs in the group define a piecewise linear surface called "efficiency frontier." Input-output relationships for the remaining DMUs are then evaluated relative to this efficiency frontier. This study applies DEA in identifying "pay-efficient" and underpaid, inefficient baseball pitchers based on the relationship between three inputs (performance indices this year) and one output (contract salary for the next year) of each DMU (pitcher). As illustrated in Figure 1, each heavy dot represents one DMU or one pitcher. Line L is calculated by the least squares regression method, while the piecewise connection of P-Q-R-S represents the efficiency frontier, forming a convex boundary. Pitchers on the frontier are "efficient" in maximizing the payout for their performance inputs. Efficient pitchers are identified in the computer output with efficiency values, or "equity metrics," equal to 1.0.

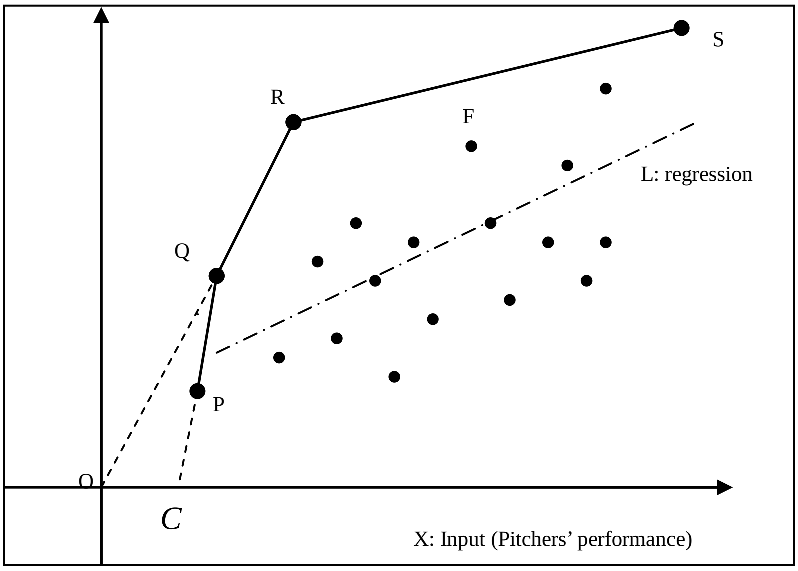

Figure 1. The efficiency frontier and the regression line

CCR models assume the constant returns to scale relationship between outputs and inputs, which does not necessarily hold in studying pay-for-performance. Hirao (2012) found most public business schools exhibit increasing returns to scale (IRTS); hence, schools that exhibit IRTS will experience more than proportionate increase in starting salary of their graduates by raising the quality of inputs such as average Graduate Management Admission Test scores. Unlike the restriction of constant returns to scale, the BCC model proposed by Banker *et al.* (1984) allows variable return to scale relationship between the inputs and the outputs. Moreover, since each pitcher have more control over his performance rather than his next-year salary, the input-oriented approach is utilized as the decision maker can control inputs but not the outputs. The input-oriented BCC model produces a scalar efficiency measure for each pitcher by selecting weights that maximizes the ratio of a linear combination of the pitcher's signed salary less a constant for returns to scale to a linear combination of his performance inputs. Each pitcher's ratio is to be maximized subject to every pitcher's ratio be one, at the most. In the input-oriented BCC model, the technical efficiency measure of the specific k_0-th DMU (pitcher) is formulated as follows.

$$\text{Max} \qquad h_{k_0} = \frac{\sum_{j=1}^{J} v_j \cdot Y_{jk_0} - C}{\sum_{i=1}^{I} u_i \cdot X_{ik_0}} \tag{1}$$

$$\text{Subject to} \quad h_k = \frac{\sum_{j=1}^{J} v_j \cdot Y_{jk} - C}{\sum_{i=1}^{I} u_i \cdot X_{ik}} \leq 1 \ ; \quad k = 1, \cdots, k_0, \cdots, \ n, \tag{2}$$

where notations are defined as:

n = the number of DMUs or n = 43 pitchers in this study;
X_{ik} = the i-th input of the k-th DMU; $i = 1, \cdots, I$; in this study, $I = 3$;
Y_{jk} = the j-th output of the k-th DMU ; $j = 1, \cdots, J$; in this study, $J = 1$;
u_i = the relative weight of i-th input; and
v_j = the relative weight of j-th output.

Note that $\{ u_i, v_j \}$ are decision variables and should be greater than a very small positive number, $\varepsilon > 0$. If the variable return to scale intercept C in equation (1) equals zero, then the returns to scale in BCC model reduces to be constant as that in CCR one. The scalar efficiency measure h_k in equation (2) represents the equity metric of the k-th DMU. When $h_k = 1$, the k-th DMU is on the efficiency frontier; if $h_k < 1$, then the k-th DMU (pitcher) is not on the frontier.

Pitchers not on the frontier represent relatively inefficient and underpaid perception; they are identified with "equity metrics" less than 1.0. The size of the equity metric indicates the proximity of a pitcher to the efficiency frontier. For example, in Figure 1 if pitcher F's equity metric were 0.82, it would suggest that pitcher F's output is 82 percent of it would be at the frontier line segment R-S. Since DEA formulation guarantees that the equity metric is maximized for all observations, there are no other weights that could be attached to either inputs or outputs of pitcher F to produce a larger equity metric. Consequently, the analyzed pitcher with efficiency value less than 1.0 must be objectively underpaid.

3.2 Non-parametric Tests

DEA does not presume the production functions between inputs and outputs, it is a nonparametric or distribution-free analysis; nonparametric tests as in Aczel and Sounderpandian (2006) thus can be applied in determining statistical differences in measures between two groups. In Brockett and Golany (1996), the Mann-Whitney (M-W) test, or called Wilcoxon rank sum test, was used to judge whether two independent samples come from populations with the same distribution. In this study we utilize the M-W statistic to test whether there are differences in DEA efficiency measures between the starting pitchers and relief ones. When the p-value is less than the significance level $\alpha = 0.05$, we reject the null hypothesis that two groups of pitchers have the equal means of efficiency measures.

4. EMPIRICAL DATA

Our data consisted of pitchers' performance inputs in the 2007 season and their salaries signed for the next contractual year 2008. During this research period, the CPBL consisted of six teams including Uni Lions, La-new Bears, Brother Elephants, Sinon Bulls, Macoto Cobras, and China-trust Whales; the last two teams did not exist in late 2009, which thus did not overlap and influence this research. According to CPBL rules, every team has to play 100 games each year, and there are 9 innings in a game under normal circumstances. Nevertheless, there are a few exceptions due to heavy rain forcing games to be stopped midway, or both teams scoring a tie after nine innings, forcing an extension game. Overall, there will be approximately 900 innings of pitches needed for each team annually. Those who pitched more than 20 innings in the CPBL 2007 season were selected for study in this article and this number comes to be 43. Table 1 shows the distributions among teams of these qualified 43 pitchers in the beginning of 2007 and their salaries for the next year (2008) singed at the end of 2007. As each pitcher served as a DMU in this study, each one was coded a unique number from P1 to P43. In this way if pitchers were later traded to other teams, their records could be still useful.

Table 1. The pitchers' codes in the 2007 season and the statistics of their signed salaries (in NTD 10,000) for the next year (i.e., year 2008)

Team (no. of pitchers)	Pitcher's codes in season 2007	Annual average in the team	Max. in the team	Min. in the team
Uni Lions (10)	P1~P10	160.20	552	66
La-new Bears (9)	P11~P19	142.68	216	96
Brother Elephants (6)	P20~P25	95.04	156	78
Sinon Bulls (6)	P26~P31	142.80	282	60
Macoto Cobras (5)	P32~P36	151.20	276	96
China-trust Whales (7)	P37~P43	140.52	216	84

Notes: The first four teams survived in CPBL till now (2011), while Macoto Cobras and China-trust Whales teams no longer existed in late 2009.

4.1 The Single Output Variable

This study utilizes the mathematical models in DEA and forms the traditional efficiency frontier by signed salary relative to the pitcher's performance. The signed salary for the next year is naturally the single and most important output for each pitcher, which is though determined by the teams. Salary data for 43 pitchers were drawn from the website of CPBL and newspaper reports alike, where listed their base salaries and singing bonuses for the term of guaranteed contracts in 2008. Each pitcher's annual salary in this study represents the sum of his signed base and singing bonus for the year. Note that the average of all 43 pitchers' annual salaries, reported in Table 1, is around 140.8 ten-thousand NTD, while the relatively large standard deviation (about 82.6 ten-thousand NTD) reveals that pitcher's pay differentiates a lot. One pitcher in team Uni Lions enjoyed the maximal annual salary at 552 ten-thousand NTD, and the team in which pitchers were paid with the least average of 95 ten-thousand NTD is Brother Elephants.

Table 2. Example of the single output (annual salary in NTD 10,000) and 3 inputs (IP, 1/ERA, 1/WHIP) data for pitchers of Uni Lions

Pitchers of Uni Lions in 2007	Signed salary for year 2008	IP	1/ERA	1/WHIP
P1	180	68.67	0.272	0.667
P2	66	34.67	0.214	0.709
P3	96	33.00	0.204	0.870
P4	108	50.67	0.171	0.524
P5	120	78.67	0.190	0.581
P6	552	123.33	0.442	0.862
P7	108	20.00	0.317	1.000
P8	120	29.00	0.358	0.909
P9	156	20.00	0.370	0.870
P10	96	33.67	0.125	0.474

4.2 Three Input Variables

The input-oriented DEA model allows the decision makers have more control on their inputs, in this study, three input variables are selected to well represent the pitchers' performance in season 2007. Firstly, the number of innings pitched (IP) by each pitcher is automatically one of the best choices. Pitchers who have more innings pitched are considered to contribute more to their teams. Secondly, the earned run average (ERA) is frequently used by the MLB in the United States as an index to evaluate pitchers' average earned runs surrendered in nine innings. For each pitcher,

*ERA = (number of earned runs*9)/ number of innings pitched.*

As the lower ERA implies the better pitching, and this is opposite to the DEA isotonicity, thus the inverse of earned run average (1/ERA) is adopted for another input variable. Finally, the number of walks and hits per inning pitched (WHIP) is considered; the WHIP has recently become an increasingly important evaluation index used by the MLB. For each pitcher,

WHIP = (number of hits and walks)/ number of innings pitched.

Again, the smaller WHIP value implies the pitcher's better performance, to meet the DEA isotonicity the reciprocal of WHIP (1/WHIP) is used as the third input variable. Ali and Seiford (1990) proved that DEA preserves the translation invariance and justified the resulting technical efficiency values remain the same. Table 2 gives an example of the three input data (IP, 1/ERA, 1/WHIP) for 10 pitchers in the Uni Lions team, where the values of IP, ERA, and WHIP are drawn from their performance data in season 2007.

5. RESULTS AND ANALYSIS

This study classifies pitchers into either starting or relief positions based on the MLB official categorization. Starting pitchers are defined as pitchers who played as starter more than twice the number of times they were in the position of relief pitcher; relief pitchers, on the other hand, are defined as pitchers who played as relief pitchers more than twice the number of times they were in starters. Under this definition, there were five pitchers (P5, P16, P22, P41 and P43) not included in the positioning classification as they played as both starter and relief pitcher at almost the same number of times. While the non-Archimedean infinitesimal constant $\varepsilon = 10^{-4}$ lower bound the decision variables $\{u_i, v_j\}$ in (1) and (2), the public software DEAP by Coelli (1996) is used for DEA efficiency computation. Table 3 presents the distribution of 8 starting pitchers and their DEA efficiency levels as well as their signed salaries. Only one pitcher is identified on the efficiency frontier comparing his salary to his performance, the majority of starting pitchers perceive they were under-paid. Table 4, on the other hand, reports the efficiency values of 30 relief pitchers. There are merely three relief pitchers who did not feel under-paid, though they were not paid the most in their teams. Tables 3 and 4 jointly indicate that there were only four pitchers perceived paid with equity relative to their performance one year before. The codes for these four pitchers are P6 (Lions) in the starting group and P7 (Lions), P9 (Lions), and P11 (Bears) in the relief group. Note that Lions and Bears (renamed as Lamingo Monkeys in early 2011) are the two among the only four CPBL teams surviving till now.

Table 3. The number of games played in 2007, the singed salaries (in NTD 10,000) for 2008, and the DEA efficiency levels for the 8 starting pitchers

Pitchers (Team)	No. of starting games	No. of relief games	Annual salary in 2008	DEA efficiency
P6 (Lions)	21	0	552	1.000
P17 (Bears)	18	9	168	0.342
P24 (Elephants)	19	3	96	0.179
P28 (Bulls)	22	5	60	0.511
P30 (Bulls)	11	4	56	0.460
P34 (Cobras)	21	10	168	0.304
P36 (Cobras)	12	5	96	0.290
P42 (Whales)	12	6	174	0.510
Average	17	5.25	171.25	0.4495

Table 4. The number of games played in 2007, the singed salaries for 2008 (in NTD 10,000), and the DEA efficiency values of the 30 relief pitchers

Team	Relief Pitchers	No. of starting games	No. of relief games	Annual salary in 2008	DEA efficiency
Lions	P1	4	40	180	0.562
	P2	0	39	66	0.311
	P3	0	34	96	0.467
	P4	3	26	108	0.395
	P7	0	13	108	1.000
	P8	0	32	120	0.681
	P9	0	19	156	1.000
	P10	5	13	96	0.461
Bears	P11	0	44	108	1.000
	P12	7	34	168	0.450
	P13	0	37	216	0.761
	P14	11	24	156	0.399
	P15	4	24	120	0.467
	P18	0	17	98	0.525
	P19	0	17	108	0.681
Elephants	P20	0	45	156	0.444
	P21	1	40	84	0.249
	P23	4	19	72	0.293
	P25	3	15	84	0.378
Bulls	P26	4	32	192	0.468
	P27	2	34	144	0.186
	P29	2	19	282	0.327
	P31	0	54	122	0.645
Cobras	P32	1	58	276	0.727
	P33	0	33	96	0.417
	P35	2	25	120	0.391
Whales	P37	6	42	144	0.322
	P38	0	23	84	0.459
	P39	0	32	84	0.453
	P40	6	23	150	0.462
Average		2.17	30.23	133.13	0.5127

Note that those 5 un-classified pitchers (P5, P16, P22, P41 and P43) all have efficiency values less than 1.0, indicating they all perceived under-paid. Tables 3 and 4 also show that there are 87.5% (7 in 8) of starting pitchers and 90% (27 out of 30) relief pitchers perceived low salary relative to their performance one year before. Our study concludes that, among the 43 pitchers in the seasons 2007-2008, there were 39 pitchers whose efficiency measures were under 1.0, indicating that most players (approximately 91%) may feel that their salaries should be adjusted higher.

Did starting pitchers deserve more pay or did they feel so? The average annual salary of the 8 starting pitchers in Table 3 was approximately 1.71 million NTD, which was higher than that of those 30 relief pitchers in Table 4 at 1.33 million NTD. On the other hand, the mean of DEA efficiency measures of starting pitchers was 0.450, which was lower compared to that of relief pitchers at 0.513. This proves that starting pitchers are usually treated the most valuable in the team, but they perceive underpaid somewhat more seriously than their counterparts. Given $\alpha = 0.05$ and the *p*-value is bigger than the significance level ($0.258 > 0.05$), the M-W test showed that the mean efficiency values of these two groups are not statistically different. This implied that there were no significant differences in terms of pay equity between only 1 out of 8 starting pitchers and 3 among the 30 relief pitchers. Pay inequity was not influenced greatly by pitching position, and their perceptions of low pay conditions were prevailing with virtually the same conditions.

6. CONCLUSION

Production efficiency is an important issue in the field of O.R. This study applies the mathematical models in DEA and forms the traditional efficiency frontier by signed salary (y-axis) relative to the pitcher's performance (x-axis) to generate objective estimates of pay equity. To the best of our knowledge, this article is among the first innovative applications of O.R. to the professional sports players. By efficiency frontier, this article conducts an objective evaluation of pay equity and estimates the proportion of the 43 CPBL pitchers who did not perceive "reasonable" salary remuneration for their performances in season 2007. The results show that only a small portion of pitchers received "reasonable" salaries, and that as high as approximately 91% pitchers (39 out of 43) perceived pay inequity and excessively low salaries. Moreover, those five un-classfied pitchers all (100%) felt under-paid, and underpayment inequities are prevailing for both starting pitchers (87.5%) and relief ones (90%) without significant differences.

Other than pitchers, models in this study can be easily extended to fielders in defensive or batters in offensive statistics, and even to different sports players, for performance assessments. Distinct from the past that subjective decisions made by administrators regarding salary levels, this study provides an objective evaluation model that can be used by both professional baseball players and team managers for concrete and practical reference on compensation administration.

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