Contemporary Management Research
Pages 351-384, Vol. 11, No. 4, December 2015
doi:10.7903/cmr.14157

Measuring Pitchers' Performance Using Data Envelopment Analysis with Advanced Statistics

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ABSTRACT

This paper evaluates starting pitchers' pitching performance during the 2008 to 2014 Major League Baseball (MLB) seasons. We use data envelopment analysis (DEA) based on two inputs (i.e., innings pitched [IPs] and per pitched innings) and three outputs (fielding independent pitching, earned run average [ERA], and skill-interactive ERA) to evaluate the performance of the 30 MLB teams' starting pitchers with IPs greater than 200 in each single season (2008 to 2014, regular season only). We used the CCR models to calculate the overall efficiency, scale efficiency, technical efficiency, efficiency value, and the slack analysis to measure a pitcher's performance in each single season. The results showed that 4, 3, 4, 3, 5, 3, and 5 pitches reached overall efficiency each year, from 2008 to 2014 (regular season). By analyzing the results and computing performance indexes and benchmarks for each starting pitcher, we determine the true value of each player to help baseball teams select highly indexed players and maximize player efficiency.

Keywords: Advanced Statistics, Pitchers, Data Envelopment Analysis, Innings Pitched, Earned Run Average

INTRODUCTION

Competitive sports interest a large number of people who watch them because of their uncertainty and unpredictability. Kao (2011) showed that the sports stars and the records in the games are the most important factors to spectators. In addition, professional sports represent a highly competitive battlefield characterized by the survival of the fittest. The games always focus on players' actual strengths and accomplishments. Thus, victory is certainly related to a player's individual performance.

Over time, the game of baseball has become increasingly complex. With the gradual improvement in baseball players' stamina and skill and increasingly varied game strategies, the division of labor in the tournament is becoming more delicately balanced. Specifically, the pitcher plays an important role in baseball. The performance of the pitcher can be crucial to the outcome of a game (Kindall, 1993; Lopez, A., & Kirkgard, J., 1996; Yeh, Lee, & Zhu, 2003).

However, how can we judge the pitcher's performance? Can we determine the pitcher's efficiency and "concretize" the results? The statistics we always hear are the earned run average (ERA) and walks plus hits per inning pitched (WHIP). Henry Chadwick defines ERA as the mean of earned runs given up by a pitcher per nine innings pitched. We determine the ERA by dividing the number of earned runs allowed by the number of innings pitched and multiplying the result by nine. Runs resulting from defensive errors (including pitchers' defensive errors) are recorded as unearned runs and are not used to determine ERA. Meanwhile, the WHIP was invented in 1979 by Daniel Okrent. In baseball statistics, the WHIP is a sabermetric measurement of the number of base runners a pitcher has allowed per inning pitched. Since the WHIP reflects a pitcher's propensity for allowing batters to reach a base, a lower WHIP indicates a better performance. We calculate the WHIP by adding the number of walks and hits allowed and dividing this sum by the number of innings pitched.

Because of the complexity of baseball, traditional statistics cannot provide a comprehensive measure of the pitcher's performance; however, advanced statistics can be credited with such a measure. Bradbury (2007) used multiple regression analysis to analyze the factor of lost points; the results showed that the pitcher's ability contributes about 73% and the defense's ability accounts for about 27% of the game's outcome. Thus, the ERA does not wholly reflect the pitcher's ability.

For example, when a runner is on base, if the relief pitcher cannot help the starting pitcher hold the runner on the base until the end of the inning, the runner will make a run or runs that affect the starting pitcher's ERA rather than the relief pitcher's ERA. This means the ERA is affected by not only the starting pitcher's, but also every other pitcher's ability. Meanwhile, the teammates' defense ability also affects the ERA and WHIP.

Therefore, the selective use of statistics to judge whether or not a pitcher performs well is bound to create bias. This explains the creation of advanced statistical metrics, such as fielding independent pitching (FIP). The 2009 American League Cy Young Award winner Zach Greinke won over the rivals using the FIP, created by Tom Tango in 2008: "That's pretty much how I pitch, to try to keep my FIP as low as possible" (Kenper, 2009). Meanwhile, 1974–2008 MLB data showed that FIP is the metric that most likely reflects the pitcher's real ability (Piette, Braunstein, McShane, & Jensen, 2010). Therefore, we seek to address the weak points of ERA and WHIP through advanced statistics, such as FIP and skill-interactive ERA (SIERA). We introduce these two statistics in the following subsections.

Fielding Independent Pitching

In 1999, Voros McCracken analyzed a record called Defense-Independent Pitching Statistic (DIPS), which is not affected by the team's defense. McCracken outlined a better way to assess a pitcher's talent level by looking at the results a pitcher can control: strikeouts, walks, hit by pitches, and home runs. Aiming to better evaluate pitchers in light of his theory, McCracken developed the Defense-Independent ERA (dERA), the most well-known DIPS. However, McCracken's formula for dERA is very complicated, with a number of steps.

Compared to DIPS, FIP can easily show what a pitcher's ERA should have looked like over a given time period, assuming that performance on balls in play and timing were in accordance with the league average. A walk is probably not as harmful as a home run, and a strikeout has less impact than both. FIP accounts for these kinds of differences, presenting the results on the same scale as ERA; it has been shown to be more effective than ERA in terms of predicting future performance and has become a mainstay in sabermetric analysis.

Tom Tango created a matrix in 2008 with run values for each play outcome. The coefficients attempt to adjust for how much each home run or each walk contributes to the other team's runs scored and how much each strikeout contributes to preventing the other team's runs scored.

$$\frac{\{(13 * HR) + [3 * (BB + HBP)] - (2 * K)\}}{IP} + constant$$

Skill-Interactive era

Skill-interactive ERA (SIERA) is the latest in a long line of ERA estimators. Like its predecessor, FIP, SIERA attempts to determine the underlying skill level of the pitchers and how well they actually pitched over the past year—namely, should their ERA have been higher or lower, or was it about right? SIERA does not ignore balls in play, but attempts to explain why certain pitchers are more successful at limiting hits and preventing runs. The strength of SIERA is that it tells us more about the *how* and *why* of pitching.

SIERA was developed by Eric Seidman and Matt Swartz. Unlike FIP, SIERA looks at not only home run (HR), hit by pitch (HBP), base on balls (BB), and strikeout (SO), but also ground balls (GB) and fly balls (FB). The coefficients are provided in Table 1.

Table 1 SIERA coefficients

Variable	SIERA coefficient
(SO/PA)	**-15.518**
(SO/PA)^2	**9.146**
(BB/PA)	**8.648**
(BB/PA)^2	*27.252*
(netGB/PA)	**-2.298**
+/-(netGB/PA)^2	**-4.920**
(SO/PA)*(BB/PA)	-4.036
(SO/PA)*(netGB/PA)	*5.155*
(BB/PA)*(netGB/PA)	4.546
Constant	**5.534**
Year coefficients (versus 2010)	From -0.020 to +0.289
% innings as SP	**0.367**

Source: Fangraphs.com

Note: SO (strike out); PA (plate appearances); BB (base on balls); GB (ground balls); SP (starting pitcher)

Statistics are also important to the baseball team. The book *MoneyBall* mentions that the Oakland Athletics team uses data analysis to determine which players it needs (Lewis, 2004). Similarly, the Tampa Bay Rays recently used the same method to improve team efficiency (Keri, 2011). In terms of performance appraisal, the data envelopment analysis (DEA) was applied in evaluate the National Football League (NFL) players' performance (Leibenstein & Maital, 1992), and Howard and Miller (1993) applied it to evaluate the relationship between MLB players' defense performance and salary.

Charnes, Cooper, and Rhodes mentioned the DEA in 1978; the idea originated from productive efficiency, which Farrell first discussed in 1957. Following this, Anderson and Sharp (1997) used DEA to analyze the MLB batters' attack performance, and Sexton and Lewis (2003) examined the manage performance in the MLB. More recently, Chen and Johnson (2010) used the DEA to analyze the dynamics of performance in MLB from 1871 to 2006. These studies have demonstrated that the DEA is a useful tool for analyzing performance in sports.

According to Lewis, Lock, and Sexton's (2009) results, professional baseball teams can split two ways—namely, players' abilities and performance—to promote the team's winning rate by efficiency programs. In terms of performance, Lin (2004) used the DEA to analyze the pitcher's performance in the Chinese Professional Baseball League (CPBL) and offer some suggestions to enhance the pitcher's performance.

As previously mentioned, baseball statistics are important to not only players, but also teams and fans. In this paper, we use DEA, an advanced statistical technique, to evaluate the starting pitcher's efficiency. This tool helps starting pitchers adjust among themselves and allow the team to choose the starting pitchers they need. Hence, our goals in this paper are two-fold:

1. To evaluate the MLB starting pitchers' performance in 2013.
2. To identify the areas that each starting pitcher needs to enhance.

METHODOLOGY

The Cy Young Award is the pitcher's highest honor, and the winner is voted on by the Baseball Writers Association of America (BBWAA). From 2000 to 2013, the pitchers who won the award had an IP greater than 200. Therefore, we selected all 30 MLB teams' starting pitchers whose IP is greater than 200 as the decision-making units (DMUs).

Data

We collected the data from the MLB's official website (http://www.mlb.com), Baseball-Reference.com (http://www.baseball-reference.com), and so on. The data include ERA, FIP, SIERA, pitches per inning pitched (P/IP), and IP. As stated by Golany and Roll (1989), DEA evaluates a group of comparable units' relative efficiency. Unlike for the batter, a lower value is better for the pitcher. Therefore, we change the ERA, FIP, and SIERA values to their reciprocals.

The DEA Technique

DEA was introduced to measure the relative efficiency of the DMUs that change inputs into outputs (Charnes, Cooper, & Rhodes, 1978). The DEA model has become a very popular management tool to measure performance in many kinds of industries, and it has proven to be a very good tool in many research studies (Lee, Shih, & Huang, 2011; Lin, 2010; Sexton & Lewis, 2003; Tsai & Chao, 2009). The DEA technique was originated by Farrell, the progenitor of the productive efficiency concept (Charnes, Cooper, & Thrall, 1991). Farrell assumed constant returns to scale in terms of a volume production curve that illustrates the relationship between the actual use of the observation point and the yield curve, such as the border, in order to achieve a technical efficiency size.

In this case, we used Cooper, Seiford, and Tone's (1999) concept; these researchers proposed the Charnes, Cooper, and Rhodes (CCR) and Banker, Charnes, and Cooper (BCC) models. The CCR model uses constant returns scale (CRS) to evaluate the overall efficiency (OE). The BCC model uses variable returns to scale (VRS), in place of CRS in the CCR model, to evaluate technical efficiency (TE) and scale efficiency (SE). Thus, these statistics provide reference points for efficiency improvement based on the individual decision-making unit's returns to scale.

Analyses

We collected all MLB teams' starting pitchers who reached 200 IP during the 2008 to 2014 regular seasons, resulting in about 30 to 45 starting pitchers in each year for the DMUs in this research. Considering that this paper aims to determine the starting pitcher's performance, we evaluated the performance rate with the chosen IP and P/IP for the input and the reciprocals of the ERA, FIP, and SIERA for the output. Because calculating the IP requires making 3 outs for 1 IP, and the 1 out equates to 1/3 IP, we make 0.1 IP for 0.33 and 0.2 IP for 0.67 to analyze the data correctly. Finally, we used DEAP 2.1 to analyze all the data collected.

RESULTS

Data Inspection

We used SPSS 20.0 to calculate the Pearson correlation coefficient to determine the relationship between inputs and outputs; the results are shown in Tables 2 and 3.

Table 2 Input Correlation Matrix

	IP	P/IP
IP	1	.886**
P/IP	.886**	1

**$p < .01$

Table 3 Output Correlation Matrix

	1/ERA	1/FIP	1/SIERA
1/ERA	1	.846**	.767**
1/FIP	.846**	1	.906**
1/SIERA	.767**	.906**	1

**$p < .01$

The results of the Pearson correlation analysis showed a positive correlation between IP and P/IP ($p < .01$) and among 1/ERA, 1/FIP, and 1/SIREA ($p < .01$). Sun (2004) maintained that a determinant relationship among all variables is a necessary condition for performance evaluation. Accordingly, we reserved all variables for this paper.

Mlb 2008–2014 Statistics on Starting Pitchers

Table 4 to Table 8 present the DMUs' input and output data collected from the MLB official website, Fangraphs, and the ESPN website.

The maximum IP pitched was CC Sabathia's 253 IP in the 2008 regular season; the maximum P/IP pitched was Ryan Dempster's 17.37 P/IP in the 2011 regular season. The best performances were those by Clayton Kershaw at 1/ERA pitched in the 2013 regular season, Roy Halladay at 1/FIP pitched in the 2011 regular season, and Felix Hernandez at 1/SIERA pitched in the 2014 regular season.

Table 4 The Maximum IP of MLB 2008-2014 Season's Starting Pitchers

	2008	2009	2010	2011	2012	2013	2014
Maximum	253	240	250.67	251	238.33	241.67	248.33
DMUs	CC. Sabathia	Justin Verlander	Roy Halladay	Justin Verlander	Justin Verlander	Adam Wainwright	David Price

Table 5 The Maximum P/IP of MLB 2008-2014 Season's Starting Pitchers

	2008	2009	2010	2011	2012	2013	2014
Maximum	17.55	17.07	16.87	17.37	17.05	17.19	16.94
DMUs	Justin Verlander	Doug Davis	C. J. Wilson	Ryan Dempster	Yovani Gallardo	C.J. Wilson	Lance Lynn

Table 6 The Best 1/ERA of MLB 2008-2014 Season's Starting Pitchers

	2008	2009	2010	2011	2012	2013	2014
Maximum	.395	.463	.441	.439	.395	.546	.467
DMUs	Johan Santana	Zack Greinke	Felix Hernandez	Clayton Kershaw	Clayton Kershaw	Clayton Kershaw	Felix Hernandez

Table 7 The best 1/FIP of MLB 2008-2014 season's starting pitchers

	2008	2009	2010	2011	2012	2013	2014
Maximum	.386	.429	.388	.455	.352	.418	.426
DMUs	Tim Lincecum	Zack Greinke	Cliff Lee	Roy Halladay	Felix Hernandez	Clayton Kershaw	Corey Kluber

Table 8 The best 1/SIERA of MLB 2008-2014 season's starting pitchers

	2008	2009	2010	2011	2012	2013	2014
Maximum	.319	.350	.347	.369	.326	.362	.400
DMUs	Tim Lincecum	Javier Vazquez	Roy Halladay	Cliff Lee	Cliff Lee	Yu Darvish	Felix Hernandez

Performance of DMUS

Table 9 shows the maximum and minimum performances among MLB starting pitchers from 2008 to 2014 in terms of overall efficiency (OE). Table 10 shows the numbers sorted by Norman and Stocker (1991); the TE values are separated into E (TE = 1), F (.90 ≦ TE ＜ 1), and G (TE ＜ .90).

Table 9 The abstract of MLB 2008-2014 Regular Season DMUs' Performance

	DMUs of Maximum OE	DMUs of Minimum OE
2008	Tim Lincecum Cliff Lee CC Sabathia Dan Haren Roy Halladay	Scott Olsen (.693)
2009	Zack Greinke Tim Lincecum Javier Vazquez	Bronson Arroyo (.621)
2010	Cliff Lee Adam Wainwright Justin Verlander Roy Halladay Felix Hernandez	Randy Wolf (.674)
2011	Roy Halladay Clayton Kershaw Cliff Lee	Carl Pavano (.662)
2012	Felix Hernandez Clayton Kershaw David Price Cliff Lee R.A. Dickey	Jason Vargas (.702)
2013	Clayton Kershaw Felix Hernandez Cliff Lee	Jeremy Guthrie (.617)
2014	Corey Kluber Felix Hernandez Stephen Strasburg Zack Greinke Cole Hamels	R.A. Dickey (.664)

Table 10 The Numbers of the Technical Efficiency Sort in 2008-2014 MLB Season

	2008	2009	2010	2011	2012	2013	2014
E (TE = 1)	11	10	14	11	8	10	11
F (.90 ≦ TE ＜ 1)	6	3	5	7	8	7	7
G (TE ＜ .90)	14	22	26	21	14	19	15

Slack Variable Analysis of TE in sort "F" in The VRS Model

In the VRS model, the sort F refers to TE values between .90 and 1, as shown in Tables 11 and 12. We used Zack Grienke (TE = .980) and Justin Verlander (TE = .987) in 2012 as examples. In 2012, when Grienke held his IP at 220.00 and lowered P/IP to 14.07, he raised his 1/ERA to .333, 1/FIP to .377, and 1/SIERA to .329; thus, his TE value equals 1. Meanwhile, Verlander needed to improve his performance by lowering his IP to 226.79 and P/IP to 15.16 and raising his 1/ERA from .379 to .384, 1/FIP from .340 to .345, and 1/SIERA from .300 to .304 to achieve a TE of 1.

Table 11 2012 Zack Grienke Slack Variable Analysis

	Technical Efficiency	IP	P/IP	1/ERA	1/FIP	1/SIERA
2012	Original value	212.33	15.93	.287	.323	.296
	Projected value	212.33	15.72	.387	.330	.310
	Adjusted rate	--	1.3%	34.8%	2.1%	4.7%

Table 12 2012 Justin Verlander Slack Variable Analysis

	Technical Efficiency	IP	P/IP	1/ERA	1/FIP	1/SIERA
2012	Original value	238.33	15.81	.379	.340	.300
	Projected value	226.79	15.16	.384	.345	.304
	Adjusted rate	-4.8%	-4.1%	1.3%	1.4%	1.3%

Slack Variable Analysis of TE in sort "G" in the VRS Model

In the VRS model, the sort G means TE values lower than .90, as shown in Tables 13 and 14. We still used Grienke and Verlander as examples, but this time Grienke in 2010 and Verlander in 2013. In 2010, Grienke needed to hold his IP steady and lower his P/IP to 14.07 as well as raise his 1/ERA to .333, 1/FIP to .377, and 1/SIERA to .329 for his TE value to equal 1. In 2013, Verlander needed to lower his IP to 211.42 and

P/IP to 15.31 as well as raise his 1/ERA to .378, 1/FIP to .381, and 1/SIERA to .355 to achieve a TE of 1.

Table 13 2010 Zack Grienke Slack Variable Analysis

	Technical Efficiency	IP	P/IP	1/ERA	1/FIP	1/SIERA
2010	Original value	220.00	15.66	.240	.299	.274
	Projected value	220.00	14.07	.333	.377	.329
	Adjusted rate	--	-10.2%	38.8%	26.1%	20.1

Table 14 2013 Justin Verlander Slack Variable Analysis

	Technical Efficiency	IP	P/IP	1/ERA	1/FIP	1/SIERA
2013	Original value	218.33	16.91	.289	.305	.277
	Projected value	211.42	15.31	.378	.381	.355
	Adjusted rate	-3.2%	-9.4%	30.8%	24.9%	28.2%

Sensitivity Analysis in The VRS Model

Sensitivity analysis is the study of how the output uncertainty of a mathematical model or system (numerical or otherwise) can be apportioned to different sources of input uncertainty. A related practice is uncertainty analysis, which has a greater focus on uncertainty quantification and propagation of uncertainty. Ideally, uncertainty and sensitivity analyses should be run in tandem.

As Table 15 shows, the result of the sensitivity analysis in the 2014 season demonstrated that 1/ERA was the biggest factor influencing the TE value. In other words, the average TE value of all DMUs in 2014 was .874. Without the 1/ERA event, the TE value would be lowered to .853 at a change rate of -2.4%.

DISCUSSION AND CONCLUSIONS

In this paper, we used the DEA technique to analyze the MLB starting pitchers' performances from 2008 to 2014. According to the analysis results, several players needed to adjust their performances.

In each single year, the IP and P/IP were not the highest for each of the pitchers who achieved the OE goal. For example, in 2013, Clayton Kershaw, Cliff Lee, and Felix Hernandez all achieved the goal, but their IP or P/IP were not the highest in the 2013 season; we found the same result in each season examined. This means a high IP or P/IP is not the most important factor affecting the pitcher's performance. Liao and Chang (2013) showed that more pitches can affect a pitcher's performance indexes, such as FIP and ERA. It is important that starting pitchers and coaches focus on controlling their IP and P/IP.

Table 15 Sensitivity Analysis in the VRS Model in 2014

The Sequentially Excluding Event	Technical Efficiency Averaged Changed Rate	Status
1/ERA	-2.4%	Will change half of pitchers' TE values. The biggest change is 16.6% for Johnny Cueto.
1/FIP	-1.9%	Will change more than half of pitchers' TE values. The biggest change is -12.2% for Jon Lester.
1/SIERA	-1.9%	Will change more than half of pitchers' TE values. The biggest change is -10.2% for Stephen Strasburg.

Second, we demonstrated a sort of technical efficiency in Table 10, which showed that many of the DMUs we collected needed to fix their performance to reach the overall efficiency to 1. Using Grienke and Verlander as examples, Grienke won the Cy Lee, Shih, & Huang Award in 2008, when his OE was 1; however, he dropped in the 2010 season. The slack variable analysis indicated that he needed a significant change to adjust his 1/ERA, 1/FIP, and 1/SIERA, as he did in 2012 and 2014. The results might conform to his speech in 2008, indicating that he knew to use these advanced statistics to adjust his performance. Meanwhile, Verlander's performance based on the analysis results showed that he dropped further and further after he won the American League Cy Lee, Shih, & Huang Award in 2011; this might be related to his IP and P/IP, as previously mentioned.

Tango (2008) pointed out that the number of HRs might be affected by the location of the game, because each of the stadiums for the 30 MLB teams is different and unique. Thus, SIERA can provide more details for FBs and GBs, but the shortcoming is that it is too complex to calculate. Although both FIP and SIERA are characterized by some shortcomings, both can predict the ERA trends. Therefore, we can effectively use these statistics to train or choose a pitcher, rather than just follow the ERA. Actually, FIP does a better job of predicting the future than measuring the present, as small samples could show considerable fluctuations. It is less effective in describing a pitcher's single-game performance and is more appropriate for a season's innings.

Finally, Chen (2006) pointed out that ERA < FIP, implying that the team is playing a good defensive game. In other words, the FIP can not only benefit the baseball pitcher, but also identify the team's deficiency in defense, which can then be addressed.

The baseball team manager can use these results to choose pitchers and justify the team's salary cap, for example. The team sponsors can also refer to them to make decisions about sponsorship relationships. Likewise the coach can prepare training schedules and control the IP and P/IP appropriately based on the results. Pitchers can rate themselves in comparison to excellent pitchers and set clear targets to avoid inefficient training and unnecessary injuries.

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APPENDIX

Stats of MLB 2008 Season's Starting Pitchers

DMUs	IP	P/IP	1/ERA	1/FIP	1/SIERA
Tim Lincecum	223.00	16.13	0.382	0.386	0.319
Cliff Lee	223.33	14.73	0.394	0.353	0.278
CC Sabathia	253.00	15.08	0.370	0.344	0.317
Dan Haren	216.00	15.46	0.300	0.332	0.313
Roy Halladay	243.67	14.52	0.356	0.328	0.318
Derek Lowe	211.00	14.87	0.309	0.307	0.297
Brandon Webb	226.67	14.82	0.303	0.305	0.310
Ervin Santana	219.00	15.65	0.287	0.303	0.301
Mike Mussina	200.33	15.65	0.297	0.301	0.282
Ryan Dempster	206.67	16.17	0.338	0.293	0.263
A.J. Burnett	220.33	16.46	0.250	0.290	0.280
Johan Santana	234.33	15.35	0.395	0.285	0.271
Zack Greinke	202.33	15.95	0.288	0.281	0.271
Gil Meche	210.33	16.90	0.251	0.277	0.249
Jon Lester	210.33	15.73	0.312	0.275	0.241
Andy Pettitte	204.00	16.05	0.220	0.270	0.263
Cole Hamels	227.33	15.08	0.324	0.269	0.275
Javier Vazquez	208.33	16.21	0.214	0.267	0.273
Aaron Cook	211.33	14.54	0.253	0.266	0.236
Ricky Nolasco	206.67	15.39	0.277	0.264	0.283
Felix Hernandez	200.67	15.94	0.290	0.263	0.254
Roy Oswalt	208.67	14.83	0.282	0.263	0.278
James Shields	215.00	14.56	0.281	0.262	0.263
Matt Cain	217.67	16.57	0.266	0.256	0.229
Mark Buehrle	218.67	15.50	0.264	0.254	0.243
Mike Pelfrey	200.67	16.56	0.269	0.253	0.217
Paul Maholm	206.33	14.74	0.270	0.241	0.246
Justin Verlander	201.00	17.55	0.207	0.239	0.223
Ted Lilly	204.67	15.83	0.244	0.227	0.255
Gavin Floyd	206.33	15.68	0.260	0.210	0.223
Scott Olsen	201.67	15.41	0.238	0.199	0.200

2008 Overview of DMUs

DMUs	Overall Efficiency	Scale Efficiency	Technical Efficiency
Tim Lincecum	1	1	1
Cliff Lee	1	1	1
CC Sabathia	0.993	1	0.993
Dan Haren	1	1	1
Roy Halladay	1	1	1
Derek Lowe	0.986	1	0.986
Brandon Webb	0.995	1	0.995
Ervin Santana	0.949	0.955	0.994
Mike Mussina	0.976	1	0.976
Ryan Dempster	0.943	1	0.943
A.J. Burnett	0.877	0.884	0.992
Johan Santana	0.962	1	0.962
Zack Greinke	0.930	0.950	0.979
Gil Meche	0.821	0.832	0.987
Jon Lester	0.854	0.896	0.952
Andy Pettitte	0.890	0.909	0.979
Cole Hamels	0.887	0.898	0.988
Javier Vazquez	0.904	0.917	0.987
Aaron Cook	0.796	1	0.796
Ricky Nolasco	0.946	0.967	0.979
Felix Hernandez	0.882	0.969	0.910
Roy Oswalt	0.927	1	0.927
James Shields	0.876	1	0.876
Matt Cain	0.734	0.738	0.995
Mark Buehrle	0.778	0.782	0.996
Mike Pelfrey	0.778	0.899	0.865
Paul Maholm	0.833	1	0.833
Justin Verlander	0.766	0.788	0.973
Ted Lilly	0.860	0.878	0.980
Gavin Floyd	0.754	0.799	0.943
Scott Olsen	0.693	1	0.693

Stats of MLB 2009 Season's Starting Pitchers

DMUs	IP	P/IP	1/ERA	1/FIP	1/SIERA
Zack Greinke	229.33	15.16	0.463	0.429	0.329
Tim Lincecum	225.33	15.26	0.403	0.427	0.344
Javier Vazquez	219.33	15.11	0.348	0.361	0.350
Justin Verlander	240.00	16.40	0.290	0.357	0.327
Roy Halladay	239.00	14.20	0.358	0.327	0.321
Josh Johnson	209.00	15.71	0.310	0.327	0.290
Felix Hernandez	238.67	15.22	0.402	0.324	0.291
Adam Wainwright	233.00	15.51	0.380	0.322	0.288
Cliff Lee	231.67	15.25	0.311	0.322	0.265
Jon Lester	203.33	16.74	0.293	0.317	0.317
Dan Haren	229.33	15.09	0.318	0.310	0.327
Joel Pineiro	214.00	13.80	0.287	0.306	0.275
Ubaldo Jimenez	218.00	16.38	0.288	0.298	0.266
CC Sabathia	230.00	15.60	0.297	0.295	0.264
Wandy Rodriguez	205.67	16.37	0.331	0.282	0.278
Josh Beckett	212.33	15.86	0.259	0.275	0.294
Jair Jurrjens	215.00	15.37	0.385	0.272	0.226
Ryan Dempster	200.00	15.80	0.274	0.258	0.260
Matt Cain	217.67	15.45	0.346	0.257	0.239
Randy Wolf	214.33	15.33	0.310	0.253	0.244
James Shields	219.67	15.15	0.242	0.249	0.251
Jered Weaver	211.00	16.12	0.267	0.248	0.235
Jason Marquis	216.00	15.03	0.248	0.244	0.217
Matt Garza	203.00	16.85	0.253	0.240	0.251
Zach Duke	213.00	14.42	0.246	0.236	0.219
Edwin Jackson	214.00	16.20	0.276	0.234	0.233
A.J. Burnett	207.00	16.72	0.248	0.231	0.239
Nick Blackburn	205.67	15.08	0.248	0.229	0.214
Mark Buehrle	213.33	15.06	0.260	0.224	0.216
Jon Garland	204.00	15.96	0.249	0.223	0.210
John Danks	200.33	16.02	0.265	0.218	0.228
John Lannan	206.33	15.12	0.258	0.213	0.203
Bronson Arroyo	220.33	15.46	0.260	0.209	0.216
Doug Davis	203.33	17.07	0.243	0.207	0.204
Jeremy Guthrie	200.00	16.80	0.198	0.188	0.198

2009 Overview of DMUs

DMUs	Overall Efficiency	Scale Efficiency	Technical Efficiency
Zack Greinke	1	1	1
Tim Lincecum	1	1	1
Javier Vazquez	1	1	1
Justin Verlander	0.868	0.939	0.924
Roy Halladay	0.994	1	0.994
Josh Johnson	0.888	1	0.888
Felix Hernandez	0.877	0.880	0.997
Adam Wainwright	0.844	0.861	0.980
Cliff Lee	0.771	0.771	1
Jon Lester	0.977	1	0.977
Dan Haren	0.936	0.936	1
Joel Pineiro	0.869	1	0.869
Ubaldo Jimenez	0.782	0.791	0.989
CC Sabathia	0.745	0.764	0.976
Wandy Rodriguez	0.890	1	0.890
Josh Beckett	0.868	0.876	0.990
Jair Jurrjens	0.887	1	0.887
Ryan Dempster	0.827	1	0.827
Matt Cain	0.787	0.874	0.901
Randy Wolf	0.766	0.858	0.893
James Shields	0.716	0.717	0.998
Jered Weaver	0.723	0.766	0.944
Jason Marquis	0.653	0.712	0.917
Matt Garza	0.778	0.853	0.911
Zach Duke	0.669	0.796	0.840
Edwin Jackson	0.716	0.748	0.956
A.J. Burnett	0.732	0.771	0.949
Nick Blackburn	0.679	0.872	0.779
Mark Buehrle	0.669	0.764	0.876
Jon Garland	0.677	0.809	0.836
John Danks	0.744	0.956	0.778
John Lannan	0.662	0.882	0.751
Bronson Arroyo	0.648	0.662	0.979
Doug Davis	0.661	0.790	0.836
Jeremy Guthrie	0.621	0.762	0.816

Stats of MLB 2010 Season's Starting Pitchers (a)

DMUs	IP	P/IP	1/ERA	1/FIP	1/SIERA
Cliff Lee	212.33	14.03	0.314	0.388	0.325
Adam Wainwright	230.33	14.57	0.413	0.350	0.322
Justin Verlander	224.33	16.70	0.297	0.337	0.289
Roy Halladay	250.67	14.23	0.410	0.332	0.347
Felix Hernandez	249.67	14.94	0.441	0.329	0.314
Jered Weaver	224.33	16.55	0.332	0.327	0.319
Ubaldo Jimenez	221.67	16.24	0.347	0.323	0.273
Clayton Kershaw	204.33	16.59	0.344	0.321	0.282
Jon Lester	208.00	16.14	0.308	0.319	0.310
Tim Lincecum	212.33	16.19	0.292	0.317	0.313
Roy Oswalt	210.67	15.08	0.366	0.305	0.299
Tommy Hanson	202.66	16.15	0.300	0.302	0.269
Zack Greinke	220.00	15.66	0.240	0.299	0.274
David Price	207.67	16.09	0.366	0.292	0.260
CC Sabathia	237.67	15.09	0.314	0.282	0.272
Colby Lewis	201.00	16.42	0.269	0.282	0.281
Brett Myers	223.67	15.46	0.318	0.281	0.265
C.J. Wilson	204.00	16.87	0.299	0.281	0.240
Ricky Romero	210.00	15.43	0.268	0.275	0.265
Matt Cain	223.33	15.68	0.318	0.274	0.255
Cole Hamels	208.67	16.14	0.327	0.272	0.309
Chris Carpenter	235.00	15.10	0.311	0.271	0.270
John Danks	213.00	15.91	0.269	0.270	0.246
Dan Haren	235.00	15.95	0.256	0.270	0.291
Gio Gonzalez	200.67	16.79	0.310	0.265	0.240
Mike Pelfrey	203.00	16.69	0.272	0.262	0.218
Clayton Richard	201.67	15.93	0.267	0.262	0.237
John Lackey	215.00	16.74	0.227	0.260	0.238
Edwin Jackson	209.33	16.04	0.224	0.259	0.261
Mark Buehrle	210.33	15.72	0.234	0.256	0.213
Livan Hernandez	211.67	15.34	0.273	0.253	0.210
Ryan Dempster	215.33	16.70	0.260	0.251	0.270
Carl Pavano	221.00	14.20	0.267	0.249	0.248
Tim Hudson	228.67	14.60	0.353	0.244	0.269
Roberto Hernandez	210.33	15.71	0.265	0.243	0.232

Stats of MLB 2010 Season's Starting Pitchers (b)

DMUs	IP	P/IP	1/ERA	1/FIP	1/SIERA
Jake Westbrook	202.67	16.45	0.237	0.237	0.247
James Shields	202.33	16.50	0.192	0.236	0.283
Ervin Santana	222.67	15.99	0.255	0.234	0.236
Jon Garland	200.00	16.27	0.288	0.227	0.225
Matt Garza	204.00	15.99	0.254	0.227	0.236
Jeremy Guthrie	209.33	15.89	0.261	0.225	0.223
Joe Saunders	203.33	16.30	0.224	0.219	0.214
Bronson Arroyo	215.67	15.10	0.258	0.217	0.220
Randy Wolf	215.67	16.58	0.240	0.206	0.212
Rodrigo Lopez	200.00	15.44	0.200	0.192	0.215

2010 Overview of DMUs (a)

DMUs	Overall Efficiency	Scale Efficiency	Technical Efficiency
Cliff Lee	1	1	1
Adam Wainwright	1	1	1
Justin Verlander	0.857	0.888	0.965
Roy Halladay	1	1	1
Felix Hernandez	1	1	1
Jered Weaver	0.950	0.962	0.987
Ubaldo Jimenez	0.913	0.916	0.997
Clayton Kershaw	0.983	1	0.983
Jon Lester	0.982	1	0.982
Tim Lincecum	0.963	0.963	1
Roy Oswalt	0.999	1	0.999
Tommy Hanson	0.906	1	0.906
Zack Greinke	0.814	0.832	0.978
David Price	0.923	1	0.983
CC Sabathia	0.793	0.808	0.981
Colby Lewis	0.913	1	0.913
Brett Myers	0.828	0.828	1
C.J. Wilson	0.859	0.887	0.969
Ricky Romero	0.836	0.840	0.994
Matt Cain	0.809	0.809	1
Cole Hamels	0.994	1	0.994
Chris Carpenter	0.793	0.807	0.982
John Danks	0.783	0.784	1
Dan Haren	0.809	0.861	0.940
Gio Gonzalez	0.865	1	0.865
Mike Pelfrey	0.795	0.860	0.924
Clayton Richard	0.805	0.997	0.807
John Lackey	0.723	0.729	0.992
Edwin Jackson	0.815	0.830	0.982
Mark Buehrle	0.704	0.709	0.994
Livan Hernandez	0.751	0.765	0.981
Ryan Dempster	0.819	0.826	0.991
Carl Pavano	0.760	0.761	0.999
Tim Hudson	0.861	0.865	0.996
Roberto Hernandez	0.759	0.761	0.997

2010 Overview of DMUs (b)

DMUs	Overall Efficiency	Scale Efficiency	Technical Efficiency
Jake Westbrook	0.796	0.858	0.928
James Shields	0.914	0.988	0.925
Ervin Santana	0.716	0.721	0.994
Jon Garland	0.804	1	0.804
Matt Garza	0.781	0.837	0.933
Jeremy Guthrie	0.739	0.743	0.994
Joe Saunders	0.704	0.748	0.942
Bronson Arroyo	0.708	0.708	0.999
Randy Wolf	0.674	0.674	1
Rodrigo Lopez	0.702	1	0.702

Stats of MLB 2011 Season's Starting Pitchers (a)

DMUs	IP	P/IP	1/ERA	1/FIP	1/SIERA
Roy Halladay	233.67	14.84	0.426	0.455	0.360
Clayton Kershaw	233.33	14.87	0.439	0.405	0.357
Cliff Lee	232.67	14.63	0.417	0.385	0.369
Madison Bumgarner	204.67	15.64	0.312	0.375	0.315
CC Sabathia	237.33	15.19	0.333	0.347	0.319
Matt Cain	221.67	15.74	0.347	0.344	0.265
Justin Verlander	251.00	15.70	0.417	0.334	0.336
Dan Haren	237.33	15.85	0.313	0.334	0.299
Cole Hamels	213.00	14.52	0.364	0.333	0.331
Doug Fister	213.33	14.79	0.348	0.330	0.273
Chris Carpenter	237.33	15.22	0.290	0.327	0.287
Felix Hernandez	233.67	15.44	0.288	0.319	0.312
Tim Lincecum	217.00	16.62	0.365	0.315	0.290
Jered Weaver	235.67	15.90	0.415	0.313	0.273
Ian Kennedy	222.00	15.42	0.347	0.311	0.291
C.J. Wilson	223.33	16.08	0.340	0.309	0.291
Justin Masterson	215.00	16.00	0.311	0.305	0.272
Daniel Hudson	222.00	15.48	0.287	0.305	0.265
David Price	224.33	16.48	0.287	0.301	0.307
Tim Hudson	215.00	14.90	0.311	0.295	0.292
James Shields	249.33	14.34	0.355	0.292	0.305
Ricky Nolasco	206.00	15.51	0.214	0.282	0.265
Yovani Gallardo	207.33	16.70	0.284	0.279	0.312
Gio Gonzalez	202.00	16.87	0.321	0.275	0.265
Shaun Marcum	200.67	15.85	0.282	0.268	0.256
Hiroki Kuroda	202.00	15.85	0.326	0.265	0.274
R.A. Dickey	207.67	15.00	0.304	0.265	0.249
Ryan Dempster	202.33	17.37	0.208	0.256	0.265
Mark Buehrle	205.33	15.32	0.279	0.251	0.229
Ervin Santana	228.67	15.10	0.296	0.250	0.254
Jason Vargas	201.00	16.17	0.235	0.244	0.226
Trevor Cahill	207.67	16.30	0.240	0.244	0.249
Carl Pavano	222.00	15.24	0.233	0.244	0.233
Ricky Romero	225.00	15.00	0.342	0.238	0.265
Brett Myers	214.00	15.49	0.224	0.236	0.260

Stats of MLB 2011 Season's Starting Pitchers (b)

DMUs	IP	P/IP	1/ERA	1/FIP	1/SIERA
Randy Wolf	212.33	15.90	0.271	0.233	0.223
Jeremy Guthrie	203.67	15.89	0.229	0.222	0.222
Colby Lewis	200.33	16.01	0.227	0.220	0.258
Joe Saunders	212.00	15.17	0.271	0.209	0.213

2011 Overview of DMUs (a)

DMUs	Overall Efficiency	Scale Efficiency	Technical Efficiency
Roy Halladay	1	1	1
Clayton Kershaw	1	1	1
Cliff Lee	1	1	1
Madison Bumgarner	0.989	1	0.989
CC Sabathia	0.853	0.869	0.981
Matt Cain	0.845	0.891	0.948
Justin Verlander	0.900	0.950	0.947
Dan Haren	0.802	0.817	0.982
Cole Hamels	0.980	1	0.980
Doug Fister	0.812	0.960	0.908
Chris Carpenter	0.772	0.786	0.982
Felix Hernandez	0.842	0.846	0.996
Tim Lincecum	0.894	0.960	0.931
Jered Weaver	0.936	0.945	0.990
Ian Kennedy	0.845	0.872	0.969
C.J. Wilson	0.833	0.846	0.985
Justin Masterson	0.806	0.850	0.948
Daniel Hudson	0.763	0.766	0.996
David Price	0.863	0.870	0.992
Tim Hudson	0.856	0.872	0.982
James Shields	0.858	1	0.858
Ricky Nolasco	0.813	0.834	0.975
Yovani Gallardo	0.949	0.975	0.974
Gio Gonzalez	0.852	1	0.852
Shaun Marcum	0.805	1	0.805
Hiroki Kuroda	0.874	1	0.874
R.A. Dickey	0.781	1	0.781
Ryan Dempster	0.826	0.932	0.886
Mark Buehrle	0.726	0.912	0.796
Ervin Santana	0.709	0.714	0.994
Jason Vargas	0.712	0.881	0.808
Trevor Cahill	0.756	0.776	0.974
Carl Pavano	0.662	0.669	0.990
Ricky Romero	0.808	0.837	0.966
Brett Myers	0.766	0.781	0.981

2011 Overview of DMUs (b)

DMUs	Overall Efficiency	Scale Efficiency	Technical Efficiency
Randy Wolf	0.683	0.746	0.915
Jeremy Guthrie	0.687	0.739	0.930
Colby Lewis	0.812	1	0.812
Joe Saunders	0.679	0.750	0.906

Stats of MLB 2012 Season's Starting Pitchers

DMUs	IP	P/IP	1/ERA	1/FIP	1/SIERA
Felix Hernandez	232.00	14.74	0.327	0.352	0.305
Clayton Kershaw	227.67	15.24	0.395	0.346	0.302
Justin Verlander	238.33	15.81	0.379	0.340	0.300
David Price	211.00	15.79	0.391	0.328	0.310
Zack Greinke	212.33	15.93	0.287	0.323	0.296
Cliff Lee	211.00	14.69	0.316	0.319	0.326
R.A. Dickey	232.66	14.37	0.375	0.311	0.309
Johnny Cueto	217.00	15.89	0.360	0.306	0.268
Cole Hamels	215.33	15.40	0.328	0.303	0.304
CC Sabathia	200.00	15.14	0.296	0.300	0.308
Matt Cain	219.33	15.25	0.358	0.294	0.271
James Shields	227.67	15.89	0.284	0.288	0.307
Madison Bumgarner	208.33	15.69	0.297	0.286	0.289
Kyle Lohse	211.00	14.82	0.350	0.285	0.242
A.J. Burnett	202.33	15.03	0.285	0.284	0.287
Jake Peavy	219.00	15.92	0.297	0.268	0.270
Mat Latos	209.33	15.63	0.287	0.260	0.262
Hiroki Kuroda	219.67	15.16	0.301	0.259	0.268
Yovani Gallardo	204.00	17.05	0.273	0.254	0.266
Wandy Rodriguez	203.67	15.57	0.263	0.253	0.234
Homer Bailey	208.00	16.03	0.272	0.252	0.255
Matt Harrison	213.33	15.22	0.304	0.248	0.230
C.J. Wilson	202.33	17.01	0.261	0.248	0.235
Ian Kennedy	208.33	16.22	0.249	0.248	0.258
Bronson Arroyo	202.00	14.64	0.267	0.245	0.235
Jon Lester	205.33	16.68	0.207	0.243	0.249
Justin Masterson	206.33	16.60	0.203	0.240	0.236
Mark Buehrle	202.33	15.13	0.267	0.239	0.229
Clayton Richard	218.67	14.48	0.251	0.216	0.233
Jason Vargas	217.33	15.43	0.260	0.213	0.224

2012 Overview of DMUs

DMUs	Overall Efficiency	Scale Efficiency	Technical Efficiency
Felix Hernandez	1	1	1
Clayton Kershaw	1	1	1
Justin Verlander	0.945	0.987	0.958
David Price	1	1	1
Zack Greinke	0.979	0.980	0.998
Cliff Lee	1	1	1
R.A. Dickey	1	1	1
Johnny Cueto	0.911	0.917	0.993
Cole Hamels	0.932	0.951	0.981
CC Sabathia	0.997	1	0.997
Matt Cain	0.920	0.930	0.990
James Shields	0.873	0.942	0.927
Madison Bumgarner	0.907	0.908	0.999
Kyle Lohse	0.930	1	0.930
A.J. Burnett	0.925	0.949	0.974
Jake Peavy	0.816	0.847	0.963
Mat Latos	0.828	0.829	0.999
Hiroki Kuroda	0.836	0.845	0.988
Yovani Gallardo	0.852	0.855	0.997
Wandy Rodriguez	0.799	0.818	0.977
Homer Bailey	0.807	0.808	0.999
Matt Harrison	0.791	0.818	0.967
C.J. Wilson	0.789	0.826	0.956
Ian Kennedy	0.802	0.802	0.999
Bronson Arroyo	0.788	1	0.788
Jon Lester	0.785	0.786	0.998
Justin Masterson	0.759	0.761	0.997
Mark Buehrle	0.764	0.862	0.886
Clayton Richard	0.737	1	0.737
Jason Vargas	0.702	0.710	0.988

Stats of MLB 2013 season's starting pitchers

DMUs	IP	P/IP	1/ERA	1/FIP	1/SIERA
Clayton Kershaw	236.00	14.53	0.546	0.418	0.334
Adam Wainwright	241.67	14.62	0.340	0.392	0.340
Felix Hernandez	204.33	15.54	0.329	0.383	0.361
Max Scherzer	214.33	15.81	0.345	0.365	0.344
Cliff Lee	222.67	14.61	0.348	0.355	0.353
Madison Bumgarner	201.33	15.91	0.361	0.328	0.300
Mat Latos	210.67	15.37	0.316	0.323	0.279
Chris Sale	214.33	15.15	0.326	0.315	0.346
Cole Hamels	220.00	15.56	0.278	0.307	0.293
Doug Fister	207.67	16.07	0.272	0.306	0.292
Yu Darvish	209.67	16.46	0.353	0.305	0.362
Justin Verlander	218.33	16.91	0.289	0.305	0.277
Lance Lynn	201.67	16.62	0.252	0.305	0.272
Homer Bailey	209.00	15.75	0.287	0.302	0.301
Jordan Zimmermann	213.33	14.45	0.308	0.298	0.278
Mike Minor	204.67	15.27	0.312	0.297	0.281
Patrick Corbin	208.33	14.79	0.293	0.292	0.281
Hisashi Iwakuma	219.67	14.12	0.376	0.291	0.300
Derek Holland	213.00	15.40	0.292	0.291	0.267
James Shields	228.67	15.99	0.317	0.288	0.265
C.J. Wilson	212.33	17.19	0.295	0.285	0.249
Eric Stults	203.67	15.88	0.254	0.283	0.238
Hiroki Kuroda	201.33	15.90	0.302	0.281	0.269
Jon Lester	213.33	16.68	0.267	0.279	0.256
Jeff Samardzija	213.67	16.20	0.230	0.265	0.283
Jose Quintana	200.00	16.68	0.285	0.262	0.260
Travis Wood	200.00	15.45	0.322	0.257	0.226
Ervin Santana	211.00	15.16	0.309	0.254	0.265
Wade Miley	202.67	15.98	0.282	0.251	0.253
Mark Buehrle	203.67	16.20	0.241	0.244	0.242
CC Sabathia	211.00	15.81	0.209	0.244	0.258
Chris Tillman	206.33	16.85	0.270	0.226	0.258
Bronson Arroyo	202.00	14.22	0.264	0.223	0.245
A.J. Griffin	200.00	16.06	0.261	0.220	0.254
R.A. Dickey	224.67	15.60	0.238	0.218	0.244
Jeremy Guthrie	211.67	15.92	0.248	0.209	0.212

2013 Overview of DMUs (a)

DMUs	Overall Efficiency	Scale Efficiency	Technical Efficiency
Clayton Kershaw	1	1	1
Adam Wainwright	0.992	0.994	0.998
Felix Hernandez	1	1	1
Max Scherzer	0.938	0.962	0.975
Cliff Lee	1	1	1
Madison Bumgarner	0.828	1	0.928
Mat Latos	0.831	0.838	0.991
Chris Sale	0.965	0.967	0.997
Cole Hamels	0.798	0.814	0.980
Doug Fister	0.801	0.810	0.989
Yu Darvish	0.999	1	0.999
Justin Verlander	0.754	0.780	0.966
Lance Lynn	0.807	0.913	0.884
Homer Bailey	0.827	0.835	0.990
Jordan Zimmermann	0.816	0.986	0.828
Mike Minor	0.830	0.921	0.901
Patrick Corbin	0.812	0.921	0.882
Hisashi Iwakuma	0.900	1	0.900
Derek Holland	0.754	0.754	1
James Shields	0.720	0.756	0.953
C.J. Wilson	0.733	0.748	0.980
Eric Stults	0.745	0.763	0.976
Hiroki Kuroda	0.811	0.898	0.903
Jon Lester	0.710	0.719	0.987
Jeff Samardzija	0.751	0.783	0.960
Jose Quintana	0.783	1	0.783
Travis Wood	0.752	1	0.752
Ervin Santana	0.773	0.819	0.944
Wade Miley	0.756	0.796	0.950
Mark Buehrle	0.692	0.708	0.978
CC Sabathia	0.700	0.714	0.980
Chris Tillman	0.741	0.755	0.980
Bronson Arroyo	0.738	1	0.738
A.J. Griffin	0.748	1	0.748
R.A. Dickey	0.659	0.680	0.969

2013 Overview of DMUs (b)

DMUs	Overall Efficiency	Scale Efficiency	Technical Efficiency
Jeremy Guthrie	0.617	0.629	0.981

Stats of MLB 2014 Season's Starting Pitchers

DMUs	IP	P/IP	1/ERA	1/FIP	1/SIERA
Corey Kluber	235.67	14.85	0.410	0.426	0.383
Felix Hernandez	236.00	14.55	0.467	0.391	0.400
Phil Hughes	209.67	14.53	0.284	0.377	0.315
David Price	248.33	15.02	0.307	0.360	0.368
Jon Lester	219.67	15.90	0.407	0.357	0.324
Jose Quintana	200.33	16.70	0.301	0.356	0.286
Max Scherzer	220.33	16.51	0.317	0.351	0.336
Adam Wainwright	227.00	14.35	0.420	0.347	0.284
Stephen Strasburg	215.00	15.33	0.318	0.340	0.379
Zack Greinke	202.33	15.87	0.369	0.337	0.348
Madison Bumgarner	217.33	15.52	0.336	0.328	0.336
Cole Hamels	204.67	15.32	0.407	0.326	0.304
Jeff Samardzija	219.67	15.20	0.334	0.313	0.327
Dallas Keuchel	200.00	15.10	0.341	0.312	0.322
Ian Kennedy	201.00	16.93	0.275	0.312	0.288
Johnny Cueto	243.67	15.02	0.444	0.303	0.317
Lance Lynn	203.67	16.94	0.365	0.299	0.260
Sonny Gray	219.00	15.05	0.325	0.289	0.281
Julio Teheran	221.00	14.80	0.346	0.287	0.272
Aaron Harang	204.33	16.61	0.280	0.280	0.239
Bartolo Colon	202.33	14.88	0.244	0.280	0.267
James Shields	227.00	16.00	0.312	0.279	0.279
Rick Porcello	202.67	14.90	0.292	0.274	0.260
Mark Buehrle	202.00	15.26	0.295	0.273	0.231
Justin Verlander	206.00	16.55	0.220	0.267	0.240
Mike Leake	214.33	15.00	0.270	0.258	0.285
Wade Miley	201.33	15.98	0.230	0.251	0.272
Chris Tillman	207.33	16.45	0.299	0.249	0.235
Jake Peavy	202.67	15.91	0.268	0.243	0.243
A.J. Burnett	213.67	16.25	0.218	0.242	0.250
Jered Weaver	213.33	15.71	0.279	0.239	0.239
R.A. Dickey	215.67	16.29	0.270	0.231	0.245
Jeremy Guthrie	202.67	15.96	0.242	0.231	0.230

2014 Overview of DMUs

DMUs	Overall Efficiency	Scale Efficiency	Technical Efficiency
Corey Kluber	1	1	1
Felix Hernandez	1	1	1
Phil Hughes	0.995	1	0.995
David Price	0.892	0.920	0.969
Jon Lester	0.962	0.971	0.990
Jose Quintana	0.983	1	0.983
Max Scherzer	0.914	0.914	1
Adam Wainwright	0.934	1	0.934
Stephen Strasburg	1	1	1
Zack Greinke	1	1	1
Madison Bumgarner	0.904	0.904	0.999
Cole Hamels	1	1	1
Jeff Samardzija	0.866	0.866	1
Dallas Keuchel	0.938	1	0.938
Ian Kennedy	0.872	0.914	0.954
Johnny Cueto	0.921	0.951	0.969
Lance Lynn	0.903	0.929	0.972
Sonny Gray	0.777	0.790	0.983
Julio Teheran	0.790	0.810	0.976
Aaron Harang	0.769	0.799	0.962
Bartolo Colon	0.792	1	0.792
James Shields	0.728	0. 728	1
Rick Porcello	0.778	1	0.778
Mark Buehrle	0.782	0.839	0.932
Justin Verlander	0.717	0.741	0.967
Mike Leake	0.764	0.793	0.964
Wade Miley	0.773	0.808	0.958
Chris Tillman	0.728	0.741	0.983
Jake Peavy	0.709	0.721	0.983
A.J. Burnett	0.681	0.681	0.999
Jered Weaver	0.670	0.681	0.983
R.A. Dickey	0.664	0.664	1
Jeremy Guthrie	0.669	0.676	0.990