Sports Economics, Management and Policy

John Ruggiero

Frontiers in Major League Baseball

Nonparametric Analysis of Performance Using Data Envelopment Analysis

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Nonparametric Analysis of Performance Using Data Envelopment Analysis

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To my wife Amy
and our daughters Kailey and Chloé

Preface

Baseball has always been my favorite sport. My childhood was defined by baseball, from playing Little League, American Legion and in the backyard with my brothers to spending an inordinate amount of time watching the New York Yankees. Growing up in Delhi, New York, I was exposed to Yankee baseball and broadcasters Phil Rizzuto, Frank Messer, and Bill White. Yankee baseball, fishing, and Skoal. With my friend Jeremy Hunter and brother Gerald. Not only did I have to watch every game, but I had to read the next day's NY Post, which I preferred to the NY Daily News.

The teams that I remember were the 1977 and 1978 teams. Mickey Rivers, Willie Randolph, Thurman Munson, Reggie Jackson, Chris Chambliss, Lou Piniella, Graig Nettles, Roy White. I remember cringing often when Bucky Dent came to bat. And of course, Billy Martin. And while my memory is not good enough to remember all of the details, I still remember I was playing ball in the front yard when my brother Michael broke the news of Thurman's death. Perhaps because Munson was my favorite player, I initially despised Reggie Jackson. Only later did I adopt Reggie as my favorite. And I promised to return to Cooperstown when Reggie got inducted; I made it down for the rained out game but not the induction ceremony.

It was in Delhi that I started listening to Pete Franklin's broadcast on 3WE out of Cleveland. When Reggie became a free agent and signed with the Angels, I became an Indians fan. And I have suffered even though I do like cheering for the underdogs. After 1995 and 1997 and the loss of Manny Ramirez, Albert Belle, Victor Martinez, and CC Sabathia, it has been difficult but I still watch the Indians whenever I can. I will admit that I am frustrated with the blackout schedule of Major League baseball. Because I live in Dayton, OH, I am unable to watch the Indians on television because this is the Reds market. The Reds had a good year, making the playoffs, but I would not watch them unless the Indians were in town. I did go see Mark McGwire play in 1998 and enjoyed watching him walk to first base a lot. Thanks, Jack. It makes no sense for MLB to not supply a good when there is a clear demand.

I had the good fortune of working under Jerry Miner at Syracuse University during my graduate days. I was able to look beyond his love for the Yankees; I benefited from his guidance. While at Syracuse, I earned my doctorate degree in economics. I learned the process of research from Jerry Miner and Bill Duncombe. I was fortunate to have the support of my wife Amy, who allowed me to spend an extra year as a graduate student. This allowed me to further develop my research expertise in performance evaluation.

During my interview at the University of Dayton, I met the late Larry Hadley, a sports economist who sparked my interest in applying nonparametric and parametric techniques to analyze sports economics. Larry was a good and generous friend who co-authored several papers with me. Our first paper, co-authored with Elizabeth Gustafson, was on the measurement of technical efficiency in baseball[1] and was published in the 1996 book *Sports Economics*. Elizabeth, Larry, and I followed this up with Gustafson et al. (1999), a paper on econometric specification of baseball production. Larry and I also published a 1999 paper in the *Baseball Research Journal* on evaluating managers. Every time I co-authored a paper we would have the same argument. He insisted that I list my name first while I preferred alphabetical order. He did this because, unlike Larry, I was an untenured junior faculty and he was looking out for my interests. In hindsight, I should have appreciated his generosity rather than find ways to win the argument. But I am happy I won the argument

Larry and I also teamed up on a few research articles, including Ruggiero et al. (1997), a paper showing that the so-called Pythagoras relationship developed by Bill James cannot be used to measure performance. The relationship between wins in a season can be determined from an identity involving total runs scored, total runs allowed, and the total excess runs. We show the relationship follows algebraically from the simple fact that a game is won if more runs are scored than allowed. Larry and I co-authored a paper with Marc Poitras and Scott Knowles on performance evaluation of NFL teams in 2000. Finally, Hadley and Ruggiero (2006) developed a nonparametric model to evaluate free agents. This model is applied to analyze free agents from the 2009 season.

Unfortunately, I was unable to work further with Larry given his health conditions. I think about Larry often and remember the good times; I will admit that I was somewhat bothered by Larry's ability to choose a favorite team during the playoffs, typically when the Reds were done for the year. Perhaps if I adopted his philosophy I would not be disappointed every year.

My research has benefitted over the years from discussions with many scholars. A special recognition goes to participants at the INFORMS annual meetings who somehow tolerate me. I guess I should extend that to anybody who has ever met me. I have benefitted from conversations with Andy Johnson, Ole Olesen, Timo Kuosmanen, and Tim Anderson. Tim presented a paper at INFORMS to evaluate players; his paper served as a useful reference for my chapter on player evaluation.

[1] Ruggiero et al. (1996).

Recently, I have had the pleasure of working on many projects with Andy, who is on pace to become one of the top researchers in performance evaluation. One of our recent papers, co-authored with Trevor Collier, develops a modified performance model useful for sports when inefficiency correlates with other teams' output.[2] This model is used in this book to measure team efficiency. I also use Collier et al. (2010b) to evaluate individual players.

Organization of the book

The topics in this book are organized into three parts:

- Data envelopment analysis and the evaluation of team performance
- Evaluation of individual players and free agents
- Historical analysis of Hall of Fame selection and the steroid era

The first two chapters of the book are devoted to a brief literature review and the development of the nonparametric models for performance evaluation known as data envelopment analysis (DEA). I do not claim to provide an exhaustive presentation of DEA; this book is intended to be an empirical analysis of Major League Baseball. I present the basic envelopment models to analyze technical and scale efficiency that form the basis for DEA. The literature is full of useful extensions that go beyond the empirical analysis conducted here. In many instances, extensions of the basic models need to be developed for specific chapter applications. Where needed, these extensions are presented in the individual chapters.

The rest of part 1 consists of two applications. I measure the team (and manager) efficiency for the 2009 season in Chap. 3. Cost efficiency for the 2009 season is measured in Chap. 4. Both these models require extensions due to the tournament nature of sports; if a team loses a game due to inefficiency, another team must gain a win. As a result, the estimated frontier from DEA is biased upward. The correction from Collier et al. (2010b) is applied.

The rest of the book is devoted to analyzing player performance. Using a model developed by Collier et al. (2010a), we measure aggregate performance using a modified linear programming model. In the second part of the book, I focus on how DEA can be used to evaluate hitters (Chap. 5), pitchers (Chap. 6), and free agents (Chap. 7). These models provide an overall measure of performance by aggregating multiple player statistics nonparametrically. The methods could be used by teams to make better decisions with respect to draft choices, trades, and free agents.

The last two chapters analyze the performance of players historically. Using DEA, we develop a measure of aggregate performance by season. This allows us to compare how a player performed relative to his peers. Using this measure,

[2]Collier et al. (2010b).

I analyze the performance of Hall of Fame players and rank the all-time greats. I also identify Hall of Fame players who arguably do not belong in the Hall. I also present arguments on noninducted players who do. The final chapter presents a detailed analysis of steroid use. Using the aggregate measure of performance, I analyze age–performance profiles of numerous players who played before and during the steroid era. Results from admitted steroid users vs. pre-steroid players provide the means to analyze other players. Of course, the results are only suggestive and are only meant for discussion purposes.

Intended Audience

I recently taught a class on DEA as an upper elective for undergraduate and MBA students at the University of Dayton. The material presented throughout this book was at the level of these classes. I spend a lot of time going over the DEA model, linking it to microeconomic production theory while stressing the importance of convexity, monotonicity, and free disposability. The class presents theoretical and methodological extensions that are not presented in this book. Topics covered in this book were used in the class, both as teaching examples and student topics.

The book is accessible to students in economics, mathematics, operations research, industrial engineering, and business programs. The empirical application to Major League Baseball would be useful for practitioners in management, sports management, and sports economics.

Acknowledgments

I would like to first thank the numerous colleagues who have collaborated with me over the years. From Syracuse University, I benefitted from working with Jerry Miner, Jan Ondrich, Johnny Yinger, Bill Duncombe, and Stuart Bretschneider. I owe special thanks to Jerry, my dissertation adviser, without whom I would not be where I am today. Jan was one of my econometrics professors who helped train me and contributed significantly to my development.

I am indebted to Larry Hadley, Ralph Frasca, Elizabeth Gustafson, and John Rapp, all colleagues at the University of Dayton. Ralph was the chair who hired me and provided me with a lot of support. In addition to co-authoring two book chapters, I thank Elizabeth for supporting me as my department chair and interim dean. John has been a quality friend who has been most supportive of me. In the past year I was promoted to Edmund B. O'Leary professor of economics. It goes without saying that this would not have been possible without John's support. Thank you. I also recognize Dean Matt Shank for his support. In addition to being my current boss and arbitrator over my future raises, Matt is genuinely nice and has a beautiful family.

Another colleague with whom I have written deserve thanks. Marc Poitras, one of the smartest people I have ever met, is a walking encyclopedia of baseball knowledge. I am envious of his ability to recall baseball statistics and other facts.

I have used many sources. I am indebted to Sean Lahman; his extensive database was the primary source for my analysis.[1] I also referenced data from http://www.mlb.com, http://go.espn.com, and http://www.baseball-reference.com. In addition, I used two books by Bill James, *The New Bill James Historical Baseball Abstract* (2001) and *Whatever Happened to the Hall of Fame?* (1995).

Numerous online articles on steroids in baseball were accessed; I have tried to provide footnote references when information was used. In preparation for the steroid chapter, I also read Jose Canseco's books *Juice* (2005) and *Vindicated* (2008). Both books were enjoyable. In hindsight, it is hard to believe the initial

[1]His data can be downloaded from http://www.baseball1.com.

negative reaction to *Juice*. It is also hard to believe how many lies have been told regarding steroid use. I benefitted from reading two other books on steroid use. *Game of Shadows* (2006) by Mark Fainaru-Wada and Lance Williams provided useful information on Barry Bonds. Kirk Radomski's *Bases Loaded* (2009) was another interesting book rich in details about steroid use and abuse. These books provided details on steroid use that allowed me to focus on outlier performance.

Over the years, I have benefitted from numerous conversations on baseball. It is impossible to list all, of course, but I will point out a few. My school bus rides with Pete Mansheffer were made enjoyable by Pete's knowledge of baseball. Thanks Pete. I have benefitted from useful discussions with Brent Macintosh, Marc Poitras, Jim and Eileen Malas, Tony Caporale, Jaime Garrett, Gary Abrams, Erica Abrams, Amy Sparks, Randy and Merritt Sparks, Scott Wentz, Jim Gross, and Jacob Fogarty. And I have been enlightened by Bob Thomas, who was a catcher in college. I would also like to thank members of Team John, including but not limited to Amy and Randy Sparks, Sally Doran, Nicole and Scott Wentz, Andrea and Gary Abrams and my wife Amy. Needless to say, their fight for justice in the face of lies is greatly appreciated. Knock it off, Amy Sparks!

I wish to thank my mother Lois, a real baseball fan, and my father Vincent. My mom has given me numerous memorabilia, including her 1949 World Series Program bought at game 1 between the Brooklyn Dodgers and the New York Yankees. Tommy Henrich hit a walk off home run to win the game. My mother was the best little league coach; needless to say we won the championship. For this, I forgive her for still liking the Yankees.

I would like to thank my brother Francis who was my teammate in backyard baseball. He was not gifted with great athletic ability and he did not understand baseball well, but he knew enough to step back to let me shine. I thank him because I suspect he will be the only family member to buy the book.

I also want to thank my facebook friends. Barb and Bob Mackey provided great assistance last year by sending me useful items for my farm. Without their support, I might still be playing farmville instead of writing this book. This has been a team project; all errors are shared by the entire team.

A special thanks goes to Dennis Coates, who asked me to write this book. I met Dennis at the Western Economic Association annual meetings when I presented a paper in Larry's honor. And to my editor Jon Gurstelle, who has consistently supported me, especially by granting me deadline extensions. This has been a team project; all errors are shared by the entire team.

Most of all, I thank my wife Amy and my daughters, Kailey and Chloé. In order to write this book, I have had to put in extra hours that should have been given to them. I promise I will make it up to you by working less in the future.

Contents

Chapter 1
Introduction

Measuring Technical Efficiency

Koopmans (1951) provided a useful framework for the measurement of efficiency by defining technical efficiency as feasible input–output combinations where it is not possible to increase output (decrease inputs) without simultaneously increasing inputs (decreasing output). In a seminal paper, Farrell (1957) showed how efficiency can be measured relative to a given isoquant as the maximum radial reduction in observed inputs holding output constant. Farrell further provided the decomposition of overall efficiency into technical and allocative parts. Farrell's paper serves as the foundation for the nonparametric and parametric models of technical efficiency estimation.[1] While Farrell provided a useful foundation for the measurement of technical efficiency, the model allowed only one output and assumed constant returns to scale. The assumption was relaxed to allow increasing returns to scale in Farrell and Fieldhouse (1962).

Data Envelopment Analysis

The Farrell measure was extended in the economics literature by Boles (1966, 1971) who showed that estimation could be achieved by linear programming. Afriat (1972) provided a variable returns to scale formulation to estimate the nonparametric frontier. Charnes et al. (1978) introduced the nonparametric linear programming formulation assuming constant returns to scale to the operations research literature. Their formulation showed that efficiency in multiple input and multiple output production technologies could be estimated by specifying a fractional programming model and provided the linear programming equivalent. Charnes, Cooper and Rhodes dubbed their technique data envelopment analysis (DEA). The Charnes, Cooper, and Rhodes version of the model has served as the foundation for the

[1] Førsund and Sarafoglou (2002) provide an excellent discussion of the history of data envelopment analysis.

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operations research literature. The model is appealing to microeconomists given the links to theoretical production theory.

Färe and Lovell (1978) introduced the Russell measure of technical efficiency to the economics literature at the same time that Charnes, Cooper, and Rhodes introduced the Farrell measure. One of the limitations of the DEA method is the projection to facets of the isoquant that are not efficient in the Koopmans sense. The Russell measure projects units to the efficient subset of the isoquant. Extensions to the Russell measure were provided by Zieschang (1984) and Ruggiero and Bretschneider (1998).

Färe et al. (1983) provided the linear programming formulation of the variable returns to scale model. Banker et al. (1984) extended the multiple-input multiple-output DEA model of Charnes, Cooper, and Rhodes to allow variable returns to scale. The extension to variable returns to scale was achieved with the inclusion of a convexity constraint in the linear programming model. Interestingly, Afriat (1972) introduced the convexity constraint to allow variable returns to scale more than a decade earlier. Banker et al. (1984) provided a decomposition of productive efficiency into technical and scale components. The decomposition requires solving the constant returns to scale model of Charnes, Cooper, and Rhodes and the variable returns to scale model of Banker, Charnes, and Cooper.

The Farrell measure in DEA can be measured using either an input orientation or an output orientation. The input orientation seeks the maximum radial reduction in inputs consistent with observed production. As such, the model can be considered as removing wasteful inputs and hence, reduce costs. The output orientation seeks maximum radial addition to observed outputs holding inputs constant. Inefficient firms that are not achieving frontier output for their input levels are forgoing additional revenues. A useful microeconomic foundation is provided by Färe et al. (1994). This book provides an advanced treatment of various models for estimating not only technical efficiency but also profit and cost efficiencies.[2]

Stochastic Frontier

Aigner and Chu (1968) extended Farrell's work by measuring a deterministic model of production assuming all deviations from the frontier are one-sided. Greene (1980) showed that OLS could be used instead of programming models to estimate the deviation from the frontier assuming one-sided errors. Because OLS produces consistent estimates, a correction to the intercept of the largest residual provides an estimate of the production frontier. This technique is referred to as corrected OLS (COLS).

[2] Färe et al. (1994) extends Färe et al. (1985). While I have found both books to be extremely valuable, the 1994 has been most useful in my research.

Collier et al. (2010a) extended the COLS approach to allow multiple outputs by developing a two-stage model. In the first stage, variable returns to scale DEA is applied using only outputs. The resulting measure is an aggregate measure of the output that can be used in the COLS model. The advantage of this approach is that the output aggregate is estimated nonparametrically, and the second stage COLS model provides useful statistical analysis.

A limitation of the COLS model is the inability to properly model measurement error and other statistical noise. Attributing all deviations to inefficiency in production is not appealing. If the data are characterized by statistical noise, measured deviations in the deterministic models of DEA and COLS caused by noise will be wrongly attributed as inefficiency. A large body of research in the econometrics literature was developed to overcome this problem. Aigner et al. (1977) and Meeusen and van den Broeck (1977) provided the foundation for the stochastic frontier models with a composed error model. It was assumed that the error term was composed of inefficiency and statistical noise, both of which are unobservable.

Jondrow et al. (1982) provided an estimate of individual inefficiency based on the expected value of inefficiency conditional on the observed composed error. The approach requires distributional assumptions for the error terms; the distributions are typically chosen based on mathematical convenience. Ruggiero (1999) and Ondrich and Ruggiero (2001) prove that the cross-sectional models do not hold any real advantages over deterministic models because the stochastic frontier estimates and the overall error have a rank correlation of 1. Distributional assumptions do allow maximum likelihood estimates of the production frontier but do not provide good estimates of inefficiency.

Schmidt and Sickles (1984) overcome this problem by using panel data with a fixed effects estimator. The necessary information for decomposing noise from inefficiency is gained not from distributional assumptions but rather from information on specific units with data across time. The approach provides consistent estimates under the assumption that inefficiency is time invariant.

Efficiency in Sports Economics

There have been numerous applications of frontier models to analyze sports. In this section, I highlight several while recognizing there are too many to list. Porter and Scully (1982) estimated managerial efficiency in MLB using linear programming. Using slugging average and the ratio of pitcher strikeouts to bases on balls as inputs and wins as the output, the authors estimate a deterministic model. They conclude that Earl Weaver was the best manager over the time period considered.[3]

[3] Berri and Bradbury (2010) have a very interesting article on sports economics that discusses academic and nonacademic researches.

One of the earliest approaches that applied frontier analysis was the one by Zak et al. (1979), who employed a deterministic regression model to estimate average efficiency in the NBA. Horowitz (1994) extended Bill James' Pythagoras approach to measure efficiency of managers. The approach estimates the relationship between wins and runs scored. However, Ruggiero et al. (1997) showed that estimating equation is a misspecified identity that provides a measure of runs in excess of the amount needed. If, for example, team A beats team B by a score of 6 to 2, then team A scored three excess runs. Hence, Horowitz' approach only captures variation in excess runs over a season.

Ruggiero et al. (1996) measured team/managerial efficiency in Major League Baseball using a production model of wins as a function of player quality. Gustafson et al. (1999) estimate baseball production using alternative econometric methods. While the paper did not measure efficiency per se, the estimated production functions could be modified to do so. Hadley et al. (2000) used a deterministic regression approach to measure team efficiency in the National Football League. Using wins as the dependent variable, the authors estimated the Poisson regression using maximum likelihood.

In addition to the papers listed above, there have been numerous other papers applying frontier models to analyze efficiency concepts in baseball. Scully (1994) analyzed managerial efficiency of baseball managers (and coaches in other sports) and how tenure is related to efficiency. Lewis and Sexton (2004) analyze performance in baseball; they develop a method to account for performance variables that violate the assumption of monotonicity. More recently, Lewis et al. (2009) provide a thorough investigation into baseball efficiency, analyzing multiple dimensions of efficiency; the authors analyze efficiency using DEA for over 100 years of baseball (the modern era).

Anderson and Sharpe (1997) and Mazur (1995) applied DEA to measure performance of individual players. Their model provides a measure of aggregate performance and is the foundation for the analysis in this book on measuring aggregate player performance.

Einolf (2004) applied DEA to measure efficiency in Major League Baseball (and the National Football League) and discussed how inefficiency was related to the financial structure of the leagues. Volz (2009) applied DEA to analyze the effect minority status has on managerial tenure in Major League Baseball. Volz finds that minority managers are about 10% more likely to return the following season after controlling for performance measures. Chen and Johnson (2010) model the dynamics of performance space using DEA and apply it to an analysis of pitchers.

There have been several papers applying frontier models to analyze performance in soccer (football).[4] Dawson et al. (2000) apply the stochastic frontier model in an analysis of English soccer teams. Carmichael et al. (2001) use a regression-based approach applied to specific match play to estimate efficiency of English

[4] Given applications to American football, we will use the term soccer, however politically incorrect.

Premiership association soccer teams. Haas (2003) applied DEA to analyze efficiency in Major League Soccer. Espitia-Escuer and Garcia-Cebrian (2004) estimated technical efficiency of Spanish soccer teams. Barros and Leach (2006) analyzed the Portuguese and English soccer leagues using DEA.

Frontier models have been applied to other sports as well. Leibenstein and Maital (1992) establish the link between Leibenstein's X-efficiency and DEA with an application to the Boston Bruins offense. Fizel and D'Itri (1996, 1997, 1999) analyzed 147 college basketball teams. Kahane (2005) measured production efficiency and hiring discrimination in the National Hockey League using the stochastic frontier approach. Kahane found that inefficiency was linked to coaching ability, local sports competition, and management experience. Nero (2001) and Fried et al. (2004) measured efficiency of golfers.

Chapter 2
Data Envelopment Analysis

Technology

Analysis of performance has economic production theory as its foundation. Firms employ inputs to produce output typically with an incentive to maximize profits. Firms that are technically inefficient could increase outputs and revenue with the same inputs or could decrease inputs and cost with the same outputs. Farrell (1957) provided a decomposition of inefficiency into technical and allocative parts. From an input-oriented perspective, firms that are not operating on the isoquant associated with observed production are technically inefficient. Farrell provided a comprehensive measure of technical efficiency as the equiproportional reduction of all inputs holding output at current levels. Allocative efficiency is then measured relative to the cost minimizing mix of inputs given observed input prices.

Farrell provided the formulation to handle a single output in the case of constant returns to scale. The paper also discussed decreasing returns to scale and the extension to multiple outputs. Farrell and Fieldhouse (1962) extended the approach as a linear program allowing increasing returns to scale. Afriat (1972) provided the formulation for technical efficiency measurement that was consistent with data envelopment analysis (DEA). The theoretical foundations of efficiency measurement are provided in Färe et al. (1994).

DEA is the term coined in the operations research literature by Charnes et al. (1978) (CCR) to measure the technical efficiency of a given observed decision-making unit (DMU) assuming constant returns to scale. Their linear programming formulation allowed multiple inputs and multiple outputs. Banker et al. (1984) (BCC) extended the CCR model to allow variable returns to scale and showed that solutions to both CCR and BCC allowed a decomposition of CCR efficiency into technical and scale components.

In this section, we introduce the representation of the technology that serves as the basis for efficiency measurement. We assume that decision-making units use a vector of m discretionary inputs $X = (x_1,\ldots,x_m)$ to produce a vector of s outputs $Y = (y_1,\ldots,y_s)$. We represent the individual inputs and outputs of netput (Y_j, X_j) for DMU_j ($j = 1, \ldots, n$) as $x_{ij}(i = 1,\ldots,m)$ and y_{kj} ($k = 1,\ldots,s$), respectively. Following Lovell (1993) we assume that production can be characterized by an input set

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$$L(Y) = \{X : (Y, X) \text{ is feasible}\}. \tag{2.1}$$

For each output vector Y we define the isoquant for input set $L(Y)$ as

$$\text{Isoq}\, L(Y) = \{X : X \in L(Y), \lambda X \notin L(Y), \lambda \in [0, 1)\}. \tag{2.2}$$

The isoquant represents the boundary such that the observed production of Y cannot be achieved with any equiproportional reduction in all inputs. The definition of the isoquant for the input set provides the theoretical basis for input-oriented models of technical efficiency. Alternatively, production can be represented by an output set

$$P(X) = \{Y : (Y, X) \text{ is feasible}\}. \tag{2.3}$$

Similar to the input set, we define the isoquant for the output set *P(X)* for each input vector X as

$$\text{Isoq}\, P(X) = \{Y : Y \in P(X), \lambda^{-1} Y \notin P(X), \lambda \in [0, 1)\}. \tag{2.4}$$

This isoquant represents the boundary of the output set; without additional resources, equiproportional expansion of all outputs is infeasible. The output set isoquant provides the basis for evaluating technical efficiency in the output-oriented model. To make the connection to the formulation of Banker, Charnes, and Cooper, we define the technology as

$$T = \{(X, Y) : Y \in P(X)\} = \{(X, Y) : X \in L(Y)\}. \tag{2.5}$$

In Sect. 2, the input-oriented models of efficiency are developed; more structure is also placed on the production technology with assumptions on scale economies.

Input-Oriented Models

The Farrell (1957) input-oriented measure of technical efficiency of DMU_j is given by

$$F(Y_j, X_j) = \min\{\lambda : \lambda X_j \in L(Y_j)\}. \tag{2.6}$$

The Farrell measure projects observed production possibilities as far as possible ensuring that the resulting projection is on $\text{Isoq}\, L(Y)$. One of the maintained assumptions in traditional DEA models is that all observed production possibilities are feasible. Consequently, the approach does not allow for measurement error or other statistical noise and requires proper selection of inputs and outputs.

Constant Returns to Scale DEA

In order to make the connection between DEA efficiency measurement and the representation of the technology, we specify the input set $L(Y)$ with a piecewise linear representation. Following Färe et al. (1994), this representation under constant returns to scale is given by

$$L_{\mathrm{C}}(Y) = \left\{ \begin{array}{ll} X : \sum_{j=1}^{n} \lambda_j y_{kj} \geq y_k, & k = 1, \ldots, s; \\ \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_i, & i = 1, \ldots, m; \\ \lambda_j \geq 0, & j = 1, \ldots, n \end{array} \right\}. \tag{2.7}$$

Likewise, the output set and technology under constant returns to scale are represented by

$$P_{\mathrm{C}}(X) = \left\{ \begin{array}{ll} Y : \sum_{j=1}^{n} \lambda_j y_{kj} \geq y_k, & k = 1, \ldots, s; \\ \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_i, & i = 1, \ldots, m; \\ \lambda_j \geq 0, & j = 1, \ldots, n \end{array} \right\} \tag{2.8}$$

and

$$T_{\mathrm{C}} = \left\{ \begin{array}{ll} (X, Y) : \sum_{j=1}^{n} \lambda_j y_{kj} \geq y_k, & k = 1, \ldots, s; \\ \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_i, & i = 1, \ldots, m; \\ \lambda_j \geq 0, & j = 1, \ldots, n. \end{array} \right\} \tag{2.9}$$

The Farrell measures of efficiency defined relative to these piecewise linear technologies were popularized by Charnes et al. (1978). The model to evaluate the overall efficiency $F_{\mathrm{C}}(Y_0, X_0)$ of observed production possibility (Y_0, X_0) is[1]

[1] The measure $F_{\mathrm{C}}(Y_0, X_0)$ is referred to as an overall measure because it is composed of technical and scale inefficiency. This is discussed further in Sect. 4.

$$
\begin{aligned}
&F_{\mathrm{C}}(Y_0, X_0) = \min\ \theta \\
&\text{subject to} \\
&\sum_{j=1}^{n} \lambda_j y_{kj} \geq y_{k0}, && k = 1, \ldots, s; \\
&\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{i0}, && i = 1, \ldots, m; \\
&\lambda_j \geq 0, && j = 1, \ldots, n.
\end{aligned}
\tag{2.10}
$$

This model seeks the maximum equiproportional reduction in all inputs consistent with observed production. Left-hand side of the input and output constraints represents feasible frontier production assuming constant returns to scale.

The Farrell measure is illustrated in input space in Fig. 2.1, where it is assumed that five DMUs (A–E) are observed producing the same output vector Y using two inputs x_1 and x_2. Data for the DMUs are given in the following chart:

DMU	X_1	X_2
A	5	30
B	10	20
C	20	10
D	30	5
E	25	25

The input set $L_{\mathrm{C}}(Y)$ and the associated isoquant Isoq $L_{\mathrm{C}}(Y)$ are shown. Four DMUs (A–D) are observed producing Y efficiently; it is not possible to reduce both inputs at the same rate while maintaining production of Y. The resulting level of efficiency for these DMUs is 1. DMU E, on the other hand, is observed producing Y using excess inputs; it is possible to reduce both inputs from 25 to 15. We note that an equally weighted convex combination of B and C results in the solution of (2.10). Based on (2.6) and the solution to (2.10), the resulting Farrell efficiency measure would be $F_{\mathrm{C}}(Y_{\mathrm{E}}, X_{\mathrm{E}}) = 15/25 = 0.6$. Hence, DMU E should be able to produce the same level of output using 60% of its current input levels.

We can also illustrate constant returns to scale input-oriented efficiency measurement using the piecewise linear technology (2.9). In Fig. 2.2, we assume for convenience that one input x_1 is used to produce one output y_1. Data from Fig. 2.2 are given in the following chart:

DMU	X_1	Y_1
A	10	10
B	14	20
C	20	28.57
D	30	32
E	20	14

Fig. 2.1 Input-oriented efficiency measurement and Isoq $L_C(Y)$

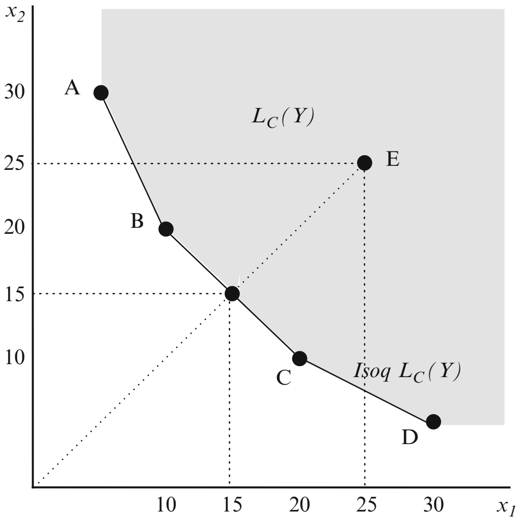
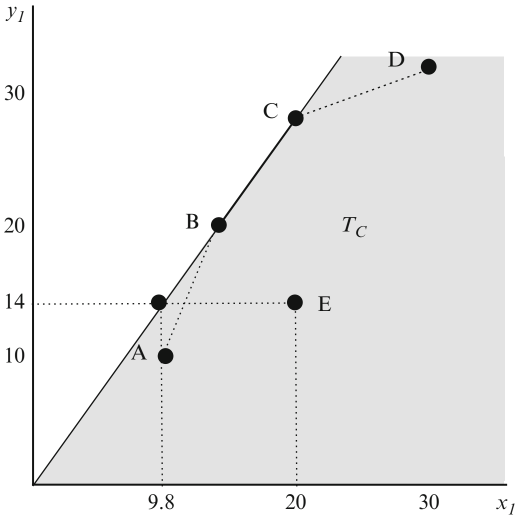


Fig. 2.2 Input-oriented efficiency measurement using T_C



Variable Returns to Scale DEA

While Farrell (1957) introduced the model for efficiency analysis, the model was restrictive with the assumption of constant returns to scale. Farrell and Fieldhouse (1962) extended this model to allow non-decreasing returns to scale. Afriat (1972) provides the variable returns to scale model that was popularized in the operations research literature by Banker et al. (1984). Banker et al. (1984) (BCC) show that the addition of a convexity constraint to the CCR model results in a DEA model that allows increasing, constant, and decreasing returns to scale. In addition, BCC provides a decomposition of CCR Farrell efficiency into scale and technical parts.

The input set under variable returns to scale is represented by

$$L_{\mathrm{V}}(Y) = \left\{ \begin{array}{ll} X : \sum_{j=1}^{n} \lambda_j y_{kj} \geq y_k, & k = 1, \ldots, s; \\ \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_i, & i = 1, \ldots, m; \\ \sum_{j=1}^{n} \lambda_j = 1; & \\ \lambda_j \geq 0, & j = 1, \ldots, n. \end{array} \right\} \tag{2.11}$$

The associated variable returns to scale, piecewise linear output sets, and technology are represented by

$$P_{\mathrm{V}}(X) = \left\{ \begin{array}{ll} Y : \sum_{j=1}^{n} \lambda_j y_{kj} \geq y_k, & k = 1, \ldots, s; \\ \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_i, & i = 1, \ldots, m; \\ \sum_{j=1}^{n} \lambda_j = 1; & \\ \lambda_j \geq 0, & j = 1, \ldots, n \end{array} \right\} \tag{2.12}$$

and

$$T_{\mathrm{V}} = \left\{ \begin{array}{ll} (X,Y) : \sum_{j=1}^{n} \lambda_j y_{kj} \geq y_k, & k = 1, \ldots, s; \\ \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_i, & i = 1, \ldots, m; \\ \sum_{j=1}^{n} \lambda_j = 1; & \\ \lambda_j \geq 0, & j = 1, \ldots, n. \end{array} \right\} \tag{2.13}$$

With these representations, the Farrell input-oriented measure of technical efficiency $F_{\mathrm{V}}(Y_0, X_0)$ for observed production possibility (Y_0, X_0) is found via the solution to the following linear program:

$$
\begin{aligned}
& F_V(Y_0, X_0) = \min\ \theta \\
& \text{subject to} \\
& \sum_{j=1}^{n} \lambda_j y_{kj} \geq y_{k0}, \qquad && k = 1, \ldots, s; \\
& \sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta\, x_{i0}, \qquad && i = 1, \ldots, m; \\
& \sum_{j=1}^{n} \lambda_j = 1; \\
& \lambda_j \geq 0, \qquad && j = 1, \ldots, n.
\end{aligned} \tag{2.14}
$$

Relative to Fig. 2.1, the variable returns to scale model will produce the same results as the constant returns to scale model. This results because all units are observed producing the same output levels.

We illustrate input-oriented efficiency assuming variable returns to scale in Fig. 2.3, which illustrates the technology defined in (2.13). The data in Fig. 2.3 is the same data used in Fig. 2.2, where it was assumed that one output y_1 produced from one input x_1.

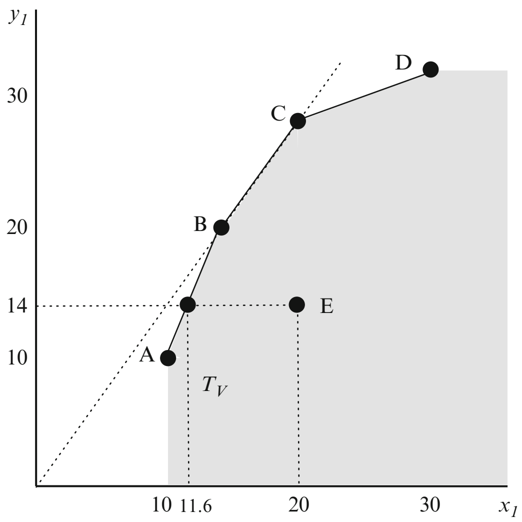


Fig. 2.3 Input-oriented efficiency using T_{V}

DMUs (A–D) are technically efficient, producing on the production frontier; it is not possible for any of these DMUs to reduce input levels while simultaneously producing at least as much output. DMU E, on the other hand, is observed producing in the interior of the technology T. DMU E is observed producing 14 units of output while using 20 units of the input. However, a convex combination of DMUs A and B with a weight on A of 0.6 and a weight on B of 0.4 produces the same output using only 11.6 units of the input. As a result, the efficiency of DMU E is $F_{\mathrm{V}}(Y_{\mathrm{E}}, X_{\mathrm{E}}) = 11.6/20 = 0.58$.

Output-Oriented Models

While the input-oriented measure projects to the boundary of Isoq $L(Y)$, the output-oriented measure projects to the boundary of $P(X)$. The output-oriented measure of technical efficiency of DMU$_j$ is given by

$$F_{\mathrm{o}}^{-1}(Y_j, X_j) = \max\{\theta : \theta Y_j \in P(X_j)\}. \tag{2.15}$$

The Farrell output-oriented measure projects observed production possibilities as far as possible ensuring that the resulting projection is on Isoq $P(X)$. For this book, we consider the output-oriented efficiency measure to be on the range of (0, 1) and hence, invert the distance function. Assuming variable returns to scale, the inverse $\tilde{F}_{\mathrm{V}}^{-1}(Y_0, X_0)$ of the output-oriented measure of efficiency for observed production possibility (Y_0, X_0) is found via the solution to the following linear program:

$$\begin{aligned}
&\tilde{F}_{\mathrm{V}}^{-1}(Y_0, X_0) = \max\ \psi \\
&\text{subject to} \\
&\sum_{j=1}^{n} \lambda_j y_{kj} \geq \psi y_{k0}, && k = 1, \ldots, s; \\
&\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{i0}, && i = 1, \ldots, m; \\
&\sum_{j=1}^{n} \lambda_j = 1; \\
&\lambda_j \geq 0, && j = 1, \ldots, n.
\end{aligned} \tag{2.16}$$

By removing the convexity constraint, we obtain the inverse of the output-oriented measure of technical efficiency under the assumption of constant returns to scale:

$$
\begin{aligned}
&\tilde{F}_{\mathrm{C}}^{-1}(Y_0, X_0) = \max\ \psi \\
&\text{subject to} \\
&\sum_{j=1}^{n} \lambda_j y_{kj} \geq\ \psi y_{k0}, \qquad && k = 1, \ldots, s; \\
&\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{i0}, && i = 1, \ldots, m; \\
&\lambda_j \geq 0, && j = 1, \ldots, n.
\end{aligned}
\tag{2.17}
$$

The output-oriented measures are illustrated in Figs. 2.4 and 2.5. In Fig. 2.4, DMU E is projected assuming constant returns to scale to the frontier, illustrated as the line from the origin through production possibilities B and C. With the assumption of constant returns to scale, any proportional change in inputs leads to the same proportional change in output. Hence, any change in the scale of operation is represented along a ray (plane) from the origin. Assuming constant returns to scale, the benchmark for E is C and the resulting distance measure is $\tilde{F}_{\mathrm{C}}^{-1}(Y_{\mathrm{E}}, X_{\mathrm{E}}) = 2857/14$. Inverting $\tilde{F}_{\mathrm{C}}^{-1}$ leads to an efficiency estimate of $\tilde{F}_{\mathrm{C}}(Y_{\mathrm{C}}, X_{\mathrm{C}}) = 0.49$. Hence, given DMU E's input level of 20, they produce only 49% (2.14) of the maximum possible output (2.20).

The variable returns to scale frontier is illustrated in Fig. 2.5, with increasing returns to scale measured along line segment AB, constant returns to scale along BC and decreasing returns to scale along CD. In the case of the inefficient production possibility E, the projection to the variable returns to scale leads to a benchmark of C.

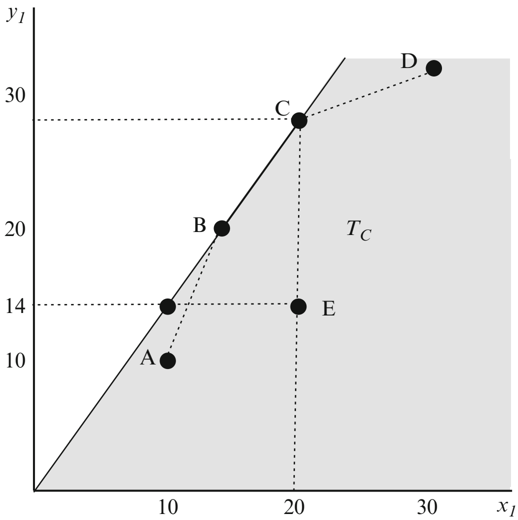


Fig. 2.4 Output-oriented efficiency using T_{C}

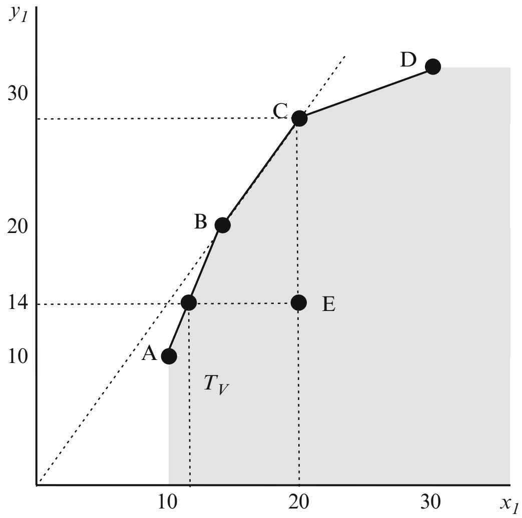


Fig. 2.5 Output-oriented efficiency using T_V

Since production possibility C is operating along the constant returns to scale portion of the frontier, the resulting efficiency assuming variable returns to scale is $\tilde{F}_V(Y_C, X_C) = 0.49$. We note that since $\tilde{F}_V(Y_C, X_C) = \tilde{F}_C(Y_C, X_C)$, production possibility C is projected to a constant returns to scale portion of the variable returns to scale frontier.

Measuring Scale Efficiency

In this section, we show that solutions to both the variable and constant returns to scale models provide relevant information on returns to scale and scale efficiency. Necessarily, notions of economies of scale exist only along a production frontier. In order to insure that unit is operating on the variable returns to scale frontier, we can apply model (2.14) to project units to the variable returns to scale frontier and remove any technical inefficiency. Then, solving (2.10) allows us to identify other deviations from the constant returns to scale frontier. First, we will consider the input oriented models.

The models developed above allow projection to either a constant returns to scale frontier or a variable returns to scale frontier. If the true technology is characterized by variable returns to scale, programming model (2.14) identifies the benchmark for measuring technical efficiency. The constant returns to scale model (2.10) overestimates true technical inefficiency by projecting to a technically infeasible point if the relevant technically efficient benchmark is characterized by either increasing or decreasing returns to scale. If the technically efficient benchmark is operating under constant returns to scale, the solution of (2.10) is feasible as a solution to (2.14) and technical efficiency is not overestimated.

Banker et al. (1984) introduce the concept of most productive scale size consistent with technically efficient production on the constant returns to scale facet of the production frontier. Production that occurs on an increasing or decreasing returns to scale facet is not most productive and hence, scale inefficient.[2] The solution of (2.10) provides a composed measure of technical and scale inefficiency. Given that (2.14) provides a measure of technical efficiency relative to the variable returns to scale technology, the ratio of $F_C(Y_0,X_0)$ to $F_V(Y_0,X_0)$ provides a measure of scale efficiency for production possibility (Y_0,X_0):

$$S(Y_0,X_0) = \frac{F_C(Y_0,X_0)}{F_V(Y_0,X_0)}. \tag{2.18}$$

A useful interpretation is that the variable returns to scale measure (the denominator) effectively removes technical inefficiency by projecting the unit to the variable returns to scale frontier; the ratio shows the additional projection that is possible only if increasing or decreasing returns to scale prevails on the frontier.

Consider inefficient DMU E in Figs. 2.2 and 2.3. Figure 2.3 illustrates the projection to the technically efficient benchmark on an increasing returns to scale portion of the frontier. Recall that DMU E is observed using 20 units of input x_1 instead of the technically efficient input level of 11.6 to produce an output level y_1 of 14. Hence, we found $F_V(Y_E,X_E) = 0.58$. The projection assuming constant returns to scale is shown in Fig 2.2. Assuming constant returns to scale, we found $F_C(Y_E,X_E) = 9.8/20 = 0.49$. We note that the technically efficient benchmark (14, 11.6) is on the increasing returns to scale portion of the frontier. The resulting scale efficiency measure for DMU E is $\mathrm{SE}(Y_E,X_E) = 0.49/0.58 = 0.84$. Hence, DMU E is only 84% scale efficient. We note that the scale efficiency of DMU E is equal to 9.8/11.6.

The measure of scale efficiency provides a measure of the proximity to most productive scale size (constant returns to scale). This is illustrated in Fig. 2.6. Consider technically efficient DMU A which is the furthest from the constant returns to scale facet BC along the increasing returns to scale facet AB. Starting at DMU A, as x_1 increases along the increasing returns to scale facet AB, the input-oriented distance between AB and the constant returns to scale frontier BC decrease. Hence, as a technically efficient benchmark gets closer to the most productive scale size, F_V approaches F_C and the scale efficiency approaches unity.

Alternatively, we can measure scale efficiency using the output-oriented model. Solving models (2.16) and (2.17), we obtain $\tilde{F}_V^{-1}(Y_0,X_0)$ and $\tilde{F}_C^{-1}(Y_0,X_0)$, respectively, for production possibility (Y_0,X_0). In this case, $\tilde{F}_V^{-1}(Y_0,X_0)$ projects the production possibility to the variable returns to scale frontier as the maximum radial expansion in output consistent with observed inputs. The scale efficiency measure for production possibility (Y_0,X_0) using the output oriented model is given by

---

[2] Panzar and Willig (1977) provide a useful discussion of returns to scale in multiple output technologies.

$$\tilde{S}(Y_0, X_0) = \frac{\tilde{F}_{\mathrm{V}}^{-1}(Y_0, X_0)}{\tilde{F}_{\mathrm{C}}^{-1}(Y_0, X_0)}. \tag{2.19}$$

The interpretation of the scale from the output oriented model is similar to the one from the input oriented model. In Fig. 2.7, we present the output-oriented measure of scale efficiency. In this case, technically efficient DMU A is projected up to the constant returns to scale frontier. As production increases along the

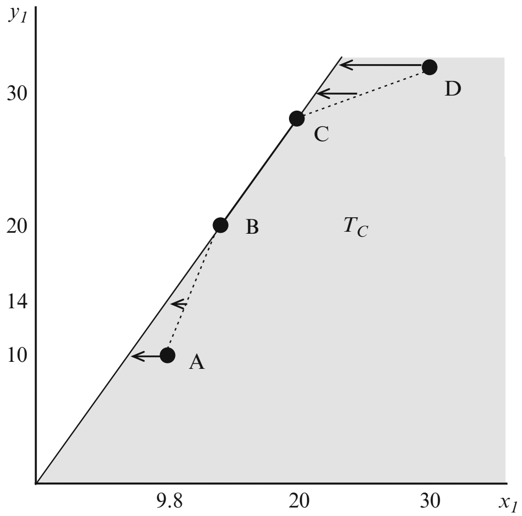


Fig. 2.6 Input orientation and scale efficiency

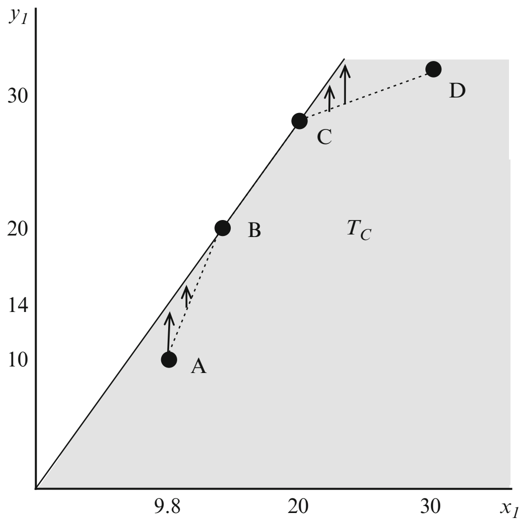


Fig. 2.7 Output orientation and scale efficiency

increasing returns to scale facet AB, the vertical distance between points on AB and the facet from the origin through the B and C narrows. As the technically efficient benchmark approaches most productive scale size B, the scale efficiency of the benchmark approaches 1. Likewise, as production increases along the decreasing returns to scale segment DC away from the most productive scale size C, scale inefficiency decreases as indicated by the larger arrows as the input level increases.

The results from the input- and output-oriented models provide information not only about scale efficiency but also about the returns to scale classification. For any production possibility (Y_0, X_0), $S(Y_0, X_0) \leq 1$ and $\tilde{S}(Y_0, X_0) \leq 1$. A benchmark[3] is operating under constant returns to scale using the input-oriented model if $S(Y_0, X_0) = 1$. If the benchmark is scale inefficient, $\sum_{j=1}^{n} \lambda_j^*$ obtained in the solution of (2.10) provides information on the scale class; if $\sum_{j=1}^{n} \lambda_j^* < 1$ the benchmark is operating on the increasing returns to scale portion of the frontier. Here, a most productive scale size production possibility is being scaled downward below the constant returns to scale frontier. If $\sum_{j=1}^{n} \lambda_j^* > 1$, the benchmark is operating under decreasing returns to scale since a most productive scale size production possibility is scaled beyond the constant returns facet.

For the output-oriented models, the same heuristic applies. If $\tilde{S}(Y_0, X_0) = 1$, the associated benchmark is operating under constant returns to scale. If the unit is scale inefficient, $\sum_{j=1}^{n} \lambda_j^* < (>)\ 1$ in the solution of (2.17) identifies increasing (decreasing returns to scale).

In this chapter, we introduced standard DEA models that will be used in this book. Models are classified as input or output oriented with either constant or variable returns to scale. These models are the basic DEA models that are widely used in the operations research and economics literatures. Modifications that are needed to apply to analyze baseball will be developed in the relevant chapters as necessary. The goal of this chapter was to present the basic models that serve as the basis for this book. Readers interested in theoretical extensions should consult Färe et al. (1994) and other sources.

[3] We refer only to the benchmark to reinforce the notion that returns to scale is not identified for technically inefficient units.

Chapter 3
Measuring Team Efficiency

Serial Correlation

In this chapter we discuss the limitation of the standard DEA models in estimating team and manager inefficiency. If all teams are efficient, the standard assumptions of the production frontier hold. However, if managerial inefficiency causes a team to lose a game that should have been won, another team wins a game that should have been lost. As a result, the departure from the frontier due to inefficiency leads to upward-biased estimates of the frontier and hence, downwardly biased efficiency estimates. Lins et al. (2003) first discussed this issue with respect to zero-sum gains in an analysis of the Olympic games. Collier et al. (2010b) provided a linear programming model to achieve the same correction.

Consider the following example where we focus on four teams, A, B, C, and D. We will assume that the output of baseball production is the number of wins W; for convenience, we will assume that only one input x_1 is used to produce the wins. Initially, we will assume that all four teams are technically efficient, achieving the maximum number of wins given their input levels. Team data are given in the following chart:

Team	X_1	W
A	8	55
B	10	80
C	10	80
D	14	90

The data are illustrated in Fig. 3.1. Teams B and C, which produce the same number of wins from using the same input level, are operating at the most productive scale size under constant returns to scale. We note that facet AB (BD) identifies increasing (decreasing) returns to scale.

Next, we allow inefficiency. Due to managerial inefficiency, team C loses 15 games, allowing teams A, B, and D to gain 5 wins each. Importantly, the additional 5 wins for each of these three teams is not due to their own production; absent the inefficiency of team C these observed production “possibilities” are infeasible. Data due to inefficiency are illustrated in Fig. 3.2.

J. Ruggiero, *Frontiers in Major League Baseball*, Sports Economics, Management and Policy 1, DOI 10.1007/978-1-4419-0831-5_3,

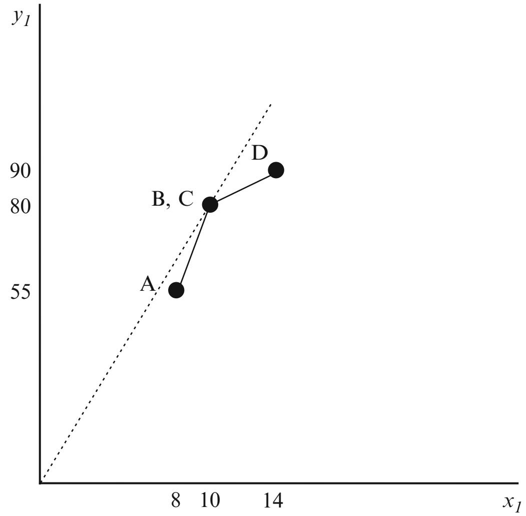


Fig. 3.1 Technically efficient production

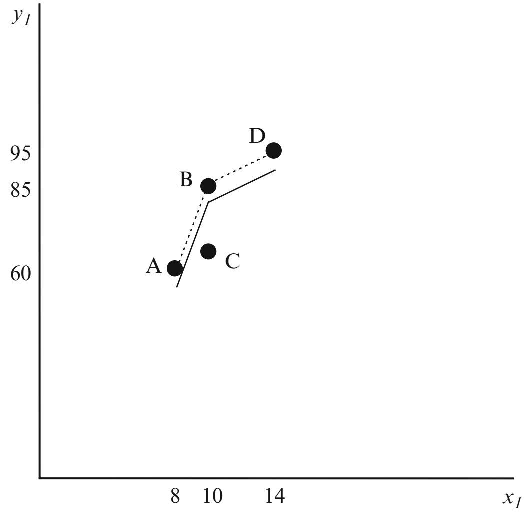


Fig. 3.2 Inefficient data

The estimated variable returns to scale frontier estimated by DEA is now biased because the inefficiency of team C is causing infeasible production to appear feasible. In this example, teams A, B, and D are correctly identified as technically efficient. However, as shown, these infeasible observations cannot serve as benchmarks for team C.

Applying the output-oriented variable returns to scale DEA model we find that $\tilde{F}_{\mathrm{V}}^{-1}(Y_{\mathrm{C}}, X_{\mathrm{C}}) = 85/65 = 1.308,$, leading to an efficiency estimate for team C of $\tilde{F}_{\mathrm{V}}(Y_{\mathrm{C}}, X_{\mathrm{C}}) = 0.765$. The identified benchmark for C is team B which produces 85 wins using the same input level. This overestimate the efficiency of team C;

assuming efficiency, the maximum level of wins given an input level of 10 is 80. In fact, after removing inefficiency, the model suggests that 315 total wins are possible. This is not possible given that only 305 games are played.

In the input-oriented model, output is held constant. It would appear that the use of input-oriented models would solve this problem. However, if inefficiency does cause losses, the problem of the serially correlated error terms still leads to infeasible projections. In Fig. 3.2, we see that any convex combination of teams A and B is outside the technology. Appealing to the input-oriented model, the problem of infeasibility still remains. Solving the variable returns to scale model, we find that the benchmark for team C is defined by weights of $\lambda_A = 0.8$ and $\lambda_B = 0.2$. This implies that C could produce 65 wins with an input level of 8.4. Based on the initial data, however, it would take an input level of 8.8 to produce 65 wins.

In Sect. 2, we introduce a corrected DEA model due to Lins et al. (2003) and Collier et al. (2010b).

Corrected DEA

The problem with standard output-oriented or input-oriented model is the projection to infeasible points due to the serial correlation of the inefficiency term. If inefficiency affects the number of wins of other teams, then it must be true that the sum of the wins above the frontier must be equal to the sum of the wins below the frontier. Adding this constraint ensures that the number of games lost due to inefficiency equals the number of wins gained from inefficiency. This further results in a total number of wins equal to the number of games played.

Collier et al. (2010b) introduced a corrected DEA model to account for serial correlation. Using our notation from Chap. 2 for inputs, we assume that n teams use a vector of m discretionary inputs $X = (x_1, \ldots, x_M)$ to produce one output wins (W). Each team's production is given by the netput vector (W_j, X_j) for team j $(j = 1, \ldots, n)$ as $x_{ij}(i = 1, \ldots, m)$ and W_j, respectively. The standard output-oriented variable returns to scale DEA model to measure the efficiency of team 0 is given by

$$
\begin{aligned}
&\tilde{F}_{\mathrm{V}}^{-1}(Y_0, X_0) = \max\ \psi \\
&\text{subject to} \\
&\sum_{j=1}^{n} \lambda_j W_j \geq\ \psi W_0, \\
&\sum_{j=1}^{n} \lambda_j x_{ij} \leq\ x_{i0}, \qquad\qquad i = 1, \ldots, m; \\
&\sum_{j=1}^{n} \lambda_j = 1; \\
&\lambda_j \geq 0, \qquad\qquad\qquad\quad j = 1, \ldots, n.
\end{aligned}
\tag{3.1}
$$

We note that the output constraint holds with equality given that there is only one output. From the solution of (3.1) for each team, DEA wrongly estimates that each team j $(j = 1, \ldots, n)$ should have won an additional $\left(\tilde{F}_{\mathrm{V}}^{-1}(Y_j, X_j) - 1\right)W_j$ games. Since $\tilde{F}_{\mathrm{V}}^{-1}(Y_j, X_j) \geq 1,$ all teams would not lose any games, making it impossible for any other team to win an additional game. Further, we find that $\sum_{j=1}^{n} \left(\tilde{F}_{\mathrm{V}}^{-1}(Y_j, X_j) - 1\right)W_j$ is the total amount of additional wins beyond the total number of games played that DEA estimates.

Collier et al. (2010b) provide a correction to the estimate of efficiency by defining a constant $k = (1/n)\sum_{j=1}^{n} \left(\tilde{F}_{\mathrm{V}}^{-1}(Y_j, X_j) - 1\right)W_j$ that represents the average number of additional wins possible and adjusting the frontier downward by this constant. The corrected number of wins possible for team j is then given by $\left(\tilde{F}_{\mathrm{V}}^{-1}(Y_j, X_j) - 1\right)W_j - k$. As a result of this correction, it is straightforward to show that $\sum_{j=1}^{n} \left[\left(\tilde{F}_{\mathrm{V}}^{-1}(Y_j, X_j) - 1\right)W_j - k\right] = 0$. Hence, this correction satisfies the constraint that the total number of wins has to equal the total number of games played.

Given the adjustment of the frontier, we now consider how to measure team efficiency relative to the adjusted frontier. The measure provided by Collier et al. (2010b) is given by

$$\hat{F}_{\mathrm{V}}(Y_j, X_j) = \begin{cases} 1 & \text{if } \left(\tilde{F}_{\mathrm{V}}^{-1}(Y_j, X_j) - 1\right)W_j - k \leq 0, \\ \dfrac{W_j}{\left(\tilde{F}_{\mathrm{V}}^{-1}(Y_j, X_j) - 1\right)W_j - k} & \text{otherwise.} \end{cases} \tag{3.2}$$

Teams that appear above the corrected frontier are identified as technically efficient. The measure of efficiency for teams below the corrected frontier is the ratio of observed wins to corrected frontier wins. The results from applying model (3.1) and correcting for efficiency using (3.2) for our illustrative example are presented in the following chart:

Team	$\tilde{F}_{\mathrm{V}}^{-1}$	$(\tilde{F}_{\mathrm{V}}^{-1} - 1)W_j$	$(\tilde{F}_{\mathrm{V}}^{-1} - 1)W_j - k$	$\hat{F}_{\mathrm{V}}$
A	1.000	0	−5	1.000
B	1.000	0	−5	1.000
C	1.308	20	15	0.813
D	1.000	0	−5	1.000

The results show that naively applying DEA to analyze efficiency in sports leads to biased results. Solution of (3.1) reveals that team C could have won 20 additional games, which is not possible. For the correction, $k = 20/4 = 5$; correcting the projections by shifting the frontier down by k leads to the proper evaluation of efficiency.

Team Efficiency in 2009

The output-oriented model and the associated correction due to Collier et al. (2010b) is applied to analyze the performance of the 30 MLB teams using 2009

Table 3.1 MLB 2009 team data

TEAM	W	L	OBP	SLG	NOBP	NSLG
Arizona	70	92	0.324	0.418	0.670	0.581
Atlanta	86	76	0.339	0.405	0.677	0.610
Baltimore	64	98	0.332	0.415	0.647	0.524
Boston	95	67	0.352	0.454	0.665	0.578
Chicago Cubs	83	78	0.332	0.407	0.676	0.609
Chicago Sox	79	83	0.329	0.411	0.675	0.586
Cincinnati	78	84	0.318	0.394	0.667	0.582
Cleveland	65	97	0.339	0.417	0.649	0.557
Colorado	92	70	0.343	0.441	0.672	0.595
Detroit	86	77	0.331	0.416	0.664	0.578
Florida	87	75	0.340	0.416	0.667	0.592
Houston	74	88	0.319	0.400	0.656	0.560
Kansas City	65	97	0.318	0.405	0.657	0.578
LA Angels	97	65	0.350	0.441	0.662	0.568
LA Dodgers	95	67	0.346	0.412	0.688	0.639
Milwaukee	80	82	0.341	0.426	0.655	0.550
Minnesota	87	76	0.345	0.429	0.669	0.569
NY Mets	70	92	0.335	0.394	0.658	0.582
NY Yankees	103	59	0.362	0.478	0.673	0.592
Oakland	75	87	0.328	0.397	0.671	0.587
Philadelphia	93	69	0.334	0.447	0.671	0.573
Pittsburgh	62	99	0.318	0.387	0.654	0.558
San Diego	75	87	0.321	0.381	0.667	0.594
San Francisco	88	74	0.309	0.389	0.686	0.628
Seattle	85	77	0.314	0.402	0.684	0.606
St. Louis	91	71	0.332	0.415	0.681	0.614
Tampa Bay	84	78	0.343	0.439	0.676	0.583
Texas	87	75	0.320	0.445	0.669	0.584
Toronto	75	87	0.333	0.440	0.661	0.566
Washington	59	103	0.337	0.406	0.648	0.550

Raw data are available on ESPN.com

season data. We considered only the regular season except in the case of Detroit and Minnesota who played a one game playoff to determine the American League Central division champions. Data are available on ESPN.com. Following the discussion above, we choose wins (*W*) as the output of interest. We consider two inputs to measure hitters: on-base-percentage (OBP) and slugging percent (SLG).[1] Pitchers are evaluated using the same measures of the opposing hitters. Monotonicity requires, however, that we transform the inputs so that higher values should lead to no less *W*. This is accomplished by subtracting both input measures from 1. For convenience, we define the inputs for pitchers as NOBP and slugging percent (NSLG).[2]

[1]We considered using total bases gained and total bases surrendered as in Lewis and Sexton (2004). The results were similar.

[2]Alternatively, we could use the approach of Lewis and Sexton (2004) which reversed the inequality constraint on the defensive variables.

Table 3.2 Correlations of production variables

	W	OBP	SLG	NOBP	NSLG
W	1.000				
OBP	0.484	1.000			
SLG	0.590	0.707	1.000		
NOBP	0.678	−0.032	0.048	1.000	
NSLG	0.559	−0.072	−0.135	0.905	1.000

Table 3.3 Technical efficiency results

Team	$\tilde{F}_{\mathrm{V}}^{-1}$	$(\tilde{F}_{\mathrm{V}}^{-1}-1)W$	$(\tilde{F}_{\mathrm{V}}^{-1}-1)$ $W-k$	$\hat{F}_{\mathrm{V}}$
Arizona	1.225	15.734	12.635	0.847
Atlanta	1.046	3.942	0.843	0.990
Baltimore	1.000	0.000	−3.099	1.000
Boston	1.034	3.218	0.119	0.999
Chicago Cubs	1.087	7.249	4.150	0.952
Chicago Sox	1.105	8.323	5.224	0.938
Cincinnati	1.000	0.000	−3.099	1.000
Cleveland	1.045	2.930	−0.169	1.000
Colorado	1.050	4.566	1.467	0.984
Detroit	1.007	0.621	−2.478	1.000
Florida	1.027	2.326	−0.773	1.000
Houston	1.000	0.000	−3.099	1.000
Kansas City	1.078	5.040	1.941	0.971
LA Angels	1.000	0.000	−3.099	1.000
LA Dodgers	1.000	0.000	−3.099	1.000
Milwaukee	1.009	0.682	−2.417	1.000
Minnesota	1.050	4.331	1.232	0.986
NY Mets	1.034	2.354	−0.745	1.000
NY Yankees	1.000	0.000	−3.099	1.000
Oakland	1.078	5.845	2.746	0.965
Philadelphia	1.000	0.000	−3.099	1.000
Pittsburgh	1.000	0.000	−3.099	1.000
San Diego	1.000	0.000	−3.099	1.000
San Francisco	1.000	0.000	−3.099	1.000
Seattle	1.007	0.619	−2.480	1.000
St. Louis	1.024	2.156	−0.943	1.000
Tampa Bay	1.143	11.971	8.872	0.904
Texas	1.000	0.000	−3.099	1.000
Toronto	1.147	11.061	7.962	0.904
Washington	1.000	0.000	−3.099	1.000

In the solution of (3.1), we find $k = (1/n)\sum_{j=1}^{n}(\psi_j^{\mathrm{V}}-1)W_j = 3.099$

The data used in this chapter are reported in Table 3.1. Correlations are reported in Table 3.2. W is relatively highly correlated with each of the inputs, ranging from a low of 0.484 with OBP to a high of 0.678 with NOBP. Interestingly, slugging percent on offense has a higher correlation with wins than does on-base-percentage.

On the defensive side, this is reversed; teams that keep the opposing team's batters off base are more likely to win. In terms of input correlations, not surprisingly we find that OBP is highly correlated with SLG (0.707) and NOBP is highly correlated with NSLG (0.905).

Model (3.1) and the appropriate correction were applied to the data. The results are reported in Table 3.3. Using the standard DEA model, we find that 40% of the teams are identified as technically efficient. Consequently, the total inefficiency in terms of lost games by the other 18 teams is approximately 93 games. This allows us to calculate $k = 3.099$ and to adjust the amount of wins that could have been gained by removing inefficiency. The corrected efficiency results are reported in the last two columns. The adjusted slacks representing losses due to inefficiency are shown in column 4 and the associated measure of technical efficiency based on (3.2) is presented in column 5.

After correction, there are seven additional teams identified as efficient: Cleveland, Detroit, Florida, Milwaukee, the Mets, Seattle, and St. Louis. The average efficiency in the overall sample has increased from 0.964 to 0.981. Interestingly, Cleveland was evaluated to be more inefficient than Boston using the standard DEA but more efficient after the transformation. This possibility exists only if the two teams have different output levels.

In this chapter, we showed that the best-practice DEA frontier is biased due to serial correlation of inefficiency. Collier et al. (2010b) provided a corrected DEA model to shift the frontier to insure that losses due to inefficiency and hence production below the frontier are equal to the wins gained from inefficiency. The associated correction to the efficiency measure is then applied. In this chapter, the Collier et al. (2010b) model was applied to 2009 season data. The results revealed that seven teams are wrongly identified as inefficient according to the standard DEA model.

Chapter 4
Measuring Cost Efficiency

Introduction

In this chapter, we extend the analysis by analyzing the cost efficiency of MLB teams. We apply the corrected DEA model introduced in Chap. 3 to analyze the relationship between team wins and team payroll. One of the concerns for competitive balance is the ability of large market teams to spend higher amounts to lure the better players. In 2009, the New York Yankees had a total payroll above $200 million, over $50 million above the second-place New York Mets. The median team payroll was only $80 million.[1] Large market teams are able to generate more local revenue from attendance, advertising, television and radio fees, etc. In 2006, a new revenue sharing program was agreed upon to restore competitive balance; teams contribute approximately one third of their local revenue into a pool and the money is split among the teams.

A criticism of the revenue sharing plan is the vague interpretation of how the shared revenue should be spent.[2] The general agreement reached in 2006 states that the revenue should be spent to improve on-field performance. However, is not clear how well the revenue sharing works. Einolf (2004) compared MLB with NFL and found baseball teams tend to be more inefficient; further, the highly inefficient teams tend to be those large market teams that spend much higher than the low market teams. Jane (2010) uses a panel model to analyze team performance and salary, finding that compressed salaries lead to better performance. Kesenne (2005) shows that competitive balance improving depends on the goals of the teams; if teams seek to maximize wins, competitive balance improves with revenue sharing. However, if the team seeks to maximize profits, then competitive balance could get worse. In baseball, given the vague instructions on how shared revenue can be spent, it is not clear that competitive balance would improve.

---

[1] Jose Canseco was brought to the New York Yankees in 2000 to prevent other teams, especially the Boston Red Sox from playing him. See Canseco (2005).

[2] Hal Steinbrenner wrote an opinion in a September 2006 Sporting News against revenue sharing, claiming it is socialist and anti-American.

J. Ruggiero, *Frontiers in Major League Baseball*, Sports Economics, Management and Policy 1, DOI 10.1007/978-1-4419-0831-5_4,

In this chapter, we seek to measure the cost efficiency of teams. Recognizing serial correlation as in Chap. 3, we develop a corrected model that adjusts for the measurement of cost efficiency. In addition, we consider the effect that outliers have on the estimation of the frontier.

Cost Efficiency

Assume that team$j$ for$j = 1,\ldots,n$ spends Exp_j to produce one output win W_j. We seek to identify the minimum expenditures necessary to produce a given number of wins. As discussed in Chap. 3, the input-oriented model is still biased if wins are serially correlated. Before we apply the cost model, we first apply the corrected DEA model. Data for the 2009 MLB season are shown in Fig. 4.1.

The standard output-oriented variable returns to scale DEA model to measure the efficiency of team 0 is given by

$$
\begin{aligned}
&\tilde{F}_{\mathrm{V}}^{-1}(Y_0, X_0) = \max\ \psi \\
&\text{subject to} \\
&\sum_{j=1}^{n} \lambda_j W_j \geq\ \psi W_0; \\
&\sum_{j=1}^{n} \lambda_j \mathrm{Exp}_j \leq\ \mathrm{Exp}_0; \\
&\sum_{j=1}^{n} \lambda_j = 1; \\
&\lambda_j \geq 0, \qquad\qquad j = 1, \ldots, n.
\end{aligned}
\tag{4.1}
$$

The resulting DEA frontier is illustrated in Fig. 4.2.

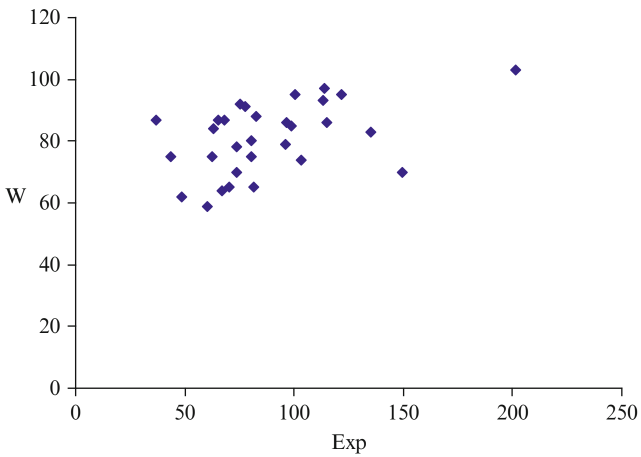


Fig. 4.1 Observed MLB 2009 team salary and wins

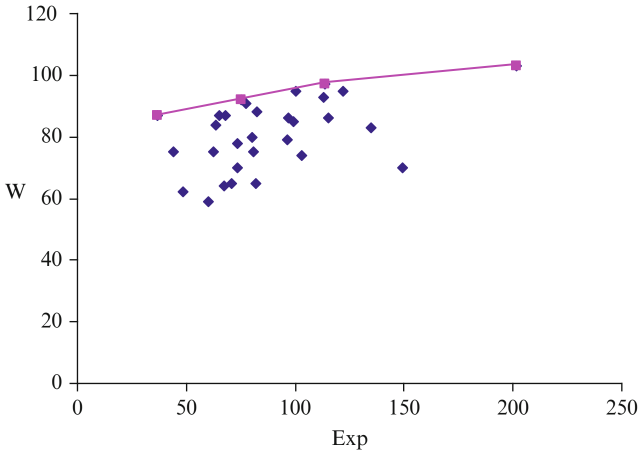


Fig. 4.2 DEA frontier

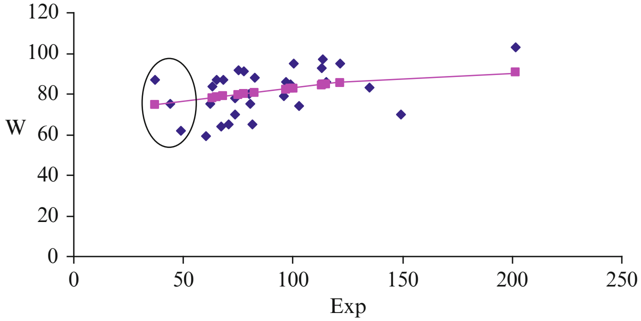


Fig. 4.3 Corrected DEA frontier

The frontier obtained from (4.1) consists of convex combinations of four teams: Colorado, Florida, the Los Angeles Angels, and the New York Yankees. Florida spent approximately \$37 million to win 87 games while the Yankees spent over \$201 million to win 103. The model indicates that approximately 372 games were lost due to inefficiency. Applying the Collier et al. (2010b) correction, we adjust the slack by the constant $k = (1/30)\sum_{j=1}^{30}\left(\tilde{F}_{\mathrm{V}}^{-1}(Y_j, X_j) - 1\right)W_j = 12.41$. The corrected frontier is illustrated in Fig. 4.3.

Outlier Correction

The resulting corrected frontier identifies Florida as the only constant returns to scale point; no team is operating under increasing returns to scale and all teams other than Florida are operating at decreasing returns to scale. Further, it appears that three teams, Florida, San Diego, and Pittsburgh (circled in Fig. 4.3) are outliers. Outliers can bias the resulting frontier, leading to improper benchmarks. Wilson (1995) provided a diagnostic test of outliers by analyzing the super efficiency scores. The super efficiency score $\tilde{F}_{\mathrm{S}}^{-1}(Y_i, X_i)$ for team i (i = 1,. . .,n) is calculated as the solution to the following linear program:

$$
\begin{aligned}
&\tilde{F}_{\mathrm{S}}^{-1}(Y_i, X_i) = \max\ \psi \\
&\text{subject to} \\
&\sum_{j=1}^{n} \lambda_j W_j \geq\ \psi W_i; \\
&\sum_{j=1}^{n} \lambda_j \mathrm{Exp}_j \leq\ \mathrm{Exp}_i; \\
&\sum_{j=1}^{n} \lambda_j = 1; \\
&\lambda_j \geq 0, \qquad\qquad j = 1, \ldots, n,\ j \neq i. \\
&\lambda_i = 0.
\end{aligned}
\tag{4.2}
$$

Model (4.2) differs from (4.1) with the extra constraint that excludes the unit under analysis from serving as a benchmark.[3] Hence, model (4.2) evaluates team$i$ relative to all other teams. It is possible that the solution of (4.2) results in $\tilde{F}_{\mathrm{S}}^{-1}(Y_i, X_i) < 1$. Andersen and Petersen (1989) proposed solving model (4.2) for ranking efficient units. For our purposes, we will employ (4.2) for outlier detection.

DMUs identified in the efficient subset that are outliers can have an effect on the measurement of efficiency of other DMUs. Consider Florida in Fig. 4.2 which won 87 games while spending only $36.834 million. As shown, Florida defines the lower facet of the frontier and is used in the calculation of efficiency for many teams. Natural questions raised by Wilson (1995) are how many other DMUs are affected by this outlier and, what is the impact on the resulting efficiency scores? Wilson provided a test for the input-oriented model; this is extended to the output-oriented model considered in this chapter.

Any DMUi with $\tilde{F}_{\mathrm{S}}^{-1}(Y_i, X_i) \leqslant 1$ from (4.2) is efficient. To determine the impact that efficient unit$i$ has on DMU 0 can be obtained from the solution of the following linear programming model:

[3] It is possible that the constraints lead to infeasibility for the variable returns to scale model; see Fig. 4.3 and the associated discussion in Wilson (1995). In this chapter, we adopt the procedure used by Wilson to handle infeasible projections.

$$
\begin{aligned}
&\tilde{F}_{S,i}^{-1}(Y_0, X_0) = \max\ \psi \\
&\text{subject to} \\
&\sum_{j=1}^{n} \lambda_j W_j \geq\ \psi W_i; \\
&\sum_{j=1}^{n} \lambda_j \mathrm{Exp}_j \leq\ \mathrm{Exp}_i; \\
&\sum_{j=1}^{n} \lambda_j = 1; \\
&\lambda_j \geq 0, \qquad\qquad j = 1, \ldots, n,\ j \neq i, 0. \\
&\lambda_i, \lambda_0 = 0.
\end{aligned}
\tag{4.3}
$$

Model (4.3) calculates the super efficiency score for any given DMU 0 with the additional constraint that efficient DMUi is excluded from the possible reference set. The total impact that DMUi has on the other DMUs is obtained from the following equation:

$$
\delta_i = \sum_{\substack{j=1 \\ j \neq i}}^{n} \left(\tilde{F}_S^{-1}(Y_j, X_j) - \tilde{F}_{S,i}^{-1}(Y_j, X_j) \right) W_j, \tag{4.4}
$$

where $\tilde{F}_S^{-1}(Y_j, X_j)$ and $\tilde{F}_{S,i}^{-1}(Y_j, X_j)$ are defined.

We note that (4.4) differs from Wilson (1995), which distinguishes between the average and total change from the input-oriented perspective. We multiply the difference in the distance functions by the number of wins to evaluate the effect of omission on the number of wins of each team. Efficient units with large values of δ have a larger influence and could be considered for removal. The process is iterated until all overly influential DMUs are removed. Of course, the method requires an arbitrary decision rule. In the next section, we apply the outlier detection methodology and estimate the corrected frontier after omitting outliers.

Cost Efficiency in 2009

As discussed above, we applied (4.1) and found only four efficient teams: Colorado, Florida, the Los Angeles Angels, and the New York Yankees. The corrected frontier appeared to be biased by the presence of outliers. Applying the outlier detection algorithm above, we found four teams that are influential outliers: Florida, San Diego, Colorado, and Pittsburgh. The results of the detection are revealed in Table 4.1.

Florida had the minimum payroll, spending less than $37 million. However, they were able to achieve 87 wins. Only eight teams had more wins. Florida's impact on

Table 4.1 Outlier detection results

Iteration	Team	δ	Decision
1	Florida	40.650	Remove Florida
	Colorado	0.127	
	LA Angels	8.637	
	NY Yankees	5.578	
2	Minnesota	2.022	Remove San Diego, Colorado
	San Diego	10.753	
	Colorado	14.882	
	LA Angels	8.474	
	NY Yankees	5.578	
3	Minnesota	8.048	Remove Pittsburgh
	LA Angels	7.736	
	NY Yankees	5.578	
	LA Dodgers	2.669	
	Pittsburgh	11.884	

Models (4.2) and (4.3) were solved to determine δ

other teams was approximately 41 wins, or about 4.5 times the influence of the next influential team (LA Angels). For this chapter, we adopt the rule that an outlier is overly influential if $\delta > 10$. Using this admittedly arbitrary rule, only Florida was omitted after the first iteration.

The procedure was repeated after omitting Florida. In the second iteration, two new teams, Minnesota and San Diego, were identified as efficient. Five teams were tested as influential outliers. Both San Diego and Colorado had $\delta > 10$ and were identified as influential and removed after the second iteration. San Diego had the second lowest team payroll in 2009 and was able to achieve a relatively high number of wins. Colorado achieved 92 wins by spending less than the median level. Only five teams had more wins than Colorado.

After omitting San Diego and Colorado, two additional teams, the LA Dodgers and Pittsburgh, achieved efficiency. Of these teams, only Pittsburgh had $\delta > 10$ and hence, was removed as an influential outlier. No other team was identified as an outlier in the next iteration. Hence, four total teams were removed from the analysis. We applied the corrected frontier model of Collier et al. (2010b) on the remaining 26 teams. The resulting constant $k = (1/26)\sum_{j=1}^{26}\left(\tilde{F}_{\mathrm{V}}^{-1}(Y_j, X_j) - 1\right)\ W_j = 9.84$. The corrected frontier is illustrated in Fig. 4.4.

Using the corrected frontier, we can define technical efficiency as the ratio of observed wins to frontier wins. For those teams that are either identified as outliers or above the corrected frontier, the team is considered technically efficient. Technical efficiency results are reported in Table 4.2. The New York Mets and the Cleveland Indians were the most technically inefficient with efficiency ratings below 0.80. Four teams (Arizona, Baltimore, Houston, and Kansas City) had technical efficiency between 80 and 90% while five teams (both Chicago teams, Detroit, Milwaukee, and Toronto) exhibited low inefficiency with efficiency ratings above 0.90.

Interestingly, many of the inefficient teams made managerial changes during or after the 2009 season. The Cleveland Indians announced in September that manager

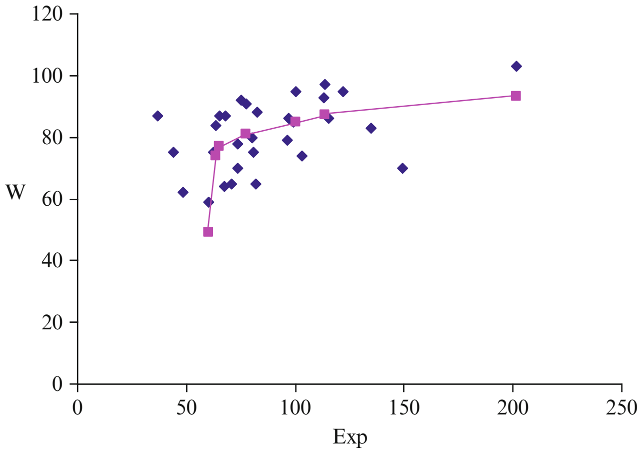


Fig. 4.4 Corrected DEA frontier with outliers omitted

Eric Wedge would not be retained and subsequently hired Manny Acta. Acta was previously fired as the manager of the Washington Nationals, who were identified as technically efficient (though not productive with only 59 wins). The New York Mets had already replaced Willie Randolph in the 2008 season with Jerry Manuel. Kansas City hired Trey Hillman to replace Clint Hurdle for the 2008 season. Additionally, inefficient teams Arizona and Houston made managerial changes. Houston replaced Cecil Cooper with interim manager Dave Clark in September 2009, while Arizona replaced Bob Melvin with A.J. Hinch.

An alternative measure of efficiency that can be calculated from the corrected frontier is cost efficiency. This measure is an input-oriented version that identifies the minimum cost of achieving a given number of wins. After iteration, seven teams (both Los Angeles teams, Minnesota, the New York Yankees, St. Louis, Tampa Bay, and Washington) are identified as on the cost frontier. In this case, we use the projected frontier wins after correcting for serial correlation and use the following program to identify minimum costs of team 0:

$$\begin{aligned}
&\text{Minimumcosts} = \min\ C_0 \\
&\text{subject to} \\
&\sum_{j=1}^{7} \lambda_j \tilde{W}_j \geq\ W_0; \\
&\sum_{j=1}^{7} \lambda_j \text{Exp}_j \leq\ C_0; \\
&\sum_{j=1}^{7} \lambda_j = 1; \\
&\lambda_j \geq 0, \qquad\qquad j = 1, \ldots, 7.
\end{aligned} \tag{4.5}$$

Table 4.2 Cost efficiency results

Team	W	*Exp*	Technical efficiency	Cost efficiency
Arizona	70	73.517	0.873	0.854
Atlanta	86	96.726	1.000	1.000
Baltimore	64	67.102	0.819	0.925
Boston	95	121.746	1.000	1.000
Chicago Cubs	83	134.809	0.933	0.654
Chicago Sox	79	96.069	0.932	0.739
Cincinnati	78	73.559	0.972	0.923
Cleveland	65	81.579	0.791	0.763
Colorado	92	75.201	1.000	1.000
Detroit	86	115.085	0.981	0.921
Florida	87	36.834	1.000	1.000
Houston	74	102.996	0.861	0.615
Kansas City	65	70.519	0.820	0.882
LA Angels	97	113.709	1.000	1.000
LA Dodgers	95	100.415	1.000	1.000
Milwaukee	80	80.183	0.976	0.923
Minnesota	87	65.299	1.000	1.000
NY Mets	70	149.374	0.778	0.421
NY Yankees	103	201.449	1.000	1.000
Oakland	75	62.310	1.000	1.000
Philadelphia	93	113.004	1.000	1.000
Pittsburgh	62	48.693	1.000	1.000
San Diego	75	43.734	1.000	1.000
San Francisco	88	82.616	1.000	1.000
Seattle	85	98.904	1.000	1.000
St. Louis	91	77.605	1.000	1.000
Tampa Bay	84	63.313	1.000	1.000
Texas	87	68.179	1.000	1.000
Toronto	75	80.538	0.914	0.793
Washington	59	60.328	1.000	1.000

Cost efficiency is measured as the ratio of minimum cost to observed spending. Teams on or above the frontier are identified as cost efficient. Spending is reported in million dollars

In (4.5),j indexes the seven teams that define the corrected frontier and $\tilde{W}_j = W_j - k$. Similar to our measure of technical efficiency, teams which are either omitted or lie above the frontier are cost efficient. Efficiency for all other teams are defined by the ratio of minimum costs to observed expenditures.[4] Cost efficiency results are reported in Table 4.2. Teams that are identified as technically efficient also appear as cost efficient. The differences in technical and cost efficiency are

[4] After eliminating outliers, it is not possible to estimate minimum costs for wins less than 59, the lowest number of wins of the frontier defining seven teams.

Table 4.3 Estimated costs

W	Total cost	Marginal cost
51	60.548	0.119
52	60.667	0.119
53	60.787	0.119
54	60.906	0.119
55	61.025	0.119
56	61.145	0.119
57	61.264	0.119
58	61.384	0.119
59	61.503	0.119
60	61.622	0.119
61	61.742	0.119
62	61.861	0.119
63	61.981	0.119
64	62.100	0.119
65	62.219	0.119
66	62.339	0.119
67	62.458	0.119
68	62.578	0.119
69	62.697	0.119
70	62.816	0.119
71	62.936	0.119
72	63.055	0.119
73	63.175	0.119
74	63.294	0.119
75	63.869	0.575
76	64.532	0.662
77	65.194	0.662
78	67.885	2.691
79	70.961	3.076
80	74.038	3.076
81	77.114	3.076
82	82.397	5.283
83	88.100	5.702
84	93.802	5.702
85	99.504	5.702
86	106.001	6.496
87	112.648	6.647
88	125.998	13.350
89	140.622	14.623
90	155.245	14.623
91	169.868	14.623
92	184.492	14.623
93	199.115	14.623

Estimated costs are obtained from the solution of (4.5). Costs are measured in million dollars large for some teams, which is not unexpected given the difference between orientations. Notably, the NY Mets could have achieved the same number of wins by spending only 42.1% of their team payroll. The Mets had the second highest payroll but won only 70 games. The efficiency measures provide similar estimates for Arizona, Baltimore, Cincinnati, Cleveland, Detroit, and Milwaukee.

Model (4.5) was also applied to estimate the minimum cost of achieving differing wins. The results are reported in Table 4.3. The minimum cost of achieving 51 wins is estimated to be $60.548 million. The marginal cost of achieving an additional win is $119,000 in the win range of 51–74. This constant marginal cost is obtained from the slope of the production frontier between Washington and Tampa Bay. We note that constant returns to scale exists along this production frontier facet. Marginal costs increase to $2.691 million (from 77 wins to 78 wins) and over $13 million for additional wins beyond 87.

In this chapter, we developed a best-practice cost frontier. The cost frontier linking wins to team payroll was estimated after correcting for outliers and the serial correlation of inefficiency.

Chapter 5
Evaluating Hitters

Measuring Aggregate Performance

Mazur (1995) applied DEA to rank the performance of MLB players. Mazur assumed that all players had the same input level and chose three outputs: batting average, home runs, and runs batted in. These three measures comprise the "triple crown" in major league baseball. Certainly, a team would prefer players with higher values of each of these variables. However, as pointed out by Anderson and Sharpe (1997), runs batted in by a particular player largely depends on the ability of the player's teammates to reach base prior to the at bat.

Anderson and Sharpe (1997) introduced a new measure of player performance using DEA. Their measure, the composite batter index (CBI), was obtained as a solution of a constant returns to scale input-oriented DEA model using one input (plate appearances) and five outputs (walks, singles, doubles, triples, and home runs). The authors argue that constant returns to scale is appropriate because a doubling of plate appearances should result in a doubling of the outputs. Anderson and Sharp differs from the method of Mazur by including plate appearances as an input. Mazur's model uses only outputs; consequently, Mazur's approach measures player's quality and not efficiency. Anderson and Sharp include a measure of input in the analysis, and hence, their measure is more properly referred to as an efficiency measure.

Collier et al. (2010a) extended DEA to provide a measure of aggregate production. One of the limitations of standard regression-based approaches is the inability to measure efficiency in multiple input and output technologies.[1] A modified DEA model is applied using only outputs. Consider the output set defined by

$$P(X) = \{Y : (Y, X) \text{ is feasible}\} \tag{5.1}$$

which has isoquant

[1] Grosskopf et al. (1997) and Coelli and Perelman (1999, 2000) apply a stochastic distance function approach that does allow multiple outputs. However, this approach treats outputs asymmetrically.

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$$\text{Isoq } P(X) = \{Y : Y \in P(X), \lambda^{-1} Y \notin P(X), \lambda \in (0,1)\}. \tag{5.2}$$

Here, the isoquant of the output set depends on the vector of inputs. The isoquants for two output sets are shown in Fig. 5.1. In this case, we assume two different input vectors $X_0 < X_1$ and highlight DMUs that are technically efficient. As shown, DMUs A–D are observed efficiently producing two outputs given their input vector X_1. DMUs E–H are also efficiently producing given their input vector $X_0 < X_1$. The nested isoquants are consistent with monotonicity.

Following Collier et al. (2010a), we define the aggregate output set as $P_A = \cup_{j=1}^{N} P(X_j)$. The aggregate output set assuming two outputs and the associated isoquant Isoq P_A are shown in Fig. 5.2.[2] DMUs A–D are observed on the isoquant, producing the maximum output possible. We consider two other DMUs E, F $\in P_A$ where E, F $\notin$ Isoq P_A. We note that DMUs E and F are not producing the maximum possible output due to either inefficiency, lower input levels, or both. As shown, DMU E produces more of both outputs than does DMU F.

Using our notation from Chap. 2, we assume that DMUs use a vector of m discretionary inputs $X = (x_1, \ldots, x_M)$ to produce a vector of s outputs $Y = (y_1, \ldots, y_S)$ with DMU j ($j = 1, \ldots, n$) data represented by the netput (Y_j, X_j) with x_{ij}($i = 1, \ldots, m$) and y_{kj} ($k = 1, \ldots, s$), respectively. We measure the distance from (Y_0, X_0) to Isoq P_A with the following linear programming model:

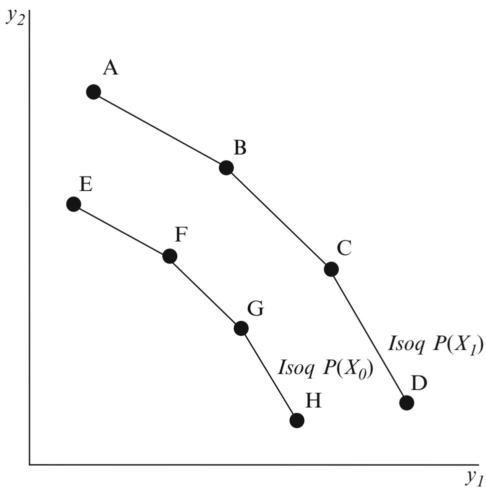

Fig. 5.1 Output sets and isoquants

[2] Figure 5.2 does not replicate data from Fig. 5.1

$$\begin{aligned}
&\eta_0 = \max\ \eta \\
&\text{subject to} \\
&\sum_{j=1}^{n} \lambda_j y_{kj} \geqslant \eta y_{k0}, \qquad k = 1, s; \\
&\sum_{j=1}^{n} \lambda_j = 1; \\
&\lambda_j \geqslant 0, \qquad j = 1, n.ç
\end{aligned} \tag{5.3}$$

In this case, the input constraints are removed from the traditional output-oriented model. This model can be considered an output-oriented model where all DMUs have the same input levels. As shown in Collier et al. (2010a), $\eta_0^{-1} \leqslant 1$ provides a measure of aggregate output with $\eta_0^{-1} = 1$ for DMUs that produce the highest level of aggregate output. Mazur (1995) used this particular model but wrongly labeled the index as an efficiency measure. Notably, in the context of evaluating baseball players, the model does not control for innate ability, and hence, is better interpreted as a measure of aggregate performance or output and not efficiency.

Returning to Fig. 5.2, we observe that $\eta_j^{-1} = 1$ where $j =$ A, B, C, and D. Hence, DMUs A–D achieve the highest aggregate output level; in this case each of these DMUs has different output mixes. Now consider DMU E where $\eta_E^{-1} = y_{1E}/y_{1F'} < 1$.

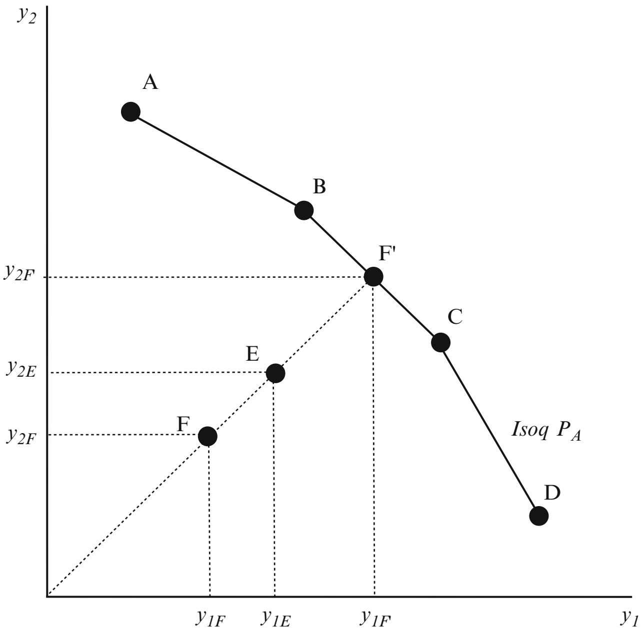

Fig. 5.2 Measuring aggregate output

For DMU F, $\eta_F^{-1} = y_{1F}/y_{1F'} < \eta_E^{-1}$. DMUs farther from the isoquant of the aggregate output set is captured by a larger η_0 and hence, a lower value of ${\eta_0}^{-1}$. Hence, the index η^{-1} provides a measure of aggregate performance.

Evaluating 2009 Hitters

The model developed is applied to analyze the performance of baseball players. Instead of assuming DMUs represent teams, we consider players and evaluate their aggregate performance using the approach of Collier et al. (2010a). Anderson and Sharp (1997) restrict the sample by considering only players who had at least 350 plate appearances and separated the players by league. In the construction of the CBI, Anderson and Sharp use plate appearances as the input measure; as a result, their measure should be considered an efficiency measure: each player is evaluated to a combination of players with no more plate appearances. Hence, a given player's outputs are evaluated relative to the input level. In this chapter, we are not interested in efficiency but rather aggregate performance.

Four outputs are considered: *Singles Plus* (singles + hit by pitch + base on balls), *Doubles*, *Triples*, and *Home Runs*. These variables are consistent with the variables selected by Anderson and Sharpe (1997). Anderson and Sharp exclude hit by pitch and separate out singles from walks. *Singles Plus* does not distinguish how a player reaches first base. A single is usually preferred to a walk or a hit by pitch, but like runs batted in, this happens in cases when other players have reached base. Also, we make no distinction between leagues; it is not clear, especially in light of inter-league play, that a distinction between leagues is relevant. We include traded players by aggregating their outputs and only consider players with at least 100 plate appearances.[3]

In this chapter, we analyze 362 MLB players using 2009 data. Data and performance results are reported for the top 25 hitters in Table 5.1. Nine players were evaluated as top performers: Derek Jeter, Brian Roberts, Shane Victorino, Ryan Howard, Chone Figgins, Prince Fielder, Denard Span, Albert Pujols, and Troy Tulowitzki. Necessarily, the player who leads the majors in any of the individual output measures will rank as top performers. Derek Jeter and Chone Figgins both led the majors in *Singles Plus* with 243. Brian Roberts, Shane Victorino, and Albert Pujols led the majors with 56 doubles, 13 triples, and 47 home runs, respectively.

[3] Since DEA is sensitive to variable selection, we ran a secondary regression to test whether runs or runs batted in should be included as relevant variables. The test employed in Ruggiero (2005) was used; the results suggested that these variables should not be included. In addition, we considered an alternative model using batting average and slugging percent. The correlation between the two models was 0.71. Interestingly, when using slugging percent and batting average, the result of the test suggests that runs batted in should be included as an additional variable. For purposes of this chapter, we will use *Singles Plus*, *Doubles*, *Triples*, and *Home Runs*.

Table 5.1 Performance of top 25 hitters

Player	Team	Singles plus	Doubles	Triples	Home runs	$\eta{-}1$
Derek Jeter	NYY	243	27	1	18	1.000
Brian Roberts	BAL	182	56	1	16	1.000
Shane Victorino	PHI	185	39	13	10	1.000
Ryan Howard	PHI	167	37	4	45	1.000
Chone Figgins	LAA	243	30	7	5	1.000
Prince Fielder	MIL	212	35	3	46	1.000
Denard Span	MIN	226	16	10	8	1.000
Albert Pujols	SL	217	45	1	47	1.000
Troy Tulowitzki	COL	171	25	9	32	1.000
Michael Bourn	HOU	196	27	12	3	0.993
Dustin Pedroia	BOS	200	48	1	15	0.980
Ryan Braun	MIL	196	39	6	32	0.976
Mark Teixeira	NYY	186	43	3	39	0.974
Shin-Soo Choo	CLE	206	38	6	20	0.964
Pablo Sandoval	SF	171	44	5	25	0.962
Michael Cuddyer	MIN	149	34	7	32	0.960
Stephen Drew	ARI	136	29	12	12	0.957
Adrian Gonzalez	SD	208	27	2	40	0.951
Robinson Cano	NYY	162	48	2	25	0.949
Billy Butler	KC	170	51	1	21	0.949
Adam Lind	TOR	161	46	0	35	0.947
Curtis Granderson	DET	170	23	8	30	0.946
Chase Utley	PHI	210	28	4	31	0.945
Todd Helton	COL	212	38	3	15	0.945
Felipe Lopez	ARI/MIL	210	38	3	9	0.939

Top 25 hitters ranked by $\eta{-}1$

Consistent with our measure, Albert Pujols was selected as the National League Most Valuable Player for 2009. Pujols led the majors with 47 home runs, resulting in $\eta^{-1} = 1$. On the other hand, Joe Mauer was selected as the Most Valuable Player of the American League. Mauer only achieved $\eta^{-1} = 0.908$.[4] Mauer was compared to a convex combination of Pujols, Derek Jeter, and Chone Figgins. Compared to Jeter, Mauer had 10 more home runs and 3 more doubles, but reached first base 33 times less. In addition to Jeter, Figgins, Prince Fielder, and Denard Span all reached first base more than Mauer. Mark Teixeira reached first base 24 less times, but had 13

[4] Mauer led the American League in OPS, the sum of on-base and slugging percentages. Mauer played in 138 games and had around 100 less at bats than did Jeter or Teixeira.

more doubles, 2 more triples, and 11 home runs. The value of η^{-1} for Teixeira was only 0.974. Interestingly, Teixeira and Jeter came in second and third, respectively, in the MVP voting.

Next, consider the large market teams. The New York Yankees and Philadelphia Phillies each had three players in the top 25. Robinson Cano joined fellow Yankees Jeter and Teixeira in the top 25, hitting 48 doubles and 25 home runs. For the Phillies, Shane Victorino and Ryan Howard were among the hitters with $\eta^{-1} = 1$. Philly Chase Utley, with 210 *Singles Plus*, 28 doubles, and 31 home runs with $\eta^{-1} = 0.945$. Of the smaller market teams, Prince Fielder, Denard Span, Albert Pujols, and Troy Tulowitzki achieved $\eta^{-1} = 1$.

A Weighted Slack Model

The model presented above is nonparametric; as a result, the individual performance variables may not be weighted properly. As an example, consider the data for Dustin Pedroia and Adrian Gonzalez reported in Table 5.1. Pedroia ranked 11th with $\eta^{-1} = 0.980$ while Gonzalez ranked 18th with $\eta^{-1} = 0.951$. Of the performance variables included, Pedroia had 21 more doubles. However, Gonzalez reached first base more, had one more triple and 25 more home runs. In this case, Pedroia was closer in percentage terms to the maximum number of doubles than Gonzalez was to the maximum number of home runs. In order to correct this problem, we consider the following weighted slack based model as an alternative:

$$
\begin{aligned}
&\mathrm{WS}_0 = \max \sum_{k=1}^{4} \omega_k \psi_k \\
&\text{subject to} \\
&\sum_{j=1}^{n} \lambda_j y_{kj} - \psi_k \geq y_{k0}, && k = 1, s; \\
&\sum_{j=1}^{n} \lambda_j = 1; \\
&\omega_k \geq 0, && = 1, s; \\
&\sum_{k=1}^{s} \omega_k = 1; \\
&\psi_k \geq 0, && k = 1, s; \\
&\lambda_j \geq 0, && j = 1, n.
\end{aligned}
\tag{5.4}
$$

This model is the additive form of the Weighted Russell measure introduced by Ruggiero and Bretschneider (1998). The weights on individual performance variables are chosen a priori.[5] For our purposes, we weight each performance variable as follows: *Singles Plus* (0.1), *Doubles* (0.2), *Triples* (0.3), and *Home Runs* (0.4). This weighting structure is based on the number of bases reached; arguably, home runs should be weighted higher given that is the only hit that guarantees a run.

The weighted slack measure $WS \geq 0$ provides a measure of inverse performance. Top performers achieve $WS = 0$ and aggregate performance declines as WS gets larger. Model (5.4) was applied to the 2009 data; the rank correlation between the performance measures was 0.984. In the case of Pedroia and Gonzalez, the performance rankings were reversed; the weighted slack measure for Pedroia (Gonzalez) was 10.16 (5.85). Given the high rank correlation, we will use η^{-1} as our performance measure in this chapter.[6]

Performance and Salary

With limited resources, small market teams are interested in finding quality players at the lowest cost. In Fig. 5.3, player performance determined by η^{-1} is plotted against player salary (in million dollars). The vertical red line indicates the 75th percentile of η^{-1} (0.753) and the horizontal red line shows the median player salary for the sample ($1.925 million). Bargain players are defined as those players in the lower right quadrant who perform higher than the 75th percentile and earn less than the median salary. The 30 players in this bargain category are listed in Table 5.2.

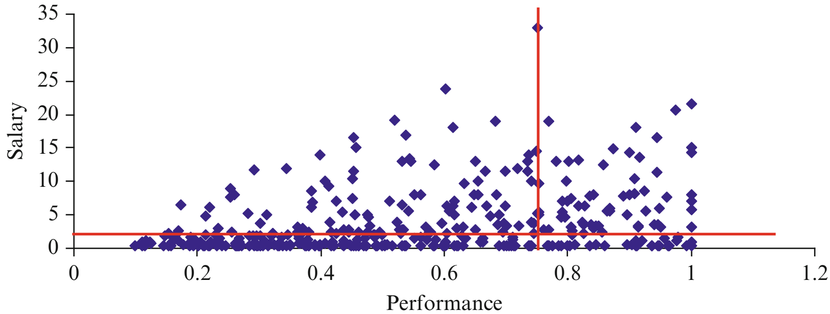

Fig. 5.3 Hitter performance vs. salary

[5] In empirical applications, expert opinion or regression analysis could be used to derive the weights.

[6] In the chapters evaluating Hall of Fame players and steroids, we use (5.4) to recognize the importance of the power game.

Table 5.2 2009 bargain players

Player	Team	Singles plus	Doubles	Triples	Home runs	Salary ($)	$\eta{-}1$
Denard Span	MIN	226	16	10	8	435,000	1.000
Troy Tulowitzki	COL	171	25	9	32	1,000,000	1.000
Michael Bourn	HOU	196	27	12	3	434,500	0.993
Dustin Pedroia	BOS	200	48	1	15	1,750,000	0.980
Ryan Braun	MIL	196	39	6	32	1,032,500	0.976
Shin-Soo Choo	CLE	206	38	6	20	420,300	0.964
Pablo Sandoval	SF	171	44	5	25	401,750	0.962
Stephen Drew	ARI	136	29	12	12	1,500,000	0.957
Billy Butler	KC	170	51	1	21	421,000	0.949
Adam Lind	TOR	161	46	0	35	411,800	0.947
Mark Reynolds	ARI	156	30	1	44	422,500	0.937
Jacoby Ellsbury	BOS	198	27	10	8	449,500	0.937
Kendry Morales	LAA	142	43	2	34	1,100,000	0.921
Alberto Callaspo	KC	166	41	8	11	415,500	0.911
Marco Scutaro	TOR	208	35	1	12	1,100,000	0.911
Ben Zobrist	TB	180	28	7	27	415,900	0.911
Evan Longoria	TB	167	44	0	33	550,000	0.903
Matt Kemp	LAN	177	25	7	26	467,000	0.895
Justin Upton	ARI	152	30	7	26	412,000	0.861
Angel Pagan	NYM	91	22	11	6	575,000	0.846
Asdrubal Cabrera	CLE	154	42	4	6	416,700	0.836
Ryan Theriot	CHC	196	20	5	7	500,000	0.812
James Loney	LAD	192	25	2	13	465,000	0.803
Hunter Pence	HOU	168	26	5	25	439,000	0.800
Skip Schumaker	SL	174	34	1	4	430,000	0.790
Joey Votto	CIN	161	38	1	25	437,500	0.785
Yunel Escobar	ATL	183	26	2	14	425,000	0.775
Dexter Fowler	COL	140	29	10	4	401,000	0.769
Daniel Murphy	NYM	119	38	4	12	401,000	0.769
Erick Aybar	LAA	155	23	9	5	460,000	0.768

Bargain players earn less than the median salary and have an aggregate performance in the top quartile

Denard Span and Troy Tulowitzki both achieved rankings $\eta^{-1} = 1$. Span reached first base 226 times and added 16 doubles and 10 triples. Span earned slightly more than the league minimum with a salary of $435,000. Tulowitzki, who finished fifth in the overall voting for the National League MVP, earned $1 million, about half of the median salary. Small to moderate size market teams had 19 of the 30 bargain players, suggesting that a viable strategy to compete with large market teams is the development of quality young players.

In this chapter, we applied the nonparametric DEA model for aggregate performance measurement to rank MLB hitters for the 2009 season. Using various measures of hits, each player was evaluated relative to all other players to index overall performance. Nine players were identified as maximum performers with observed production on the furthest isoquant. Interestingly, while National League MVP Albert Pujols defined the frontier, American League MVP Joe Mauer did not. Thirty-seven players were ranked higher than Mauer, including 19 American League players.[7]

[7] This excludes Matt Holliday, who was traded from Oakland to St. Louis in July.

Chapter 6
Evaluating Pitchers

Measuring Aggregate Performance

In this chapter, we evaluate both starting pitchers and relief pitchers using the aggregate performance model presented in the Chap. 5. For both classes of pitchers, we choose three outputs: innings pitched (IP), innings pitched per earned run (IP/ER), and innings pitched per hit (IP/H). The measures chosen here are consistent with Mazur (1995), who used earned run average, hits per inning pitched, and the ratio of base on balls to strike outs.[1]

The sample for 2009 consisted of pitchers who recorded at least 40 outs (13.33 innings). Since some pitchers were both starters and relievers, we classified a pitcher as a starter if at least 40% of his appearances were as the starting pitcher. Using this classification, there were 148 starting pitchers and 172 relief pitchers. For each class, the following linear program was solved to evaluate the performance of pitcher "0"″:

$$
\begin{aligned}
&\eta_0 = \max\ \eta \\
&\text{subject to} \\
&\sum_{j=1}^{n} \lambda_j y_{kj} \geq\ \eta y_{k0}, && k = 1, \ldots, s; \\
&\sum_{j=1}^{n} \lambda_j = 1; \\
&\lambda_j \geq 0, && j = 1, \ldots, n.
\end{aligned}
\tag{6.1}
$$

Solving this program for each pitcher, we obtain $\eta_0^{-1} \leq 1$ as the measure of aggregate performance.

[1] Mazur redefined and standardized the variables to insure that the measures were consistent with DEA.

J. Ruggiero, *Frontiers in Major League Baseball*, Sports Economics, Management and Policy 1, DOI 10.1007/978-1-4419-0831-5_6,

Evaluating 2009 Starting Pitchers

In this section, we report the results for the starting pitchers using 2009 data. Our measure of performance is the inverse of the solution of (6.1) for the 148 pitchers who recorded at least 40 outs and started at least 40% of games in which they appeared. Results for the top 25 performers are reported in Table 6.1.

Six pitchers identified the outer frontier, achieving the highest performance ranking. Included in the list of top performers was Zack Greinke, the American League Cy Young award winner. Greinke pitched over 225 innings and led the AL with 4.17 innings per earned run. Greinke, however, had only 16 wins. Other AL starters who achieved the highest ranking included the Detroit Tiger Justin Verlander (19 wins), Toronto Blue Jay Roy Halladay (17 wins), and Seattle Mariner Felix Hernandez (19 wins). All these top DEA performers were included in the top five voting for the Cy Young award. Interestingly, the Yankee's C.C. Sabathia received the fourth most votes but had $\eta^{-1} = 0.963$. Sabathia also had 19 wins.

The wins of any individual pitcher are determined not only by the quality of the pitcher but also by the performance of the hitters and fielders. Hence, the choice of Greinke is consistent with the measure of performance used in this paper. Greinke had the lowest earned run average in both leagues and his 16 wins accounted for

Table 6.1 Performance of top 25 starting pitchers

Pitcher	Team	IP	IP/H	IP/ER	η^{-1}
Chris Carpenter	SL	192.67	0.959	4.014	1.000
Justin Verlander	DET	240.00	0.833	2.609	1.000
Roy Halladay	TOR	239.00	0.872	3.230	1.000
Felix Hernandez	SEA	238.67	0.855	3.616	1.000
Zack Greinke	KC	229.33	0.917	4.170	1.000
Danny Haren	ARI	229.33	0.980	2.867	1.000
Tim Lincecum	SF	225.33	0.931	3.634	0.988
Javier Vazquez	ATL	219.33	0.958	3.133	0.986
Adam Wainwright	SL	233.00	0.818	3.426	0.976
Cliff Lee	CLE/PHI	231.67	0.791	2.791	0.967
C.C. Sabathia	NYY	230.00	0.842	2.674	0.963
Ted Lilly	CHC	177.00	0.937	2.902	0.959
Randy Wolf	LAD	214.33	0.886	2.784	0.927
Matt Cain	SF	217.67	0.837	3.110	0.926
Bronson Arroyo	CIN	220.33	0.765	2.344	0.918
Jair Jurrjens	ATL	215.00	0.814	3.468	0.917
James Shields	TB	219.67	0.752	2.175	0.915
Joel Pineiro	SL	214.00	0.846	2.578	0.914
Ubaldo Jimenez	COL	218.00	0.784	2.595	0.911
Jake Peavy	SD/CHW	101.67	0.884	2.607	0.902
Josh Beckett	BOS	212.33	0.817	2.333	0.900
Jason Marquis	COL	216.00	0.715	2.227	0.900
Josh Johnson	FL	209.00	0.843	2.787	0.898
Edwin Jackson	DET	214.00	0.778	2.488	0.895
Mark Buehrle	CHW	213.33	0.784	2.344	0.894

Top 25 starting pitchers ranked by η^{-1}

approximately 25% of the team wins. Verlander, Hernandez, and Sabathia led the American League with 19 wins. However, both Verlander and Hernandez accounted for about 22% of the Tiger's wins while Sabathia accounted for just over 18%.

In the National League, San Francisco standout Tim Lincecum won the Cy Young award, narrowly beating out the St. Louis Cardinal's Chris Carpenter by 6 votes and Adam Wainwright by 10 votes. Carpenter joined Dan Haren as the only starters in the National League to achieve a performance rating of $\eta^{-1} = 1.000$. Lincecum won only 15 games, accounting for only about 17% of the Giant's wins. Carpenter had the lowest earned run average in the National League, giving up 2.24 earned runs per game. Interestingly, compared to Lincecum, Carpenter accounted for a higher percentage of team wins (about 19%) and gave up nearly one fourth of an earned run less. Haren only won 14 games (20% of the Arizona Cardinal's total wins), but pitched nearly an inning for every hit surrendered. Based on this analysis, Carpenter would have been a better choice for the National League Cy Young award.[2]

Bargain starting pitchers are reported in Table 6.2. Pitchers are sorted by descending performance and are included if their salary was below the median starting pitcher salary of $2.35 million and if their performance was in the top quartile (η^{-1}>0.848). Data for starting pitcher salary and performance are presented in Fig. 6.1.

Cy Young winner Tim Lincecum had the highest performance rating of the group and earned only $650,000 (33.5 percentile). His value was compensated via

Table 6.2 2009 bargain starting itchers

Pitcher	Team	IP	IP/H	IP/ER	Salary ($)	η^{-1}
Tim Lincecum	SF	225.33	0.931	3.634	650,000	0.988
Jair Jurrjens	ATL	215.00	0.814	3.468	450,000	0.917
James Shields	TB	219.67	0.752	2.175	1,500,000	0.915
Ubaldo Jimenez	COL	218.00	0.784	2.595	750,000	0.911
Josh Johnson	FLO	209.00	0.843	2.787	1,400,000	0.898
Edwin Jackson	DET	214.00	0.778	2.488	2,200,000	0.895
Jered Weaver	LAA	211.00	0.793	2.398	465,000	0.889
Zach Duke	PIT	213.00	0.753	2.219	2,200,000	0.889
Josh Outman	OAK	67.33	0.863	2.590	400,000	0.882
Jon Lester	BOS	203.33	0.804	2.641	1,000,000	0.868
Scott Baker	MIN	200.00	0.826	2.062	750,000	0.864
John Lannan	WAS	206.33	0.727	2.318	424,000	0.861
Nick Blackburn	MIN	205.67	0.724	2.236	440,000	0.858
Matt Garza	TB	203.00	0.760	2.281	433,300	0.855

Bargain pitchers earn less than the median starting pitcher salary and perform in the top quartile

[2] Lincecum was voted the Cy Young winner in 2008. Greinke edged Lincecum in the fan voting for This Year in Baseball top starter honor.

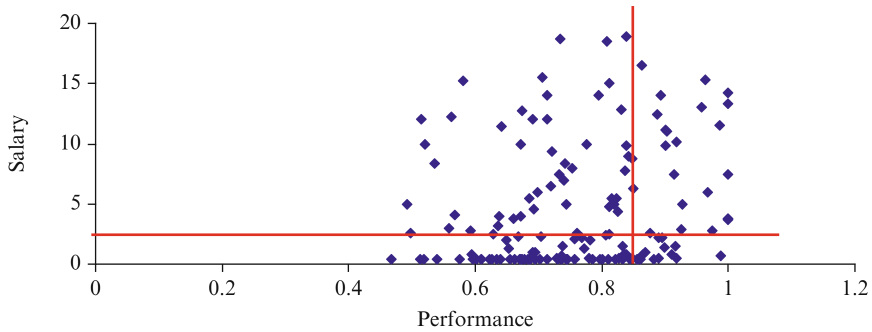

Fig. 6.1 Starting pitcher salary vs. performance

arbitration when he settled with San Francisco, leading to an increased average salary of $11.5 million over 2 years.[3] Other bargain players who settled were Josh Johnson (4 years, $39 million), Edwin Jackson (2 years, $13.35 million), Jered Weaver (1 year, $4.265 million), Zach Duke (1 year, $4.3 million), and Matt Garza (1 year, $3.35 million.)

Evaluating 2009 Relief Pitchers

Based on the classification of starter vs. relief pitcher discussed above, there were 172 relief pitchers.[4] As we did for hitters and starting pitchers, we solved model (6.1) to obtain the inverse of our aggregate performance measure. Results for the top 25 relievers are reported in Table 6.3.

Three pitchers achieved the maximum performance rating of $\eta^{-1} = 1$: Brian Bass (Baltimore), Andrew Bailey (Oakland), and Mike Adams (San Diego). Bass achieved this rating by pitching in the most innings. Relative to the top 25 relief pitchers, Bass had the highest earned run average and gave up the most hits per inning. Bass' high rating is indicative of a durable relief pitcher who can give innings but not of a quality pitcher. Indeed, Bass was nontendered by the Orioles and joined the Pirates by signing a minor-league contract with an invitation to spring training.

While Adams only pitched 37 innings and did not qualify for any pitching titles, his ratio of innings pitched was a remarkable 12.33 per earned run. Mariano Rivera, who was selected as the closer of the year in This Year in Baseball awards, only achieved a rating of $\eta^{-1} = 0.881$. Compared to Rivera, Andrew Bailey pitched more innings, gave up fewer hits per inning but had a slightly higher earned run

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[3] Salary arbitration information was obtained from http://www.bizofbaseball.com.

[4] We chose to analyze relief pitchers together. One could argue that the closer is a special type of relief pitcher. The advantage of this classification comes at using a relative small sample for inference.

Table 6.3 Performance of top 25 relief pitchers

Pitcher	Team	IP	IP/H	IP/ER	η^{-1}
Brian Bass	BAL	86.33	0.557	1.837	1.000
Andrew Bailey	OAK	83.33	1.142	4.902	1.000
Mike Adams	SD	37.00	1.682	12.333	1.000
Todd Coffey	MIL	83.67	0.837	3.099	0.986
Ramon Troncoso	LAD	82.67	0.689	3.307	0.975
Mark Lowe	SEA	80.00	0.800	2.759	0.943
Michael Wuertz	OAK	78.67	1.049	3.420	0.942
Shawn Camp	TOR	79.67	0.752	2.570	0.936
Brandon Lyon	DET	78.67	0.884	3.147	0.933
Ryan Madson	PHI	77.33	0.789	2.762	0.912
Matt Guerrier	MIN	76.33	0.979	3.817	0.912
Jonathan Broxton	LAD	76.00	1.027	3.455	0.911
Lance Cormier	TB	77.33	0.766	2.762	0.911
Nick Masset	CIN	76.00	0.974	3.800	0.908
Rafael Soriano	ATL	75.67	0.934	3.027	0.902
George Sherrill	BAL/LAD	69.00	0.873	5.308	0.896
Fernando Rodney	DET	75.67	0.670	2.045	0.887
Luke Gregerson	SD	75.00	0.781	2.778	0.886
Mike Gonzalez	ATL	74.33	0.774	3.717	0.885
Mariano Rivera	NYY	66.33	1.087	5.103	0.881
Brandon League	TOR	74.67	0.747	1.965	0.880
C.J. Wilson	TEX	73.67	0.708	3.203	0.871
Joe Nathan	MIN	68.67	1.040	4.292	0.871
Carlos Marmol	CHC	74.00	0.617	2.643	0.869
Brad Ziegler	OAK	73.33	0.661	2.933	0.865

Top 25 relief pitchers ranked by η^{-1}

average. Bailey was selected as the American League Rookie of the Year. Not surprisingly, Rivera was compared to a convex combination of Bailey and Adams, with weights of 0.827 and 0.173, respectively.

We also considered bargain players based on the criteria that the relief pitcher had to be paid below the median salary ($800,000) for relief pitchers but above the 75th percentile in performance (0.824). Data for relief pitcher's salary and performance are presented in Fig. 6.2.

There were 19 bargain relief pitchers; data are reported in Table 6.4 ranked in descending order of performance. Interestingly, all three top-rated pitchers were bargain players earning near the league minimum. As mentioned above, Bass was released by the Orioles and signed a minor-league contract with the Pittsburgh Pirates. As of this writing, Bass is not performing well in 2010 having appeared in only three games with an earned run average of 12.79. Andrew Bailey is continuing to play well for the Athletics in 2010, with an earned run average of 1.88 (almost identical to 2009) with 12 saves out of 14 opportunities. To date, Bailey has appeared in 23 games and has pitched 24 innings. Mike Adams settled for a 1-year contract in 2010 with a salary of $1 million. In 26 appearances in 2010, he has already given up more hits and earned runs while pitching 26.33 innings. Currently, his earned run average is 2.73.

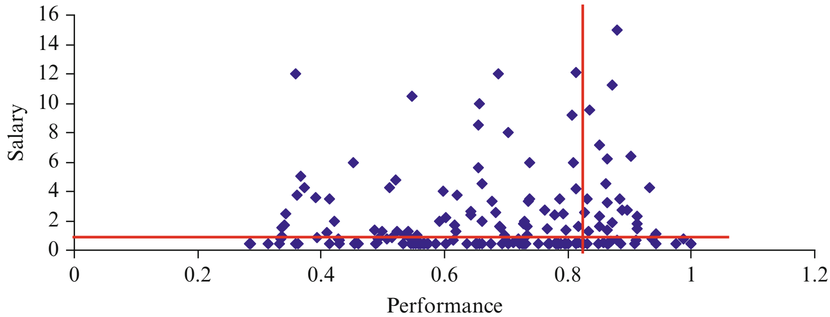

Fig. 6.2 Relief pitcher salary vs. performance

Table 6.4 2009 bargain relief pitchers

Pitcher	Team	IP	IP/H	IP/ER	Salary ($)	η^{-1}
Brian Bass	BAL	86.33	0.557	1.837	405,000	1.000
Andrew Bailey	OAK	83.33	1.142	4.902	400,000	1.000
Mike Adams	SD	37.00	1.682	12.333	414,800	1.000
Ramon Troncosc	LAD	82.67	0.689	3.307	401,000	0.975
Mark Lowe	SEA	80.00	0.800	2.759	418,000	0.943
Shawn Camp	TOR	79.67	0.752	2.570	750,000	0.936
Lance Cormier	TB	77.33	0.766	2.762	675,000	0.911
Nick Masset	CIN	76.00	0.974	3.800	418,000	0.908
Luke Gregerson	SD	75.00	0.781	2.778	400,000	0.886
Brandon League	TOR	74.67	0.747	1.965	640,000	0.880
Carlos Marmol	CHC	74.00	0.617	2.643	575,000	0.869
Brad Ziegler	OAK	73.33	0.661	2.933	405,000	0.865
Peter Moylan	ATL	73.00	0.716	3.174	410,000	0.864
Brian Wilson	SF	72.33	0.822	3.288	480,000	0.858
David Aardsma	SEA	71.33	0.859	3.567	419,000	0.849
Craig Breslow	MIN	69.67	0.871	2.679	422,000	0.831
Ramon Ramirez	BOS	69.67	0.718	3.167	441,000	0.826
Jim Johnson	BAL	70.00	0.707	2.188	420,000	0.826
Brian Stokes	NYM	70.33	0.628	2.269	409,500	0.825

Bargain pitchers earn less than the median starting pitcher salary and perform in the top quartile

Of the 19 bargain players, 11 were eligible for free agency and settled before arbitration. In addition to Adams, Mark Lowe ($1.15 million), Shawn Camp ($1.15 million), Lance Cormier ($1.2 million), Brandon League ($1.0875 million), Carlos Marmol ($2.125 million), Peter Moylan ($1.15 million), Brian Wilson ($4.4375 million), David Aardsma ($2.75 million), and Ramon Ramirez ($1.155 million) agreed to 1-year contract. Additionally, Nick Masset signed a 2-year contract for a total salary of $2.58 million. All the free agents signed and will earn well above the previous year minimum salary.

In this chapter, we focused on the performance of starting and relief pitchers for the 2009 season. The results indicated that the DEA measure does a good job of capturing individual performance. The top-performing starting pitchers were all in the running for the Cy Young award, including Zack Greinke, the eventual winner in the American League. Based on the DEA measure, Chris Carpenter and Danny Haren were more deserving than the National League winner, Tim Lincecum, who achieved a relative high rating of 0.99.

Chapter 7
Arbitration and Free Agency

Introduction

The first collective bargaining agreement was negotiated in 1968 and has been modified over time. The current agreement in Major League Baseball was negotiated to expire after the 2011 season.[1] In this chapter, we analyze arbitration cases and nontendered free agents. In most cases, after the player or team files for arbitration, a settlement is reached, negating the need for a hearing.

The collective bargaining agreement between owners and players is used to help resolve salary disputes between owners and eligible players. A player who has at least 3 years but less than 6 years of experience is eligible for salary arbitration.[2] If the player has not signed a long-term contract he may file for arbitration, with the owners providing a salary offer and the player a salary demand. Assuming an agreement is not reached prior to the scheduled hearing date, the arbitrator selects either the team offer or the player demand after both sides present their case.

The player and the team are allowed to present evidence based on the player's contribution to the club in the previous year (including but not limited to player performance). Other criteria include consistency of performance, comparative baseball salaries, and other measures. Importantly, for players with less than 5 years of experience, the arbitration panel gives "particular attention" to player contracts of other players who have one more year of service, though a player is entitled to argue comparisons to other players regardless of service. In this chapter, we focus on arbitration cases and nontendered free agents using these criteria. As stated in the collective bargaining agreement, other evidence can be submitted; the model presented here can be extended to evaluate other criteria.

[1] The current agreement is available online at http://mlbplayers.mlb.com/pa/index.jsp Information pertaining to the current agreement that is discussed in this chapter was taken from this agreement. Additional information was taken from Hadley and Ruggiero (2006).

[2] Players with a minimum of 2 full years of service may also be eligible; these players must have accumulated 86 full days during the past season. Only the top 17% of such players based on total service qualify for arbitration. These players are known as the "Super Twos".

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Nonparametric Estimation of the Contract Zone

We focus on comparisons of player performance and salaries from the prior season. The nonparametric model of Hadley and Ruggiero (2006) is illustrated in Fig. 7.1. Here, we plot performance η^{-1} against salary for seven hypothetical players. The upper frontier consists of segments AB, BC, and CD and illustrates the salary benchmarks from the perspective of the player. The lower frontier is defined by segments AE, EF, and FD and identifies salary as a cost to the team. Players A, B, C, and D all earn the maximum observed salary for their associated level of performance. On the other hand, players A, E, F, and D all earn the minimum observed salary given their associated level of performance. As shown, players A and D define both the lower and upper frontiers; player A (D) has the minimum (maximum) level of performance and hence, has no comparison set for reference.

Now consider player G who does not belong to either frontier. In an arbitration case, player G would argue that his current salary of S_{G} is too low because a combination of players B and C earns a higher salary $(S_{\mathrm{G}}^{\mathrm{u}})$ for the same level of performance. This represents the upper bound for negotiation purposes. On the other hand, the owners would counter with $(S_{\mathrm{G}}^{\mathrm{l}})$, since player E has a lower salary with the same level of performance. This represents the lower bound based only on performance.[3]

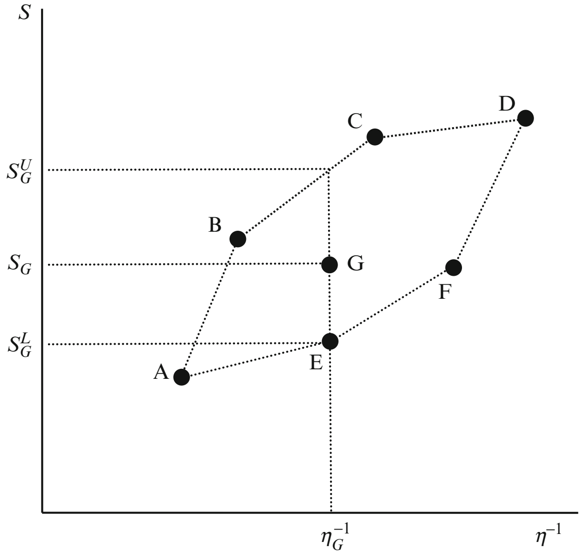

Fig. 7.1 Dual representation and the contract zone

[3] The lower bound is constrained because the team must offer a minimum of 80% of the previous year's salary and performance bonuses and 70% of the salary and bonus earned 2 years earlier.

Following Chap. 5, we assume that each player j ($j = 1, \ldots, n$) has a vector of s performance variables $Y = (y_1, \ldots, y_S)$ and salary S with player j ($j = 1, \ldots, n$) data represented by y_{kj} ($k = 1, \ldots, s$) and S_j. The upper bound from the players perspective for player 0 is given as the solution to the following linear program:

$$\begin{aligned} \gamma_0^u &= \max\ \gamma \\ &\text{subject to} \\ \sum_{j=1}^{n} \lambda_j S_j &\geqslant \gamma S_0 \\ \sum_{j=1}^{n} \lambda_j y_{kj} \leqslant y_{k0}, \quad & k = 1, s; \\ \sum_{j=1}^{n} \lambda_j &= 1; \\ \lambda_j \geqslant 0, \quad & j = 1,, n. \end{aligned} \tag{7.1}$$

Here, we seek the maximum possible expansion in observed salary consistent with observed performance[4] In this case, the set of comparison players defined by n should take into consideration the relevant comparison set as set forth by the collective bargaining agreement. Solution of (7.1) provides the upper bound $S_0^{\mathrm{u}} = (\gamma_0^{\mathrm{u}} S_0)$ of the contract zone

Using the same notation, we can also derive the lower bound for player 0 as the solution to the following linear program:

$$\begin{aligned} \gamma_0^l &= \min\ \gamma \\ &\text{subject to} \\ \sum_{j=1}^{n} \lambda_j S_j &\leqslant \gamma S_0 \\ \sum_{j=1}^{n} \lambda_j y_{kj} \geqslant y_{k0}, \quad & k = 1, s; \\ \sum_{j=1}^{n} \lambda_j &= 1; \\ \lambda_j \geqslant 0, \quad & j = 1,, n. \end{aligned} \tag{7.2}$$

Once again, the appropriate comparison set as specified in the collective bargaining agreement determines n. Based on the collective bargaining agreement, it might be

[4] While η^{-1} can be used, it is more appropriate to use the original performance variables to facilitate a proper convex comparison

necessary to adjust the lower bound to reflect that teams have a floor that is based on previous seasons' salaries. In this case, the lower bound of the contract zone would be $S_0^{\mathrm{l}} = \max(\gamma_0^{\mathrm{l}} S_0, 0.8S_0, 0.7S_0^{t-1})$, where S_0 and S_0^{t-1} reflect the previous two year salaries of player 0

Based on the solutions of (7.1) and (7.2), Hadley and Ruggiero (2006) defined the relative contract position for player 0 as

$$\mathrm{RCP}_0 = \frac{S_0 - S_0^{\mathrm{l}}}{S_0^{\mathrm{u}} - S_0^{\mathrm{l}}}. \tag{7.3}$$

The relative contract position positions the players' observed salary relative to the contract zone. If the lower bound is equal to the upper bound (as for players A and D) in Fig. 7.1, the relative contract position is not defined. If the contract zone, however, does not have a range of zero, we see that a player with current salary on the lower frontier (like player E), the relative contract position is zero. A player who has a current salary on the player's frontier, the contract position is unity. Hence, where defined, (7.3) provides a rescaling of the contract position to be on the range of [0,1]

In Sect. 3, we apply these models to select free agents for illustrative purposes

Hitter's Contract Zone

In order to properly measure the upper and lower bounds of the contract zone for a particular player, it is required to compare the player to an appropriate comparison set. For example, it is not relevant for a player to compare a hitter relative to the salary structure of a starting pitcher. Likewise, a shortstop should not evaluate his salary relative to a catcher. Necessarily, a classification of hitters is necessary to facilitate useful comparisons [5] Hitters are evaluated using the same hitting variables from Chap. 5. Fielding statistics could be included in the modeling or could be used to inspect the comparisons that define the upper and lower bounds. For our purposes in this chapter, we separate out the players based on position played and do not try to account for fielding. Hence, we are taking the second approach that would require secondary analysis to insure that appropriate comparisons are made

Furthermore, for our empirical analysis, we apply the criteria specified in the collective bargaining agreement that limits the potential comparison based on number of years served. Players with less than 5 years of service that file for arbitration need to provide comparisons to players with no more than 1 more year

[5] Admittedly, the classification used in this chapter is arbitrary. Hadley and Ruggiero (2006) evaluated hitters without further classification. A trade-off exists between enriching the information set and making inappropriate comparisons. Future research might try to shed light on this particular issue

of service. In order to restrict the comparison set, we apply the model developed by Ruggiero (1996). Let t_j represent the number of years of service for player j ($j = 1,\ldots,n$). For players with $t_j \leqslant 4,$ the upper bound is restricted as follows:[6]

$$\begin{aligned}
&\gamma_0^{\mathrm{u}} = \max\ \gamma \\
&\text{subject to} \\
&\sum_{j=1}^{n} \lambda_j S_j \geqslant \gamma S_0 \\
&\sum_{j=1}^{n} \lambda_j y_{kj} \leqslant y_{k0}, && k = 1, s; \\
&\sum_{j=1}^{n} \lambda_j = 1; \\
&\lambda_j = 0 \text{ if } t_j > t_0 + 1; \\
&\lambda_j \geqslant 0, && j = 1, , n.
\end{aligned} \tag{7.4}$$

In order to classify players, we need to make assumptions about the opportunities available to a given player. Any hitter, even one in the National League, has an option of being a designated hitter in the American League, perhaps via trade. Hence, in analyzing the hitters, we allow comparisons with the American League designated hitters

The position of the catcher is unique. While there may be exceptions, in general, there are no other positions that can catch at the major league level. Thus, catchers are not included in the reference set for other players. However, we allow the possibility that catchers can also play first base. In fact, catchers do play first base (or other positions) during a given season to alleviate the bodily stress from catching. Victor Martinez, for example, started at first base 44 times for Cleveland and 22 times for Boston in 2009. Nonetheless, we assume that catchers could play first base (or be designated hitters)

Results for catchers are reported in Table 7.1. Fifteen catchers were either subject to arbitration or became nontendered free agents. Kansas City Royal John Buck became a free agent in December 2009 and signed a 1-year contract for 2010 to catch for the Toronto Blue Jays. According to our analysis, Buck's salary, if he went through arbitration, would have been between \$2.32 and \$3.55 million. However, after being released, he agreed on a 1-year contract for 2010 of only \$2 million, below the lower bound. Mike Rivera was nontendered by the Brewers in 2009 and is currently under minor-league contract with the Dodgers

[6] The model presented in Ruggiero (1996) was developed for public sector applications where environmental variables that are nondiscretionary affect production. The model is similar because the reference set is restricted by the rules of collective bargaining agreement

Table 7.1 Contract zone analysis for catchers, 2009

		Contract zone				New contract		
Player	2009 salary	S^u	S^l	Average	RCP 2009	Years	Average salary	Arbitration
Jeff Mathis	450,000	3,330,205	400,000	1,865,102	0.017	1	1,300,000	Won hearing
Miguel Montero	425,000	7,666,666	406,348	4,036,507	0.003	1	2,000,000	Settled
Chris Iannetta	415,000	7,666,666	403,498	4,035,082	0.002	3	2,766,667	Settled
Carlos Ruiz	475,000	7,666,666	400,206	4,033,436	0.010	3	2,833,333	Settled
Russell Martin	3,900,000	6,051,851	3,120,000	4,585,926	0.266	1	5,050,000	Settled
Mike Napoli	2,000,000	9,500,000	1,600,000	5,550,000	0.051	1	3,600,000	Settled
Kelly Shoppach	1,950,000	7,666,666	1,560,000	4,613,333	0.064	2	1,250,000	Settled
Dioner Navarro	2,100,000	7,438,462	1,680,000	4,559,231	0.073	1	2,100,000	Settled
Koyie Hill	475,000	505,000	400,093	452,547	0.714	1	700,000	Settled
Humberto Quintero	610,000	610,000	488,000	549,000	1.000	1	750,000	Settled
Gerald Laird	2,800,000	7,333,333	2,240,000	4,786,667	0.110	1	3,950,000	Settled
Wil Nieves	445,000	445,000	400,000	422,500	1.000	1	700,000	Settled
Mike Rivera	415,000	415,000	400,000	407,500	1.000	NA	NA	Nontendered
John Buck	2,900,000	3,550,000	2,320,000	2,935,000	0.472	1	2,000,000	Released
Ronny Paulino	440,000	6,241,862	400,147	3,321,005	0.007	1	1,100,000	Settled

Salaries are measured in dollars. Upper and lower bounds were calculated using Models (7.2) and (7.3)

Jeff Mathis was the only catcher to win his arbitration hearing. Mathis won his demand of $1.3 million instead of the $700,000 offer by the Angels. Based on his hitting performance, we calculated his upper bound to be $3.3 million; however, his lower bound was only $400,000 (below the 2010 minimum). Interestingly, Mathis was a platoon player with relatively poor hitting statistics. His performance rating of $\eta^{-1} = 0.263$ placed him in the 14th percentile of overall performance. However, his work behind the plate compared to teammate Mike Napoli was helpful in the decision

Twelve of the catchers settled with their teams. Koyie Hill settled for $700,000, which was above our calculated upper bound. In his seventh season, Hill has only played in just over 200 games with a career batting average of 0.220. His 2009 salary of $475,000 placed him closer to the upper boundary. All other catchers settled above the lower frontier. In addition to Hill, only Russell Martin and Wil Nieves settled above the average of the contract zone bounds. Martin's contract zone was between $3.12 and $6.05 million; he settled for just over $5 million for 1 year with the Dodgers. Of the catchers on the list, Martin's salary is the highest. He also had the highest performance rating with $\eta^{-1} = 0.741$ (72nd percentile). Like Hill, Nieves settled for a 1-year contract for $700,000, nearly $250,000 above the contract zone upper bound. Nieves is currently hitting below the Mendoza line with a 0.176 batting average

Next, we consider the first basemen (Table 7.2). Ryan Garko, traded by the Cleveland Indians to the San Francisco Giants in 2009, was signed by the Seattle Marines as a free agent. On April 1, 2010, Garko was claimed off waivers by the Texas Rangers and given a 1-year contract for $550,000. The upper bound for his salary was calculated to be $2.28 million while the lower bound was just above the 2009 league minimum. Garko has appeared in only 15 games to date in the 2010 season, and has only three hits in 33 at bats. However, over his five plus seasons, he has a 0.275 batting average. From 2009, his performance rating $\eta^{-1} = 0.47$ was below the median from the majors

Los Angeles Dodger James Loney, with $\eta^{-1} = 0.803$ (80th percentile) in 2009, settled for a 1-year contract worth $3.1 million. His settlement placed him closer to the upper bound of his contract. Florida Marlin Jorge Cantu, who achieved $\eta^{-1} = 0.826$ (83rd percentile), settled for $6 million, just above the average of the contract zone upper and lower bounds. Seattle Mariner Casey Kotchman, traded from the Red Sox in the off-season, also earns just above the midpoint of the contract zone. Kotchman had a performance rating of only $\eta^{-1} = 0.528$ (48th percentile)

The comparison set for the other infielders is more problematic (Table 7.3). Recognizing that playing third requires different skills than playing either second or short stop, we compared all in one classification to enrich potential comparisons. This assumes that these infielders can argue during arbitration that salaries of other infield positions are comparable based on hitting performance. Empirically, we do know that some players rotate around the infield. Nonetheless, if this assumption is problematic further restrictions can be added to (7.4)

Two infielders, Kelly Johnson (Atlanta Braves) and Garrett Atkins (Colorado Rockies), signed as free agents with other teams. Johnson signed with Arizona for

Table 7.2 Contract zone analysis for first basemen, 2009

		Contract zone				New contract		
Player	2009 salary	S^u	S^l	Average	RCP 2009	Years	Average salary	Arbitration
James Loney	465,000	4,786,792	465,000	2,625,896	0.000	1	3,100,000	Settled
Jorge Cantu	3,500,000	11,500,000	2,800,000	5,959,324	0.080	1	6,000,000	Settled
Casey Kotchman	2,885,000	5,734,375	2,308,000	3,067,688	0.168	1	3,157,500	Settled
Ryan Garko	446,100	2,277,155	401,624	1,339,390	0.024	1	550,000	Nontendered

See notes to Table 7.1

Table 7.3 Contract zone analysis for infielders, 2009

		Contract zone				New contract		
Player	2009 salary	S^u	S^l	Average	RCP 2009	Years	Average salary	Arbitration
Kelly Johnson	2,825,000	4,879,928	2,260,000	3,569,964	0.216	1	2,350,000	Signed as free agent
Brendan Harris	466,100	2,686,638	400,148	1,543,393	0.029	2	1,600,000	Settled
Ramon Santiago	825,000	2,929,339	660,000	1,794,670	0.073	2	1,250,000	Settled
Mark Teahen	3,575,000	17,011,304	2,860,000	9,935,652	0.051	3	4,666,667	Settled
Stephen Drew	1,500,000	7,050,000	1,500,000	4,275,000	0.000	1	3,400,000	Settled
Erick Aybar	460,000	3,641,304	460,000	2,050,652	0.000	1	2,050,000	Settled
Ronny Cedeno	822,500	1,511,231	658,000	1,084,615	0.193	1	1,125,000	Settled
J.J. Hardy	4,650,000	15,676,125	3,720,000	9,698,063	0.078	1	5,000,000	Settled
Jason Bartlett	1,981,250	18,925,926	1,585,000	10,255,463	0.023	1	4,000,000	Settled
Eric Bruntlett	800,000	800,000	640,000	720,000	1.000	NA	NA	Settled
Alex Gordon	457,000	457,000	400,000	428,500	1.000	1	1,150,000	Settled
Kevin Kouzmanoff	432,400	3,823,945	400,792	2,112,368	0.009	1	3,100,000	Settled
Jeff Keppinger	427,500	5,748,020	400,000	3,074,010	0.005	1	1,150,000	Settled
Howie Kendrick	465,000	6,901,613	400,101	3,650,857	0.010	1	1,750,000	Settled
Dan Uggla	5,350,000	7,050,000	4,280,000	5,665,000	0.386	1	7,800,000	Settled
Mike Fontenot	430,000	3,653,846	400,140	2,026,993	0.009	1	1,000,000	Settled
Jeff Baker	415,000	2,760,971	400,000	1,580,486	0.006	1	975,000	Settled
Maicer Izturis	1,600,000	13,574,783	1,280,000	7,427,391	0.026	3	3,333,333	Settled
Rickie Weeks	2,450,000	4,688,771	1,960,000	3,324,386	0.180	1	2,750,000	Settled
Clint Barmes	1,625,000	7,050,000	1,300,000	4,175,000	0.057	1	3,225,000	Settled
Augie Ojeda	712,500	3,375,000	570,000	1,972,500	0.051	1	825,000	Settled
Ryan Theriot	500,000	6,287,500	500,000	3,393,750	0.000	1	2,600,000	Lost hearing
Garrett Atkins	7,050,000	12,225,875	5,640,000	8,932,938	0.214	1	4,000,000	Signed as free agent
Skip Schumaker	430,000	2,374,043	406,467	1,390,255	0.012	2	2,350,000	Settled

See notes to Table 7.1

$2.35 million, an amount just above the lower bound. Atkins signed with the Baltimore Orioles after being nontendered by the Rockies for only $4 million, more than $1.5 million below the lower bound. And the Orioles hold a club option of $8.5 million for the 2011 season. Both players had $\eta^{-1} < 0.44$ and were around the 36th percentile in performance in 2009

The only infielder (as defined by our classification) who went to hearing was Chicago Cub Ryan Theriot, who was asking for $3.4 million. Theriot lost the hearing, leading to a 1-year contract for the team's offer of $2.6 million. According to our calculations, Theriot's contract zone was calculated on the range of $500,000 to $6.3 million. The average of the upper and lower bounds was approximately $3.4 million, nearly identical to the amount that Theriot was seeking. Theriot achieved an overall performance rating of $\eta^{-1} = 0.812$ for 2009, placing him in the 82nd percentile. Based on our analysis, Theriot's asking price was more than fair

Eric Bruntlett was nontendered by the Philadelphia Phillies after the 2009 season. He was signed as a free agent by the Washington Nationals but was released in May 2010. Bruntlett's contract zone narrowly ranged from $640,000 to $800,000 due to his relatively poor performance in 2009. Bruntlett's overall rating was $\eta^{-1} = 0.125$, placing his performance in the second percentile

The rest of the players settled. Three players, Brendan Harris (Minnesota Twins), Erick Aybar (Los Angeles Angels), and Ronny Cedeno (Pittsburgh Pirates) all settled for approximately the average of their contract zone values. The rest of the players who settled earned more than the lower bound on the contract zone. Interestingly, Florida Marlin Dan Uggla settled for more than the upper bound, increasing his salary from $5.35 to $7.8 million. His performance of $\eta^{-1} = 0.791$ placed him in the 79th percentile overall

We view the centerfielder as a special position, requiring more speed (Table 7.4). Typically, centerfielders are not power hitters and provide a different dimension. These players can, however, play left or right field. Because we are basing our analysis on hitting, we allow all outfielders in the referent set for centerfielders. In other words, we allow the centerfielder to compare hitting performance and salary with other outfielders. However, in the evaluation of left and right fielders (who are grouped together), we do not allow comparisons to centerfielders. Again, modifications can be made to our classification to test the robustness of the results

Two centerfielders went through the arbitration: Cody Ross (Florida Marlins) won $4.45 million while B.J. Upton (Tampa Bay Rays) lost. Ross was offered an amount ($4.2 million) that was not much different than his demand. Upton, eligible for the first time, was seeking $3.3 million but was awarded the offer of $3 million. Based on hitting performance, both players had a rating around 0.745 (72nd percentile). In percentage terms, Upton's salary increased almost 600% while Ross' salary doubled

Ryan Church signed as a free agent with the Pittsburgh Pirates from the Atlanta Braves. His salary decreased from $2.8 million to $1.5 million. Church was earning above the lower bound and near the average; his rating of $\eta^{-1} = 0.531$ was in the 49th percentile. Currently, in the 2010 season, Church is batting below the Mendoza line with a batting average of 0.190

Table 7.4 Contract zone analysis for center fielders, 2009

		Contract zone				New contract		
Player	2009 salary	S^u	S^l	Average	RCP 2009	Years	Average salary	Arbitration
Cody Ross	2,225,000	4,987,500	1,780,000	3,383,750	0.139	1	4,450,000	Won hearing
Ryan Church	2,800,000	3,714,286	2,240,000	2,977,143	0.380	1	1,500,000	Signed as free agent
Carlos Gomez	437,500	3,823,644	400,035	2,111,840	0.011	1	1,100,000	Settled
Josh Hamilton	555,000	5,197,162	444,000	2,820,581	0.023	1	3,250,000	Settled
Rajai Davis	410,000	4,081,818	400,714	2,241,266	0.003	1	1,350,000	Settled
Michael Bourn	434,500	4,081,818	434,500	2,258,159	0.000	1	2,400,000	Settled
Matt Kemp	467,000	8,009,429	467,000	4,238,214	0.000	2	5,475,000	Settled
Angel Pagan	575,000	5,893,980	460,000	3,176,990	0.021	1	1,450,000	Settled
Franklin Gutierrez	455,000	4,782,844	409,987	2,596,416	0.010	4	5,062,500	Settled
Scott Hairston	1,250,000	5,809,318	1,000,000	3,404,659	0.052	1	2,450,000	Settled
Jody Gerut	1,775,000	7,707,407	1,420,000	4,563,704	0.056	1	2,000,000	Settled
Shane Victorino	3,125,000	11,475,000	3,125,000	7,300,000	0.000	3	7,333,333	Settled
B.J. Upton	435,000	19,907,478	404,051	10,155,765	0.002	1	3,000,000	Lost hearing
Ryan Ludwick	3,700,000	4,407,268	2,960,000	3,683,634	0.511	1	5,450,000	Settled

See notes to Table 7.1

All other centerfielders settled with their teams. Philadelphia Philly Shane Victorino negotiated a 3-year contract for an annual salary of \$7.33 million. In 2009, Victorino was one of nine players to achieve a top rating of $\eta^{-1} = 1$. Seattle Mariner Franklin Gutierrez ($\eta^{-1} = 0.709$, 69th percentile) negotiated a 4-year contract approximately \$5 million per year. The average salary was above the upper bound of his contract zone. Los Angeles Dodger Matt Kemp also signed a multiyear contract, paying him nearly \$5.5 per year for 2 years. The annual amount was above the average contract zone value

The last group of hitters evaluated consisted of the left and right fielders. The results are reported in Table 7.5. Corey Hart (Milwaukee Brewers) was the only player in this category who had a hearing. Hart won \$4.8 million against the team offer of \$4.15 million. Both the offer and the demand were above Hart's upper bound based on his performance. His hitting rating of 0.570 was only in the 53rd percentile

Three outfielders were not tendered. Jack Cust (Oakland Athletics) signed with Oakland as a free agent, taking a cut in pay. His 2009 was the upper bound of his contract zone and he negotiated a 1-year contract for \$2.6 million (from \$2.8 million). His new salary is still above the average of the contract zone. Overall, his hitting rating was $\eta^{-1} = 0.770$, which placed him in the 76th percentile

Gabe Gross (Tampa Bay Rays) and Jeremy Reed (New York Mets) were also nontendered. Gross signed a 1-year contract with the Athletics for \$750,000. His 2010 salary is about \$250,000 below his lower bound. Gross had a poor hitting year in 2009 with a performance rating $\eta^{-1} = 0.378$ (29th percentile). Currently, his batting average is 0.274, over 30 points higher than his career average. It appears that the Athletics' decision was excellent. Reed signed a minor-league contract with the Blue Jays and is currently on the Blue-Jays roster. In 2009, Reed was paid at the upper bound of his contract zone resulting from a rating of $\eta^{-1} = 0.205$ (seventh percentile)

Los Angeles Dodger Andre Ethier led the rest of the group that settled. He signed a 2-year contract with an annual salary of \$7.625 million. His $\eta^{-1} = 0.913$ placed him in the 91st percentile. New York Met Jeff Francoeur settled for \$5 million, well below his average. His rating of 0.720 put him in the 71st percentile. Francoeur's upper bound salary is nearly \$22 million, due to the reference set inclusion of Manny Ramirez and Magglio Ordonez[7]

Interestingly, the outfielder group had a large number of players who settled for salaries above the upper bounds of their contract zones. Corey Hart (Milwaukee Brewers), Jeremy Hermida (Boston Red Sox via the Florida Marlins), Melky Cabrera (Atlanta Braves via the New York Yankees), Carlos Quentin (Chicago White Sox), Luke Scott (Baltimore Orioles), Josh Will (Washington Nationals), and Ryan Ludwick (St. Louis Cardinals) all settled higher

[7] After removing Ordonez and Ramirez from the reference set, the upper bound was reduced by \$5 million. A limitation of the models in this chapter is comparisons to players who have off years. Outlier analysis, as discussed in Chap. 4 could be applied to narrow the upper bounds

Table 7.5 Contract zone analysis for outfielders, 2009

		Contract zone				New contract		
Player	2009 salary	S^u	S^l	Average	RCP 2009	Years	Average salary	Arbitration
Corey Hart	3,250,000	3,250,000	2,600,000	2,925,000	1.000	1	4,800,000	Won hearing
Jack Cust	2,800,000	2,800,000	2,240,000	2,520,000	1.000	1	2,650,000	Signed as free agent
Hunter Pence	439,000	3,700,000	413,957	2,056,978	0.008	1	3,500,000	Settled
Andre Ethier	3,100,000	5,400,000	2,480,000	3,940,000	0.212	2	7,625,000	Settled
Jeremy Hermida	2,250,000	2,616,216	1,800,000	2,208,108	0.551	1	3,345,000	Settled
Jeff Francoeur	3,375,000	21,846,948	2,700,000	12,273,474	0.035	1	5,000,000	Settled
Melky Cabrera	1,400,000	2,778,462	1,120,000	1,949,231	0.169	1	3,100,000	Settled
Matt Diaz	1,237,500	2,904,054	990,000	1,947,027	0.129	1	2,550,000	Settled
Delmon Young	1,152,000	2,674,324	921,600	1,797,962	0.131	1	2,600,000	Settled
Carlos Quentin	550,000	1,979,658	440,000	1,209,829	0.071	1	3,200,000	Settled
Ryan Spilborghs	415,000	2,327,988	404,102	1,366,045	0.006	2	1,625,000	Settled
Luke Scott	2,400,000	4,018,750	1,920,000	2,969,375	0.229	1	4,050,000	Settled
Josh Willingham	2,950,000	2,950,000	2,360,000	2,655,000	1.000	1	4,600,000	Settled
Jose Bautista	2,400,000	2,544,257	1,920,000	2,232,128	0.769	1	2,400,000	Settled
Gabe Gross	1,255,000	12,316,612	1,004,000	6,660,306	0.022	1	750,000	Nontendered
Jeremy Reed	925,000	925,000	740,000	832,500	1.000	NA	NA	Nontendered
Ryan Ludwick	3,700,000	3,722,368	2,960,000	3,341,184	0.971	1	5,450,000	Settled

See notes to Table 7.1

Pitcher's Contract Zone

In this section, we turn our attention to the pitchers. We separate out starting pitchers (Table 7.6) from relief pitchers (Table 7.7). It can be argued that starting pitchers could also relieve; given that the sample size is much larger for pitchers we chose to separate them in this analysis. There were 32 starting pitchers who were part of the arbitration process

Three pitchers, Tim Redding (New York Mets), Chien-Ming Wang (New York Yankees), and Scott Olsen (Washington Nationals), were not tendered. Olsen became a free agent who re-signed with the Nationals. His salary decreased from \$2.8 million in 2009 to \$1 million, which was below the lower bound of his contract zone. Olsen was being paid near the bottom of his contract zone as evidenced by his RCP = 0.098. His performance for 2009, however, was only $\eta^{-1} = 0.592$ (10th percentile)

Redding, who earned \$2.25 million was not tendered by the Mets and is not currently pitching in the major leagues. His performance rating of $\eta^{-1} = 0.704$ (36th percentile), however, was higher than Olsen's. Redding signed as a free agent with the Colorado Rockies, released and signed by the New York Yankees. Currently, Redding is pitching for Scranton/Wilkes-Barre in Triple A. Wang was granted free agency and signed in the off season with the Washington Nationals. Wang signed for \$2 million with even more in performance incentives. Wang is currently on the disabled list after undergoing surgery on his right soldier

Wandy Rodriguez was the only starting pitcher who had a decision via arbitration. He lost his hearing and will earn \$5 million in 2010. Rodriguez was asking for \$7 million. His asking price was above the contract zone average by approximately \$200,000. Rodriquez' performance rating of $\eta^{-1} = 0.876$ placed him in the 80th percentile of starting pitchers

The rest of the starting pitchers settled. With few exceptions, most of the pitchers who settled were paid below the average of the contract zone upper and lower bounds. Cleveland Indian Anthony Reyes became a free agent after being non-tendered by the Indians. He signed a minor-league contract with the Indians and is currently on the disabled list, recovering from Tommy John surgery. Reyes came off a poor season, starting only eight games with an earned run average of 6.57. His performance rating of $\eta^{-1} = 0.602$ placed him in the 12th percentile. Dustin Nippert (Texas Rangers) started half of the games he appeared in during 2009. His performance rating of $\eta^{-1} = 0.737$ placed him in the 45th percentile. Currently, he is a reliever for the Rangers

The pitchers who settled above the average included Tim Lincecum (San Francisco Giants), Josh Johnson (Florida Marlins), Edwin Jackson (traded from the Detroit Tigers to the Arizona Cardinals), Justin Verlander (Detroit Tigers), and Felix Hernandez (Seattle Mariners). Verlander and Hernandez achieved the highest performance rating of $\eta^{-1} = 1$ and both were locked up with 5-year contracts with

Table 7.6 Contract zone analysis for starting pitchers, 2009

		Contract zone				New contract		
Player	2009 salary	S^u	S^l	Average	RCP 2009	Years	Average salary	Arbitration
Scott Olsen	2,800,000	7,965,327	2,240,000	5,102,664	0.098	1	1,000,000	Signed as free agent
Chad Billingsley	475,000	10,871,794	416,189	5,643,992	0.006	1	3,850,000	Settled
Brandon McCarthy	650,000	10,229,235	520,000	5,374,618	0.013	1	1,300,000	Settled
Tim Lincecum	650,000	12,433,333	650,000	6,541,667	0.000	2	11,500,000	Settled
Josh Johnson	1,400,000	12,118,812	1,120,000	6,619,406	0.025	4	9,750,000	Settled
Edwin Jackson	2,200,000	11,349,484	1,760,000	6,554,742	0.046	2	6,675,000	Settled
Jered Weaver	465,000	11,528,842	441,751	5,985,296	0.002	1	4,265,000	Settled
Zach Duke	2,200,000	11,045,237	1,760,000	6,402,619	0.047	1	4,300,000	Settled
Matt Garza	433,300	11,136,392	427,068	5,781,730	0.001	1	3,350,000	Settled
Justin Verlander	3,675,000	12,006,694	3,675,000	7,840,847	0.000	5	16,000,000	Settled
Felix Hernandez	3,800,000	12,270,081	3,800,000	8,035,040	0.000	5	15,600,000	Settled
John Danks	520,000	11,188,007	425,134	5,806,570	0.009	1	3,450,000	Settled
Kevin Correia	750,000	11,081,881	600,000	5,840,940	0.014	1	3,600,000	Settled
Jeremy Guthrie	650,000	9,437,179	520,000	4,978,590	0.015	1	3,000,000	Settled
Carl Pavano	1,500,000	16,045,003	1,200,000	8,622,501	0.020	1	7,000,000	Settled
Joe Blanton	5,475,000	18,432,613	4,380,000	11,406,306	0.078	3	8,000,000	Settled
Scott Feldman	434,680	11,045,182	411,731	5,728,456	0.002	1	2,425,000	Settled
Ricky Nolasco	2,400,000	9,403,381	1,920,000	5,661,690	0.064	1	3,800,000	Settled
Jorge de la Rosa	2,000,000	10,426,861	1,600,000	6,013,431	0.045	1	5,600,000	Settled
Joe Saunders	475,000	10,225,068	406,361	5,315,715	0.007	1	3,700,000	Settled
John Maine	2,600,000	9,888,505	2,080,000	5,984,253	0.067	1	3,300,000	Settled
Dustin Nippert	411,760	9,063,793	400,000	4,731,896	0.001	1	650,000	Settled
Jonathan Sanchez	455,000	10,575,679	400,000	5,487,840	0.005	1	2,100,000	Settled
Brian Tallet	1,015,000	8,972,207	812,000	4,892,104	0.025	1	2,000,000	Settled
Anibal Sanchez	400,000	9,899,332	400,000	5,149,666	0.000	1	1,250,000	Settled
Kyle Davies	1,300,000	9,056,383	1,040,000	5,048,192	0.032	1	1,800,000	Settled

(continued)

Table 7.6 (continued)

		Contract zone				New contract		
Player	2009 salary	S^u	S^l	Average	RCP 2009	Years	Average salary	Arbitration
Francisco Liriano	430,000	8,208,850	400,000	4,304,425	0.004	1	1,600,000	Settled
David Bush	4,000,000	14,186,712	3,200,000	8,693,356	0.073	1	4,215,000	Settled
Anthony Reyes	414,200	4,477,520	400,000	2,438,760	0.003	1	425,000	Settled
Tim Redding	2,250,000	16,048,639	1,800,000	8,924,320	0.032	NA	NA	Nontendered
Wandy Rodriguez	2,600,000	11,502,537	2,080,000	6,791,268	0.055	1	5,000,000	Lost hearing
Chien-Ming Wang	5,000,000	5,000,000	4,000,000	4,500,000	1.000	1	2,000,000	Nontendered

See notes to Table 7.1

Table 7.7 Contract zone analysis for relief pitchers, 2009

		Contract zone				New contract		
Player	2009 salary	S^u	S^l	Average	RCP 2009	Years	Average salary	Arbitration
Rafael Soriano	6,350,000	6,350,000	5,080,000	5,715,000	1.000	1	7,250,000	Traded
Clay Condrey	650,000	6,095,683	520,000	3,307,842	0.044	1	900,000	Signed as free agent
Heath Bell	1,255,000	6,183,492	1,004,000	3,593,746	0.148	1	4,000,000	Settled
Mike Adams	414,800	1,371,270	414,800	893,035	0.000	1	1,000,000	Settled
Mark Lowe	418,000	1,758,195	400,000	1,079,097	0.013	1	1,150,000	Settled
Shawn Camp	750,000	13,028,710	600,000	6,814,355	0.028	1	1,150,000	Settled
Lance Cormier	675,000	5,636,395	540,000	3,088,197	0.053	1	1,200,000	Settled
Nick Masset	418,000	6,350,000	400,000	3,375,000	0.003	2	1,290,000	Settled
Brandon League	640,000	4,235,789	512,000	2,373,895	0.063	1	1,087,500	Settled
Carlos Marmol	575,000	1,390,021	460,000	925,010	0.177	1	2,130,000	Settled
Peter Moylan	410,000	1,398,581	400,000	899,290	0.010	1	1,150,000	Settled
Brian Wilson	480,000	1,764,659	400,000	1,082,330	0.059	1	4,437,500	Settled
David Aardsma	419,000	6,154,747	400,000	3,277,374	0.003	1	2,750,000	Settled
Ramon Ramirez	441,000	4,978,337	400,000	2,689,169	0.009	1	1,155,000	Settled
Todd Coffey	800,002	6,247,190	640,002	3,443,596	0.068	1	2,025,000	Settled
Michael Wuertz	1,100,000	13,690,612	880,000	7,285,306	0.053	1	2,200,000	Settled
Matt Guerrier	1,475,000	13,999,130	1,180,000	7,589,565	0.079	1	3,150,000	Settled
Jonathan Broxton	1,825,000	6,350,000	1,460,000	3,905,000	0.239	2	5,500,000	Settled
George Sherrill	2,750,000	6,287,974	2,200,000	4,243,987	0.399	1	4,500,000	Settled
C.J. Wilson	1,850,000	6,111,413	1,480,000	3,795,707	0.254	1	3,100,000	Settled
Huston Street	4,500,000	13,313,119	3,600,000	8,456,560	0.318	3	7,500,000	Settled
Aaron Heilman	1,625,000	6,099,361	1,300,000	3,699,681	0.215	1	2,150,000	Settled
Tony Pena	430,000	4,429,102	400,000	2,414,551	0.007	1	1,200,000	Signed by White Sox
Sean Green	471,000	1,417,799	400,000	908,899	0.070	1	975,000	Settled
Chad Durbin	1,635,000	12,586,063	1,308,000	6,947,032	0.101	1	2,125,000	Settled
Leo Nunez	412,500	4,978,710	400,000	2,689,355	0.003	1	2,000,000	Settled
Brandon Medders	475,000	6,102,487	400,000	3,251,244	0.013	1	820,000	Settled
Grant Balfour	1,400,000	1,400,000	1,120,000	1,260,000	1.000	1	2,050,000	Settled
J.P. Howell	433,700	1,759,140	400,000	1,079,570	0.025	1	1,800,000	Settled
Matt Albers	410,000	1,239,023	400,000	819,511	0.012	1	680,000	Settled
Angel Guzman	421,500	1,750,000	400,000	1,075,000	0.016	1	825,000	Settled

(continued)

Table 7.7 (continued)

Player	2009 salary	Contract zone				New contract		Arbitration
		S^u	S^l	Average	RCP 2009	Years	Average salary	
Cla Meredith	430,900	3,872,931	400,000	2,136,466	0.009	1	850,000	Settled
Rafael Betancourt	3,350,000	13,574,652	2,680,000	8,127,326	0.061	2	3,775,000	Settled
Pedro Feliciano	1,612,500	5,830,908	1,290,000	3,560,454	0.071	1	2,900,000	Settled
Tim Byrdak	1,000,000	1,751,667	800,000	1,275,833	0.210	1	1,600,000	Settled
Hideki Okajima	1,750,000	5,675,800	1,400,000	3,537,900	0.082	1	2,750,000	Settled
Renyel Pinto	404,000	3,486,068	400,000	1,943,034	0.001	1	1,075,000	Settled
Jared Burton	420,000	4,352,706	400,000	2,376,353	0.005	1	810,000	Settled
Manny Delcarmen	476,000	1,316,631	400,000	858,315	0.083	1	905,000	Settled
Frank Francisco	1,615,000	1,615,000	1,292,000	1,453,500	1.000	1	3,265,000	Settled
Chad Qualls	2,535,000	12,931,769	2,028,000	7,479,884	0.046	1	4,185,000	Settled
Bobby Jenks	5,600,000	6,163,929	4,480,000	5,321,965	0.665	1	7,500,000	Settled
Blaine Boyer	432,500	1,514,750	400,000	957,375	0.029	1	750,000	Settled
Matt Capps	2,425,000	4,788,419	1,940,000	3,364,210	0.170	1	3,500,000	Nontendered
Bobby Seay	1,300,000	6,105,027	1,040,000	3,572,513	0.051	1	2,475,000	Settled
Jesse Crain	1,700,000	12,495,936	1,360,000	6,927,968	0.031	1	2,000,000	Settled
Rafael Perez	436,300	871,624	400,000	635,812	0.077	1	795,000	Settled
Hong-Chih Kuo	437,000	6,005,036	400,000	3,202,518	0.007	1	950,000	Settled
Jeff Bennett	437,500	1,204,538	400,000	802,269	0.047	NA	NA	Settled
Jason Grilli	800,000	12,308,321	640,000	6,474,161	0.014	1	975,000	Settled
Chris Ray	850,000	1,765,726	680,000	1,222,863	0.157	1	975,000	Settled
Joel Zumaya	735,000	4,142,754	588,000	2,365,377	0.041	1	915,000	Settled
Mike MacDougal	2,650,000	12,355,117	2,120,000	7,237,558	0.052	NA	NA	Nontendered
Jose Veras	432,975	1,169,967	400,000	784,984	0.043	1	550,000	Nontendered
Logan Kensing	660,000	660,000	528,000	594,000	1.000	NA	NA	DFA
Saul Rivera	475,000	1,104,621	400,000	752,311	0.106	NA	NA	Released
John Bale	1,200,000	2,365,694	960,000	1,662,847	0.171	NA	NA	Released
Jason Frasor	1,450,000	13,818,744	1,160,000	7,489,372	0.023	1	700,000	Settled
Chris Sampson	449,000	3,701,290	400,000	2,050,645	0.015	1	815,000	Settled
Santiago Casilla	420,000	1,139,111	400,000	769,555	0.027	NA	NA	Nontendered
Sean Burnett	408,500	1,588,548	400,000	994,274	0.007	1	750,000	Lost hearing
Brian Bruney	1,250,000	6,044,565	1,000,000	3,522,283	0.050	1	1,500,000	Lost hearing

See notes to Table 7.1

an annual salary above the upper bound[8] Lincecum (2 years) and Johnson (4 years) were rewarded with multiple year contracts at an annual salary near their upper bounds. Lincecum had consecutive strong years, winning the National League Cy Young award both years. Johnson had a strong year with a performance rating of $\eta^{-1} = 0.898$, placing him in the 85th percentile. Edwin Jackson negotiated a contract for 2 years with an annual salary just above the average of his contract zone values

In 2009, there were 62 relief pitchers who were part of the arbitration process (Table 7.7). Only two relief pitchers, Sean Burnett and Brian Bruney, of the Washington Nationals, had hearings. Both pitchers lost; Burnett was seeking $925,000 but was awarded $750,000. Burnett's performance of $\eta^{-1} = 0.725$ ranked in the 53rd percentile of the relief pitchers. Bruney, who was traded from the Yankees in the off-season to the Nationals, was seeking $1.85 million. The Nationals offer of $1.5 million was selected by the arbitrators. Bruney's rating of $\eta^{-1} = 0.523$ (22nd percentile). Based on 2009 performance, a case could be made for both pitchers. Both players were asking for salaries within the contract zone below the average. Bruney was released by the Nationals in May 2010 and signed as a free agent with the Milwaukee Brewers

Tony Pena (Chicago White Sox) was arbitration eligible but resigned with the White Sox for $1.2 million. Pena was traded by Arizona to the White Sox in 2009; based on his performance in 2009, Pena's contract zone average was about $2.4 million, more than double his 2010 salary. Clay Condrey (Philadelphia Phillies) was granted free agency and signed with the Minnesota Twins. His negotiated salary of $900,000 was near the lower bound; however, Condrey is on the disabled list with an elbow injury. Matt Capps (Pittsburgh Pirates) was nontendered and signed with the Nationals for $3.5 million, just above the average of the contract zone. Capps' rating of $\eta^{-1} = 0.643$ placed his performance in the 37th percentile

Mike MacDougal was released by the Chicago White Sox at the beginning of the 2009 season and signed with the Washington Nationals as a free agent. He was granted free agency and signed with the Florida Marlins before being released at the end of spring training. He was subsequently signed as a free agent with the Washington Nationals. MacDougal is currently playing minor league ball. His performance rating of $\eta^{-1} = 0.643$ placed him in the 37th percentile with Matt Capps. Jose Veras was not tendered by the Cleveland Indians and signed as a free agent with the Florida Marlins. His 2010 salary was below the average contract zone value given his performance rating of $\eta^{-1} = 0.602$ (33rd percentile)

Logan Kensing (Washington Nationals) was granted free agency and resigned with the Nationals before being released during spring training. He was signed to a minor-league contract at the beginning of the season by the Tampa Bay Rays. His performance in 2009 placed him in the 13th percentile. Santiago Casilla was

[8] A player who signs a multiple year contract faces less risk of poor performance and the effect that will have on future negotiations. Likewise, a team reduces the risk of having to pay even more over the total length if the player performs well

nontendered by the Oakland Athletics and signed as a free agent with the San Francisco Giants. His performance rating of 0.531 placed him in the 31st percentile. Currently, he is enjoying success with the Giants with an earned run average of 1.17 in ten appearances

Several players settled for a salary above their contract zone. Rafael Soriano (free agent signed by the Atlanta Braves), Carlos Marmol (Chicago Cubs), Brian Wilson (San Francisco Giants), Grant Balfour (Tampa Bay Rays), J.P. Howell (Tampa Bay Rays), Frank Francisco (Texas Rangers), and Bobby Jenks (Chicago White Sox) all signed 1-year contracts. Of these, Soriano ($\eta^{-1} = 0.902$), Marmol (0.869), and Wilson (0.858) were all in the top 20 percentile of performance. The rest of the relievers settled for a salary above the contract zone minimum

In this chapter, we applied the Hadley and Ruggiero (2006) model to evaluate player salaries. Unlike Hadley and Ruggiero, we adjusted the lower bound to be consistent with the collective bargaining agreement's restriction on team offers. Further, we restricted comparisons based on similar years of experience and based on position played

Chapter 8
The Hall of Fame

Introduction

Selection into the MLB hall of fame is a special honor reserved for the all-time great players and managers. And, over time, the selection or nonselection of players has provided controversies for discussion. Many fans believe that Pete Rose belongs in the HOF based solely on his playing career; other fans are less forgiving about his admitted gambling on baseball games as a manager. Similar arguments are made about Shoeless Joe Jackson. On the other side, arguments arise over some players who have been inducted into the hall. Notably, did Phil Rizzuto deserve the honor when he was voted in by the Veteran's Committee in 1994?[1] Bill James (1995) argued that Rizzuto's career statistics did not warrant his selection.[2]

In this chapter, we analyze current HOF inductees and notable players who are not currently in the Hall. In Chap. 5, we introduced our nonparametric measure of performance to evaluate hitters. In that chapter, we analyzed players from the 2009 season. We extend that model to analyze all major league players by season. In addition, we analyze all major league pitchers using the model from Chap. 6. Players will be evaluated on aggregate measures of performance based on η^{-1} The model used for measuring aggregate performance for any player is given by

[1] As a Yankee fan in my childhood, I enjoyed Rizzuto on the WPIX broadcasts. But I have never been swayed that Rizzuto deserved selection. Likewise, perhaps due to fan bias, I did not support the induction of Pete Rose. In this chapter, however, I focus only on the nonparametric performance measure and draw conclusions from this analysis.

[2] James' *Whatever Happened to the Hall of Fame* is an interesting read rich in analysis. Many of the examples in this chapter were studied by James.

J. Ruggiero, *Frontiers in Major League Baseball*, Sports Economics, Management and Policy 1, DOI 10.1007/978-1-4419-0831-5_8,

$$
\begin{aligned}
&\eta_0 = \max\ \eta \\
&\text{subject to} \\
&\sum_{j=1}^{n} \lambda_j y_{kj} \geqslant \eta y_{k0}, && k = 1, \ldots, s; \\
&\sum_{j=1}^{n} \lambda_j = 1; \\
&\lambda_j \geqslant 0, && j = 1, \ldots, n.
\end{aligned}
\tag{8.1}
$$

We evaluate hitters and starting pitchers for every season using η_0^{-1}. In Sect. 4, we identify highly rated players (current and retired) who should be in the Hall of Fame.[3]

Players are selected in one of two ways: via voting by the Baseball Writers Association of America (BBWAA) or by the Veterans Committee, composed of living inductees.[4] The typical path into the hall of fame requires a waiting period of 5 years after the player retires and selection by a screening committee. A player is voted on by BBWAA members with a minimum of 10 years of membership. If the player is selected on at least 75% of the ballots cast, the player is inducted into the hall of fame. However, if the player is selected on less than 5% of the ballots cast, the player is dropped from future consideration. If a player does not get voted in by the BBWAA after 20 years since retirement, the player is then eligible for selection by the Veterans Committee. Many of the controversies resulted from selection by this committee.

Evaluating Hitters

The performance rating η^{-1} was calculated for all players for each season. Following the analysis from Chap. 5, we specified four performance variables: *Singles Plus* (singles + hit by pitch + base on balls), *Doubles*, *Triples*, and *Home Runs*. If a player had less than 100 plate appearances, they were removed from the season's analysis. Additionally, we do not include postseason performance. Importantly, the approach used is nonparametric and does not place weight restrictions on the individual variables. Rather, distance functions are used to measure aggregate performance relative convex combinations of frontier performers.

In order to derive an overall measure of performance, a weighted average of each player's individual season ratings is considered; at bats are used to weight the performance. The mean is not appropriate given the variance in at bats for a player

[3] In this chapter, we ignore the steroid issue and evaluate players only on their performance rating. The issue of steroids will be analyzed in Chaps. 9 and 10.

[4] Prior to 2001, the Veterans Committee did not restrict members to HOF inductees. Controversies arose over the selection of a few for partisan reasons. Examples are detailed in James (1995).

Table 8.1 Top 25 Hall of Famers ranked by performance rating

Player	Position	AB	H	HR	Rating
Lou Gehrig	1B	7,935	2,700	492	0.975
Richie Ashburn	CF	8,365	2,574	29	0.936
Babe Ruth	RF	8,224	2,829	704	0.934
Ted Williams	LF	7,605	2,613	507	0.932
Tris Speaker	CF	10,176	3,511	117	0.931
Hank Aaron	RF	12,364	3,771	755	0.925
Hank Greenberg	1B	5,079	1,594	328	0.923
Eddie Collins	2B	9,869	3,293	47	0.921
Stan Musial	LF	10,925	3,610	474	0.920
Mike Schmidt	3B	8,318	2,227	547	0.920
Rogers Hornsby	2B	7,858	2,841	295	0.917
Ralph Kiner	LF	5,205	1,451	369	0.913
Sam Crawford	RF	9,570	2,961	97	0.912
Billy Williams	LF	9,270	2,693	424	0.911
Joe DiMaggio	CF	6,821	2,214	361	0.906
Elmer Flick	RF	5,457	1,715	47	0.903
Charlie Gehringer	2B	8,784	2,818	183	0.898
Ty Cobb	CF	11,434	4,189	117	0.890
Earle Combs	CF	5,711	1,852	58	0.887
Earl Averill	CF	6,281	2,002	237	0.887
Frank Baker	3B	5,953	1,829	96	0.884
Arky Vaughan	SS	6,622	2,103	96	0.883
Joe Morgan	2B	9,195	2,499	268	0.880
Honus Wagner	SS	10,430	3,415	101	0.878
Willie Mays	CF	10,832	3,274	660	0.878

The position reported is the primary position of the Hall of Famer. The reported rating is the average seasonal performance weighted by at bats

across time and between players during a season. The top 25 Hall of Famer hitters based on the weighted average are reported in Table 8.1.[5]

Based on our measure, New York Yankee Lou Gehrig is the highest rated player of all time, with an average performance rating of 0.975. Gehrig is best known for the consecutive games (2,130) played record that was subsequently broken by Baltimore Oriole Cal Ripken, Jr. Gehrig collected 493 career home runs, 2,721 hits, and 1,995 runs batted in with a career batting average of 0.340. His numbers are even more impressive given his early retirement at the age of 36. Gehrig received the most votes among fans in the MLB All-Century Team.[6] Gehrig was voted into the Hall via a special election.

[5] The team listed for the Hall of Famer is the team associated with the player's induction. In many cases, the player contributed to more than one team. For this table, we consider only those who played a majority of years in the modern era. Five players with a majority of years before 1900 would have been included: Roger Connor (0.943), Dan Brouthers (0.937), Jesse Burkett (0.922), Sam Thompson (0.915), and Billy Hamilton (0.907).

[6] The list of players and the number of votes received are available at http://static.espn.go.com/mlb/news/1999/1023/129008.html.

Centerfielder Richie Ashburn (Philadelphia Phillies) had the second highest rating with a weighted average of 0.936. Ashburn had career batting average of 0.308, but only hit 29 home runs. In 1978, he received the most votes (158) for induction but fell short of the required number. He was voted in by the Veterans Committee in 1995.

New York Yankee is arguably the greatest baseball player of all time. His rating of 0.934 placed him in the top 3. Ruth still holds the record for career slugging percentage (0.690); he finished his career with 714 home runs and a 0.342 batting average. Ruth was voted into the Hall in 1936 by the BBWAA, receiving 215 out of 227 possible votes, becoming one of the first five players inducted. Ruth was the top vote getter among outfielders in the MLB All-Century Team. Christy Mathewson, Ty Cobb, Honus Wagner, and Walter Johnson joined Ruth in the 1936 class. Interestingly, Ty Cobb received seven more votes than Ruth.

Boston Red Sox left fielder Ted Williams was elected to the Hall in his first year of eligibility, garnering 282 votes out of 303 ballots. Williams played in 21 seasons but lost 5 years to military service in World War II and the Korean War. Williams finished his Hall of Fame career with a 0.344 batting average and 521 home runs. Williams made the MLB All-Century Team, receiving the third highest fan votes for outfielders behind Babe Ruth and Hank Aaron. Cleveland Indian centerfielder Tris Speaker had an overall performance rating just below Williams. Speaker had a career batting average of 0.345 (fifth all time) with over 3500 hits. He had the most career doubles and outfield assists and was a finalist for the MLB All-Century Team. In 1936, Speaker received only 133 votes for induction, falling short by 36. He was inducted in 1937, receiving 165 out of 201 votes.

Milwaukee and Atlanta Brave Hank Aaron is also considered to be one of the greatest baseball players of all time. His rating based on the nonparametric measure of DEA is 0.925, placing him sixth in the list and second behind fellow right fielder Babe Ruth. Aaron had a career batting average of 0.305 while hitting a total of 755 home runs. Aaron surpassed Babe Ruth's career home run total and held the record for 33 years. Aaron was the first player of four to achieve career total of over 3,000 hits and 500 home runs. Willie Mays joined Aaron two months later; Eddie Murray and Rafael Palmeiro joined during a later era. Aaron received the second most votes for outfielders behind Babe Ruth in joining the MLB All-Century Team. Aaron was voted into the Hall by the BBWAA; he received 406 out of 416 votes in his first year of eligibility in 1982.

The next two spots in the top 10 ranked hitters were Hank Greenberg (Detroit Tiger first-baseman) and Eddie Collins (Philadelphia Athletics). Greenberg had a career batting average of 0.313 while hitting 331 home runs (58 during the 1938 season). Greenberg's career numbers were affected by his service in the military; he only had 67 at bats during the 1941 season and did not play again until 1945. Greenberg was voted into the Hall by the BBWAA in 1956. Collins had a career batting average of 0.333 and had 3,315 hits. He was nominated for the MLB All-Century Team but came in sixth in the voting for second basemen. Collins was voted into the Hall of Fame by the BBWAA in his fourth try, garnering 213 votes, seven more than required for induction.

The final two spots in the top ten belong to St. Louis Cardinals leftfielder Stan Musial (0.920) and Philadelphia Phillies' third baseman Mike Schmidt (0.920). Musial was voted into the Hall on his first year of eligibility in 1969 by the BBWAA. Musial was nominated for inclusion on the All-Century Team but finished behind Ken Griffey, Jr., Pete Rose, and Roberto Clemente. He was later added to the team. His rating of 0.920 placed him behind only Ted Williams for left fielders in the modern era. Musial amassed 3,630 career hits including 475 home runs and had a career batting average of 0.331 and a career slugging percentage of 0.559.[7]

Schmidt only had a career batting average of 0.267 but hit 548 home runs. He is widely considered the greatest third baseman of all time and was voted onto the All-Century Team. Schmidt was voted into the Hall in his first year of eligibility, receiving 444 votes from 460 ballots cast.

Other All-Century Hall of Famers ranked in the top 25 include St. Louis Cardinals second baseman Rogers Hornsby (0.917), New York Yankee centerfielder Joe DiMaggio (0.906), Detroit Tigers' centerfielder Ty Cobb (0.890), Cincinnati Reds second baseman Joe Morgan (0.880), Pittsburgh Pirates shortstop Honus Wagner (0.878), and San Francisco Giant centerfielder Willie Mays (0.878). Hornsby, who retired after the 1937 season, was voted into the Hall by the BBWAA in 1942, after being turned down from 1936 to 1939. Likewise, DiMaggio was voted into the Hall in 1955, after being rejected the two previous years.

In Table 8.2, we consider the top two rated hitters for each position.[8] The two highest rated catchers were Cincinnati Red Johnny Bench (0.776) and Detroit Tiger Mickey Cochrane (0.776). Bench is considered by many to be the greatest catcher of all time; he was selected as the top catcher by fan voting for the All-Century Team. Cochrane was nominated for the All-Century Team but came in sixth in the voting behind Yankee Yogi Berra (0.664), Red Sox Carlton Fisk (0.686), Brooklyn Dodger Roy Campanella (0.666), and Homestead Gray Josh Gibson, who unfortunately never played in the major leagues.[9]

The top first basemen were Gehrig (0.975) and Greenberg (0.923), both of whom made the top 25 list (see Table 8.1). Eddie Collins (0.921) was the top second baseman, followed by Rogers Hornsby (0.917).[10] Both Collins and Hornsby appear in the top 25 list. Mike Schmidt (0.920) and Frank "Home Run" Baker (0.884) were identified as the two top three basemen. Schmidt (and Baltimore Oriole HOFer Brooks Robinson) made the All-Century Team. Baker, who was inducted as a

[7] Musial lost a year serving in noncombat duty in the U.S. Navy.

[8] In Table 8.2, we consider only Hall of Famers who played the majority of time after the modern era began in 1900.

[9] James (2001) ranks Berra as the top catcher, followed by Bench, Campanella, and Cochrane.

[10] In James (2001), Joe Morgan was chosen as the best second baseman while Collins and Hornsby were ranked second and third, respectively.

Table 8.2 All Hall of Fame hitters by position

Position	Player	AB	H	HR	Rating
Catcher	Johnny Bench	7,572	2,034	388	0.776
	Mickey Cochrane	5,071	1,622	117	0.746
First base	Lou Gehrig	7,935	2,700	492	0.975
	Hank Greenberg	5,079	1,594	328	0.923
Second base	Eddie Collins	9,869	3,293	47	0.921
	Rogers Hornsby	7,858	2,841	295	0.917
Third base	Mike Schmidt	8,318	2,227	547	0.920
	Frank Baker	5,953	1,829	96	0.884
Shortstop	Arky Vaughan	6,622	2,103	96	0.883
	Honus Wagner	10,430	3,415	101	0.878
Leftfield	Ted Williams	7,605	2,613	507	0.932
	Stan Musial	10,925	3,610	474	0.920
Centerfield	Richie Ashburn	8,365	2,574	29	0.936
	Tris Speaker	10,176	3,511	117	0.931
Rightfield	Babe Ruth	8,224	2,829	704	0.934
	Hank Aaron	12,364	3,771	755	0.925

We only consider Hall of Famers who played the majority of time after 1900

Philadelphia Athletic, never received enough votes by the BBWAA but was voted in by the Veterans Committee in 1955.[11]

Pittsburgh Pirate shortstops Arky Vaughan (0.883) and Honus Wagner (0.878) had the highest ratings among shortstops. Vaughan had a career batting average of 0.318 and had 2,103 career hits. Wagner is considered one of the all-time greats with a 0.327 batting average and 3,415 career hits. Wagner qualified for inclusion for 22 seasons while Vaughan only had 14. Wagner was hurt by a few seasons with poor numbers; Wagner should be considered the top short-stop of all time.[12] James (2001) ranks Wagner first and Vaughan second in his all-time rankings.

In leftfield, Ted Williams (0.932) and Stan Musial (0.92) achieved the highest rating. Both players are on the All-Century Team for outfielders and widely considered the two best of all time. Both players appear in Table 8.1 in the Top 25 rated Hall of Famers. More controversial is the selection of Richie Ashburn and Tris Speakers as the top centerfielders. Both players are rated in the top 10 based on the DEA measure. This results because the method is nonparametric; Ashburn reached first base enough to warrant overall high scores, but lacked power. While Speaker is ranked fourth, Ashburn appears 16th on James (2001) list. The top three according to James are Willie Mays, Ty Cobb, and Mickey Mantle. While not considered in this chapter, weight structures could be placed on the individual performance measures to account for the differences.[13]

[11] James (2001) ranking has Schmidt first, followed by Kansas City Royal George Brett, Milwaukee Braves Eddie Mathews, Boston Red Sox Wade Boggs, and Frank Baker.

[12] No attempt was made to discount for longer careers and outlier seasons.

[13] Ruggiero and Bretschneider (1998) introduced the weighted Russell measure to allow weighting of individual variables.

In Table 8.3, we consider the position players inducted into the Hall of Fame who had the lowest rating. Often, arguments about who belongs in the Hall center on comparisons of a given player to Hall of Famers. Of course, such comparisons assume that all players who were selected deserve to be in the hall. A better comparison would be to median values for each position.

According to the DEA measure, Cincinnati Reds catcher Ernie Lombardi (0.513) and Chicago Cubs catcher Gabby Hartnett (0.559) are the lowest rated. The maximum number of votes Lombardi received by the BBWAA was 34, falling short by 193 votes. He was selected in 1986 by the Veterans Committee. From 1947 to 1954, Harnett was unsuccessful in garnishing enough votes. He did receive enough votes from the BBWAA in 1955. James (1995) argues that Chicago White Sox catcher Ray Schalk (0.561) was the worst catcher selected to the Hall. Based on our measure, his rating is similar to Harnett's and St. Louis Browns' catcher Rick Ferrell (0.560).

At first base, Chicago Cub Frank Chance (0.669) and George Kelly (0.691) were rated the lowest. Both players failed to get enough votes to be voted in by the BBWAA but were selected by the Veterans Committee. Both players made James (1995) of undeserving Hall of Famers. At second base, Pittsburgh Pirate Bill Mazeroski (0.650) and Chicago Cub Johnny Evers (0.677) were the lowest rated hitters. Mazeroski was elected to the Hall of Fame by the Veterans Committee while Evers earned enough votes from the BBWAA. James (1995) argued that Evers was not a good choice; in James (2001) he ranks Mazeroski, who was voted into the Hall in 2001, even lower than Evers and would likely agree with this selection.

As mentioned in Chap. 5, the measure of performance η^{-1} does not parametrically weight each of the performance variables. Instead, performance is measured using a distance function. As a result, and as illustrated in Chap. 5, it is possible that a player is ranked higher having more doubles even with less home runs as another player.

Table 8.3 Lowest rated Hall of Fame hitters by position

Position	Player	AB	H	HR	Rating	Voted By
Catcher	Ernie Lombardi	5,855	1,792	190	0.513	Veterans
	Gabby Hartnett	6,274	1,875	234	0.559	BBWAA
First base	Frank Chance	4,180	1246	19	0.669	Veterans
	George Kelly	5,849	1758	147	0.691	Veterans
Second base	Bill Mazeroski	7,691	2,004	138	0.650	Veterans
	Johnny Evers	5,961	1,623	12	0.677	BBWAA
Third base	Freddie Lindstrom	5,532	1,727	103	0.672	Veterans
	George Kell	6,437	1,978	77	0.719	Veterans
Shortstop	Travis Jackson	6,078	1,768	135	0.600	Veterans
	Joe Tinker	6,357	1,668	31	0.643	BBWAA
Leftfield	Chick Hafey	4,475	1,423	161	0.699	Veterans
	Willie Stargell	7,763	2,189	472	0.761	BBWAA
Centerfield	Lloyd Waner	7,670	2,423	27	0.741	Veterans
	Edd Roush	7,284	2,362	68	0.748	Veterans
Rightfield	Kiki Cuyler	7,118	2,289	128	0.772	Veterans
	Tommy McCarthy	5,031	1,478	44	0.784	Veterans

Players are listed according to lowest ratings by position

The weighted slack model (5.4) from Chap. 5 was estimated as an alternative. The resulting rank correlation for 2009 hitters was 0.984, suggesting robustness with respect to the DEA modeling.

Evaluating Pitchers

In this section, we derive an overall rating for the Hall of Fame pitchers. We apply model (8.1) using three individual performance variables: innings pitched (IP), innings pitched per earned run (IP/ER), and innings pitched per hit (IP/H). Only five pitchers who were predominately relief pitchers have been inducted into the Hall. Only Oakland Athletic Dennis Eckersley was voted in by the BBWAA in his first year of eligibility. Goose Gossage (New York Yankees) was inducted by the BBWAA in 2008 on his ninth try. Chicago White Sox pitcher Hoyt Wilhelm was elected in 1985 by the BBWAA in his eighth year of eligibility. After falling 42 votes short in his first vote in 1991, Rollie Fingers (Oakland Athletics) was voted in the next year by the BBWAA. St. Louis Cardinal Bruce Sutter received ten votes beyond the minimum needed in 2006, his 13th year of eligibility. Given the predominance of starting pitchers in the Hall, and the increased importance of the relief pitcher after the 1960s, we only consider starting pitchers in this analysis. The model was applied for each season for pitchers who started at least ten games.

Similar to hitters, we derive an overall rating of performance using a weighted average of each season's performance. For the pitchers, we use outs recorded to weight season performance. The top 25 Hall of Fame pitchers based on the weighted average are reported in Table 8.4. Included in the table are career earned run average (ERA), winning percent (WPCT), strike outs (K), the strike out to base on balls ratio (K/BB), and innings pitched (IP). Pitchers are listed according to their weighted rating.

We only include pitchers who played the majority of time from 1900 on. There were some very good pitchers who played in the 1800s that would have been included. New York Giant Amos Rusie (0.935) had a career earned run average of 3.073 with 1,934 strikeouts and 293 wins. As pointed out by James (2001), the quality of play in the nineteenth century was lower than in the modern era. Rusie was voted in by the Veteran's Committee in 1977. Other top pitchers in this category include Boston Beaneaters Kid Nichols (0.930) and John Clarkson (0.927), New York Giants Tim Keefe (0.914) and Mickey Welch (0.857), Providence Gray Charley Radbourn (0.904), and Buffalo Bison Pud Glavin (0.876).

Using our method, Cleveland Spider Cy Young was the best pitcher of all time, achieving an average rating of 0.937. Young won a career 511 games and pitched over 7,354 innings, both major league records. Walter Johnson (417 wins) is the only other pitcher to reach the 400 mark. Young placed third in fan voting for the All-Century Team behind Nolan Ryan and Sandy Koufax. Young's greatness was

Table 8.4 Top 25 Hall of Fame starting pitchers by performance rating

Player	ERA	WPCT	K	K/BB	IP	Rating
Cy Young	2.627	0.618	2,803	2.303	7354.7	0.937
Addie Joss	1.887	0.623	920	2.527	2327.0	0.930
Dazzy Vance	3.240	0.585	2,045	2.435	2966.7	0.913
Sandy Koufax	2.761	0.655	2,396	2.933	2324.3	0.912
Carl Hubbell	2.978	0.622	1,677	2.313	3590.3	0.911
Ed Walsh	1.816	0.607	1,736	2.814	2964.3	0.910
Walter Johnson	2.167	0.599	3,509	2.574	5914.7	0.897
Pete Alexander	2.560	0.642	2,198	2.311	5190.0	0.897
Warren Spahn	3.086	0.597	2,583	1.801	5243.7	0.881
Christy Mathewson	2.133	0.665	2,502	2.964	4780.7	0.877
Robin Roberts	3.405	0.539	2,357	2.613	4688.7	0.877
Tom Seaver	2.862	0.603	3,640	2.619	4782.7	0.876
Dizzy Dean	3.024	0.644	1,163	2.567	1967.3	0.876
Lefty Grove	3.058	0.680	2,266	1.909	3940.7	0.874
Juan Marichal	2.889	0.631	2,303	3.248	3507.3	0.870
Whitey Ford	2.745	0.690	1,956	1.801	3170.3	0.863
Jim Palmer	2.856	0.638	2,212	1.687	3948.0	0.861
Catfish Hunter	3.256	0.574	2,012	2.109	3449.3	0.859
Mordecai Brown	2.057	0.648	1,375	2.043	3172.3	0.856
Don Sutton	3.261	0.559	3,574	2.661	5282.3	0.854
Rube Waddell	2.161	0.574	2,316	2.884	2961.3	0.854
Fergie Jenkins	3.338	0.557	3,192	3.202	4500.7	0.849
Stan Coveleski	2.891	0.602	981	1.223	3082.0	0.835
Gaylord Perry	3.105	0.542	3,534	2.563	5350.3	0.833
Don Drysdale	2.948	0.557	2,486	2.908	3432.0	0.833

The reported rating is the average seasonal peformance weighted by outs recorded

established a year after his death with the annual awarding of the Cy Young Award given to the best pitcher(s) in baseball.[14]

Cleveland Indian Addie Joss was the second highest rated pitcher of all time with a rating of 0.930. Joss pitched from 1902 to 1910 and was inducted by the Veterans Committee in 1978. While Joss only had 160 wins, his career earned run average of 1.89 is second best all time.[15] Importantly, the rating system used here evaluates a player relative to his peers.[16] Brooklyn Dodger Dazzy Vance was the third highest rated pitcher; he was voted into the Hall in 1955 by the BBWAA. Vance won the Triple Crown (lowest earned run average, most wins, most strikeouts) in 1924.

Los Angeles Dodger Sandy Koufax was the fourth highest rated pitcher of all time. Koufax played only 11 seasons with the Dodgers and was forced to retire due to arthritis at the age of 30. Koufax had a career earned run average of 2.76 and

[14] Beginning in 1967, the Cy Young Award was given to the best pitcher from each league.

[15] James (2001) rescales the earned run average by the league average and discounts for parks. After adjustment, Joss still ranks in the top 10 all time.

[16] Only players who played a majority of the time after 1900 were considered.

struck out 2,396 batters. He was a three-time Cy Young Award winner and four-time World Series champion. Koufax was the youngest person elected to the Hall, gaining entry on his try in 1972.

Carl Hubbell (New York Giants) and Ed Walsh (Chicago White Sox) placed fifth and sixth all time. Hubbell was voted in on his third try in 1947 by the BBWAA while Walsh was voted in by the Veterans Committee in 1946. Hubbell was a World Series champion who won 253 games while posting a 2.98 earned run average. Walsh won 195 games with the lowest career earned run average (1.82) of all time.

Washington Senator Walter Johnson was inducted into the Hall in 1936 as one of the first five members. Johnson, a member of the All-Century Team, won 417 games (second only to Cy Young) and had a 2.17 earned run average. His 110 shutouts is still the major league record. James (2001) argues that Johnson was the best pitcher of all time.

Grover Cleveland (Pete) Alexander (Philadelphia Phillies) finished just behind Walter Johnson. He was voted into the Hall in 1938, 2 years after the initial inductions. Alexander won 373 games (third best all time) and had a 2.56 earned run average over 20 seasons. Alexander pitched 90 shutouts, second only to Johnson. He won the Triple Crown four times and was nominated to be on the All-Century Team. James (2001) rates Alexander as the third best of all time.

The final two spots in the top 10 belong to Milwaukee Brave Warren Spahn (0.881) and New York Giant Christy Mathewson (0.877). Spahn was voted in by the BBWAA in 1973 while Mathewson was one of the initial five inducted in 1936. Both Spahn and Mathewson are members of the All-Century Team. Spahn was a 17-time All Star selection who won 363 games with a career earned run average of 3.09. He won the Cy Young Award in 1957. Mathewson won 373 games and had a career earned run average of 2.13 (eighth best all time). He was a two Triple Crown winner who was rated fifth best of all time by James (2001). Mathewson ranks seventh all time according to James.

Players Deserving Induction

In this section, we consider highly rated players who deserve to be in the Hall of Fame. Using the nonparametric rating system, we consider players who should be in the Hall but who are not. For some players, this is because they have not yet qualified or who are still playing. Table 8.5 lists players who have played in at least ten seasons by the end of the 2009 season. We use the weighted ratings defined above.

Players who appear in Table 8.5 have a rating that is higher than the median Hall of Fame player rating at that position. Next, we consider specific players who have appeared in at least nine seasons, including current players.[17]

[17] Ratings of current players are expected to go down. Most players realize a decline in their seasonal ratings as they play beyond their age of peak performance.

Table 8.5 Players rated above median Hall of Fame rating by position

	Player	Years	Rating
Pitcher	Pedro Martinez	14	0.900
	Tiny Bonham	10	0.895
	Don Newcombe	10	0.883
	Deacon Phillippe	10	0.883
	Babe Adams	14	0.881
	Red Lucas	13	0.878
	Harry Brecheen	11	0.874
	Dolf Luque	13	0.870
	Sal Maglie	10	0.868
	Andy Messersmith	10	0.868
	Curt Schilling	16	0.863
	John Candelaria	13	0.859
	Greg Maddux	22	0.855
	Billy Pierce	15	0.852
Catcher	Jason Kendall	15	0.783
	Joe Torre	18	0.767
	Ted Simmons	21	0.767
	Thurman Munson	11	0.728
	Gene Tenace	15	0.717
	Mickey Tettleton	14	0.698
	Mike Piazza	18	0.692
	Jorge Posada	15	0.663
	Manny Sanguillen	13	0.662
	Ivan Rodriguez	21	0.657
	Lance Parrish	20	0.652
	Bill Freehan	15	0.646
	Paul Lo Duca	13	0.642
	Earl Battey	13	0.634
	Darrell Porter	17	0.619
First base	Todd Helton	13	0.937
	Pete Rose	25	0.928
	Jeff Bagwell	15	0.901
	Lance Berkman	11	0.881
	Mark McGwire	17	0.868
	Henry Larkin	10	0.858
	Dick Allen	15	0.857
	Harry Davis	25	0.852
	Rafael Palmeiro	20	0.851
	Carlos Delgado	17	0.844
	Bill White	13	0.842
	Lu Blue	13	0.839
	Don Mattingly	14	0.837
	Fred Luderus	13	0.837
Second base	Eddie Stanky	12	0.860
	Chuck Knoblauch	12	0.859
	Craig Biggio	20	0.846
	Alfonso Soriano	11	0.824
	Jim Gilliam	14	0.824
	Roberto Alomar	19	0.821
	Cupid Childs	13	0.820

(continued)

Table 8.5 (continued)

	Player	Years	Rating
Third base	Al Rosen	10	0.868
	Ron Santo	15	0.853
	Harlond Clift	13	0.849
	Chipper Jones	16	0.848
	Eddie Yost	18	0.841
	Stan Hack	16	0.840
	Buddy Lewis	11	0.818
	Red Rolfe	10	0.815
	Ken Boyer	17	0.809
	Ned Williamson	13	0.802
	Darrell Evans	22	0.794
	Sal Bando	16	0.794
	Deacon White	20	0.792
Shortstop	Jimmy Rollins	10	0.939
	Derek Jeter	15	0.912
	Alex Rodriguez	16	0.896
	Michael Young	10	0.862
	Donie Bush	17	0.848
	Johnny Pesky	12	0.844
	Maury Wills	15	0.840
	Dick Groat	15	0.828
	Ed McKean	13	0.826
	Harvey Kuenn	17	0.819
	Rafael Furcal	10	0.809
	Nomar Garciaparra	15	0.805
	Miguel Tejada	13	0.793
	Tony Fernandez	19	0.792
Leftfield	Joe Jackson	14	0.938
	Barry Bonds	22	0.918
	Minnie Minoso	18	0.914
	George Burns	15	0.880
	Albert Belle	12	0.878
	Topsy Hartsel	14	0.870
	Bob Johnson	13	0.862
	Manny Ramirez	18	0.852
Centerfield	Roy Thomas	14	0.926
	Brett Butler	18	0.893
	Jimmy Barrett	10	0.890
	Dom DiMaggio	11	0.876
Rightfield	Bobby Abreu	15	0.928
	Gavvy Cravath	12	0.909
	Rocky Colavito	16	0.857
	Ken Singleton	15	0.850
	Tony Oliva	15	0.850
	Buck Freeman	11	0.850
	Vladimir Guerrero	14	0.842
	Bobby Bonds	15	0.840
	Brian Giles	16	0.840
	Jackie Jensen	12	0.840
	Mike Tiernan	13	0.839

Only players with a majority of seasons after 1900 are considered

Pete Rose

As a long time critic of Rose who has always argued that he does not deserve the honor of being in the Hall of Fame, I certainly understand why many argue against his inclusion. Whether or not he bet for or against his team winning is irrelevant; he could have made improper decisions to win a game he bet on by using players inappropriately and consequently, sacrificing the next few games.

He broke the rules.
He bet on baseball.

His lifetime ban from participating begs the question "Who would hire him anyway?" Of course there will be an owner who would exploit the opportunity to make quick money on the publicity stunt. But would somebody really want Rose to manage his/her team given his inactivity and history? Rose's rating was 0.928, placing him 15th. Rose belongs in the Hall of Fame.

Ichiro Suzuki[18]

Suzuki began his career in 2001 with the Seattle Mariners after playing 9 years in Japan. In Japan, he had a career batting average of 0.353 with 1,278 hits. In 2001, he collected 242 hits with a batting average of 0.350, becoming the American League Rookie of the Year and Most Valuable Player. In his 10 years (as of June 25, 2010) in MLB, Suzuki has 2,130 hits with a career batting average of 0.333. He is a nine-time All-Star and nine-time Gold Glove Award winner. Absent an injury in 2010, he is set to tie Pete Rose's record ten 200-hit seasons; unlike Rose, Suzuki has done it consecutively.

Suzuki's current rating of 0.983 ranks higher than Gehrig. He will be a member of the Hall of Fame.

Albert Pujols

Current St. Louis Cardinal Albert Pujols rating of 0.974 places him in third place behind Gehrig. Like Suzuki, Pujols is in his tenth season and hence, qualifies for the Hall. Currently, Pujols has 381 home runs, 1,798 hits with a career batting average of 0.333. Pujols is an eight-time All-Star who won a Gold Glove Award in 2006. Pujols is also a World Series champion. Pujols will be a member of the Hall of Fame.

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[18] Suzuki does not appear in Table 8.5 because he only had 9 years of service at the end of 2009.

Joe Jackson

Shoeless Joe Jackson ranks seventh all time with a rating of 0.938. Jackson had a career batting average of 0.356, collecting 1,772 hits in 13 seasons. In his last season before he was banned from baseball, Jackson had 218 hits and a 0.382 batting average. There is no question that Jackson's statistics warrant membership in the Hall of Fame. Jackson was acquitted but was banned from baseball. While he admitted guilt, it is not clear he was actually guilty. Joe Jackson belongs in the Hall of Fame.

Todd Helton

Todd Helton began his career with the Colorado Rockies in 1997. In his 13+ seasons, he has 2,192 hits with a career batting average of 0.326. Helton also has 327 home runs. Helton is a five-time All-Star and three-time Gold Glove Award winner. His current rating of 0.937 places him ninth all time.

Bobby Abreu

Bobby Abreu began his career in 1996 with the Houston Astros. He was drafted by the Tampa Bay (Devil) Rays in the 1997 expansion draft and was traded to the Philadelphia Phillies. In 2006, Abreu was traded to the New York Yankees and was granted free agency in 2008, signing with the Angels. In 14+ seasons, Abreu has a career 0.298 batting average with 2,186 hits, 195 home runs and 358 stolen bases. Abreu's rating of 0.928 currently places him 14th. As pointed out in footnote 17, however, it is expected that Abreu's rating will decline as his career advances beyond his peak age.

Barry Bonds

Barry Bonds holds the single season home run (73) and career home run (762). He also has the most career walks (2,558) and intentional walks (688). Bonds is a 14-time All-Star, eight-time Gold Glove Award winner and seven-time NL Most Valuable Player. Without a doubt, his statistics and the associated rating of 0.918 make Bonds a shoo-in for the Hall.

But what about the steroids? We analyze Bonds' enhanced performance in Chap. 9.

Put Bonds in the Hall of Fame. Perhaps they can build a special room for the steroid users. Maybe in the basement.

Minnie Miñoso

Miñoso's rating of 0.914 places him in the 26th spot. Miñoso played in 17 seasons (though two were publicity stunts), collecting 1,963 hits with a career batting average of 0.298. Miñoso was a nine-time All-Star selection and a three-time Gold Glove Award winner.

Miñoso is the highest rated left fielder, excluding Shoeless Joe Jackson and Barry Bonds, who is not in the Hall of Fame. His rating is only lower than Hall of Fame left fielders Ted Williams and Jesse Burkett. Miñoso deserves to be in the Hall of Fame.

Billy Pierce

Billy Pierce began his career with the Detroit Tigers in 1945 at the age of 18. He pitched only ten innings that year. After a lopsided trade, Pierce became a starter with the Chicago White Sox in 1949, posting a 7–15 record with a 3.88 earned run average. In his 12 seasons with the White Sox, he won 186 games with an earned run average of 3.19. In his career, Pierce won 211 games, had an earned run average of 3.27 and struck out 1,999. He was a seven-time All-Star selection and a member of the 1945 Tigers World Series team. Pierce's DEA rating (0.852) is higher than notable Hall of Fame pitchers Gaylord Perry, Don Drysdale, Jim Bunning, Bob Gibson, Steve Carlton, Bob Lemon, Bob Feller, and Nolan Ryan. Billy Pierce deserves to be in the Hall of Fame.

Joe Torre

Joe Torre played 18 seasons with the Milwaukee (Atlanta Braves), St. Louis Cardinals, and the New York Mets. Torre was a nine-time All-Star selection, a Gold Glove Award winner in 1965, and the 1971 National League Most Valuable Player. In his career, he had a 0.297 batting average with 2,342 hits including 252 home runs. His DEA rating of 0.767 ranks higher than all Hall of Fame catchers except for Johnny Bench. Overall, Torre's statistics are comparable to Yogi Berra's and Gary Carter's. For example, Torre had more hits, a higher batting average than Berra and Carter (2,092), a higher batting average, and more combined doubles and triples. Torre's slugging percentage was higher and he had more total bases than Carter. Torre, however, had less home runs (252) than Berra (358) and Carter (324). Joe Torre deserves to be in the Hall of Fame as a player.

Ron Santo

Ron Santo played 15 years in the Majors, all of them in Chicago. He played his first 14 seasons with the Cubs and played his final season with the White Sox. Over his career, Santo collected 2,254 hits including 342 home runs. Santo was a nine-time All-Star selection who won five Gold Gloves. James (1995) argues that Santo would be the first player he would choose to induct into the Hall if he could. His rating of 0.853 is just below George Brett's (0.861) and above Brooks Robinson's (0.763). Robinson is considered to be the best defensive third baseman of all time, winning 16 Gold Gloves. Santo, in contrast, only won 5. Offensively, however, Santo was better. Per season, Santo had more hits (163 vs. 159), home runs (25 vs. 15), and runs batted in (96 vs. 76). Santo had a higher batting average (0.277 vs. 0.267) and a higher slugging percentage (0.464 vs. 0.401). Santo deserves to be in the Hall of Fame.

Chapter 9
Steroids in MLB: An Analysis of Hitters

Introduction

Among the most controversial topics in major league baseball is the steroid era, apparently beginning in the mid-1980s and continuing until the mid-2000s.[1] Steroids not only help players rehabilitate injuries faster, but with proper diet and weight training, they help build muscle and increase strength. Steroids have been linked to many of the top stars in baseball and much has been written about the topic.[2]

Some remarkable feats were accomplished in the steroid era; notably Maris' individual season home run record of 61 was shattered by Mark McGwire with 70 home runs. In that 1998 season, both McGwire and Sammy Sosa (66 home runs) topped Maris in a drawn out battle that McGwire eventually won. Barry Bonds later shattered McGwire's record, hitting 73 home runs in 1971. Did steroids or other performance-enhancing drugs contribute to these remarkable seasons? If the athletes did take the illegal drugs, the natural question is "why?." Were they taken to help recover from injuries? In this chapter and Chap. 10, we analyze the impact that steroids had on performance. In this chapter we focus on the hitters.[3]

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[1] Tom House, a relief pitcher who played in the 1970s with the Atlanta Braves, Boston Red Sox, and Seattle Mariners admits to steroid use during his career. Widespread use did not begin until the 1990s.

[2] Other than the players who have admitted using steroids, it is not possible to know with certainty who has taken steroids. In this chapter, we will investigate not only players who have admitted steroid use but also those players who have been implicated. The true frequency of use will never be known. In this chapter, we only analyze performance of various players and do not draw definitive conclusions as to if or when a player used steroids. Canseco (2005, 2008), Radomski (2009), Fainaru-Wada and Williams (2006), and the Mitchell Report (2007) provided information that was used for this chapter. Other information was obtained from the website http://thesteroidera.blogspot.com.

[3] I have been told by a former college star that Canseco's claim about the widespread use is probably accurate. He told me that steroids were openly used in summer traveling leagues. Most use apparently was to help the body heal and not to gain massive muscle and power. The best we can do with our analysis is identifying if steroid use allowed the players to enhance their relative performance.

J. Ruggiero, *Frontiers in Major League Baseball*, Sports Economics, Management and Policy 1, DOI 10.1007/978-1-4419-0831-5_9,

In 2010, McGwire admitted to steroid use beginning before the 1990 season, and on a regular basis since 1993 including 1998. He claims that his usage was at a low dosage and that he did not gain strength nor enhance his performance. The admission provided vindication for Jose Canseco who claimed to have personally injected McGwire, a charge that McGwire has denied numerous times. Obviously, McGwire's belief that his steroid use did not enhance his performance is not shared by many.

In addition to McGwire, several other players have admitted steroid use during their playing days. Notably, Jason Giambi, Benito Santiago, and Gary Sheffield (among others) testified before a grand jury investigating BALCO (Bay Area Laboratory Co-operative) that they used illegal performance-enhancing drugs made by BALCO and provided by Greg Anderson, the personal trainer of Barry Bonds. Bonds also testified that he used the "Clear" and the "Cream" from BALCO but was unaware that the products were steroids. The products were used as complements to mask steroid use. Testimony was leaked that Bonds name was on documents from 2001 to 2003 that implicated him steroid use.[4]

Victor Conte, the owner of BALCO, and Anderson pleaded guilty to one count of conspiracy to distribute anabolic steroids. The revelations from the BALCO prompted MLB Commissioner Bud Selig to appoint George Mitchell in March 2006 to investigate steroid use. The results of the report suggested widespread use of illegal performance-enhancing drugs for over a decade. In an anonymous survey conducted in 2003, about 5–7% of the players tested positive. It is possible that the percentage was much higher because players knew when the tests would be conducted and the use of human growth hormones (HGH) was undetectable. Mitchell concludes that the problem is serious and undermines the integrity of the game and calls into question baseball records.

The implications with respect to the analysis in this book is clear. If steroids do in fact improve performance, then the ranking of individual player performance would be distorted, leading to an undervaluing for the honest player. This in turn has large financial implications for players who chose to use the illegal performance-enhancing drugs. Further, to the degree that a team had more players using performance-enhancing drugs, the team could end up winning more games and perhaps, influence the outcome of division races. According to the Mitchell report, all teams had a player test positive. But the degree of use likely varied between teams.

In this chapter, we focus on some of the known cases of steroid use. In addition, we analyze some players who have been implicated in an attempt to discern a pattern that could help shed light on the topic. For benchmarking purposes, we first focus on players who were not part of the steroid era. We also analyze some stars who played during the steroid era but who have not been implicated.

[4] http://www.sfgate.com/cgi-bin/article.cgi?file=/c/a/2004/12/03/MNGGFA0UDU65.DTL, the online article from the San Francisco Chronicle, provides more details.

Profiles, Pre-steroids

In this section, we analyze the age-performance profiles of noted hall of fame hitters prior to the mid-1980s. Given the physical demands placed on ballplayers and the eventual decline due to age, it is natural to consider the effect that steroids and other performance-enhancing drugs had on performance by comparing how a player performed across time. We would expect that young players improve with experience with diminishing returns eventually setting in. The reduction in abilities of a given player due to aging will be compounded by an increase in the proportion of younger players as time increases. In cases of steroid use, we can try to identify outliers given knowledge on player usage.[5]

The measure of performance considered for hitters is the weighted slack-based measure introduced in Chap. 5:

$$
\begin{aligned}
& WS_0 = \max \sum_{k=1}^{4} \omega_k \psi_k \\
& \text{subject to} \\
& \sum_{j=1}^{n} \lambda_j y_{kj} - \psi_k \geq y_{k0}, && k = 1, \ldots, s; \\
& \sum_{j=1}^{n} \lambda_j = 1; \\
& \omega_k \geq 0, && k = 1, \ldots, s; \\
& \sum_{k=1}^{s} \omega_k = 1; \\
& \psi_k \geq 0, && k = 1, \ldots, s; \\
& \lambda_j \geq 0, && j = 1, \ldots, n.
\end{aligned}
\tag{9.1}
$$

A lower value of this slack measure indicates better performance. We calculate the slack measure for all players in all seasons. Given the purported widespread use of steroids in the previous decades and the denial of many who have been implicated, it is not possible to develop baseline cases from the same era. A player who has not been implicated might have actually used steroids. Likewise, it is possible that a player has been wrongly implicated. To insure proper baseline cases, we consider several outstanding players from previous time periods.

Under the assumption that performance improves as a rookie gains experience and eventually declines due to age, we estimate a quadratic regression of the form

[5] Admittedly, the analysis requires assumptions and interpretation. Absent actual admissions of usage, this may be the best we can hope for.

$$\mathrm{WS}_t = \alpha + \beta_1 \mathrm{Age}_t + \beta_2 \mathrm{Age}_t^2 + \varepsilon_t. \tag{9.2}$$

In order to observe the theoretical shape of the age–performance curve, the parameters will be economically significant if $\alpha > 0,\ \beta_1 < 0, \text{and} \beta_2 > 0$. The equation for each player was estimated using Tobit to account for the truncation arising from observing only relative and not absolute performance. From (9.2), we can identify the predicted age that maximizes performance as:

$$\mathrm{Age}^* = \frac{-\hat{\beta}_1}{2\hat{\beta}_2}. \tag{9.3}$$

The age of optimal or peak performance Age^* was calculated using a separate regression for each player. We were unable to calculate this age for some players due primarily to a lack of observations of full seasons. In Table 9.1, we report the results for all players with at least 400 career home runs. Estimates with the wrong parameter sign or that were statistically insignificant were excluded. For example, Mark McGwire (583 home runs) was not included; we discuss his case in Sect. 3.2. Players are ranked in descending order according to the number of home runs that were hit.

Current career home run record holder Barry Bonds had the highest $\mathrm{Age}^* = 33.03$ among the sluggers with at least 400 home runs. The second highest age was achieved by Dave Winfield with $\mathrm{Age}^* = 32.49$, suggesting Winfield peaked about half a year earlier than Bonds.[6] Winfield retired in 1995; while he played during the early steroid years, there has been no evidence tying him to steroid use.

Two steroid era players, Ralfael Palmeiro (31.59) and Jim Thome (31.28), are ranked third and fourth. Palmeiro allegedly tested positive for Stanzolol, an anabolic steroid, in 2005 and was identified by Canseco (2005) as a user. Palmeiro denies that he ever intentionally used steroids. Thome has never been implicated as a steroid user. Both players are analyzed in the next section. Willie Stargell's age of peak performance was estimated to be $\mathrm{Age}^* = 31.14$, placing him in fifth place and nearly 2 years below Barry Bonds. Stargell retired before the beginning of the steroid era.

Next, we turn to age–performance profiles of some notable Hall of Fame hitters to serve as benchmarks for other players.

Babe Ruth

We first consider Babe Ruth, arguably the best player of all time. Ruth held the long-standing career home run record with 714. The age–performance relationship

[6] Winfield was born in October, about 2.5 months after Bonds' birthday.

Table 9.1 Estimated age of optimal performance

Name	Position	HR	AB/HR	Age	Age2	Age*
Barry Bonds	Lf	762	12.92	−14.005	0.212	33.03
Hank Aaron	Rf	755	16.38	−10.175	0.181	28.14
Babe Ruth	Rf	714	11.76	−30.079	0.495	30.36
Willie Mays	Cf	660	16.49	−17.152	0.287	29.92
Sammy Sosa	Rf	609	14.47	−21.086	0.347	30.38
Frank Robinson	Rf	586	17.08	−7.601	0.138	27.50
Alex Rodriguez	Ss	583	14.24	−21.019	0.373	28.17
Harmon Killebrew	1b	573	14.22	−15.084	0.264	28.60
Rafael Palmeiro	1b	569	18.40	−13.868	0.219	31.59
Jim Thome	1b	564	13.66	−17.702	0.283	31.28
Reggie Jackson	Rf	563	17.52	−10.563	0.173	30.46
Mike Schmidt	3b	548	15.24	−29.840	0.479	31.12
Mickey Mantle	Cf	536	15.12	−16.664	0.304	27.42
Jimmie Foxx	1b	534	15.23	−29.587	0.520	28.43
Willie McCovey	1b	521	15.73	−14.725	0.240	30.71
Eddie Mathews	3b	512	16.67	−10.001	0.189	26.47
Mel Ott	Rf	511	18.50	−10.908	0.191	28.52
Gary Sheffield	Rf	509	18.11	−9.520	0.155	30.62
Eddie Murray	1b	504	22.49	−8.731	0.159	27.48
Lou Gehrig	1b	493	16.23	−110.063	1.920	28.66
Fred McGriff	1b	493	17.76	−9.634	0.171	28.23
Willie Stargell	Lf	475	16.69	−18.284	0.294	31.14
Stan Musial	1b	475	23.10	−16.088	0.270	29.79
Carlos Delgado	1b	473	15.40	−17.512	0.288	30.42
Dave Winfield	Rf	465	23.66	−14.293	0.220	32.49
Carl Yastrzemski	Lf	452	26.52	−3.684	0.068	27.05
Jeff Bagwell	1b	449	17.37	−20.142	0.343	29.33
Andre Dawson	Rf	438	22.66	−10.255	0.174	29.52
Juan Gonzalez	Rf	434	15.11	−18.540	0.368	25.17
Cal Ripken	Ss	431	26.80	−7.682	0.147	26.22
Mike Piazza	C	427	16.19	−5.781	0.115	25.14
Billy Williams	Lf	426	21.95	−25.038	0.423	29.58
Jason Giambi	1b	409	16.20	−31.867	0.522	30.50
Duke Snider	Cf	407	17.59	−30.660	0.534	28.69
Vladimir Guerrero	Rf	407	17.20	−22.795	0.419	27.19

To bit regression results reported for each player. All parameters were statistically significant at the 5% level

for Ruth is shown in Fig. 9.1. Weighted slack, measured on the vertical axis, captures the distance from best practice performance using model (5.4) from Chap. 5. If the weighted slack is zero, the player achieved the frontier during that season; lower values of slack indicate better performance. The age of any player was approximated as the year under analysis less the birth year. To the degree that this inaccurately measures a player's actual age relative to a season, the horizontal axis is affected, but not the qualitative results.

In Fig. 9.1, each observation plots the age and associated season's slack.

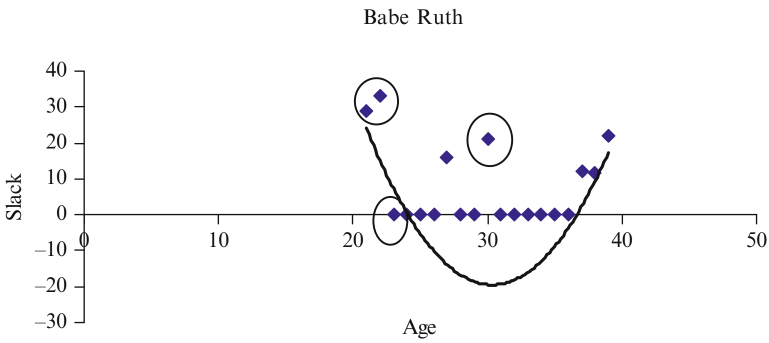

Fig. 9.1 Age–performance profile of Babe Ruth

The parameter estimates for Ruth are $\hat{\alpha} = 437.135, \hat{\beta}_1 = -30.079$, and $\hat{\beta}_2 = 18.097$. The associated predicted performance for Ruth's age is illustrated with the curve.

Based on our estimates, Ruth's performance was maximized at $\text{Age}^* = 30.36$.[7] This occurred during the 1925 season where Ruth was suffering from some mysterious illness. From this point on, we predict diminishing returns have set in. Ruth went on to perform relatively well, producing on the frontier for 6 more years. The circled observations represent some of the observations where Ruth did not have 400 at bats. These included his first three seasons and the 1925 season. We note that Ruth achieved the frontier in 1918 with only 317 at bats; in his last year he only had 365 at bats but the resulting predicted performance is consistent with observed performance.

Hank Aaron

In Fig. 9.2 we consider the age–performance profile of Hank Aaron, the player who shattered Ruth's mark with 755 career home runs. Aaron started out with a weighted slack of approximately 22 in his rookie season. He performed relatively worse only once (in his last major league season when he had only 271 at bats). The profile of Aaron indicates a clear decrease in performance just before he turned 30. Based on the regression results, this occurred at $\text{Age}^* = 28.14$. Importantly, like Ruth, Aaron still had some frontier performances after this age.

Like Ruth's profile, nearly all of the observed age–performance observations for Aaron lie above the trend line. One notable exception for Aaron occurred in 1971 at the age of 37; Aaron performed on the frontier while the predicted value was about 7.

[7] Since Ruth was born on February 6, he turned 30 right before the beginning of the 1925 season. That season turned out to be one of his worst; Ruth only played in 98 games during that season.

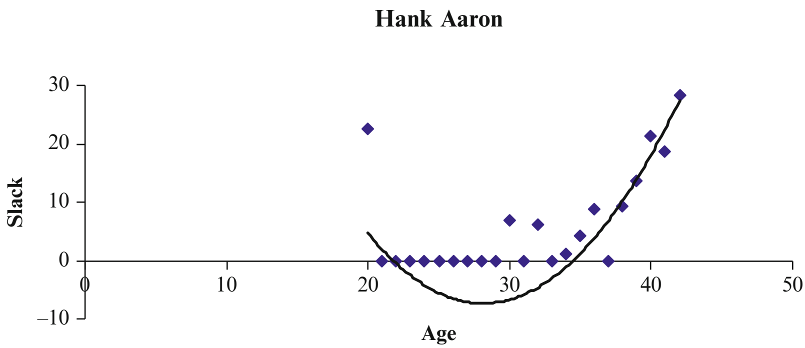

Fig. 9.2 Age–performance profile of Hank Aaron

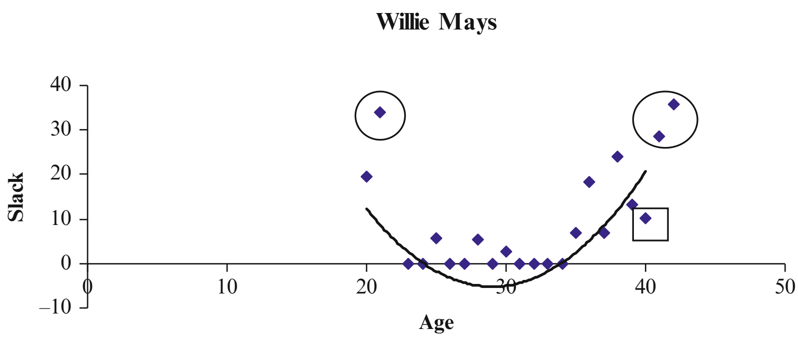

Fig. 9.3 Age–performance profile of Willie Mays

Willie Mays

Next, we consider the age–performance profile of Willie Mays, a superstar who hit 660 career home runs. Mays was inducted into the hall in his first year of eligibility. He was voted on the All-Century Team and placed second (behind Ruth) on the list of the 100 greatest players ever. Mays' age–performance profile is illustrated in Fig. 9.3. The trend is clear; Mays' performance increased until about age 30 and declined thereafter.

Based on the parameter estimates, Mays' optimal performance occurred at $\text{Age}^* = 29.92$. The three circled observations represent the points where Mays had only 127 at bats (1952), 195 at bats (1972), and 209 at bats (1973). The squared box represents an outlier where his performance was better than predicted; his actual weighted slack value was 10.3, half of his predicted value (20.67).

Mike Schmidt

Mike Schmidt's career overlapped with the beginning of the steroid era. He retired in May 1989 after only 148 at bats. Schmidt's Age* = 31.12 is nearly identical to that of Stargell's. Schmidt has not been implicated in steroid use, and his age–performance profile (Fig. 9.4) provides evidence that he did not use steroids.

In 1986, at the age of 37, Schmidt appeared on the frontier. Based on the regression analysis, we predict a small slack of 5.56 for that year. The amount is consistent with about an extra home run and double and is consistent with non-enhanced performance.

Pete Rose

We also consider the age–performance profile of Pete Rose, the all-time hit leader. Rose was a career 0.303 hitter, collecting 4,256 hits. His case is included because Rose was not a slugger, hitting only 160 career home runs. His age–performance profile is presented in Fig. 9.5.[8]

The estimated age of Rose's optimal performance was Age* = 31.79, about 1.5 years later than Ruth's; the trend is consistent with theory. Nearly all observations lie above the trend and there are no significant outliers. This suggests that the age–performance profile is robust across types of batters. Nearly all the profiles considered in the pre-steroid era took on this basic shape.

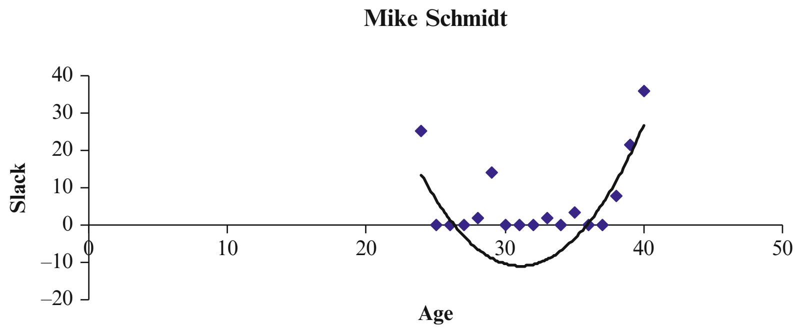

Fig. 9.4 Age–performance profile of Mike Schmidt

[8] According to Radomski (2009), Pete Rose Jr. claimed that his father was a regular user of amphetamines, which were widespread in baseball. Amphetamines increase focus and energy levels and are considered a performance-enhancing drug. MLB banned amphetamine use in 2006.

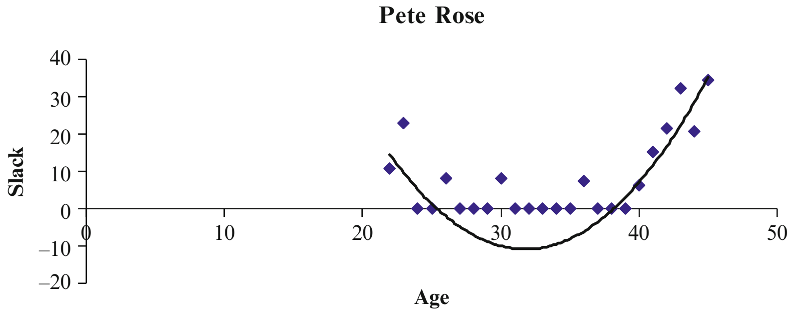

Fig. 9.5 Age–performance profile of Pete Rose

Profiles, Admitted and Implicated Steroid Users

In this section, we analyze age–performance profiles of players who have either admitted using steroids or who have been implicated. Of course, it is possible that some of the players discussed in this section did not take steroids; hopefully the analysis can shed light on the innocent.

Lenny Dykstra

First, we will analyze Lenny Dykstra, who was implicated in the Mitchell report. According to Mitchell, Philadelphia's General Manager Lee Thomas suspected Dykstra's steroid use in 1993 after he reported to spring training. In addition, Radomski (2009) claims that Dykstra was improperly using steroids in 1990 and placed him on a better regimen.

The age–performance profile of Dykstra is presented in Fig. 9.6. Two trend lines are included. The dashed line represents the predicted slack from the tobit regression results using all 12 observations. The estimated peak age is Age$^* = 27.17$. Three circled observations appear to be outliers, indicating better performance than would have been expected. We reran the regression after excluding these three observations. The resulting predictions are shown with the solid trend line. The three years in question correspond to the 1990, 1993, and 1994 seasons. After removing these three observations, his estimated peak age falls to 25.33.

According to Radomski (2009), Dykstra showed up over 30 pounds heavier for spring training and claims that Dykstra admitted to steroid use. He further claims that Dykstra was hitting the ball better and harder in the first half of the 1990 season. Dykstra's incorrect use of steroids, however, purportedly led to a poor second half of the season. After his 1990 season, Dykstra played the next two seasons with injuries caused by a car accident and being hit by a pitch. According to the Mitchell report, Dykstra admitted using steroids throughout his career.

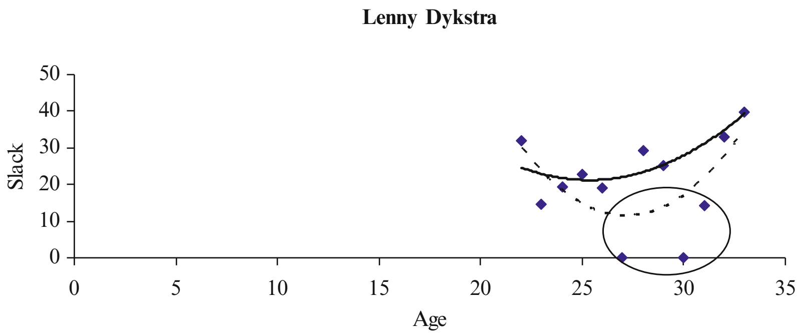

Fig. 9.6 Age–performance profile of Lenny Dykstra

The analysis for Dykstra is informative. Unlike the age–performance profiles in Sect. 2, there are clear outliers with performance better than predicted.

Mark McGwire

In his first book *Juiced*, Canseco (2005) claims that he and Mark McGwire often injected steroids together. For a long time, McGwire denied using steroids and declined to talk about his past use in 2005 while under oath and testifying to Congress.[9] McGwire was first implicated during Operation Equine, an FBI steroid investigation in the 1990s. McGwire and Canseco's names came up during the investigation and evidence suggested that McGwire was a hardcore user.[10] McGwire admitted to using steroids prior to the 1990 season.

In Fig. 9.7, we present the age–performance profile of McGwire. McGwire had a dominant rookie year (1987), batting 0.289 while hitting 49 home runs and driving in 118 runs. Based on his performance, McGwire won the Rookie of the Year award, winning all first place votes. He had a strong second year, but it was not as good as his rookie season. In 1987, at the age of 23, his slack of zero placed him on the frontier.[11] In 1988, his slack increased to about 9; a year later his slack increased

[9] According to 60 minutes, McGwire denied the allegations in 2005 by stating "Once and for all, I did not use steroids nor any illegal substance." See http://www.cbsnews.com/stories/2005/08/05/60minutes/main761932_page2.shtml?tag=contentMain;contentBody. By his own admission in 2010, this statement was a lie.

[10] The implication was discussed in a March 2005 New York Daily News article "Hitting the Mark: FBI informants say McGwire was juiced," by Michael O'Keefe, Christian Red and T.J. Quinn. The article was accessed online.

[11] McGwire was born on October 1 and would have turned 24 before the end of the season. For convenience, and without loss of generality, we use our measure of age for the discussion.

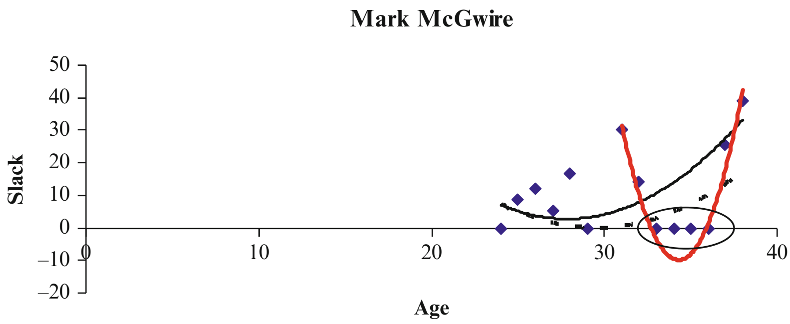

Fig. 9.7 Age–performance profile of Mark McGwire

to 12. It was around this time that Canseco claimed that the “Bash Brothers” were regularly using steroids.

McGwire’s age–performance profile is not typical because he had a dominant rookie season. Even after that, while his performance declined, his performance was near the frontier. Furthermore, given that he has admitted using steroids throughout his career, it is harder to discern a pattern. We estimated three separate trend lines from three separate regressions. The dashed line represents the predicted values from estimating the Tobit regression using all observations. From this regression, it appears that peak performance occurred at $Age^* = 29.53$.

Based on the dashed trend line, there are four observations (circled) that appear to be outliers. These correspond to the 1996–1999 seasons; in all these years McGwire performed on the frontier, including the infamous 1998 season. In addition, in the 1994 season, there is an outlier due to having only 135 at bats. We removed the low at bat year and the last three seasons for which he performed on the frontier (1997, 1998, and 1999 seasons) and reran the regression. The resulting trend is illustrated with the solid black line. This further illustrates the 4 years of outliers. The corresponding age of optimal performance was calculated to be $Age^* = 27.83$. From this, it appears that his age of peak performance by 1.5 years.

We also consider fitting a regression line using only observations after the 1993 season. This trend line is illustrated in red. The red trend line does the best job of capturing the performance in the second half of McGwire’s career. The associated peak performance occurs at $Age^* = 34.30$. This suggests that McGwire gained at least 4 years of optimal performance. McGwire hit 583 career home runs; during these four outlier years, he hit 245 (42%) of his 583 home runs. If we project the four outliers to the black trend line, we estimate that McGwire would have hit 119 (using similar points from earlier years). Hence, McGwire likely gained around 125 career home runs given his steroid use. Would McGwire have hit over 500 career home runs absent steroids? Unfortunately, we will never know.

Jose Canseco

The other half of the "Bash Brothers," Jose Canseco, was among the first to admit steroid use. Canseco's 2005 book *Juiced: Wild Times, Rampant Roids, Smash Hits, and How Baseball Got Big* was a best-selling book "that started the steroid scandal."[12] Canseco admits to having used steroids as early as 1984 in the minor leagues and throughout his major league career. In addition, he claims to have injected Rafael Palmeiro, Juan Gonzalez, Ivan Rodriguez, Jason Giambi, Wilson Alvarez, and Dave Martinez, among others, and implicates Brett Boone. An analysis of Canseco is harder because his steroid use was spread out over his entire career. In addition, Canseco was often injured and his performance was influenced by his number of at bats. The correlation between his slack at bats was 0.86; as he got more at bats, he performed better.

Canseco's age–performance profile is revealed in Fig. 9.8. Looking at the original data, a pattern is not apparent. He only achieved the frontier twice in his career and his performance fluctuated from year to year. We note first that in two of his seasons he had less than 250 at bats. These observations are circled. We consider two trend lines based on his number of at bats. The lower trend line indicates better performance; for these observations he had at least 425 hits. The lower trend indicates an age of optimal performance of $\text{Age}^* = 26.61$. The higher trend line indicates lower performance and occurred when Canseco had less than 400 at bats. The associated age of optimal performance occurs at $\text{Age}^* = 30.14$. It is not clear how to interpret these results, especially without detailed knowledge of the actual steroid use and nature of the injuries. Perhaps extensive play on steroids in a given year resulted in nagging injuries.

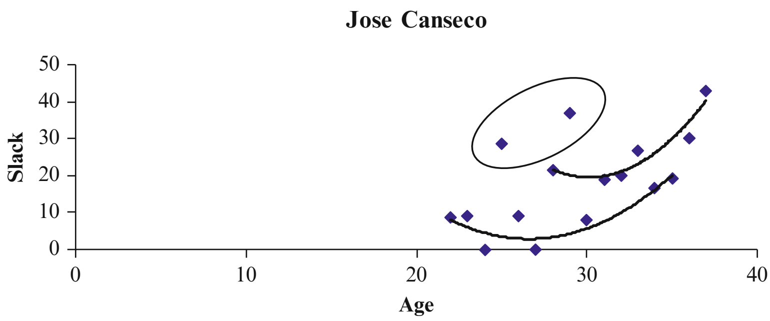

Fig. 9.8 Age–performance profile of Jose Canseco

[12] This description is written on the cover of *Juiced*.

Ken Caminiti

Ken Caminiti played Major League baseball during the steroid era. Unlike many others, Caminiti admitted his steroid use.[13] In an interview with *Sports Illustrated* conducted in 2002, Caminiti claimed that he began using steroids in 1996. According to the Mitchell Report, however, former teammates claimed that Caminiti was openly using steroids in 1995. Caminiti speculated that at least half of Major League players used steroids. During the 1996 season, he hit 0.326 with 40 home runs and 130 runs batted in. For his performance, Caminiti won the National League Most Valuable Player Award. Caminiti's age–performance profile is presented in Fig. 9.9.

Like other players who started using steroids in the middle of the their careers, Caminiti's profile has the expected shape. The age of his optimal performance was estimated to be $Age^{*} = 30.62$. The largest outlier where performance is better than expected occurs at age 33 during his MVP 1996 season. Interestingly, the years before and after his MVP season also appear to be outliers, though closer to the predicted value. This is consistent with the claims in the Mitchell Report that Caminiti started using steroids earlier than 1996 and continued after.

Jason Giambi

Jason Giambi started his Major League career in Oakland in 1995. In 2001 he signed a 7 year, $120 million contract with the New York Yankees. While in Oakland, he played with Jose Canseco in 1997. Canseco names Giambi as one of

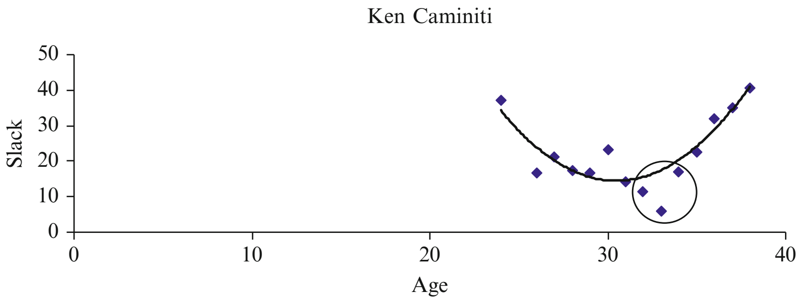

Fig. 9.9 Age–performance profile of Ken Caminiti

[13] Caminiti suffered from other substances abuse, admitting to a problem with alcohol and cocaine. Caminiti died of an overdose of cocaine and opiates in 2004.

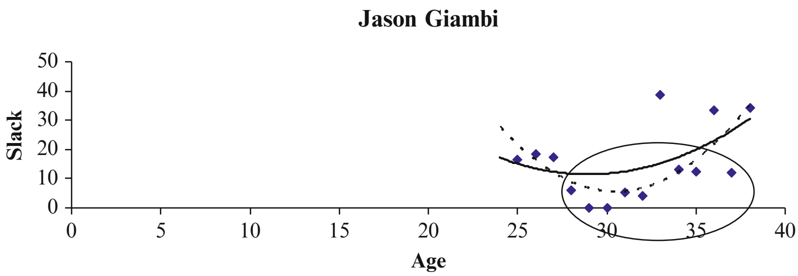

Fig. 9.10 Age–performance profile of Jason Giambi

the players whom he personally injected with steroids.[14] Chapter 15 of Canseco's 2005 book *Juiced* is titled "Giambi, The Most Obvious Juicer in the Game." In the chapter, Canseco alleges that Giambi and McGwire were open and casual about their steroid use. In Canseco's opinion, Giambi had average abilities that were greatly enhanced by steroid abuse.

Giambi's age–performance profile is presented in Fig. 9.10. Given the admitted use of steroids, we are able to construct two trends. In the first regression, we consider all data points. This trend line is dashed and indicates an age of optimal performance of $\mathrm{Age}^* = 30.50$. For the second regression, we omitted his first year due to low at bats (176) and the corresponding seasons where he admitted steroid use (2001–2003). This regression resulted in $\mathrm{Age}^* = 28.97$, suggesting that Giambi was able to defy nature by 1.5 years. The circled range contains many questionable years where he performed better than expected. These outliers include the 1999–2003, 2005, 2006, and 2008 seasons. In 2004, Giambi was treated for a tumor and only had 264 at bats. Likewise, in 2007 he only had 254 at bats due to injuries.

The results confirm Canseco's assessment of Giambi. Our analysis reveals that his performance was enhanced; if Giambi did in fact stop taking performance-enhancing drugs after 2003, it is not clear what explains his outlier performance during the 2008 season. Do steroids have lasting performance benefits after a player stops using?

Gary Sheffield

Gary Sheffield began his Major League career with the Milwaukee Brewers in 1988 and has played on several other teams. Sheffield is a career 0.292 hitter with 509 home runs. Sheffield was implicated in the BALCO scandal and testified before the

[14] Giambi was also implicated in the BALCO scandal. According to the Mitchell report, BALCO founder Victor Conte sold and advised numerous athletes (including Barry Bonds) on the "Clear" and the "Cream." Giambi was one of the implicated. Testifying before Congress in the BALCO investigation, Giambi admitted steroid use but focused on the links to BALCO.

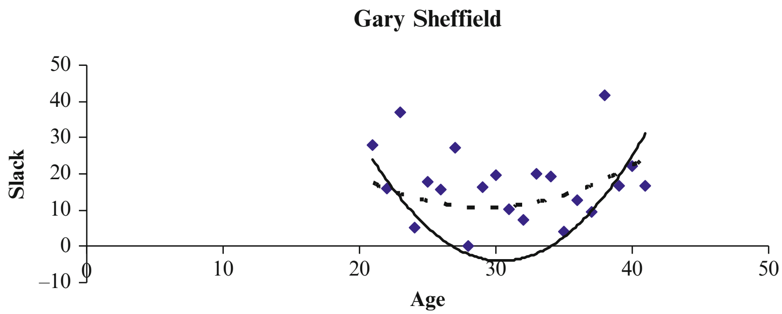

Fig. 9.11 Age–performance profile of Gary Sheffield

grand jury in 2003 that he had used undetectable steroids. Sheffield was implicated in the Mitchell Report as one of the athletes who not only bought the BALCO drugs but also were advised on the use. Evidence of a transaction involving BALCO and Sheffield was found in a search of Greg Anderson (Barry Bonds' personal trainer) condominium. Sheffield denied knowledge that the "Cream" was a steroid and that it was only applied to heal his knee.

Sheffield's profile is presented in Fig. 9.11. We consider two trend lines; the dashed line is based on all observations. In this case, the estimated peak age is $Age^* = 29.19$. Using this trend, however, reveals many outlier performances. This results because Sheffield had a lot of years that were above the trend. As an alternative, I considered a trend line based on only the lower envelope of performance. This solid trend line reveals only one outlier (2009 season) that results from only 268 at bats. The peak age under with this specification is 30.42 which is not inconsistent with expectations. These results suggest that Sheffield did not benefit from steroid use or other performance-enhancing drugs. While this may not be the case given the dispersion of the data, I believe Sheffield should be given the benefit of the doubt.

Barry Bonds

Barry Bonds is perhaps the most controversial case involving steroids. Bonds began his Major League career with the Pittsburgh Pirates in 1986. In 7 years with the Pirates he hit 176 home runs. In 1992, he signed as a free agent with the San Francisco Giants. Bonds played 15 seasons with the Giants, hitting another 586 home runs. His batting average increased from 0.275 with the Pirates to 0.312 with the Giants. In the 1998 home run battle between Sosa and McGwire, Bond hit only 37. In 2000, Bonds had his best home run total to date, hitting 49 home runs. The next year, Bonds hit 73 home runs, shattering the single season mark. He is the career leader in home runs and walks and is in the top five all time in runs batted in, total bases and runs scored. Bonds is the only player to hit at least 500 home runs and steal at least 500 bases.

In 2006, Mark Fainaru-Wada and Lance Williams released *Game of Shadows*, an explosive book that alleges that Bonds used many steroids including stanozolol. According to Fainaru-Wada and Williams, the home run chase between Sosa and McGwire was at the root of Bonds' decision to start using steroids. The book alleges that Greg Anderson, Bonds' weight trainer, started injecting Bonds with stanozolol after the 1998 season. The case against Bonds is damning and the story told in *Game of Shadows* is more plausible than the denials issued by Bonds.[15]

In the appendix of the book, the authors present evidence that supports the case of steroid use. The details include collaborating evidence regarding the relationship between Anderson, Bonds, and BALCO. Bonds' former girlfriend, Kimberly Bell, testified that Bonds admitted steroid use to her in 2000 and blamed steroids for the 1999 injury. Bonds only appeared in 102 games that year. In addition, the raid on Anderson's condominium uncovered damning documentation that detailed Bonds' steroid use. The evidence suggests Bonds paid for growth hormones, the Cream and the Clear and Depo-testosterone. A calendar provided details about his regimen.

Bonds' age–performance profile is shown in Fig. 9.12. The results are consistent with theory from the beginning of his career through the mid-1990s. In his first six seasons, Bonds did not achieve the frontier. In his last season with the Pirates he performed on the frontier. During this time, he had impressive numbers, hitting 176 home runs and stealing 251 bases. Bonds continued on the frontier (except for the strike-shortened 1994 season) until 1998. Two trend lines are illustrated. The dashed trend line reflects predictions using all observations. The associated age of peak performance is estimated to be Age* = 33.03. As discussed earlier, Bonds' age was 2.5 years after Ruth's estimated peak age. Other than this estimate, the dashed age–performance trend does not contain the usual outliers that we have

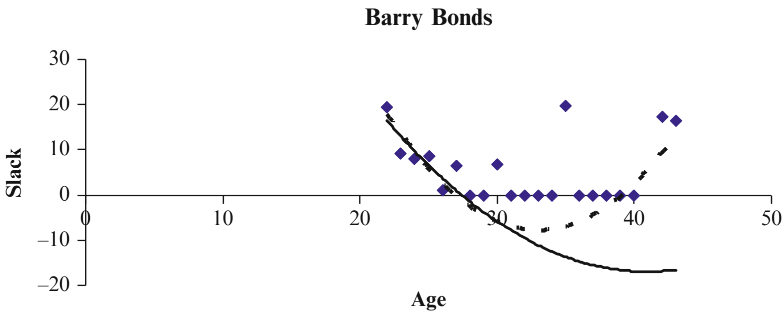

Fig. 9.12 Age–performance profile of Barry Bonds

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[15] Bonds sued because the book contained sealed grand jury testimony. Bonds dropped the lawsuit. See http://sports.espn.go.com/mlb/news/story?id=2381381 for more information.

observed from other admitted steroid users. Part of the reason is that the positively sloped portion of the trend line is derived from the relatively lower performance observed in Bonds' last two seasons. In these seasons, he had less than 400 at bats.

The second (solid) trend line was estimated without the last two observations. In this case, the positively portioned segment is estimated by exploiting the observed downward sloping relationship earlier in his career and the symmetry of the quadratic function. In this case the estimated peak age was $\text{Age}^* = 40.88$.[16]

The well-documented change in Bonds' physique, together with the available evidence, should leave little doubt regarding his steroid use. The resulting effects on his performance are undeniable. Unfortunately, Bonds' steroid use will likely prevent his inclusion into the Hall of Fame, which would have likely happened if he never used steroids. It is also unfortunate that the cherished baseball records dating back to Ruth, Maris, and Aaron are held by the steroid users. Bonds did earn nearly $200 million as salary from playing baseball. Whether or not the money is worth is another question.

Sammy Sosa

Sammy Sosa is best known for his 1998 season when he competed with McGwire to see who would break Maris' single season home run (61) record. Sosa lost that race but managed to hit 66 home runs, 5 more than Maris. In 1999 and 2001, Sosa also hit more home runs than Maris, hitting 63 and 64, respectively. Later in his career, he joined Ruth, Mays, Aaron, and Bonds in the exclusive 600 career home run club. Sosa was one of the players who tested positive for performance-enhancing drugs, but he has denied it. Figure 9.13 illustrates his age–performance profile.

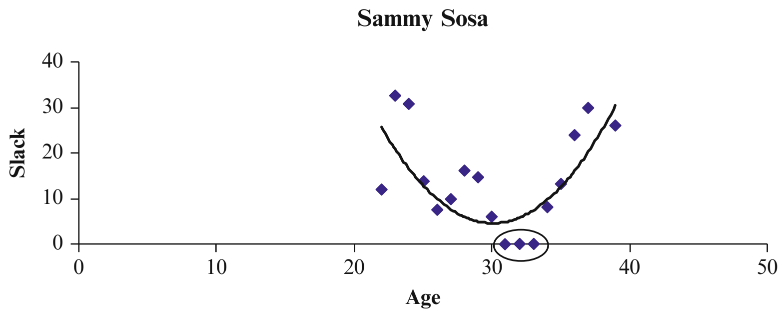

Fig. 9.13 Age–performance profile of Sammy Sosa

[16] As we remove the frontier performance from the end of his career, the peak age decreases, but the resulting trend line illustrates outlier performance.

Sosa's profile is straight forward. The years he appeared on the frontier are all outliers. In that time frame, Sosa hit 177 home runs. Sosa's trend line also reveals the difficulty of identifying steroid usage. Sosa did not appear on the frontier in 1998, and the observation is not an outlier with respect to the trend. But this results because of the comparison with McGwire, who has admitted using performance-enhancing drugs. Assuming Sosa did use steroids in 1998, the data will not reveal it without a more dynamic analysis. In Sosa's case, his peak age was estimated to be $\text{Age}^* = 30.06$, which coincides with his 1998 season.

If a player only uses steroids between the ages of 28 and 32, the age-profile analysis would likely not capture outlier performance.

Manny Ramirez

Former Cleveland Indian Manny Ramirez tested positive in 2009 for human chorionic gonadotropin (HCG), a fertility drug used between steroid cycles to restore natural testosterone production. It is alleged that Ramirez also tested positive for artificial steroids.[17] Ramirez received a 50 game suspension but claimed the drug was prescribed for a personal health reason, implying that he did not use performance-enhancing drugs. Ramirez claims to have passed 15 drug tests in the 5 years prior.

Ramirez' age–performance profile is shown in Fig. 9.14. The trend line that best captured his performance was obtained by omitting 3 years of relatively poor performance.[18] His peak performance happened at an estimated $\text{Age}^* = 29.30$. However, his 2008 season is an outlier, suggesting enhanced performance.

There are other players who have been implicated, tested positive or who have admitted steroid use. Alex Rodriguez, for example, admitted steroid use. However,

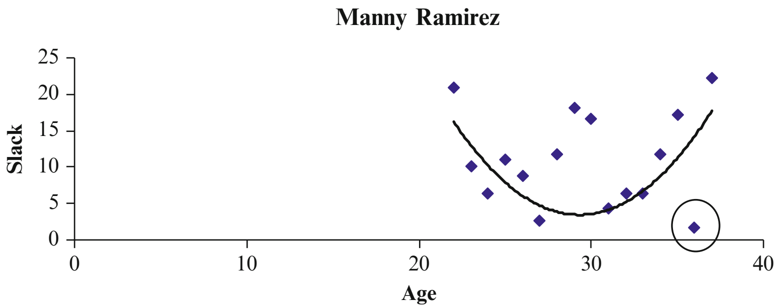

Fig. 9.14 Age–performance profile of Manny Ramirez

[17] http://thesteroidera.blogspot.com/2009/05/manny-ramirez-suspended-50-games-for.html.

[18] By removing these observations, we obtain a more favorable trend for Ramirez.

given that he turned 34 years old during the 2009 season, there is insufficient data to conduct a proper analysis. Our goal was to analyze the steroid issue using DEA. We have analyzed some of the greats from the pre-steroid era and some of the major stars who were either known or suspected of steroid use. For completeness, we turn our attention to a few players who played during the era but who have not been implicated.

Other Steroid-Era Players

In this section, we consider other players who played during the steroid era. We make no claim as to actual steroid use but provide age–performance profiles. We focus on the three superstars: Ken Griffey Jr., Carlos Delgado, and Jim Thome.

Ken Griffey Jr.

Ken Griffey Jr. began his Major League career with the Seattle Mariners. He played in 22 seasons before retiring in the 2010 season. Griffey finished with a career 0.284 batting average with 630 career home runs. Griffey was voted to the All-Century Team and was a 13 time all-star and 1997 American League MVP. Griffey was known not only for his hitting but also for his fielding, winning ten gold gloves. Griffey was traded in 2000 to the Cincinnati Reds, his father's original team.

Whereas Griffey was considered among the best ever based on his career in Seattle, his career declined due to injuries while he was a Red. From 2001 until 2006, Griffey appeared in an average of 93 games. Griffey suffered a serious injury in 2004 in which his hamstring tore off the bone.[19] While it is not known with certainty, it is widely believed that Griffey was steroid free throughout his career.

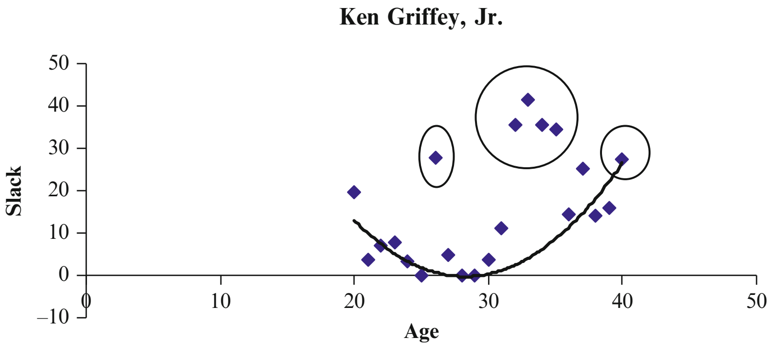

Fig. 9.15 Age–performance profile of Ken Griffey Jr.

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[19] There was some speculation that this type of injury results from steroid use.

Griffey's age–performance profile is presented in Fig. 9.15. The circled observations represent the years where Griffey had less than 400 at bats. The trend line obtained after removing these points is illustrated. As shown, there are no significant outliers before the trend. Griffey's peak age was estimated to be Age* = 28.25. Based on this analysis, there is no reason to believe Griffey's performance was enhanced.

Carlos Delgado

Carlos Delgado began his career with the Toronto Blue Jays in 1993. His first strong season was in 1996 at the age of 24. Delgado has had a solid year with 473 career home runs and a 0.280 batting average. And, like Griffey, he has not been implicated in steroid use. His age–performance profile is presented in Fig. 9.16.

Until 2009, Delgado has played relatively injury free. In 1994, he only had 130 at bats; this observation is circled. There are a few seasons (2001, 2002, and 2004) with worse than expected performance. In those years, he hit 39, 33, and 32 home runs, respectively. We note that he played well during these seasons; the calculated slack is relative to the performance of other in this period, including admitted steroid users. The trend line was estimated without these four observations. Delgado's peak age was estimated to be Age* = 30.20. As shown, only his 2008 season appears to be an outlier with possible enhanced performance. During 2008, at the age of 36, Delgado hit 38 home runs for the Mets while batting 0.271.

I would conclude that Delgado's performance was not enhanced.

Jim Thome

Jim Thome began playing for the Cleveland Indians in 1991. The 1995 season was Thome's first playing in over 100 games. In that year, he hit 25 home runs while

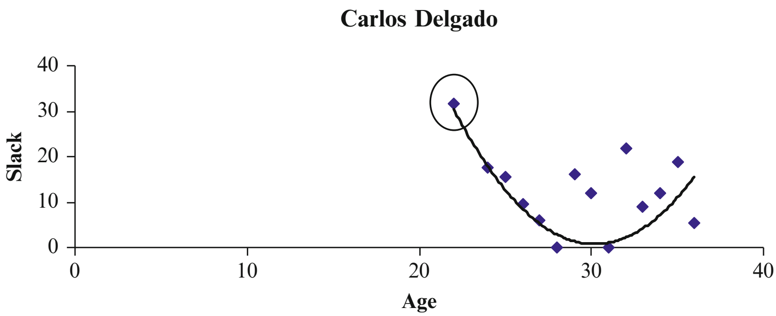

Fig. 9.16 Age–performance profile of Carlos Delgado

batting 0.314. Thome played in 12 seasons for the Indians, hitting 334 home runs at that time. In 2002, he hit his single season high 52 home runs for the Indians. Thome was a key player for the Indians in both years (1995 and 1997) the team made the World Series. In 2002, he signed as a free agent with the Philadelphia Phillies, and in 2006 he was traded to the Chicago White Sox. Thome has also played for the Dodgers (2009) and is currently playing for the Twins. Overall, Thome has an impressive record, with a career batting average of 0.277 with 570 home runs (11th all time). As a slugger, Thome (13.70) ranks behind only McGwire (10.61), Ruth (11.76), Ryan Howard (12.54), and Barry Bonds (12.92) in at bats per home run.

Jim Thome has not been implicated using performance-enhancing drugs. A search of the Internet reveals some speculation, claiming that Thome's power numbers increased in the early 2000s.[21] Thome's maximum home run production occurred at age 31. Ruth's highest home run total was achieved at the age of 32. At the same age, Thome hit more home runs than Ruth only four times: 27, 30, 31, and 39. Over those four ages, Thome hit only 20 more home runs than Ruth. The primary reason was at age 30, Ruth suffered a mysterious illness and hit 21 (22) less home runs than his previous (following) year. Ruth and Thome hit the same number of home runs at the same age twice; both hit 2 at age 22 and both hit 34 at age 38. In 12 instances, Ruth hit on average 16.5 more home runs at the same age.

Thome's age–performance profile is presented in Fig. 9.17. Two profiles are considered; the dashed trend line illustrates predictions using all observations. The trend is clearly biased because the middle years indicate relatively low performance, even though these were Thome's best years. Of course, his relative performance was low because he was being compared to other players with enhanced performance. The solid trend line controls for those years; in this case, Thome achieved a peak age at Age* = 31.16. This is similar to Mike Schmidt's peak age. From this trend, it does not appear that Thome's performance was enhanced.

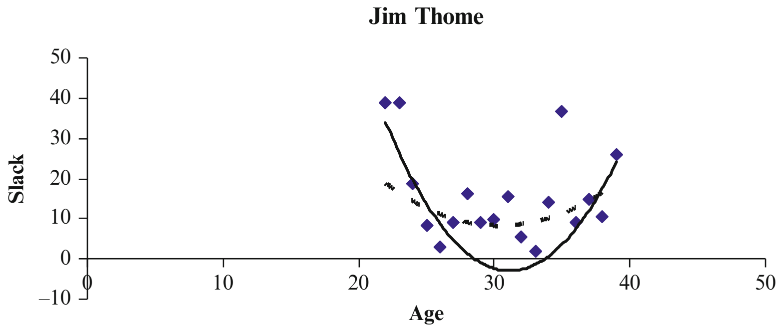

Fig. 9.17 Age–performance profile of Jim Thome

[21] See, for example, http://bleacherreport.com.

Chapter 10
Steroids in MLB: An Analysis of Pitchers

Introduction

In the last chapter, we applied DEA to obtain a measure of aggregate performance by each hitter in each season. We then analyzed each player's age–performance profile to identify unusual performances. The theory is that eventually, diminishing returns sets in as a player gets older. A quadratic specification was chosen to identify the age of peak performance and to predict performance as age increases. Using stars who played prior to the steroid era, we established benchmark age–performance profiles. We then applied the method to known steroid users to see if enhancement allowed players to defy the standard profiles. The results do provide insight into potential steroid use.

Most of the public attention on steroid use is focused on the hitters. After all, some of the historic hitting records that have been held for decades were shattered. Roger Maris' single season home run mark of 61 established in 1961 was broken 37 years later by Mark McGwire's record 70. McGwire bested Maris again in 1999 with 65. Sammy Sosa beat Maris' mark three times when he hit 66, 63, and 64 home runs in 1998, 1999, and 2001. McGwire's new record did not last long as Barry Bonds hit 73 home runs in 2001. This was the first season Bonds ever hit more than 50 home runs and he did it in only 476 at bats.

Hank Aaron broke Babe Ruth's career home run mark by hitting his 715th on April 8, 1974. Aaron hit 40 more home runs in his career, establishing 755 as the new mark to beat. Aaron's record fell on August 7, 2007 when Barry Bonds hit his 756th career home run. Another great record shattered by an alleged steroid user.

We know that there have been pitchers who have tested positive for steroid use. In the case of the pitcher, however, we have not seen the transformation into body building types who gain 30 pounds of muscle in a short period of time. Pitchers might take it to increase strength, perhaps to add velocity to a fastball or to help in the recovery process. Nonetheless, because most notable records are hitting and the obvious case of steroid abuse has been by hitters, pitchers have not been scrutinized.

Major League Baseball instituted a new drug policy in 2004 which included random testing and suspensions. In 2005, players and owners agreed to harsher penalties including a 50 game suspension for first time offenses. Manny Ramirez

J. Ruggiero, *Frontiers in Major League Baseball*, Sports Economics, Management and Policy 1, DOI 10.1007/978-1-4419-0831-5_10,

was perhaps the biggest name to have tested positive, receiving a 50 game suspension in 2009. Interestingly, nearly 50% of those who have tested positive since 2004 have been pitchers.

In this chapter, we employ model (6.1) from Chap. 6 to evaluate pitcher 0:

$$
\begin{aligned}
&\eta_0 = \max\ \eta \\
&\text{subjectto} \\
&\sum_{j=1}^{n} \lambda_j y_{kj} \geqslant \eta y_{k0}, && k = 1,\ldots, s; \\
&\sum_{j=1}^{n} \lambda_j = 1; \\
&\lambda_j \geqslant 0, && j = 1,\ldots, n.
\end{aligned} \tag{10.1}
$$

This model was applied to analyze pitchers in all Major League seasons; the resulting estimate η_{it}^{-1} measures the performance of pitcher i in time period t. Following Chap. 6, we choose three individual performance statistics: innings pitched (IP), innings pitched per earned run (IP/ER), and innings pitched per hit (IP/H). We solved (10.1) for each pitcher who started at least ten games in a given season.

Maintaining our assumption that marginal performance decreases eventually as the player gets older, we estimate a quadratic regression of the form (we suppress the pitcher subscript)

$$\eta_t^{-1} = \alpha + \beta_1 \mathrm{Age}_t + \beta_2 \mathrm{Age}_t^2 + \varepsilon_t. \tag{10.2}$$

In order to observe the theoretical shape of the age–performance curve, the parameters will be economically significant if $\beta_1 \geqslant 0$ and $\beta_2 \leqslant 0$. We note that this differs from the measure used in Chap. 9 because a higher value of η_{it}^{-1} is associated with better performance. The equation for each player was estimated using Tobit, with an upper bound of 1, to account for the truncation arising from observing only relative and not absolute performance. Given the quadratic function, the estimated age of optimal performance is the same as in Chap. 9:

$$\mathrm{Age}^* = \frac{-\hat{\beta}_1}{2\hat{\beta}_2}. \tag{10.3}$$

Profiles, Pre-steroids

In this section we consider age–performance profiles of some of the all-time great pitchers who pitched before the steroid era.

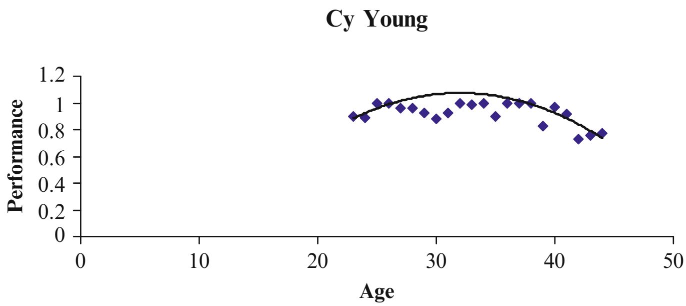

Fig. 10.1 Age–performance profile of Cy Young

Cy Young

We first consider Cy Young, identified in Chap. 8 as the highest rated pitcher of all time. Young still holds the record for the most wins (511) and had a career earned run average of 2.63 with 2,803 strikeouts. Young began his career in 1890 with the Cleveland Spiders at the age of 23 and pitched in 22 seasons. His age–performance profile is presented in Fig. 10.1.

We note that there are instances where some years Young performed consistently below the trend line. The effect is to pull the trend line down. We delete some of these observations to obtain a better estimate of the curvature. The qualitative results are not changed. Young's profile reveals the expected quadratic trend. His age of peak performance was estimated to be $\text{Age}^* = 32.01$.

Walter Johnson

Walter Johnson began his career for the Washington Senators in 1907. He pitched in 21 seasons, all for the Senators, winning 417 games with a career earned run average of 2.17. Johnson was voted onto the All-Century Team and is considered one of the greatest pitchers of all time. Johnson still holds the record for career shutouts with 110. His age–performance profile is shown in Fig. 10.2.

Like Young's, Johnson's quadratic trend line is a good predictor of actual performance. We see that his performance declines as he gets older after his peak performance $\text{Age}^* = 29.57$.

Warren Spahn

Warren Spahn began his career with the Boston Braves in 1942. He pitched with the Braves (Boston and Milwaukee) for 20 of his 21 seasons and is considered one of

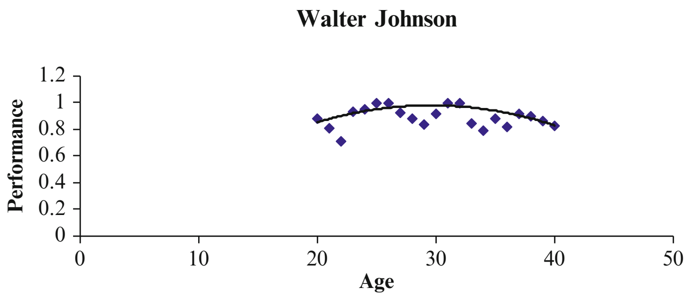

Fig. 10.2 Age–performance profile of Walter Johnson

the best left-handed pitchers of all time. Spahn won 363 games, fifth best all time and best among left-handed pitchers, with a career earned run average 3.09. Spahn missed three full seasons due to World War II beginning when he was 22. Spahn's career is a useful benchmark given that he appeared in 14 all-star games. His profile is presented in Fig. 10.3.

Spahn's trend reveals the typical pattern, with peak performance estimated to be at Age* = 33.03. This age should be discounted because he lost 3 years of pitching due to the war. Spahn's profile appears to have several outliers; two outliers appear in his first two full seasons and several appear at the end of his career. The lost years together with the lower than expected performances in the middle of his career, we conclude that Spahn's profile is not a useful benchmark.

Whitey Ford

Whitey Ford spent his entire career (18 seasons) with the New York Yankees, winning 236 games (a club record) with an earned run average of 2.75. Ford was a ten-time all-star, 1961 Cy Young Award winner, and a six times World Series champion. Ford did not pitch at ages 22 and 23 due to service during the Korean War. Ford's profile is shown in Fig. 10.4.

Observing the data, it appears that Ford's first season was an outlier. This was his only season prior to his service. After removing this outlier, the resulting trend presents a good fit. His peak age was estimated to be Age* = 30.32 and there do not appear to be any enhanced outliers beyond this age.

Tom Seaver

Tom Seaver began his career with the New York Mets in 1967 at the age of 22. He pitched in 20 seasons, winning 311 games with a career 2.86 earned run average. Seaver was a 12-time all-star and three-time National League Cy Young Award

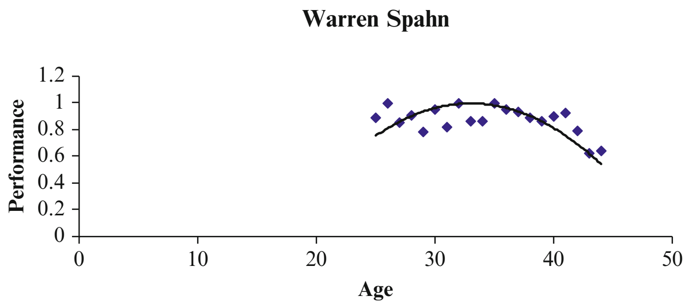

Fig. 10.3 Age–performance profile of Warren Spahn

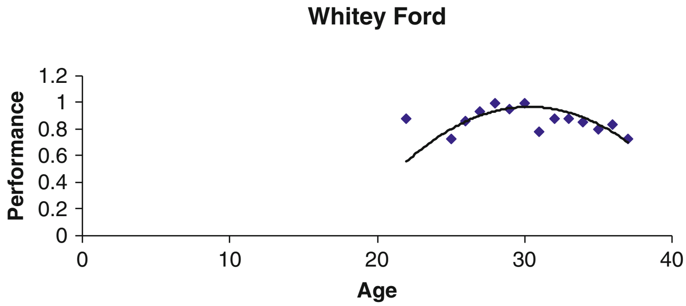

Fig. 10.4 Age–performance profile of Whitey Ford

winner (1969, 1973, and 1975). Seaver's age–performance profile is presented in Fig. 10.5

Seaver's profile reveals a trend consistent with diminishing returns. His peak age was estimated to be $\text{Age}^* = 31.36$. As expected, there are no performance-enhanced outliers in Seaver's profile.

Profiles, Admitted and Implicated Steroid Users

In this section, we analyze profiles of players who have either admitted using steroids or who have been implicated.

Paul Byrd

Paul Byrd began his Major League career in 1995 with the New York Mets. He has played with seven teams over 14 seasons; in his first three seasons he was used in a relief role but became a starter in 1998. Byrd first had ten starts in 1999 with the

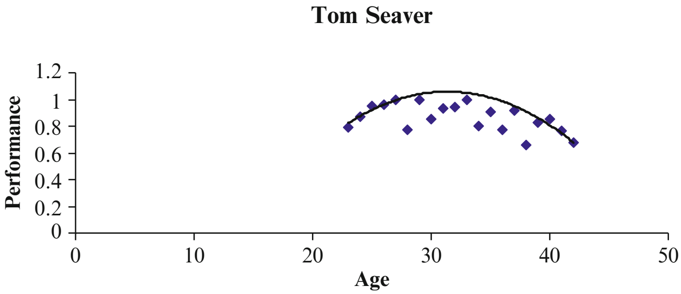

Fig. 10.5 Age–performance profile of Tom Seaver

Philadelphia Phillies. Byrd was among the players listed in the Mitchell Report as one of the alleged purchasers of HGH from Florida rejuvenation centers between 2002 and 2005. The San Francisco Chronicle broke the story on Byrd, who bought over 1,000 vials of HGH. In response, Byrd admitted using HGH, but claimed it was legitimate use because he suffered from growth-hormone deficiency and that he took only what was prescribed by his doctor. According to the Chronicle, two of Byrd's prescriptions were written by a dentist. In his career, Byrd has won 107 games with a 4.39 earned run average.[1]

Byrd's age–performance profile is illustrated in Fig. 10.6. We recognize that Byrd only has nine observations in our sample, beginning at the age of 29. This makes establishing a pattern more difficult. Using all observations, the trend line is shown with a suspected outlier at age 32 during the 2002 season. The evidence linking Byrd to HGH use started at the end of the season, however. The estimated age of peak performance was $Age^* = 35.53$. This is higher than would be expected, but may partly result from the limited sample.

Kevin Brown

Kevin Brown started pitching in the Major Leagues in 1986 with the Texas Rangers. Brown has played for six major league teams over 19 seasons, winning 211 games with a career earned run average of 3.28. Brown was implicated by Radomski, who claims Kevin Brown was a knowledgeable steroid user before he started selling him steroids and HGH after 2001. Evidence of a transaction between Brown and Radomski was seized by federal agents; the receipt is included in the Mitchell Report. In addition, the Mitchell Report reveals that the Dodgers officials suspected steroid use by Brown in 2003. Brown's prolife is presented in Fig. 10.7.

Brown's profile contains observations of relative low performance relative to the trend. In addition, the circled observations appear to suggest enhanced

[1] See http://www.sfgate.com/cgi-bin/article.cgi?file=/c/a/2007/10/22/MN69STUND.DTL.

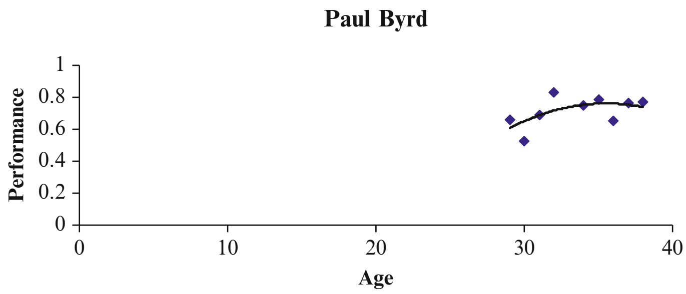

Fig. 10.6 Age–performance profile of Paul Byrd

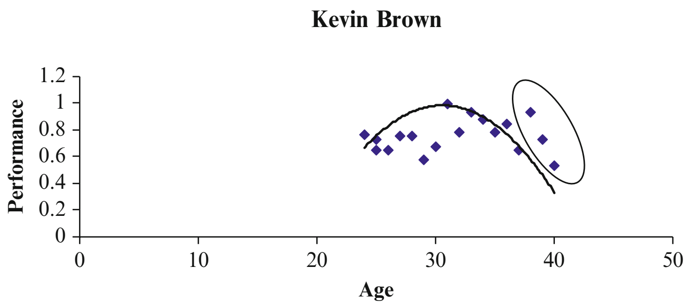

Fig. 10.7 Age–performance profile of Kevin Brown

performance. The associated age of peak performance is estimated to be $Age^* = 30.57$.[2] We note that the circled observations are consistent with the available evidence.

Roger Clemens

Roger Clemens began his career with the Boston Red Sox in 1984 at the age of 21. He played 13 seasons with the Red Sox, winning 192 games with an earned run average of 3.06. During his last season with the Red Sox, Clemens went 10–13 with an earned run average of 3.63. In December 1996, he signed as a free agent with the Toronto Blue Jays. In his first two seasons, he regained his old form, winning 20 games each season and posting an earned run average of 2.05 and 2.65, respectively. In 2002, he signed as a free agent with the New York Yankees and spent five seasons, where he won another 77 games. In 2004, he signed as a free agent with the

[2] Other trends were considered; this appears to provide the most reasonable fit. In order to include the circled observations within the trend, more observations have to be removed, and the age of peak performance increases.

Houston Astros. In his first year, at the age of 41, Clemens won 18 games and had a 2.98 earned run average. In 2005, Clemens posted his lowest earned run average of 1.87, winning 13 games. Overall, Clemens won 354 games with a career earned run average of 3.12. Clemens won 7 Cy Young Awards; he won his first in 1986 and his last in 2004 at the age of 41.

Clemens was implicated as a steroid and/or HGH user by Canseco (2005) and Radomski (2009) and is mentioned nearly 100 times in the Mitchell Report. One of Radomski's customers was Brian McNamee, a bullpen catcher for the New York Yankees (1993–1995). McNamee was hired by the Toronto Blue Jays as its strength and conditioning coach (1998–1999). In 2000, McNamee was hired by the Yankees as an assistant strength and conditioning coach. According to McNamee, he injected Clemens with steroids during the 1998, 2000, and 2001 seasons. McNamee was released by the Yankees after the 2001 season, but he apparently kept working with Clemens. Radomski sold HGH and steroids to McNamee from 2000 to 2004.

Clemens has repeatedly and forcefully denied using performance-enhancing drugs. In January 2008, Randy Hendricks, Clemens' agent, released a report purportedly providing statistical analysis showing Clemens did not take steroids.[3] In the report, they provide comparisons to Randy Johnson, Curt Shilling, and Nolan Ryan (all of whom also pitched during the steroid era). However, comparisons are not made to the great pitchers from the past. Bradlow et al. (2008) provided an alternative analysis by analyzing trajectories assuming a quadratic specification. Their analysis is similar to the age-profile regressions used here; however, they use individual statistics instead of an overall measure of performance. The authors conclude that Clemens' trajectory is atypical and hence, does not provide evidence against performance enhancing drug use.[4]

Clemens age–performance profile is presented in Fig. 10.8. Unlike the other pitchers analyzed, Clemen's profile indicates a tale of two pitchers. Two trends are apparent, both of which are consistent with our expectations if they were not for the

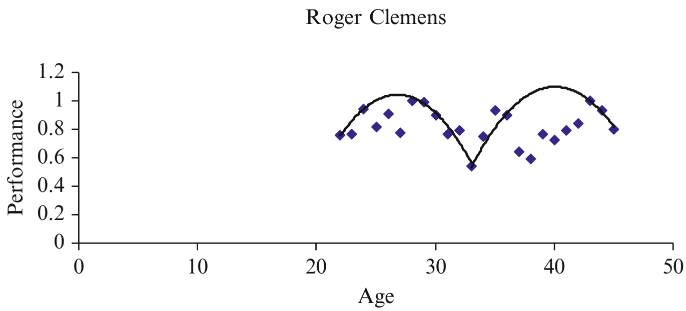

Fig. 10.8 Age–performance profile of Roger Clemens

[3] http://www.rogerclemensreport.com/reports/ClemensReport.pdf.

[4] http://bpp.wharton.upenn.edu/jwolfers/Papers/ClemensAnalysis.pdf.

same pitcher. During August in the 1995 season, Clemens turned 33 years old. The first trend line captures his career from 1984 until 1995. His age of peak performance was estimated to be Age* = 26.81 for this trend. The first trend is indicative of standard performance over a career, but the peak performance of 27 is a few years short of expected. The 1995 season also appears as the starting point for the second trend, which has an estimated Age* = 40.05. The results are consistent with an enhanced performance.

Chuck Finley

Chuck Finley pitched for the California/Anaheim Angels from 1986 through 1999; in these 14 seasons he won 165 games with an earned run average of 3.72. He signed as a free agent with the Cleveland Indians in December 1999. In his two and a half seasons with the Indians, he won an additional 29 games with a 4.59 earned run average. Cleveland traded him to the Cardinals in July 2002. Over his career, he won 200 games with earned run average of 3.85. After filing for divorce from her husband, Tawny Kitaen claimed that Finley used steroids and boasted that he was able to beat MLB steroid tests.

Finley's profile is illustrated in Fig. 10.9. The initial trend line (not shown) had the wrong first and second derivatives. While not as obvious as Clemens' profile, it turns out two trends work well in explaining his performance. Like Clemens, his profile is split at the age of 33 in 1995. The first (second) trend line has a peak age of Age* = 28.37 (36.44). Unlike Clemens, his predicted peak performance declined at the second maximum. The results suggest some enhancement, as suggested by Kitaen. Absent additional information, however, not much more can be said.

Other Steroid-Era Pitchers

In this section, we consider other pitchers who played during the steroid era. Of course, no claim is made regarding the use of performance-enhancing drugs.

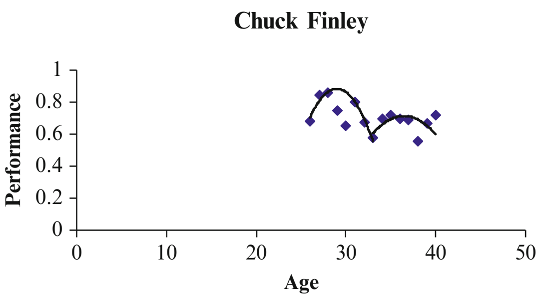

Fig. 10.9 Age–performance profile of Chuck Finley

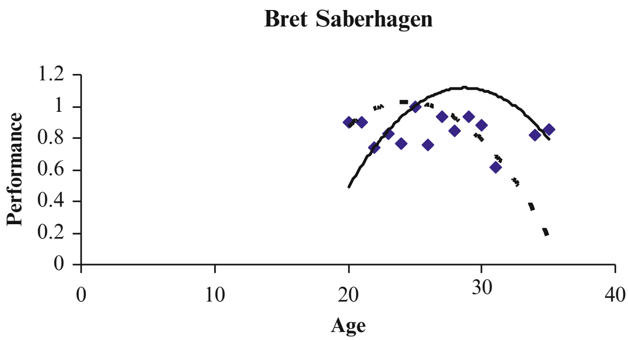

Fig. 10.10 Age–performance profile of Bret Saberhagen

Bret Saberhagen

Bret Saberhagan began his Major League career in 1984 with the Kansas City Royals. Saberhagen won 167 games over 16 seasons with a career earned run average of 3.34. Saberhagen also played for the Mets, the Rockies, and the Red Sox. Saberhagen was a two-time American League Cy Young Award winner and was selected to three all-star games. In 1998, Saberhagen won the AL Comeback Player of the Year Award. Saberhagen's profile is presented in Fig. 10.10.

We consider two trends for Saberhagen. The dashed trend excludes his good seasons in 1998 and 1999. The excluded observations, of course, appear as outliers in this case because we do not observe performance beyond these seasons. The associated peak age of performance was calculated as $Age^* = 24.41$. If instead, we exclude the first two years when he was 20 and 21, we obtain the solid trend line. In this case, the last two seasons are not outliers. Peak age in this case is estimated to be $Age^* = 28.73$. Since this age is below most pitchers peak ages, we should conclude that Saberhagen's performance was not enhanced.

Nolan Ryan

Nolan Ryan began his Major League career in 1966 with the New York Mets at the age of 19. He pitched in only two games. In 1968, he started 10 games, won 6, and had an earned run average of 3.09. Over his career, he pitched in a major league record 27 seasons, recording 324 wins with an earned run average of 3.19. Ryan holds the record for career strikeouts with 5,714. Ryan holds the record with seven no-hitters and is known for his 100+ mph fastball. Ryan's career overlapped with the steroid era, so we include him as a benchmark. His profile is shown in Fig. 10.11.

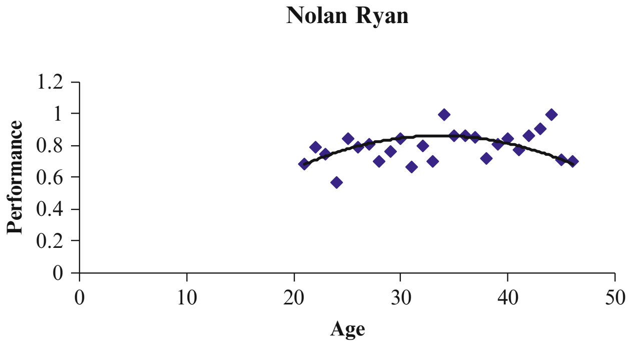

Fig. 10.11 Age–performance profile of Nolan Ryan

Ryan's peak age was estimated to be Age* = 33.54. Based on the trend, there appear to be three enhanced outliers corresponding to the 1990–1992 seasons when he played for the Texas Rangers. Ryan has never been implicated.

Randy Johnson

Randy Johnson started his major league career in 1988 for the Montreal Expos. He was traded the next season to the Seattle Mariners, where he played in ten seasons, winning 130 games with a 3.42 earned run average. In 1998 he was traded to the Houston Astros where he won ten games with a 1.28 earned run average. In December 1998 he signed as a free agent with the Arizona Diamondbacks. In 2002, at the age of 38, Johnson won 24 games while posting a 2.32 earned run average. Johnson later played for the Yankees, the Diamondbacks, and the San Francisco Giants in 2009. In his career, he won 303 games and had a 3.29 earned run average.

Johnson was selected to ten all-star games, won the 1995 American League Cy Young Award, and won the National League Cy Young Award four times (1999, 2000, 2001, and 2002). At the age of 40, Johnson became the oldest pitcher to throw a perfect game. Johnson ranks first all-time in strikeouts per nine innings pitched and second all time with 4,875 strikeouts. Johnson's profile is presented in Fig. 10.12.

After removing some relatively poor performances, we estimated his performance; the resulting trend line is shown. Interestingly, there appear no enhanced outliers; however, his peak age is estimated to be a remarkable Age* = 38.08.

Curt Schilling

Curt Schilling's major league career lasted 20 seasons; he did not start ten games in a season until he pitched for the Philadelphia Phillies in 1992. While with the Phillies, he won 101 games with an earned run average of 3.35. After the Phillies,

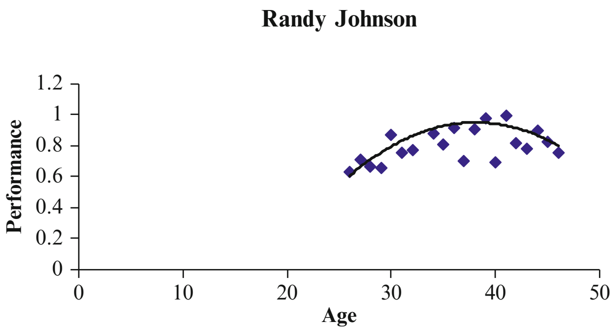

Fig. 10.12 Age–performance profile of Randy Johnson

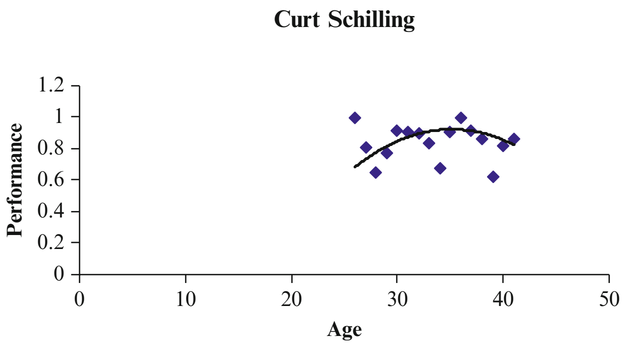

Fig. 10.13 Age–performance profile of Curt Schilling

he played for the Diamondbacks and finished his career with the Red Sox. Overall, his earned run average was 3.46, and he won 216 career games. Schilling was a six-time all-star selection and a member of three World Series champion teams. Schilling's profile is presented in Fig. 10.13. Based on the profile, there are no enhanced outlier years. His age of peak performance is estimated to be $\text{Age}^* = 35.12$. While this appears high, we note that he only pitched in 132.33 innings in his first four seasons, less than the amount he pitched as a regular starter in 1992. Schilling has not been implicated in steroid use.

Pedro Martinez

The final pitcher we consider is Pedro Martinez, who began with the Los Angeles Dodgers. Martinez was a relief pitcher while with the Dodgers became a starter in his third after being traded to the Montreal Expos. In his four season with the Expos, Martinez won 55 games while posting a 3.06 earned run average. After the 1997 season, Montreal traded Martinez to the Boston Red Sox, where he pitched won 117

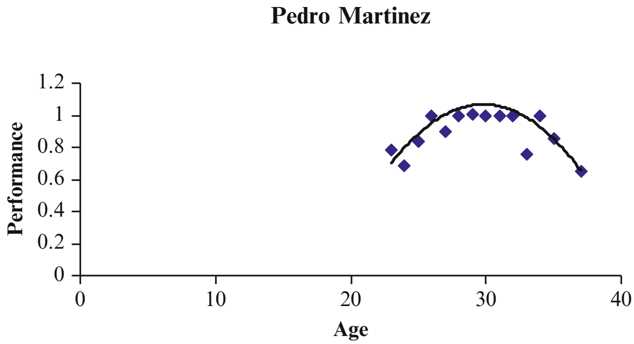

Fig. 10.14 Age–performance profile of Pedro Martinez

games in 7 seasons. Overall, he has won 219 games. His winning percentage of 0.687 is sixth all time. Martinez was an eight-time all-star selection, three-time Cy Young Award winner, a World Series Champion, and won the American League Triple Crown in 1999 at the age of 27. Martinez' profile is presented in Fig. 10.14.

Martinez' profile does not indicate any performance enhancement; his age of peak performance is estimated to be $Age^{*} = 29.80$.

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