Chapter 20
Performance Measurement of Major League Baseball Teams Using Network DEA

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Abstract Data envelopment analysis (DEA) has been extensively applied to measure the performance of individual athletes and teams in a variety of sports as well as to analyze nations competing in the Olympics. Most of the models presented in the literature are single-stage DEA models which treat the underlying process of converting inputs into outputs as a "black box." In many situations, analysts are interested in investigating the sources of inefficiency within the organization in order to improve organizational performance. To accomplish this, researchers have developed two-stage and network DEA methodologies.

In this chapter, we model an MLB team as comprised of a front office operation which consumes money in the form of player salaries to acquire offensive and defensive talent and an on-field operation which uses the talent to outscore opponents and win games. We present a network DEA methodology to measure performance of the front office operation, the on-field operation, and the overall team. Finally, we conduct two industry-wide studies of Major League Baseball which utilize the network DEA methodology.

Keywords Two-stage DEA • Network DEA • Major League Baseball • Efficiency measurement in sports

20.1 Introduction

Baseball is a sport in which two teams, each consisting of nine players, compete on a field referred to as a baseball diamond due to its shape. Each team takes turns on offense (batting) and defense (pitching and playing the field). Traditionally, the visiting team begins on offense. The batting team sends its players one at a time to

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try to hit a hard ball (thrown by a defensive player called a pitcher) with a wooden bat. For a batter to be successful, he must safely arrive at a base, which he can accomplish in several ways. Once the batter arrives safely at a base, he becomes a base runner. A base runner scores a run by advancing four bases and touching home plate. A base runner can advance along the bases by the actions of future batters or by stealing bases.

The defense tries to prevent offensive players from advancing around the bases, which it can accomplish in several ways. Each success by the defense records one out; when three outs are recorded, the teams switch roles (the fielding team becomes the batting team and the batting team becomes the fielding team). When both teams have batted, they have completed one inning. A game consists of nine innings. The winning team is the team that has scored the most runs by the end of the game. If there is a tie at the end of nine innings, the game continues until one team has more runs than the other does at the end of an inning. See Lorimer (2002) for a more extensive discussion on baseball.

Major League Baseball (MLB) is a professional baseball league in the United States and Canada. MLB is made up of two leagues: the National League (NL) and the American League (AL). From 1901 until the early 1960s, each league consisted of eight teams. At this time, each league began to expand. By 1969, each league was comprised of 12 teams, making it necessary to split each league into two divisions. Expansion continued and in 1994, each league further split into three divisions. Currently, MLB is comprised of 30 teams. There are 15 teams in the NL and 15 in the AL. Each of the three divisions within each league contains five teams.

The leagues play under essentially identical rules with one major exception: since the early 1970s, the American League allows the use of a designated hitter who bats in place of the pitcher. This potentially leads to generally greater offensive production in the AL because pitchers are commonly poor batters and designated hitters are often very good offensively.

Prior to 1961, each team played 154 regular season intra-league games. Since then, each team plays 162 regular season games. Until 1997, these games were all intra-league. Since then, each team plays roughly 144 intra-league games and 18 interleague games.

Major League Baseball has become a multi-billion dollar industry with many individual player salaries in the tens of millions of dollars. With so much money at stake, it is important for MLB teams to manage resources efficiently. Thus, in this chapter, we present a model framework for measuring the performance of MLB teams and use it to perform industry-wide analyses of Major League Baseball. Our model framework utilizes recent extensions to the *data envelopment analysis* (DEA) methodology: namely, *two-stage DEA* and *network DEA*. DEA is a linear programming-based methodology that is widely used to evaluate relative efficiency of decision making units (DMUs) in situations in which there are multiple inputs and multiple outputs. Its mathematical development can be traced to Charnes et al. (1978), who built on the work of Farrell (1957) and others.

The remainder of this chapter is organized as follows. The next section surveys the application of DEA in baseball and other sports. In Sect. 20.3, we briefly describe two-stage DEA and network DEA and review the related literature. In Sect. 20.4, we present our network DEA model framework for measuring the efficiency of MLB teams. Section 20.5 presents two previously published MLB industry-wide studies that apply the two-stage and network DEA methodology. Finally, we present concluding remarks in Sect. 20.6.

20.2 DEA in Baseball and Other Sports

DEA has been extensively applied to measure the performance of individual athletes and teams in baseball and other sports as well as nations in the Olympics. In this section we summarize the literature.

20.2.1 DEA in Baseball

Howard and Miller (1993) use DEA to identify underpaid, equitably paid, and overpaid MLB players. For each of the 433 players in the study, stolen bases, games played, at-bats, runs scored, hits, doubles, triples, home runs, runs batted in, batting average, put outs, assists, errors, fielding average, and years in the league are used as the inputs to the DEA model. Player salary is the output of the DEA model. A separate analysis is performed for each position. A reference set for each player is provided from which an equitable salary can be determined.

Mazur (1994) measures efficiency of MLB batters, pitchers, and teams during the 1986, 1987, and 1988 seasons. The author performs separate analyses for each league in each season. The model for batters uses standardized batting average, standardized number of home runs, and standardized number of runs batted in for batters having at least 200 at bats in a given season. These measures define the triple crown frontier (TCF). The model for pitchers uses standardized earned run average, standardized hits to innings pitched ratio, and standardized base on balls to strike-outs ratio for pitchers having at least 100 innings pitched in a given season. These measures define the pitching dominance frontier (PDF). A TCF efficiency score is determined for each batter and team and a PDF efficiency score is determined for each pitcher and team in each season. Regression models for each league and season suggest that a team's TCF efficiency score and a team's PDF efficiency score are significant indicators of its winning percentage.

Anderson and Sharp (1997) present a radial input-oriented CCR DEA model (Charnes et al. 1978) for measuring performance of MLB batters called the Composite Batter Index (CBI). Their model uses one input (plate appearances) and five outputs (dominance transformations of walks, singles, doubles, triples, and home runs). The authors compute CBI scores for players in both the American League and the National League from 1901 to 1993 resulting in 186 analyses. Players with fewer than 350 at-bats with one team in a given season are omitted from the analysis. Historical results indicate that batting has matured over the decades.

Specifically, league-wide CBI scores have increased over time. In addition, the proportion of players with low CBI scores has increased and the proportion of players with high CBI scores has increased over the study period. Finally, the authors develop and test a method for reducing the effect of noise in DEA. Thus allowing the CBI score to estimate a player's skill as opposed to his productivity.

Sueyoshi et al. (1999) present a goal programming model to rank Japanese baseball players in the Central League during the 1995 season. The goal program utilizes the offensive earned-run average (OERA) index (Cover and Keilers 1977) and results from a slack-adjusted DEA. The DEA model uses at-bats and double plays as input measures and singles, doubles, triples, home runs, runs batted in, steals, sacrifices, and walks as output measures. The authors compare the player rankings resulting from the OERA index, the DEA model, and the goal program.

Einolf (2004) applies two BCC DEA models (Banker et al. 1984) to measure efficiency of teams in MLB from 1985 to 2001 and in the National Football League (NFL) from 1981 to 2000. The model for MLB team efficiency has two inputs (total salary paid to position players and total salary paid to pitchers) and three outputs (team wins, team batting average, and team earned-run average). Similarly, the model for NFL team efficiency has two inputs (total salary paid to offensive players and total salary paid to defensive players) and three outputs (team wins, team offensive yards per attempt, and team defensive yards per attempt). The author uses the DEA results to compare the leagues and concludes that, on average, MLB teams are less efficient than NFL teams. MLB teams in large markets tend to spend more and tend to be less efficient than those in small markets. A second conclusion is that, on average, NFL teams became more efficient after the salary cap was introduced.

Hadley and Ruggiero (2006) apply two BCC DEA models (Banker et al. 1984) to determine the contract zone for arbitration-eligible MLB players. One DEA model reflects the player's point of view, measuring worth relative to players who earn more and have relatively lower performance. The other model reflects the owner's point of view, measuring worth relative to players who earn less and have relatively higher performance. A double frontier is generated based on these two models. The authors demonstrate the approach on position players eligible for arbitration between the 2001 and 2002 seasons. They use the contract zone determined by the DEA models and the player's final arbitrated salary to calculate each player's Relative Contract Position (RCP). The RCP is a measure of whether the final arbitrated salary is favorable to the player (RCP close to 1) or to the owner (RCP close to 0). Finally, a tobit regression indicates that player performance is the only significant independent variable in predicting RCP. Player characteristics (race and position), team characteristics (winning percentage and market size), and whether a player is a free agent or arbitration-eligible are unrelated to RCP.

Volz (2009) uses an output oriented BCC DEA model (Banker et al. 1984) and survival time analysis to analyze the effect of minority status on managerial survival in MLB over the period from 1985 to 2006. Team position player salaries, team pitching salaries, and average salary of all other in-division teams are used as the inputs to the DEA model and regular season winning percentage is used as the output of the DEA model. The efficiency scores computed by the DEA are included as covariates in the survival time analysis. The author concludes that on average, minorities are 9.6 % more likely to return the following season. In addition, managerial survival is independent of winning percentage.

20.2.2 DEA in Other Sports

DEA has been used to measure individual and team performance in other sports such as basketball, soccer, and European football. DEA has also been used to measure efficiency of athletes in non-team sports such as golf and tennis. In addition, DEA has been applied to evaluate efficiency of nations competing in the Olympics.

20.2.2.1 Basketball

Fizel and D'Itri (1997, 1999) apply DEA to measure the efficiency of coaches in NCAA Division I college basketball from 1984 to 1991. The DEA models use player talent and opposition power as the inputs and winning percentage as the output. In these studies, the authors examine the importance of team effectiveness (winning percentage) and managerial efficiency on hiring and firing of coaches. Results indicate that, although hiring and firing of coaches is often based on team effectiveness, managerial efficiency may be a better measure when making these decisions.

Cooper et al. (2009) use the two-step procedure for the selection of weights proposed in Cooper et al. (2007) to measure effectiveness of basketball players in the Spanish Premier League. They focus on player outputs such as points scored and percentage of free throw successes and leave out such things as player salaries and other inputs.

20.2.2.2 Soccer and European Football

Haas (2003a) investigates the efficiency of 20 English Premier League clubs during the 2000/2001 season using DEA. The input variables are wage bills for players and coaches and the output variables are points awarded and total revenues. Population of each club's home town is introduced in the model as a site characteristic. The author finds that efficiency and club effectiveness are unrelated. The sensitivity of results is analyzed with regard to different model specifications and variable combinations. In all models at least 25 % of the clubs are on the efficient frontier.

Haas (2003b) applies DEA to measure the technical and scale efficiencies of teams in Major League Soccer (MLS) during the 2000 season. This study uses the same inputs and outputs as in Haas (2003a). Absolute number of spectators is also included as an output. The author finds that efficiency scores are highly correlated with league performance and that the largest part of team inefficiency can be explained by scale inefficiency as opposed to technical inefficiency.

Haas et al. (2004) study the efficiency of football teams in the German Bundeslign during the 1999/2000 season using DEA. The input variables and output variables are the same as those in Haas (2003a). In addition, average stadium utilization is included as an output variable in the model. Findings indicate that efficiency scores are not correlated with effectiveness in the league. Medium-sized and small-sized teams tend to outperform large-sized teams. The authors also decompose the sources of inefficiency into technical inefficiency and scale inefficiency.

Espitia-Escuer and GarcÍa-CebriÁn (2004) use DEA to measure the efficiency of teams in the Spanish First Division from 1998 to 2001. The number of players used, attacking moves, the minutes of possession of the ball, and the shots and headers are the input variables and the number of points achieved is the output variable. The authors conclude that the efficient teams do not always correspond with those that finished highest in the league at the end of the season.

Espitia-Escuer and GarcÍa-CebriÁn (2006) use an output oriented DEA model to evaluate the performance of Spanish First-Division soccer teams between the years 1998 and 2005. The authors use the same inputs and output as in Espitia-Escuer and GarcÍa-CebriÁn (2004). The main finding is that the final league position of a team depends more on its efficient use of resources than on its potential.

Barros and Leach (2006) apply an input oriented DEA model to panel data on English Premier League Football Clubs in the years 1998/1999 to 2002/2003. The authors measure three outputs (points obtained in the season, attendance and turnovers) and four inputs (number of players, wages, net assets, and stadium facilities expenditures). The main conclusion is that the clubs display equivalent managerial skills, but they do not display equivalent scale efficiency.

García-Sánchez (2007) present a three-stage DEA model to measure performance of teams in the Spanish Professional Football League during the 2004/2005 season. The first stage consumes offensive talent (attacking moves, passes to the penalty area and shots at goal) and defensive talent (ball recovery and goalkeeper's actions) as inputs and produces goals scored by the team and the inverse of goals scored by the opposing teams as outputs. The outputs from the first stage determine the inputs to the second stage. The second stage outputs reflect the final ranking of the team. Finally, the third stage input is determined from the output of the second stage and the output is the number of spectators who attended the team's home games. Site characteristics related to province population and stadium size are considered in the third stage of the model. Results indicate that technical inefficiency of the defense is greater than that of the offense. In addition, teams with the most experience are more effective than those with little experience.

Guzmán and Morrow (2007) use an input oriented DEA to measure the efficiency of clubs in the English Premier League from 1997/1998 to 2002/2003. The authors consider two inputs (directors' remuneration and general expenses) and two outputs (points won in a season and total revenue for the corresponding financial year). A second study is performed using the Malmquist productivity index (Malmquist 1953) to measure the change in productivity over the study period.

Results indicate that clubs which were successful on the field achieved relatively low efficiency scores, while other clubs that enjoyed less success on the field were relatively more efficient. In addition, there was little evidence that teams improved their productivity over time.

Boscá et al. (2009) analyze the performance of Italian and Spanish football clubs using DEA during the 2000/2001, 2001/2002, and 2002/2003 seasons. The authors select goals scored as the offensive output, goals conceded as the defensive output, four offensive inputs (shots-on-goal, attacking plays made by the team, passes into the opposing team's centre area, and minutes of possession) and four defensive inputs (the inverse of shots-on-goal made by the opposing team, the inverse of attacking plays made by the opposing team, the inverse of passes to the centre area made by the opposing team, and the inverse of minutes of possession by the opposing team). Results indicate that the Spanish league is more homogeneous and competitive than the Italian league. In addition, to improve competitiveness in the Italian league, it is more important to improve defensive, rather than offensive, efficiency. On the other hand, to improve the ranking in the Spanish league, the best strategy is to improve offensive efficiency when playing at home and then to improve offensive efficiency when playing away from home.

González-Gómez and Picazo-Tadeo (2010) use DEA to measure performance of Spanish professional football teams at competition level (League, King's Cup, and European competitions) from season 2001/2002 to season 2006/2007 and use the results as a proxy of fan satisfaction. The DEA model has three outputs (the points obtained in the league at the end of each season, the number of rounds played in the King's Cup, and the number of matches played in European competitions) and four inputs (the number of players in each season, the average number of spectators per match, the number of seasons played in the First Division, and the trophies in national and international competitions).

20.2.2.3 The Olympics

Lozano et al. (2002) present a variable returns-to-scale DEA model to measure performance of nations competing in five summer Olympic games (from 1984 to 2000). The authors use two inputs (GNP and population of the country under consideration) and three outputs (the numbers of gold, silver, and bronze medals won by the country under consideration). Weights are used to differentiate between the value associated with each medal type.

Churilov and Flitman (2006) use DEA to generate a ranking of the nations that participated in the Sydney 2000 summer games. Their goal is "to design an objective impartial system of analysis of the Olympics results which the majority of participating countries would agree upon as a measuring tool without significant bias." The inputs to the DEA model are population of the country under consideration, its GDP per capita (in U.S. dollars), its disability adjusted life expectancy, and its index of equality of child survival. The model consists of four outputs determined from utility functions on the numbers of gold, silver, and bronze medals won by the country under consideration.

Li et al. (2008) use a variable returns-to-scale context-dependent assurance region DEA model (Cook and Zhu 2008) to “fairly” rank the performance of 78 different nations that participated in six summer Olympics (from 1984 to 2004). Nations are classified into four groups based on wealth. This classification is used to impose the assurance region restrictions. Inputs to the model include population of the country under consideration and its GDP per capita (in U.S. dollars). Outputs are the numbers of gold, silver, and bronze medals won by the country under consideration.

Wu et al. (2009) use cross efficiency evaluation (Sexton et al. 1986) to measure performance of nations that competed in six summer Olympic games (from 1984 to 2004). The authors use the same inputs and outputs as in Li et al. (2008) and weight the outputs as in Lozano et al. (2002).

Wu et al. (2010) use an integer-valued DEA model to evaluate efficiency of nations involved in the Beijing Olympics. The inputs and outputs are the same as those in Li et al. (2008). In this analysis, the target outputs (number of gold, silver, and bronze medals) determined from the DEA must be integer values.

20.2.2.4 Golf and Tennis

Fried et al. (2004) use DEA to measure the efficiency of golfers on the PGA, LPGA, and SPGA tours during the 1998 season. For each golfer, a performance under pressure index and an athletic ability performance index are determined.

Ruiz et al. (2013) use DEA to measure efficiency of professional tennis players. The authors provide an index of the overall performance of players by aggregating the Association of Tennis Professionals (ATP) statistics and compare the results to the ATP rankings.

20.3 Two-Stage and Network DEA

With the exception of García-Sánchez (2007), who presents a three-stage DEA model for teams in the Spanish Professional Football League, the DEA models discussed in the previous section are all variations of the standard single-stage DEA model. Such models treat the production process in which inputs are converted into outputs as a “black box” and provide little insight as to the sources of inefficiency. These single-stage DEA models are appropriate in many situations including when the objective of the study is to rank DMUs based on performance. However, in many other situations, analysts and DMU managers seek more detailed information to assist them in improving managerial performance.

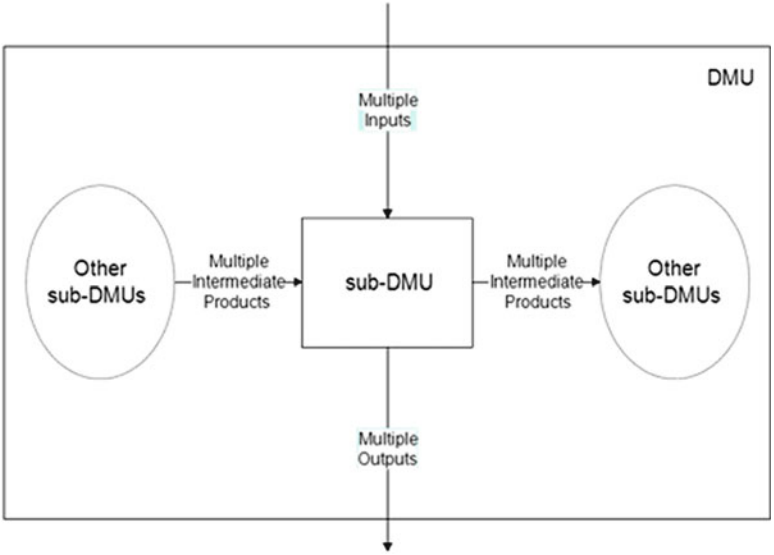

Fig. 20.1 Internal structure of a DMU in a network DEA model

20.3.1 Two-Stage and Network DEA Methodology

To address this issue, researchers have proposed two-stage and network DEA models. In network DEA, each DMU is comprised of two or more sub-DMUs. Each resource consumed by a sub-DMU either enters the DMU from outside (input to the DMU) or is produced by another sub-DMU (intermediate product). Each product produced by a sub-DMU either exits the DMU (output of the DMU) or is consumed by another sub-DMU (intermediate product). Figure 20.1 shows the internal structure of a DMU in a network DEA model. The DMU is a directed acyclic graph in which the nodes correspond to sub-DMUs and the arcs correspond to inputs to the DMU, outputs from the DMU, or intermediate products from one sub-DMU to another.

In this chapter, we apply the two-stage methodology and network DEA methodology proposed by Sexton and Lewis (2003) and Lewis and Sexton (2004a), respectively. The methodologies allow the analyst to measure the efficiency of each sub-DMU as well as the efficiency of the DMU itself. To measure the efficiency of a given sub-DMU, solve a standard single-stage DEA model for the sub-DMU. To evaluate the DMU-level efficiency use the directed acyclic structure of the underlying graph to identify a partial order of the sub-DMUs. Resolve the DEA model for each sub-DMU in accordance with the partial order, assuming that all sub-DMUs that precede the sub-DMU under analysis are efficient. Then, for an input (output) oriented model, the DMU-level efficiency (inverse efficiency) is the largest (smallest) of the ratios, computed for each input (output) of what could have been consumed (produced) to what was actually consumed (produced).

20.3.2 Two-Stage and Network DEA Literature

Over the past two decades, several papers have been published on the theory, methodology, and application of two-stage and network DEA. Färe and Whittaker (1995) apply an input oriented two-stage DEA model to study relative efficiency of dairy production. Seiford and Zhu (1999) evaluate the performance of 55 U.S. commercial banks using a two-stage network DEA model. In another study, Färe and Grosskopf (2000) present a network DEA model for the Swedish Institute for Health Economics. Zhu (2000) applies two-stage network DEA to develop a multi-factor financial performance model to examine Fortune Global 500 companies. Castelli et al. (2001) describe a DEA-like model that evaluates the efficiencies of each of a number of interdependent sub-DMUs within a larger DMU. Their analysis assesses sub-DMU efficiency relative to other sub-DMUs within the same DMU. Chen and Zhu (2004) develop an efficiency model that identifies the efficient frontier of a two-stage production process linked by intermediate measures. They illustrate the approach on a set of firms in the banking industry. Yang (2006) creates a two-stage DEA model to provide managerial insights for the Canadian life and health insurance industry. Chen et al. (2006) contend that two-stage DEA with a single intermediate product can behave as a parametric linear model. They develop a nonlinear DEA model to evaluate the impact of information technology on multiple stages of a business operation along with information on how to distribute IT-related resources so that efficiency is achieved. Färe et al. (2007) survey network DEA models and present three network DEA examples. Liang et al. (2008) examine and extend the two-stage DEA model using game theory concepts. They also investigate the relationship among non-cooperative, centralized, and standard DEA approaches. Kao and Hwang (2008) develop a two-stage DEA model and apply it to measure efficiency of non-life insurance companies in Taiwan. Chen et al. (2009a) develop an additive efficiency decomposition approach to generalize the two-stage DEA model presented by Kao and Hwang (2008). Chen et al. (2009b) examine the relationship and equivalence between the two-stage DEA approaches of Chen and Zhu (2004) and Kao and Hwang (2008). Tone and Tsutsui (2009) present a slacks-based measure approach to network DEA that applies to differing model orientations. They demonstrate their methodology by measuring the efficiency of electric power companies. Chen et al. (2010) develop an approach for determining the frontier points for inefficient DMUs within the framework of two-stage DEA. Tone and Tsutsui (2010) present a dynamic slacks-based measure model that can evaluate the overall efficiency of the DMUs as well as the efficiencies of the individual sub-DMUs in a network DEA. In a survey paper, Cook et al. (2010) review and classify several two-stage network DEA structures. In many of these models, the first stage processes the DMU's inputs into intermediate products and the second stage converts the intermediate products into outputs. Lewis and Mazvancheryl (2011) develop a network DEA model to measure the efficiency of the customer satisfaction process and apply it to the automobile industry. Holod and Lewis (2011) present a two-stage DEA model to measure efficiency of bank holding companies which resolves a long time dilemma by treating deposits as an intermediate product as opposed to an input or an output to the process. Mallikarjun et al. (2013) study the relationship between efficiency and government subsidization of the U.S. commuter rail system using an unoriented network DEA model.

20.4 Network DEA Model for a Major League Baseball Team

Sexton and Lewis (2003) present a sequential two-stage DEA model for measuring the efficiency of MLB teams. Each MLB team consists of a front office operation and an on-field operation. The methodology provides efficiency scores for the front office operation and the on-field operation as well as the overall organization. The two-stage methodology is then extended in Lewis and Sexton (2004a) to a network DEA model which allows for efficiency measurement of organizations with more complex internal structures. The network DEA model further divides the front office operation and on-field operation of an MLB team. The two-stage and network DEA methodologies allow for constant or variable returns-to-scale processes and permit input oriented or output oriented models. In addition, Lewis et al. (2013) present an unoriented two-stage DEA methodology and apply it to measure efficiency of MLB teams during the 2009 season.

Figure 20.2 presents our network representation of an MLB team. The front office operation consumes money in the form of position player and pitcher salaries to acquire offensive and defensive talent. The on-field operation uses this talent to score runs and to prevent the team's opponents from scoring runs in order to win games.

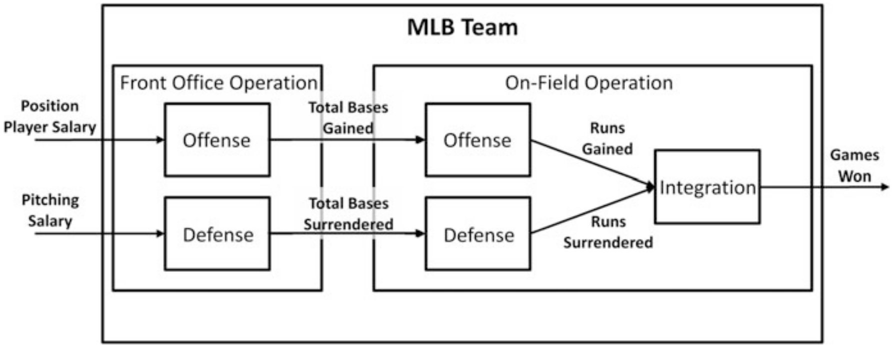

Fig. 20.2 Network model of an MLB team consisting of a front office operation and an on-field operation

20.4.1 Inputs, Intermediate Products, and Outputs

Total player salary (*TPS*) of a team in a season consists of position player salaries (*POS*) which reflect the offense and pitching salaries (*PIT*) which reflect the defense. Offensive talent can be measured by total bases gained (*TBG*) by the team in a season. MLB uses a statistic called total bases (*TB*) to measure offensive performance. Specifically, MLB's definition of total bases for a team in a season is $TB = S + 2D + 3T + 4HR$ where *S* is the number of singles, *D* is the number of doubles, *T* is the number of triples, and *HR* is the number of home runs hit by the team. We extend this definition by adding *BB*, the number of walks received by the team and *E*, the number of fielding errors committed by the opposing team. Thus, $TBG = TB + BB + E$. We point out that, with the exception of the relatively rare hit by pitch and catcher, fielder, or umpire interference, our definition of *TBG* includes all the ways in which a batter can reach first base without an out being recorded. We recognize that not every error results in the batter reaching first base. However, each error results in at least one runner (and in many cases the batter) advancing at least one base. We elect to model errors as the approximate equivalent of singles and walks. Defensive talent can be measured by total bases surrendered (*TBS*) to the team's opponents in a season. We define *TBS* identically to *TBG* except that the summands refer to the number of such hits and walks surrendered by the team, and the number of fielding errors committed by the team, in the given season. Runs gained (*RG*) is the number of runs scored by the team in a season. Runs surrendered (*RS*) is the number of runs scored by the team's opponents in a season. We note that *TBS* and *RS* are "reverse quantities," in the sense that larger values correspond to less, rather than more, defensive contribution. We use the methodology developed by Lewis and Sexton (2004b) to incorporate reverse quantities in our models. The output of the process is games won (*GW*) by the team in a season. We note that various inputs, intermediate products, and outputs may be aggregated or disaggregated and sub-DMUs may be split or combined depending on the analyst's preferences and the data available.

20.4.2 Model Orientation and Returns-to-Scale

We select an output orientation for each MLB team as well as its front office operation and its on-field operation because we feel that the appropriate improvement for an inefficient team is to increase the number of games it wins rather than decrease its total player salary. This orientation is consistent with each team's long-term goal of qualifying for post-season play. The input orientation would imply that all teams seek to hold its games won at current levels, an assumption that, we believe, contradicts the fundamental competitive nature of baseball teams. We recognize that individual teams may make economic decisions to spend less (or more) on player salaries. However, we see this as a scale change, not evidence of an input orientation.

We select a variable returns-to-scale model for the front office operation because of the "threshold" nature in which player salaries result in offensive and defensive production. At very low levels of player salary, we expect the marginal return to be less than the average return. Low budget teams will tend to sign weaker players and yet must conform to minimum salary levels set by the Major League Baseball Players Association contract with MLB. Below a certain threshold, therefore, we expect non-increasing returns-to-scale. Eventually, as player salary increases beyond this threshold, the team is better able to sign superior players who contribute significantly on the field. Here we expect non-decreasing returns-to-scale. At very high salary levels, we again expect the marginal return to be less than the average return. Superstar players who command the highest salaries are unlikely to provide offensive and defensive performance commensurate with their salaries. Above a second threshold, therefore, we expect non-increasing returns-to-scale.

We select a variable returns-to-scale model for the on-field operation because of the "threshold" nature in which offensive and defensive performance combine to win games. At very low levels of total bases gained and total bases surrendered, we would expect the marginal return to be less than the average return. Weak teams are likely to lose many games by several runs and therefore experience only a small increase in games won for a given increase in offensive and defensive performance. Below a certain threshold, therefore, we expect non-increasing returns-to-scale. Eventually, as performance increases beyond this threshold, the average margin of loss diminishes and the marginal return increases as the team begins to win some close games that they would otherwise have lost. Here we expect non-decreasing returns-to-scale. At very high levels of total bases gained and total bases surrendered, we again expect the marginal return to be less than the average return. Strong teams are likely to win many games by several runs and would therefore experience only a small increase in games won for a given increase in offensive and defensive performance. Above a second threshold, therefore, we expect non-increasing returns-to-scale. In addition, the limit on the number of games that a team can win – it cannot win more than it plays – must lead eventually to non-increasing returns-to-scale. Given our selection of variable returns-to-scale in both the front office operation and the on-field operation, we select a variable returns-to-scale model for the MLB organization.

20.4.3 Network DEA Model Formulation

Let POS_j be the total salary remunerated to position players by team j in a season, PIT_j be the total salary remunerated to pitchers by team j in a season, TBG_j be the total bases gained by team j in a season, TBS_j be the total bases surrendered by team j in a season, RG_j be the runs gained by team j in a season, RS_j be the runs surrendered by team j in a season, and GW_j be the games won by team j in a season. Define θ_{1k} to be the inverse efficiency of the front office offense for team k, ε_{2k} to be the efficiency of the front office defense for team k, θ_{3k} to be the inverse efficiency of the on-field offense for team k, ε_{4k} to be the efficiency of the on-field defense for team k, and θ_{5k} to be the inverse efficiency of the on-field integration for team k. Further, define λ_{1j} to be the weight placed on the front office offense of team j by team k, λ_{2j} to be the weight placed on the front office defense of team j by team k, λ_{3j} to be the weight placed on the on-field offense of team j by team k, λ_{4j} to be the weight placed on the on-field defense of team j by team k, and λ_{5j} to be the weight placed on the on-field integration of team j by team k.

The output oriented variable returns-to-scale model for the front office offense is:

$$
\begin{aligned}
&\text{Max } \theta_{1k} \\
&\text{s.t.} \\
&\quad \sum_{j=1}^{n} \lambda_{1j} POS_j \le POS_k \\
&\quad \sum_{j=1}^{n} \lambda_{1j} TBG_j \ge \theta_{1k} TBG_k \\
&\quad \sum_{j=1}^{n} \lambda_{1j} = 1 \\
&\quad \lambda_{1j} \ge 0; \quad j = 1, 2, \ldots, n \\
&\quad \theta_{1k} \ge 0
\end{aligned}
$$

The output oriented variable returns-to-scale model for the front office defense is:

$$
\begin{aligned}
&\text{Min } \varepsilon_{2k} \\
&\text{s.t.} \\
&\quad \sum_{j=1}^{n} \lambda_{2j} PIT_j \le PIT_k \\
&\quad \sum_{j=1}^{n} \lambda_{2j} TBS_j \le \varepsilon_{2k} TBS_k \\
&\quad \sum_{j=1}^{n} \lambda_{2j} = 1 \\
&\quad \lambda_{2j} \ge 0; \quad j = 1, 2, \ldots, n \\
&\quad \varepsilon_{2k} \ge 0
\end{aligned}
$$

The output oriented variable returns-to-scale model for the on-field offense is:

$$
\begin{aligned}
&\text{Max } \theta_{3k} \\
&\text{s.t.} \\
&\quad \sum_{j=1}^{n} \lambda_{3j} TBG_j \leq TBG_k \\
&\quad \sum_{j=1}^{n} \lambda_{3j} RG_j \geq \theta_{3k} RG_k \\
&\quad \sum_{j=1}^{n} \lambda_{3j} = 1 \\
&\quad \lambda_{3j} \geq 0; \quad j = 1, 2, \ldots, n \\
&\quad \theta_{3k} \geq 0
\end{aligned}
$$

The output oriented variable returns-to-scale model for the on-field defense is:

$$
\begin{aligned}
&\text{Min } \varepsilon_{4k} \\
&\text{s.t.} \\
&\quad \sum_{j=1}^{n} \lambda_{4j} TBS_j \geq TBS_k \\
&\quad \sum_{j=1}^{n} \lambda_{4j} RS_j \leq \varepsilon_{4k} RS_k \\
&\quad \sum_{j=1}^{n} \lambda_{4j} = 1 \\
&\quad \lambda_{4j} \geq 0; \quad j = 1, 2, \ldots, n \\
&\quad \varepsilon_{4k} \geq 0
\end{aligned}
$$

The output oriented variable returns-to-scale model for the on-field integration is:

$$
\begin{aligned}
&\text{Max } \theta_{5k} \\
&\text{s.t.} \\
&\quad \sum_{j=1}^{n} \lambda_{5j} RG_j \leq RG_k \\
&\quad \sum_{j=1}^{n} \lambda_{5j} RS_j \geq RS_k \\
&\quad \sum_{j=1}^{n} \lambda_{5j} GW_j \geq \theta_{5k} GW_k \\
&\quad \sum_{j=1}^{n} \lambda_{5j} = 1 \\
&\quad \lambda_{5j} \geq 0; \quad j = 1, 2, \ldots, n \\
&\quad \theta_{5k} \geq 0
\end{aligned}
$$

To determine the organizational inverse efficiency for team k, we use the network DEA methodology presented in Lewis and Sexton (2004a). Let $TBG_k^* = \sum_{j=1}^{n} \lambda_{1j}^* TBG_j$

and $TBS_k^* = \sum_{j=1}^{n} \lambda_{2j}^* TBS_j$ where λ_{1j}^* and λ_{2j}^* are the optimal weights obtained when solving the front office offense model for team k and the front office defense model for team k, respectively. We next resolve the on-field offense model for team k using TBG_k^* as the RHS of the first constraint and resolve the on-field defense model for team k using TBS_k^* as the RHS of the first constraint.

$$
\begin{aligned}
&\text{Max } \theta_{3k} \\
&\text{s.t.} \\
&\quad \sum_{j=1}^{n} \lambda_{3j} TBG_j \leq TBG_k^* \\
&\quad \sum_{j=1}^{n} \lambda_{3j} RG_j \geq \theta_{3k} RG_k \\
&\quad \sum_{j=1}^{n} \lambda_{3j} = 1 \\
&\quad \lambda_{3j} \geq 0; \quad j = 1, 2, \ldots, n \\
&\quad \theta_{3k} \geq 0 \\
&\text{Min } \varepsilon_{4k} \\
&\text{s.t.} \\
&\quad \sum_{j=1}^{n} \lambda_{4j} TBS_j \geq TBS_k^* \\
&\quad \sum_{j=1}^{n} \lambda_{4j} RS_j \leq \varepsilon_{4k} RS_k \\
&\quad \sum_{j=1}^{n} \lambda_{4j} = 1 \\
&\quad \lambda_{4j} \geq 0; \quad j = 1, 2, \ldots, n \\
&\quad \varepsilon_{4k} \geq 0
\end{aligned}
$$

Let ${}^*RG_k^* = \sum_{j=1}^{n} {}^*\lambda_{3j}{}_{3j}^* RG_j$ where ${}^*\lambda_{3j}^*$ are the optimal weights obtained when solving the on-field offense model for team k, assuming the front office offense is efficient and ${}^*RS_k^* = \sum_{j=1}^{n} {}^*\lambda_{4j}^* RS_j$ where ${}^*\lambda_{4j}^*$ are the optimal weights obtained when solving the on-field defense model for team k, assuming the front office defense is efficient. We next resolve the on-field integration model for team k using ${}^*RG_k^*$ and ${}^*RS_k^*$ as the RHS of the first and second constraints, respectively.

$$
\begin{aligned}
&\text{Max } \theta_{5k} \\
&\text{s.t.} \\
&\quad \sum_{j=1}^{n} \lambda_{5j} RG_j \leq {}^{*}RG_k^{*} \\
&\quad \sum_{j=1}^{n} \lambda_{5j} RS_j \geq {}^{*}RS_k^{*} \\
&\quad \sum_{j=1}^{n} \lambda_{5j} GW_j \geq \theta_{5k} GW_k \\
&\quad \sum_{j=1}^{n} \lambda_{5j} = 1 \\
&\quad \lambda_{5j} \geq 0; \quad j = 1, 2, \ldots, n \\
&\quad \theta_{5k} \geq 0
\end{aligned}
$$

Finally, let ${}^{*}GW_k^{*} = \sum_{j=1}^{n} {}^{*}\lambda_{5j}{}_{5j}^{*} GW_j$ where ${}^{*}\lambda_{5j}^{*}$ are the optimal weights obtained when solving the on-field integration model for team k, assuming the front office offense, the front office defense, the on-field offense, and the on-field defense are all efficient. The organizational (overall team) inverse efficiency for team k is $\theta_k = {}^{*}GW_k^{*}/GW_k$.

20.4.4 Extension to Other Team Sports

The model can be applied to measure the performance of teams in other sports. In football, for example, total player salary (*TPS*) of a team in a season consists of offensive team salary (*OS*), defensive team salary (*DS*), and special team salary (*SS*). Offensive talent can be measured by total yards gained (*TYG*) by the team in a season. *TYG* is the sum of passing and rushing yards gained (while on offense), kickoff and punt return yards gained (while on special teams), interception and fumble return yards gained (while on defense) and penalty yards gained (while on offense or special teams) by the team in a season. Defensive talent can be measured by total yards surrendered (*TYS*) to the team's opponents in a season. *TYS* is the sum of passing and rushing yards surrendered (while on defense), kickoff and punt return yards surrendered (while on special teams), interception and fumble return yards surrendered (while on offense) and penalty yards surrendered (while on defense or special teams) to the team's opponents in a season. Points gained (*PG*) is calculated from the number of touchdowns, extra points, two-point conversions, field goals, and safeties scored by the team in a season. Points surrendered (*PS*) is calculated from the number of touchdowns, extra points, two-point conversions, field goals, and safeties scored by the team's opponents in a season. The output of the process is games won (*GW*) by the team in a season.

20.5 Two Studies of MLB Using Two-Stage and Network DEA

In this section, we present two published studies which apply two-stage and network DEA models to measure MLB team efficiency. The first study (Lewis et al. 2007) is published in the *Journal of Sports Economics*. The second study (Lewis et al. 2009) is published in the *European Journal of Operational Research*.

20.5.1 Player Salaries, Organizational Efficiency, and Competitiveness in MLB

In this study published in the *Journal of Sports Economics* (Lewis et al. 2007), we use a two-stage DEA model as part of a larger analysis to determine the minimum total player salary required for a team to be competitive for each season and count the number of teams that are noncompetitive due to low total player salary in each season. Next, we determine the salary at which a team is overspending on total player salary for each season and count the number of teams that overspend on total player salary in each season. Finally, we examine the relationship between market size, efficiency, and competitiveness. The study period is the non-strike seasons from 1985 to 2002.

20.5.1.1 Motivation and Research Questions

MLB, unlike other business enterprises, depends on stiff competition for economic survival. Baseball is entertainment; tight division races, unpredictable playoff series, and the periodic emergence of new champions enhance the entertainment value of the sport, ensuring the league's future fan base. However, while individual teams need the league to succeed, winning is the key to their economic success. Winning increases fan interest, brings more people to the ballpark, improves television ratings, and bolsters sales of team-related merchandise, all of which add to the team's prosperity.

Baseball entered the era of free agency on December 23, 1975, and player salaries have since grown to extraordinary levels. In 1975, the average player salary was $44,676; in 2002, it was $2,384,779, an average annual growth rate of nearly 16 % per year (nearly 11 % per year adjusted for inflation) for 27 years. During this period, MLB grew by 25 %, expanding from 24 to 30 teams. Some teams, notably those located in larger markets and those possessing greater financial resources, found it easier than other teams to sign free agents to high-salary, multi-year contracts, thereby cornering the market on the most talented players and threatening the competitive balance on the field.

In July 2000, the *Commissioner's Blue Ribbon Panel on Baseball Economics* (Levin et al. 2000) reported on the revenue disparities in MLB. The Panel found that these disparities were affecting competition, that the disparities were becoming worse, and that the limited revenue sharing and payroll taxes approved in the 1996 labor agreement with the players were having little effect. Moreover, the Panel concluded that the cost of trying to be competitive was raising ticket and concession prices, jeopardizing MLB's position as the affordable family spectator sport. The Panel's recommendations included greater revenue sharing and a competitive balance tax, both of which are part of the 2002 labor agreement with the players.

In 2002, the total player salary for the New York Yankees was $125.93 million while that of the Tampa Bay Devil Rays was $34.38 million. With one team's total player salary equal to 3.66 times that of another team, it is reasonable to ask whether the team with the lower salary can effectively compete with the team with the higher salary, and the extent to which market size influences competitiveness. More specifically, we pose the following research questions for the study period:

1. How much does a team need to spend on total player salary to be competitive?
2. What is the maximum total player salary that a team can pay without overspending?
3. How many teams are noncompetitive due to low total player salary?
4. How many teams are overspending on total player salary?
5. How does noncompetitiveness due to low total player salary relate to market size?
6. How does overspending on total player salary relate to market size?

20.5.1.2 Study Methodology

We present an overview of the study methodology in Fig. 20.3. In a given season, we apply two-stage DEA to measure the relative efficiency of each MLB team. We use a logistic regression model to classify teams as competitive versus noncompetitive. For each season, we use the Gini index to determine the minimum total player salary to be competitive and the maximum total player salary without overspending. Finally, we model the transitions of teams among the competitive and noncompetitive states according to a Markov process.

On page 5 of the report (Levin et al. 2000), the Commissioner's Blue Ribbon Panel defines *competitive balance* as the state in which "... every well-run club has a regularly recurring reasonable hope of reaching post-season play." Our analysis entails parsing this statement into operational definitions of "well-run" and "reasonable hope of reaching post-season play."

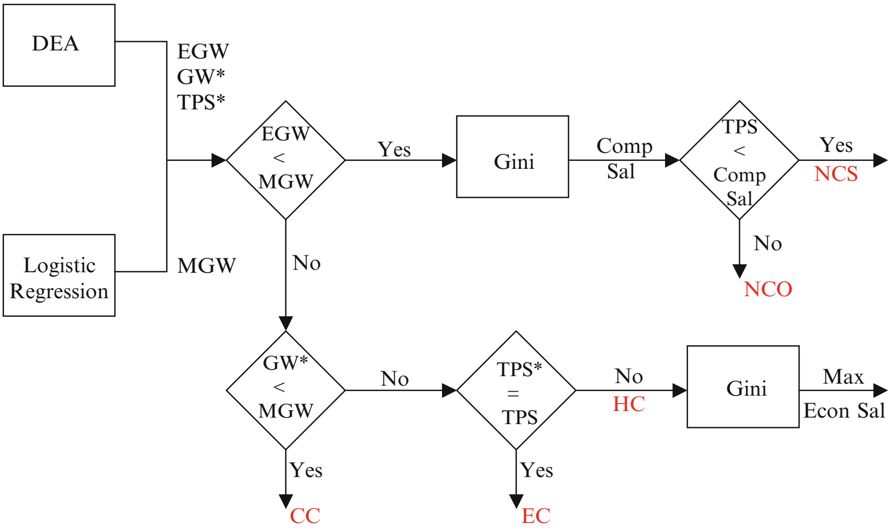

Fig. 20.3 An overview of the methodology used in this study to classify MLB teams

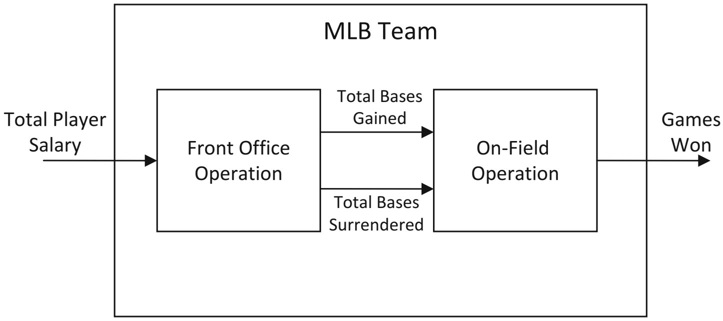

Fig. 20.4 Sequential two-stage model of an MLB team consisting of a front office operation and an on-field operation

Efficiency Measurement

To define “well-run,” we turn to the theory of productive efficiency in the management science and economics literature. We apply the two-stage DEA methodology described in Sexton and Lewis (2003) to compute the efficiency of every MLB team in the study period relative to the frontier created by all other teams in the same season. The two-stage production model is presented in Fig. 20.4.

Define λ_{1j} to be the weight placed on the front office operation of team j by the front office operation of team k, λ_{2j} to be the weight placed on the on-field operation of team j by the on-field operation of team k, λ_j to be the weight placed on the team j by team k when determining the organizational inverse efficiency of team k, ε_{1k} to be the efficiency of the front office operation of team k, θ_{1k} to be the inverse efficiency of the front office operation of team k, θ_{2k} to be the inverse efficiency of the on-field operation of team k, and θ_k to be the organizational inverse efficiency of team k.

First, we solve the following DEA model to determine the front office inverse efficiency of team k:

$$
\begin{aligned}
&\text{Max } \theta_{1k} \\
&\text{s.t.} \\
&\quad \sum_{j=1}^{n} \lambda_{1j} TPS_j \leq TPS_k \\
&\quad \sum_{j=1}^{n} \lambda_{1j} TBG_j \geq \theta_{1k} TBG_k \\
&\quad \sum_{j=1}^{n} \lambda_{1j} TBS_j \leq \varepsilon_{1k} TBS_k \\
&\quad \theta_{1k}\varepsilon_{1k} = 1 \\
&\quad \sum_{j=1}^{n} \lambda_{1j} = 1 \\
&\quad \lambda_{1j} \geq 0; \quad j = 1, 2, \ldots, n \\
&\quad \theta_{1k}, \varepsilon_{1k} \geq 0
\end{aligned}
$$

Next, we solve the following DEA model to determine the on-field inverse efficiency of team k:

$$
\begin{aligned}
&\text{Max } \theta_{2k} \\
&\text{s.t.} \\
&\quad \sum_{j=1}^{n} \lambda_{2j} TBG_j \leq TBG_k \\
&\quad \sum_{j=1}^{n} \lambda_{2j} TBS_j \geq TBS_k \\
&\quad \sum_{j=1}^{n} \lambda_{2j} GW_j \geq \theta_{2k} GW_k \\
&\quad \sum_{j=1}^{n} \lambda_{2j} = 1 \\
&\quad \lambda_{2j} \geq 0; \quad j = 1, 2, \ldots, n \\
&\quad \theta_{2k} \geq 0
\end{aligned}
$$

Let $TBG_k^* = \sum_{j=1}^{n} \lambda_{1j}^* TBG_j$ and $TBS_k^* = \sum_{j=1}^{n} \lambda_{1j}^* TBS_j$ where λ_{1j}^* are the optimal weights obtained when solving the front office model for team k. Then, we solve the following DEA model to determine the organizational inverse efficiency for team k using TBG_k^* and TBS_k^* as the RHS of the first and second constraints, respectively:

$$\begin{aligned}
&\text{Max } \theta_k \\
&\text{s.t.} \\
&\quad \sum_{j=1}^{n} \lambda_j TBG_j \leq TBG_k^* \\
&\quad \sum_{j=1}^{n} \lambda_j TBS_j \geq TBS_k^* \\
&\quad \sum_{j=1}^{n} \lambda_j GW_j \geq \theta_k GW_k \\
&\quad \sum_{j=1}^{n} \lambda_j = 1 \\
&\quad \lambda_j \geq 0; \quad j = 1, 2, \ldots, n \\
&\quad \theta_k \geq 0
\end{aligned}$$

We compute the number of games each team would have won had it been efficient, i.e., the team's efficient games won (*EGW*), using the formula $EGW = {}^*GW_k^* = \sum_{j=1}^{n} {}^*\lambda_j^* GW_j$, where $*\lambda_j^*$ are the optimal weights obtained when solving the organizational model for team k, assuming the front office is efficient. The organizational (overall team) inverse efficiency for team k is $\theta_k = {}^*GW_k^* / GW_k$.

Logistic Regression

We interpret the phrase "reasonable hope of reaching post-season play" to mean that a team must have at least the same probability of reaching post-season play as it would have if all teams in its league were equally talented. We refer to this probability as the team's *balanced probability*. The balanced probability for a given team in a given season depends on the playoff qualification condition in effect. Before 1969, the two leagues had no division structure and only the league champions qualified for post-season play. Thus, the balanced probability for a team before 1969 depended on only the number of teams in its league. Between 1969 and 1993, each league consisted of two divisions and each division winner qualified for post-season play. During this period, the balanced probability for a team depended on only the number of teams in the team's division. Since 1994, each league consists of three divisions. Between 1994 and 2011, each division winner qualified for post-season play, as does the "wild card" team, which is the non-division winner with the highest winning percentage in the league. Thus, between 1994 and 2011, the balanced probability for a team depends on both the number of teams in its division and the number of teams in its league.

For each of the playoff qualification conditions, we compute its balanced probability. We interpret each probability as the minimum probability of qualifying for post-season play that a team must achieve to be competitive under its playoff qualification condition.

Next, we construct a logistic regression model for a team's probability of qualifying for post-season play. We use data for the seasons 1903 through 2002 (except 1904, when there was no post-season, and the strike seasons 1981, 1994, and 1995). For each team in each season, we use *GW* as the independent variable and a binary indicator variable equal to 1 if the team qualified for post-season play in that season, or equal to zero if it did not qualify. We also include indicator variables that identify the playoff qualification condition that applied to the league and division in which the team played in that season. Therefore, the logistic regression computes a team's probability of qualifying for post-season play given its number of games won and the playoff qualification condition that applied to the league and division in which the team played in that season.

We use the logistic regression model to compute *MGW*, the minimum number of games a team must win to be competitive under each playoff qualification condition. Thus, a team is competitive if and only if it would have won at least *MGW* had it been efficient. In other words, we say that a team is competitive if and only if $EGW \geq MGW$.

Gini Index

We then determine the minimum total player salary needed to be competitive in each season, which we call the *competitive salary* for that season. To do this, within each season, we sort the teams according to total player salary from low to high and use the Gini index to identify a total player salary that partitions the teams into two sets, one of which consists primarily of competitive teams and one of which consists primarily of noncompetitive teams. The competitive salary in that season is the total player salary of the lowest paid team in the primarily competitive set.

We now partition the noncompetitive teams into two groups:

- **Noncompetitive Due to Low Total Player Salary (NCS)**: A noncompetitive team is *noncompetitive due to low total player salary* if its total player salary is less than the competitive salary.
- **Noncompetitive for Other Reasons (NCO)**: A noncompetitive team is *noncompetitive for other reasons* if its total player salary is greater than the competitive salary.

Next, we analyze the competitive teams. In order to do this, we need to provide more definitions. Define GW^* to be the number of games that an efficient on-field operation would have won given the actual performance of the front office. We note that $GW \leq GW^* \leq EGW$. We obtain GW^* from the DEA of the on-field operation of the two-stage model. Let TPS^* be the total player salary of the efficient front office operation. We note that $TPS^* \leq TPS$. We obtain TPS^* from the DEA of the front office operation.

We now partition the competitive teams into three groups:

- **Conditionally Competitive (CC)**: A competitive team is *conditionally competitive* if $GW^* < MGW$. The team is spending enough money on total player salary but inefficiency in the front office has resulted in insufficient player performance to win enough games to achieve the balanced probability of qualifying for post-season play. The front office must become more efficient for this to happen. We note that a conditionally competitive team may be overspending on player salaries if $TPS^* < TPS$.
- **Economically Competitive (EC)**: A competitive team is *economically competitive* if $GW^* \geq MGW$ and $TPS^* = TPS$. The team has sufficient player performance on the field to achieve the balanced probability of qualifying for post-season play. Moreover, there is no evidence that the team is overspending on total player salary.
- **Hypercompetitive (HC)**: A competitive team is *hypercompetitive* if $GW^* \geq MGW$ and $TPS^* < TPS$. The team has sufficient player performance on the field to achieve the balanced probability of qualifying for post-season play. However, there is evidence that the team is overspending on total player salary.

We use the Gini index again, this time to determine the value of total player salary that partitions hypercompetitive teams from other teams. We call this value of total player salary the *hypercompetitive salary* for the given season.

Markov Analysis

Finally, we model the transitions of teams among these five states (NCS, NCO, CC, EC, and HC) according to a Markov process. We test the five row distributions for statistical independence and compute the steady-state probabilities and the mean first passage times from each state to each other state.

20.5.1.3 Data for the Study

We obtain market size data from the *United States Census Bureau* and *Statistics Canada*. We extract player salary data from the *USA Today Website*. We gather games won, whether the team qualified for post-season play, and the team performance data required to compute total bases gained and total bases surrendered from the *Baseball Archive Database* and the *Major League Baseball Official Website*.

We were unable to find data on the number of opposition errors, which is required in the calculation of total bases gained. We estimated this number for each team in each season by subtracting the team's own errors committed from the total committed in that team's league and dividing by one less than the number of teams in the league. This approximation ignores the minor effects of interleague play and the somewhat different schedules played by different teams, and assumes that teams are equally likely to commit errors against each team they play. In addition, we were unable to find data to support MLB's definition of total bases in the calculation of total bases surrendered for seasons prior to 1999. We estimated this quantity by identifying the relationship between total hits and total bases using regression analysis.

20.5.1.4 Study Results

We apply the two-stage DEA model to measure the efficiency of the front office operation, the on-field operation, and the overall organization of each team in each season of the study period and explore the relationship between efficiency and competitiveness. Next, we determine the competitive salary and hypercompetitive salary for each season in the study period and classify teams as competitive and noncompetitive. Finally, we examine how market size relates to efficiency and competitiveness.

Efficiency, Wins, and Competitiveness

Figure 20.5 illustrates the relationship between *EGW* and *GW* for all teams in the study period as determined by the DEA. The teams that lie along the line defined by $EGW = GW$ are organizationally efficient. All organizationally inefficient teams lie above this line. Different symbols indicate whether the team was noncompetitive due to low total player salary, noncompetitive due to other reasons, conditionally competitive, economically competitive, or hypercompetitive.

Table 20.1 shows, for each playoff qualification condition, the probability that a team would qualify for the playoffs if every team in its league or division were equally talented. For example, consider a team playing in a four-team division within a 14-team league with a wild card. This team has a balanced probability of 0.318 of qualifying for post-season play. Figure 20.6 shows the logistic regression model for this condition. The model indicates that a team playing under this condition must win at least 86.1 games to have a probability of qualifying for the playoffs equal to or greater than 0.318. Thus, under this playoff qualification condition, $MGW = 86.1$. Similar analyses lead to the *MGW* values shown in Table 20.1.

Competitive and Hypercompetitive Salary

Figure 20.7 shows the relationship between *TPS* and *EGW* for the 2000 season. Similar relationships hold in all other seasons in the study period. Three teams were noncompetitive in 2000, when the *MGW* was 85.6 in the American League East and Central, 86.1 in the American League West, 88.2 in the National League East and

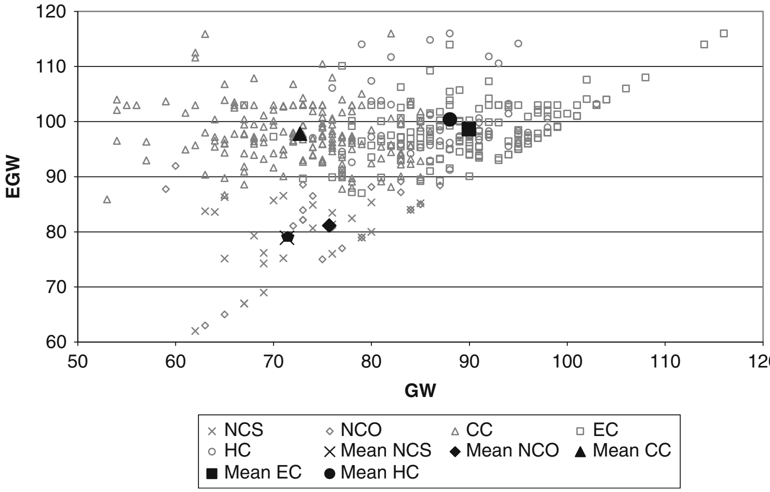

Fig. 20.5 The relationship between efficient games won and games won for all teams in the study period

Table 20.1 The balanced probability of a team qualifying for the playoffs given its playoff qualification condition and the minimum number of games a team needs to win to have a probability of qualifying for the playoffs at least as large as the balanced probability

Number of teams in league	Number of teams in division	Wild card	Balanced probability	MGW
10	–	No	0.100	92.8
8	–	No	0.125	88.9
14	7	No	0.143	89.5
12	6	No	0.167	88.2
16	6	Yes	0.231	87.3
16	5	Yes	0.262	88.2
14	5	Yes	0.272	85.6
14	4	Yes	0.318	86.1

West, and 87.3 in the National League Central. They were the Minnesota Twins, the Florida Marlins, and the Houston Astros – their efficient games won were 74.3, 79.0, and 81.1, respectively. The Gini index analysis indicates that the two teams with the lowest total player salaries (the Minnesota Twins and the Florida Marlins) were noncompetitive due to low total player salary. The lowest total player salary in the primarily competitive group is $23.13 million, belonging to the Kansas City Royals. Thus, the competitive salary in 2000 was $23.13 million.

We cannot explain why the Houston Astros were noncompetitive in 2000 other than to say that it was not due to low total player salary. However, we point out that 2000 was the Astros' first season in their new ballpark, one with dramatically

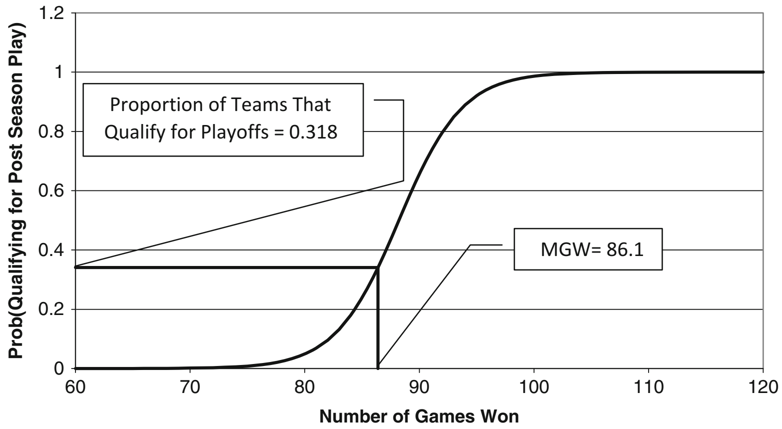

Fig. 20.6 The logistic regression model represents the probability that a team in a four-team division within a 14-team league, with a wild card, qualifies for the playoffs

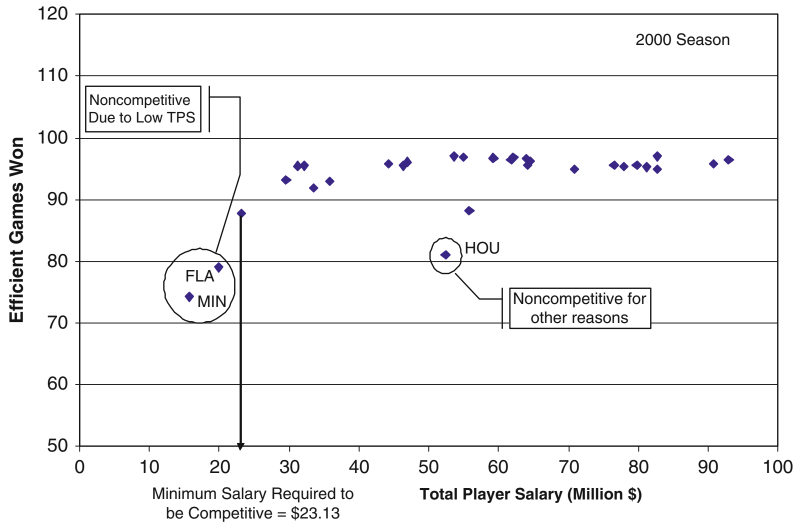

Fig. 20.7 The relationship between total player salary and efficient games won in the year 2000

different playing conditions than those found in the Astrodome. We also note that the Astros were competitive in both 1999 and 2001.

Table 20.2 and Fig. 20.8 show the competitive and hypercompetitive salary along with the team minima, mean, and maxima salaries for the non-strike seasons between 1985 and 2002. We find that the competitive salary ranges from $6.19 million in 1985 to $38.67 million in 2002, an average annual growth rate of 10.7 %

Table 20.2 The minimum, maximum, and mean total player salaries for the non-strike seasons between 1985 and 2002 along with the minimum total player salary to be competitive and hypercompetitive salaries

Season	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
Minimum	50.10	4.26	3.56	5.41	7.19	9.50	10.72	8.46	8.83			16.26	10.77	9.16	16.18	15.65	24.13	34.38
Competitive	6.19	9.19	4.09	6.00	9.09	12.66	14.05	13.49	18.20			23.02	17.27	22.73	22.20	23.13	24.13	38.67
Mean	10.64	11.46	10.79	11.63	13.82	17.20	22.95	30.04	30.38			33.94	40.25	40.34	47.37	56.20	65.48	67.49
Hypercompetitive	9.81	12.31	11.47	15.27	19.68	20.52	25.96	35.86	28.85			49.70	53.45	63.46	73.59	77.88	74.72	125.93
Maximum	16.20	19.64	20.01	19.44	20.27	23.57	37.28	44.46	45.75			54.71	62.24	68.99	85.03	92.94	112.29	125.93

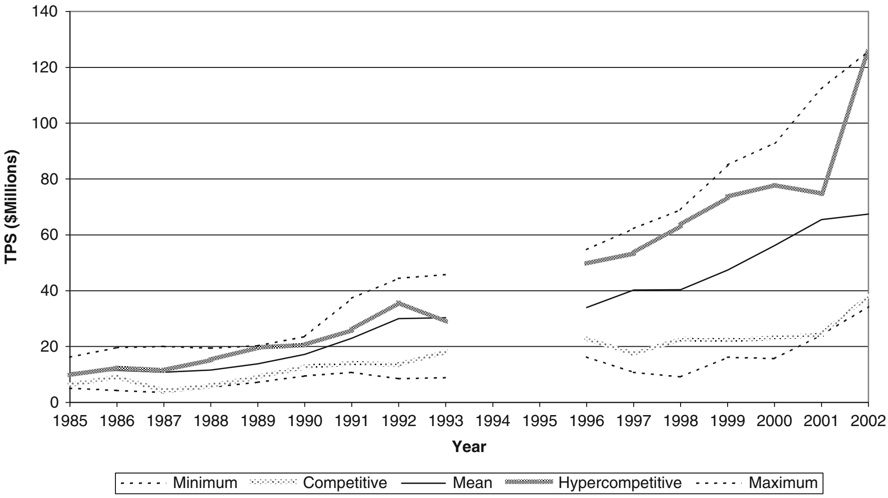

Fig. 20.8 The minimum, maximum, and mean total player salaries for the non-strike seasons between 1985 and 2002 along with the minimum total player salary to be competitive and hypercompetitive salaries

per year, adjusted for inflation. The hypercompetitive salary ranges from $9.81 million in 1985 to $125.9 million in 2002, an average annual growth rate of 12.6 % per year, adjusted for inflation. Interestingly, we observe that the team minimum, mean, and maximum salaries have risen at nearly the same average annual percentage rate, namely 11.2 % for the minimum, 10.8 % for the mean, and 12.1 % for the maximum. This suggests that, over the study period, it has not become relatively more costly to be competitive in MLB.

Moreover, the competitive salary has remained low relative to the mean total player salary in each season. As Fig. 20.9 shows, the ratio of the competitive salary in a given season to the minimum total player salary in the same season has remained stable around its mean of 1.5. Therefore, a rule of thumb is that a team's total player salary must be at least 50 % larger than the lowest total player salary in a given season to be competitive. The least squares regression line in Fig. 20.9 has a slope that is very nearly zero (0.0012 per year).

Classifying Teams as Competitive or Noncompetitive

We find that, in each season, there were between zero and four teams that were noncompetitive due to low total player salary, as shown in Fig. 20.10. We conclude that, in each season in the study period except for 2001, there existed teams that were noncompetitive due to low total player salary and that the number of such teams was relatively small. As Fig. 20.10 also shows, there were between zero and eight teams that were noncompetitive for reasons other than salary. These are teams

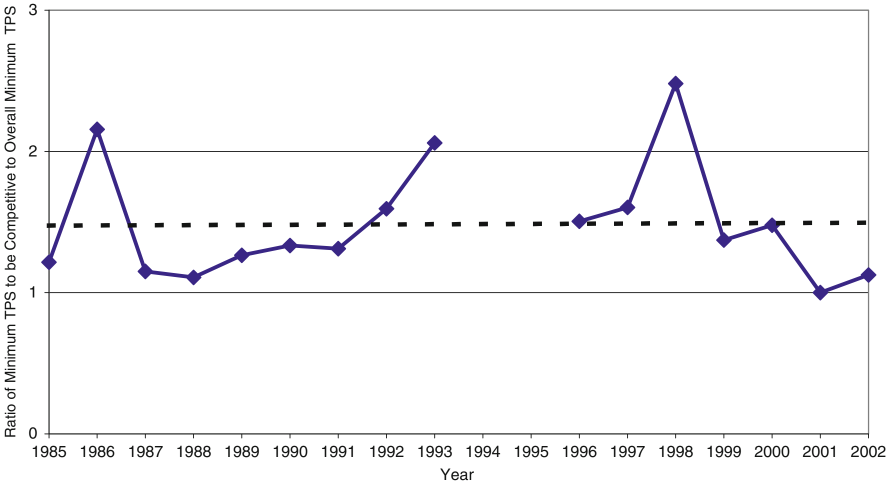

Fig. 20.9 The ratio of the minimum total player salary to be competitive to the overall minimum total player salary has remained stable around a mean of approximately 1.5 between 1985 and 2002

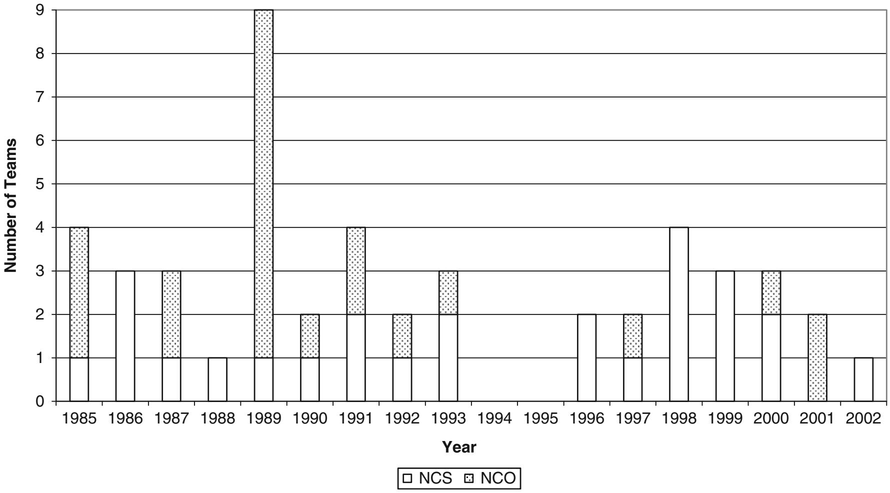

Fig. 20.10 The number of teams which are noncompetitive due to low total player salary and noncompetitive for other reasons in each non-strike season

whose total player salaries exceeded the minimum required to be competitive but had $EGW < MGW$. We cannot say why these teams are noncompetitive. During the study period, 49 of 442 teams (11.1 %) have been noncompetitive. Of these 49 teams, 27 (55.1 %) were noncompetitive due to low total player salary, while 22 (44.9 %) were noncompetitive for other reasons.

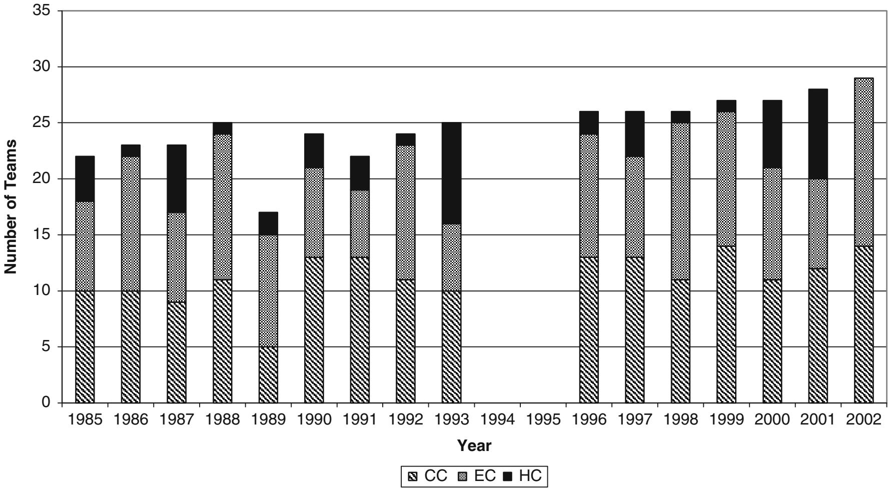

Fig. 20.11 The number of conditionally competitive, economically competitive, and hypercompetitive teams in each non-strike season

We find that, in each season, there were between zero and nine teams that were hypercompetitive, as shown in Fig. 20.11. During the study period, 95 of the 442 teams (21.5 %) overspent on player salaries.

We find that 51 of these 95 teams (54.7 %) were hypercompetitive, 41 (43.2 %) were conditionally competitive, and 2 (2.1 %) were noncompetitive for other reasons. We also find that, in each season, there were between 6 and 14 economically competitive teams, and that there were between 5 and 14 conditionally competitive teams. None of these categories demonstrate significant trends over time.

Figure 20.12 displays the competitive status of each team in each season during the study period. We observe that 16 teams have never been noncompetitive due to low total player salary during the study period. Note that only the Minnesota Twins have been noncompetitive due to low total player salary in four of the 18 seasons in the study period, and no team has been noncompetitive due to low total player salary more often. The Cleveland Indians and the Montreal Expos were each noncompetitive due to low total player salary three times. The Seattle Mariners (1985–1986), the Cleveland Indians (1992–1993), the Pittsburgh Pirates (1997–1998), the Montreal Expos (1998–1999), the Minnesota Twins (1986–1987 and 1999–2000), and the Florida Marlins (1999–2000) were noncompetitive due to low total player salary for two consecutive seasons. Thus, there is no evidence that being noncompetitive due to low total player salary is a chronic condition.

We observe that two teams (the Anaheim/California Angels and the Milwaukee Brewers) were conditionally competitive 12 times during the 16 seasons analyzed. In addition, three teams (the Chicago Cubs, the Kansas City Royals, and the San Diego Padres) were conditionally competitive 11 times, while the Philadelphia

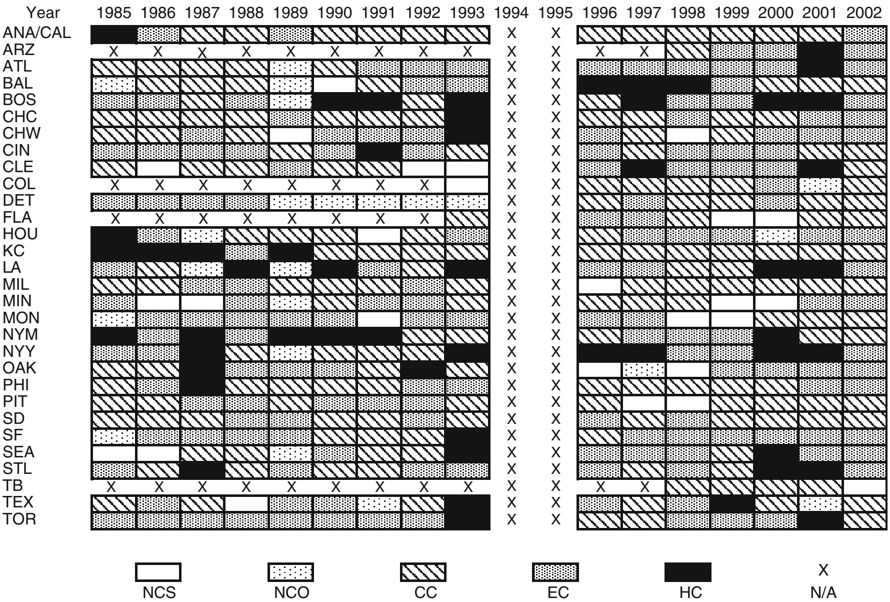

Fig. 20.12 The competitive status of each team in each season during the study period

Phillies and the Pittsburgh Pirates were conditionally competitive 10 and 9 times, respectively. Thus, this competitive status, in which the team has spent sufficient money on player salary but the front office has failed to produce sufficient talent on the field to be competitive, has been a persistent problem in these seven franchises.

We find that one team (the Toronto Blue Jays) was economically competitive in 11 seasons, while two teams (the Cincinnati Reds and the San Francisco Giants) were economically competitive in 10 seasons and two teams (the Atlanta Braves and the Montreal Expos) were economically competitive in 9 seasons. These franchises consistently paid sufficient player salaries to be competitive, and their front offices used the money to place sufficient talent on the field.

Three teams (the Boston Red Sox, the New York Mets, and the New York Yankees) were hypercompetitive six times, while the Los Angeles Dodgers and the Kansas City Royals were hypercompetitive five and four times, respectively. Moreover, nine teams have never been hypercompetitive and another nine teams have been hypercompetitive only once.

Markov Analysis

We model the transition of teams among the five states according to a Markov process. Ignoring transitions that spanned the strike seasons, the estimated transition matrix is

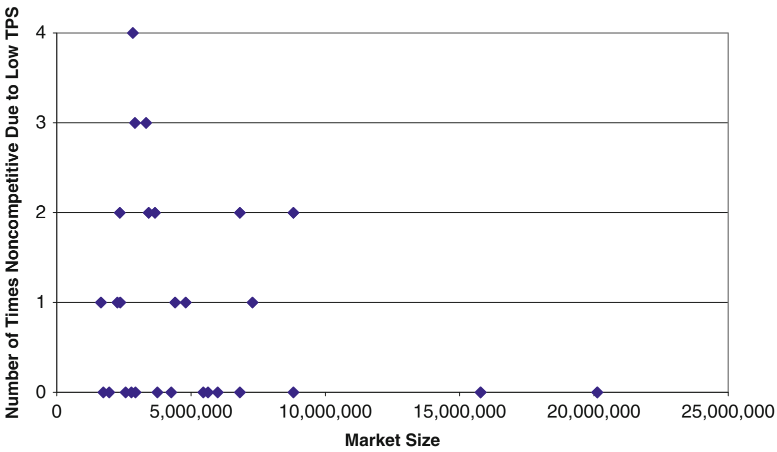

Fig. 20.13 The number of times that a team has been noncompetitive due to low total player salary between 1985 and 2002 is negatively related to the size of the market in which it plays

$$\mathbf{P} = \begin{pmatrix} 0.304 & 0.044 & 0.391 & 0.261 & 0 \\ 0.095 & 0.191 & 0.381 & 0.191 & 0.143 \\ 0.064 & 0.039 & 0.564 & 0.244 & 0.090 \\ 0.021 & 0.050 & 0.270 & 0.539 & 0.121 \\ 0 & 0.023 & 0.256 & 0.442 & 0.279 \end{pmatrix}$$

where the order of the states is NCS, NCO, CC, EC, and HC. A chi-square test shows that the probability distributions in the rows are significantly different ($\chi^2 = 92.75$ with df $= 16$, $P < 0.00005$). The steady-state probabilities associated with this transition matrix are $\boldsymbol{\pi} = (0.055 \quad 0.048 \quad 0.397 \quad 0.378 \quad 0.122)$.

The matrix of mean first passage times is

$$\mathbf{M} = \begin{pmatrix} 18.3 & 24.1 & 3.0 & 3.8 & 11.5 \\ 23.4 & 20.6 & 3.1 & 4.0 & 9.7 \\ 24.3 & 24.3 & 2.5 & 3.8 & 10.3 \\ 25.8 & 23.9 & 3.6 & 2.6 & 9.8 \\ 26.6 & 24.7 & 3.7 & 2.9 & 8.2 \end{pmatrix}$$

Market Size, Efficiency, and Competitiveness

Figure 20.13 shows the number of times each team was noncompetitive due to low total player salary versus the team's market size, defined as the population of the team's metropolitan area according to the 2000 U.S. census and the 2001 Canadian census. We find evidence that the number of times that a team has been noncompetitive due to low total player salary between 1985 and 2002 is negatively related to the size of the market in which it plays ($P = 0.0464$ in a

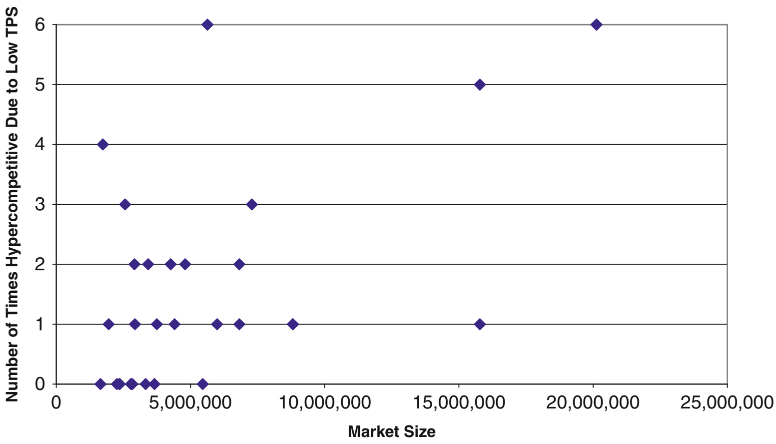

Fig. 20.14 The number of times that a team has been hypercompetitive between 1985 and 2002 is positively related to the size of the market in which it plays

Poisson regression). The teams that played in markets below five million people were NCS in 8.4 % of their seasons while teams that played in markets above five million people were NCS in 3.1 % of their seasons ($P = 0.027$). We note that, while the four teams in the two largest markets – two in New York and two in Los Angeles/Anaheim – were never noncompetitive due to low total player salary, the Chicago White Sox, who play in the third largest market, were noncompetitive due to low total player salary in two seasons (1989 and 1998). In addition, we see that seven of the 18 teams that play in markets below five million people have not been noncompetitive due to low total player salary in the study period.

Figure 20.14 shows the number of times each team was hypercompetitive versus the team's market size. We find evidence that the number of times that a team has been hypercompetitive between 1985 and 2002 is positively related to the size of the market in which it plays ($P < 0.00005$ in a Poisson regression). The teams that played in markets above five million people were hypercompetitive in 17.2 % of their seasons while teams that played in markets below five million people were hypercompetitive in 7.6 % of their seasons ($P = 0.0027$). Of the 18 teams with market size below five million, eight have never been hypercompetitive and four have been hypercompetitive once. Of the 12 teams with market size above five million, 11 have been hypercompetitive at least once, including the Boston Red Sox, the New York Mets, and the New York Yankees six times each and the Los Angeles Dodgers five times.

Figure 20.15 shows the relationship between efficient games won and market size for MLB teams during the study period. The regression line shown in Fig. 20.15 has a slope of 2.262 games per 10 million people (P-value = 0.0019), suggesting that an efficient New York team, with market size approximately equal to 20.13 million, would win roughly four more games in a season than would an efficient Milwaukee team, with market size equal to 1.65 million.

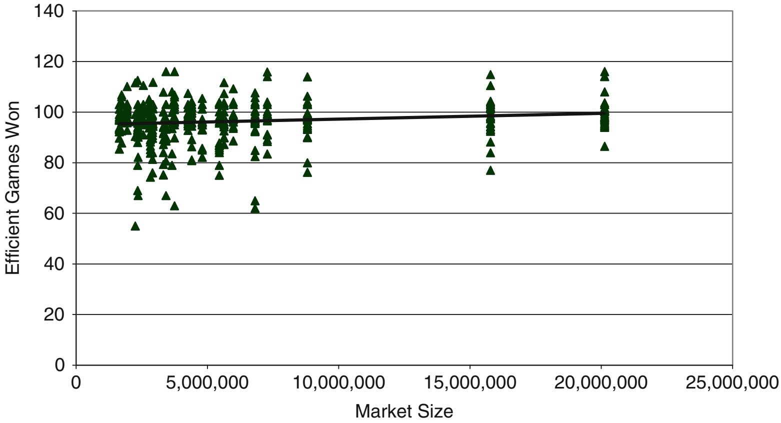

Fig. 20.15 Efficient games won versus market size for MLB teams between 1985 and 2002 excluding the strike seasons of 1994 and 1995

20.5.1.5 Conclusions of the Study

In this section, we summarize our results by responding to each research question.

How much does a team need to spend on total player salary to be competitive?
The competitive salary ranges from \$6.19 million in 1985 to \$38.67 million in 2002, an average annual growth rate of 10.7 % per year, adjusted for inflation. The team minimum, mean, and maximum salaries have risen at nearly the same average annual percentage rate. This suggests that, over the study period, it has not become relatively more costly to be competitive in MLB. Moreover, the competitive salary has remained low relative to the mean total players salary in each season. We find that the ratio of the competitive salary to the minimum total player salary has remained stable around its mean of 1.5.

What is the maximum total player salary that a team can pay without overspending?
The hypercompetitive salary is \$125.9 million in 2002, up from \$9.81 million in 1985. This is an average annual increase of 12.6 % (adjusted for inflation) per year. It is increasing over time as a percentage of maximum total player salary.

How many teams are noncompetitive due to low total player salary?
We find that, in each season, there were between zero and four teams that were noncompetitive due to low total player salary. We conclude that, in each season in the study period except for 2001, there existed teams that were noncompetitive due to low total player salary and that the number of such teams was relatively small. There were between zero and eight teams that were noncompetitive for other reasons. The Markov analysis suggests that, in any given season, 5.5 % of the teams (1.65 out of 30 teams) will be noncompetitive due to low total player salary, while another 4.8 % of the teams will be noncompetitive for other reasons (1.44 out of 30 teams).

How many teams are overspending on total player salary?
We also find that between zero and nine teams are hypercompetitive in a given season. During the study period, 95 of 442 teams (21.5 %) have been overspending on total player salary. Of these overspending teams, 52 (54.7 %) were hypercompetitive, 41 (43.2 %) were conditionally competitive, and two (2.1 %) were noncompetitive due to other reasons. The Markov analysis suggests that, in a given season, 12.2 % (3.66 out of 30 teams) of the teams will be hypercompetitive.

How does noncompetitiveness due to low total player salary relate to market size?
We find evidence that the number of times that a team has been noncompetitive due to low total player salary between 1985 and 2002 is negatively related to the size of the market in which it plays. However, we see that seven of the 18 teams that play in markets below five million people have not been noncompetitive due to low total player salary in the study period. Six of the 18 teams have been noncompetitive due to low total player salary more than once in this period. While the four teams in the two largest markets were never noncompetitive due to low total player salary, the Chicago White Sox, who play in the third largest market, were noncompetitive due to low total player salary in two seasons.

The size of the team's market relates to the number of games it can win if it is efficient. An efficient New York team, playing in the largest market, can expect to win roughly four more games per season than an efficient Milwaukee team, playing in the smallest market.

How does overspending on total player salary relate to market size?
Large market teams are more likely to be hypercompetitive than small market teams. Of the 18 teams with market size less than five million, eight have never been hypercompetitive, while four have been hypercompetitive only once. Meanwhile, of the 12 teams with market size greater than five million, 11 have been hypercompetitive at least once.

20.5.2 Organizational Capability, Efficiency, and Effectiveness in MLB

In this study published in the *European Journal of Operational Research* (Lewis et al. 2009), we use a network DEA model as part of a larger analysis to explore the relative contributions of team capability and managerial efficiency to team effectiveness in the context of Major League Baseball. We analyze every MLB team over the past century to capture long-term, persistent relationships. We perform separate analyses of regular season effectiveness and post-season effectiveness. The study period for the regular season analysis is from 1901 through 2002 (excluding the strike-shortened seasons in 1981, 1994, and 1995), during which there are 1934 observations. The study period for the post-season analysis is from 1903 through 2002 (excluding 1904 when there was no post-season play and the strike-shortened seasons in 1981, 1994, and 1995), during which there are 282 observations.

20.5.2.1 Motivation and Research Questions

To be effective, organizations need capabilities relevant to their missions and they must manage those capabilities efficiently. Without adequate talent, even a well-managed organization will fail to achieve its goals. Similarly, the inefficient utilization of resources will cause a well-equipped organization to fail. Of course, a powerfully equipped organization can compensate for managerial inefficiencies more easily than can a marginally equipped organization.

We anticipate that the relative contributions of capability and managerial efficiency are significant factors in organizational resource allocation decisions. Capability will be relatively more important in industries in which labor is highly paid. Examples of such industries include high-tech manufacturing, universities, hospitals, and professional sports. Efficiency will be relatively more important in industries in which labor is inexpensive. Examples of such industries include low-tech manufacturing, fast-food restaurant chains, janitorial services, and retail services.

MLB team owners, general managers, scouts, field managers, and coaches acquire, develop, and manage talent. Knowing the relative impact of talent and efficient use of that talent on team effectiveness can greatly enhance decisions both on and off the field. In this context, we pose the following research questions for the regular season and post-season study periods, respectively:

1. How much does team capability and managerial efficiency contribute to regular season effectiveness in MLB?
2. How much does team capability and managerial efficiency contribute to post-season effectiveness in MLB?

20.5.2.2 Study Methodology

We present mathematical models to measure regular season team capability, regular season team efficiency, regular season team effectiveness, and post-season team effectiveness. We then use weighted linear regression to evaluate the contributions of regular season team capability and regular season team efficiency to the variation in regular season and post-season team effectiveness.

Measuring Regular Season Capability

We measure the organizational capability of an MLB team during the regular season using offensive and defensive measures based on a variant of MLB's definition of total bases. We refer to these measures as *O-Capability* and *D-Capability*.

The capability of a team depends on its ability to get players on base and its ability to prevent its opponent's players from reaching base. We measure offensive capability in any season as $(TB_{Off} + BB_{Off} + E_{Off})/GP$ where TB_{Off} is the team's total bases gained on offense, BB_{Off} is the number of walks received by the team, E_{Off} is the number of fielding errors committed by the opposing team, and GP is the number of games played by the team. This approach to measuring offensive capability assumes constant returns-to-scale, i.e., that the sum in the numerator is proportional to the number of games played.

Defensive capability is defined identically except that the terms refer to the number of total bases and walks surrendered by the team, and number of fielding errors committed by the team, in the given season. Thus, we measure defensive capability in any season as $(TB_{Def} + BB_{Def} + E_{Def})/GP$ where TB_{Def} is the team's total bases surrendered on defense, BB_{Def} is the number of walks surrendered by the team, and E_{Def} is the number of fielding errors committed by the team. Observe that *D-Capability* has the property that larger numerical values are representative of less rather than more defensive capability. Thus, *D-Capability* is a reverse quantity. Note that we also assume constant returns-to-scale for defensive capability.

Measuring Regular Season Efficiency

To measure efficiency of an MLB team, we use the network DEA model developed by Lewis and Sexton (2004a). Figure 20.16 shows our network representation of the on-field operation of an MLB team.

The on-field operation of an MLB team is comprised of three sub-DMUs. The offense sub-DMU consumes offensive contributions (TB_{Off}, BB_{Off}, and E_{Off}) to produce runs gained on offense (R_{Off}), the defense sub-DMU consumes defensive contributions (TB_{Def}, BB_{Def}, and E_{Def}) to prevent runs surrendered on defense (R_{Def}), and the integration sub-DMU consumes R_{Off} and R_{Def} to produce games won (GW). Note that TB_{Def}, BB_{Def}, E_{Def} and R_{Def} are reverse quantities.

We use four efficiency scores to evaluate managerial performance. The first – the *O-Efficiency* – measures the efficiency of the offense sub-DMU. A team increases its *O-Efficiency* by clustering its hits, walks, and the errors committed by the opposing team, by stealing more bases and taking extra bases on hits, and by leaving fewer runners on base. The DEA model for *O-Efficiency* is

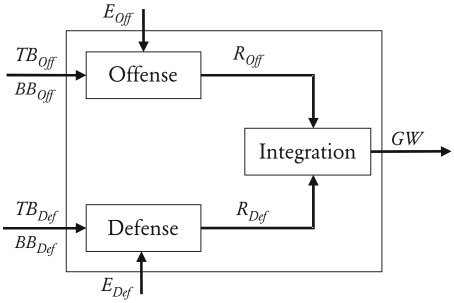

Fig. 20.16 Network model of the on-field operation of an MLB team

$$
\begin{aligned}
&\text{Max} \;\; \theta_{1k} \\
&\text{s.t.} \\
&\quad \sum_{j=1}^{n} \lambda_{1j} TB_{Off\,j} \le TB_{Off\,k} \\
&\quad \sum_{j=1}^{n} \lambda_{1j} BB_{Off\,j} \le BB_{Off\,k} \\
&\quad \sum_{j=1}^{n} \lambda_{1j} E_{Off\,j} \le E_{Off\,k} \\
&\quad \sum_{j=1}^{n} \lambda_{1j} R_{Off\,j} \ge \theta_{1k} R_{Off\,k} \\
&\quad \sum_{j=1}^{n} \lambda_{1j} = 1 \\
&\quad \lambda_{1j} \ge 0; \quad j = 1, 2, \ldots, n \\
&\quad \theta_{1k} \ge 0
\end{aligned}
$$

In this model, λ_{1j} represent the weight that DMU k places on DMU j when measuring the efficiency of the offense sub-DMU and θ_{1k} is the inverse efficiency of the offense sub-DMU.

The second efficiency score – the *D-Efficiency* – measures the efficiency of the defense sub-DMU. A team increases its *D-Efficiency* by scattering the hits, walks, and the errors it commits, by preventing stolen bases and extra bases on hits, and by leaving more opposition runners on base. The DEA model for *D-Efficiency* is

$$\begin{aligned}
&\text{Min } \varepsilon_{2k}\\
&\text{s.t.}\\
&\quad \sum_{j=1}^{n} \lambda_{2j} TB_{Def\,j} \geq TB_{Def\,k}\\
&\quad \sum_{j=1}^{n} \lambda_{2j} BB_{Def\,j} \geq BB_{Def\,k}\\
&\quad \sum_{j=1}^{n} \lambda_{2j} E_{Def\,j} \geq E_{Def\,k}\\
&\quad \sum_{j=1}^{n} \lambda_{2j} R_{Def\,j} \leq \varepsilon_{2k} R_{Def\,k}\\
&\quad \sum_{j=1}^{n} \lambda_{2j} = 1\\
&\quad \lambda_{2j} \geq 0; \quad j = 1, 2, \ldots, n\\
&\quad \varepsilon_{2k} \geq 0
\end{aligned}$$

In this model, λ_{2j} represent the weight that DMU k places on DMU j when measuring the efficiency of the defense sub-DMU and ε_{2k} is the efficiency of the defense sub-DMU.

The third efficiency score – the *W-Efficiency* – measures the efficiency of the integration sub-DMU. A team increases its *W-Efficiency* by winning more close games. The DEA model for *W-Efficiency* is

$$\begin{aligned}
&\text{Max } \theta_{3k}\\
&\text{s.t.}\\
&\quad \sum_{j=1}^{n} \lambda_{3j} R_{Off\,j} \leq R_{Off\,k}\\
&\quad \sum_{j=1}^{n} \lambda_{3j} R_{Def\,j} \geq R_{Def\,k}\\
&\quad \sum_{j=1}^{n} \lambda_{3j} GW_{j} \geq \theta_{3k} GW_{k}\\
&\quad \sum_{j=1}^{n} \lambda_{3j} = 1\\
&\quad \lambda_{3j} \geq 0; \quad j = 1, 2, \ldots, n\\
&\quad \theta_{3k} \geq 0
\end{aligned}$$

In this model, λ_{3j} represent the weight that DMU k places on DMU j when measuring the efficiency of the integration sub-DMU and θ_{3k} is the inverse efficiency of the integration sub-DMU.

The fourth efficiency score – the *F-Efficiency* – measures the efficiency of the entire DMU. The *F-Efficiency* is computed as the efficiency of the integration sub-DMU using the optimal values R^*_{Off} and R^*_{Def} produced by the offense sub-DMU and the defense sub-DMU, respectively. The DEA model for *F-Efficiency* is

$$
\begin{aligned}
&\text{Max} \ \ \theta_k \\
&\text{s.t.} \\
&\quad \sum_{j=1}^{n} \lambda_j R_{Off\,j} \leq R^*_{Off_k} \\
&\quad \sum_{j=1}^{n} \lambda_j R_{Def\,j} \geq R^*_{Def_k} \\
&\quad \sum_{j=1}^{n} \lambda_j GW_j \geq \theta_k GW_k \\
&\quad \sum_{j=1}^{n} \lambda_j = 1 \\
&\quad \lambda_j \geq 0; \quad j = 1, 2, \ldots, n \\
&\quad \theta_k \geq 0
\end{aligned}
$$

In this model, λ_j represent the weight that DMU k places on DMU j when measuring the efficiency of the entire DMU and θ_k is the inverse efficiency of the entire DMU.

All of the DEA models assume variable returns-to-scale, an output orientation, and use a common frontier over teams in all seasons in the study period. We justify the use of a common frontier for all seasons based on the observation that the process by which MLB teams convert inputs into outputs has remained essentially unchanged throughout the study period. While it may be true that offensive and defensive capabilities have evolved during the study period, the variable returns-to-scale assumption neither rewards nor penalizes a team based on the season in which it played. During this period, there were 1934 observations. All the models except for the *O-Efficiency* model involve reverse quantities, which we incorporate using the methodology presented in Lewis and Sexton (2004b).

Measuring Regular Season Effectiveness

The number of games an MLB team wins in a given season is a measure of its effectiveness. However, during the study period, not all teams played the same number of regular season games. Therefore, we define the regular season organizational effectiveness of an MLB team as the team's winning percentage during the season, defined as $WPct = GW/GP$.

Table 20.3 The first column shows the possible seven-game post-season series outcomes, ranked from best to worst for Team A. The second column shows the probabilities of the possible seven-game post-season series outcomes, where p is the probability that Team A wins any given game, and $q = 1 - p$. The third column shows the seven-game post-season series effectiveness of Team A for each possible series outcome

Team A	Probability	Post-season series effectiveness
Wins in 4	p^4	1
Wins in 5	$4p^4q$	$q^4(1 + 4p + 10p^2 + 20p^3) + p^4(20q^3 + 10q^2 + 4q)$
Wins in 6	$10p^4q^2$	$q^4(1 + 4p + 10p^2 + 20p^3) + p^4(20q^3 + 10q^2)$
Wins in 7	$20p^4q^3$	$q^4(1 + 4p + 10p^2 + 20p^3) + 20p^4q^3$
Loses in 7	$20p^3q^4$	$q^4(1 + 4p + 10p^2 + 20p^3)$
Loses in 6	$10p^2q^4$	$q^4(1 + 4p + 10p^2)$
Loses in 5	$4pq^4$	$q^4(1 + 4p)$
Loses in 4	q^4	q^4

Analyzing Regular Season Effectiveness

We use *WPct* as the dependent variable in a weighted linear regression with *O-Capability*, *D-Capability*, *O-Efficiency*, *D-Efficiency*, *W-Efficiency*, and *F-Efficiency* as the independent variables and regular season games played as the weights. We evaluate the contributions of each independent variable to the variation in regular season effectiveness in three ways. First, we compute the coefficient of partial determination for each independent variable. Second, we compute the R^2 contribution of a given independent variable. Third, we compare (absolute) regression coefficients between the two capability measures and within the efficiency measures.

Measuring Post-season Effectiveness

We measure a team's post-season series effectiveness as the probability that the team would have performed at least as well as it actually did. For a given team A, we rank the series outcomes from best to worst. For example, in a best-of-seven game series, the ranked outcomes for team A are shown in the first column of Table 20.3. Next, we determine the probability that team A wins a given game versus an opposing team B. Let α be the regular season winning percentage of team A and β be the regular season winning percentage of team B. Then, the probability that team A wins a given game is $p = \alpha/(\alpha + \beta)$ and the probability that team B wins a given game is $q = 1 - p = \beta/(\alpha + \beta)$. The second column of Table 20.3 shows the probability distribution for team A in a best-of-seven series. We measure the post-season series effectiveness of team A as the sum of the probabilities from the worst outcome for team A to the outcome that occurred. The third column of Table 20.3 shows these values.

Prior to 1969, we measure a team's post-season effectiveness as its World Series effectiveness. Since 1969, we measure a team's post-season effectiveness as a weighted average of its individual series effectiveness measures, using the maximum series lengths as the weights.

Analyzing Post-season Effectiveness

We examine how capability and efficiency during the regular season relate to post-season effectiveness. We use post-season effectiveness as the dependent variable in a weighted linear regression with (regular season) *O-Capability*, *D-Capability*, *O-Efficiency*, *D-Efficiency*, *W-Efficiency*, and *F-Efficiency* as the independent variables and post-season games played as the weights. We evaluate the contributions of each independent variable to the variation in post-season effectiveness using the coefficient of partial determination, the R^2 contribution, and the (absolute) regression coefficients.

20.5.2.3 Data for the Study

We obtained games won, post-season records, and team performance data (such as runs, total bases, walks, and errors) from the *Baseball Archive Database* and the *Major League Baseball Official Website*. We were unable to find data on the number of opposition errors and the number of opposition total bases for seasons prior to 1999. We estimated these quantities as described in Sect. 20.5.1.3.

20.5.2.4 Study Results

In this section, we present summary statistics of our capability, efficiency, and effectiveness measures of all MLB teams and post-season teams. We also perform a series of hypothesis tests to compare the capability, efficiency, and effectiveness measures of post-season and non-post-season teams. In addition, we report the results of our regular season and post-season regression analyses.

Summary Statistics of Capability, Efficiency, and Effectiveness Measures

Table 20.4 presents descriptive statistics of regular season capability for all regular season teams and post-season teams. Figures 20.17 and 20.18 are histograms of *O-Capability* for all regular season teams and post-season teams, respectively, while Figs. 20.19 and 20.20 are histograms of *D-Capability* for all regular season teams and post-season teams, respectively. On average, a regular season team gains (and surrenders) 17.24 total bases per game. We note that a typical post-season team gains 18.40 total bases and surrenders 16.42 total bases during a regular

Table 20.4 Descriptive statistics of regular season *O-Capability* and *D-Capability* for all regular season and post-season teams

Variable	Teams	N	Mean	SD	Minimum	1st quartile	Median	3rd quartile	Maximum
Regular season	All	1,934	17.24	1.66	12.50	16.11	17.25	18.31	23.10
O-Capability	Post-season	282	18.40	1.62	13.88	17.36	18.44	19.47	23.10
Regular season	All	1,934	17.24	1.63	12.34	16.20	17.25	18.30	24.13
D-Capability	Post-season	282	16.42	1.40	12.34	15.52	16.53	17.25	20.22

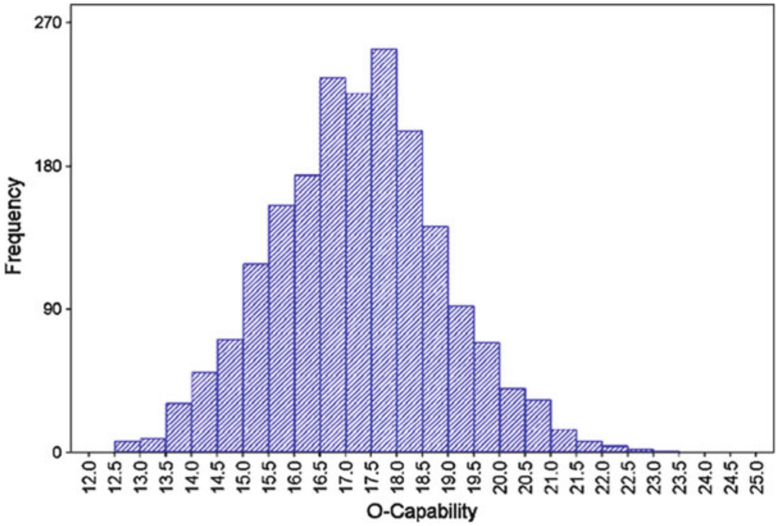

Fig. 20.17 Histogram of regular season *O-Capability* for all regular season teams

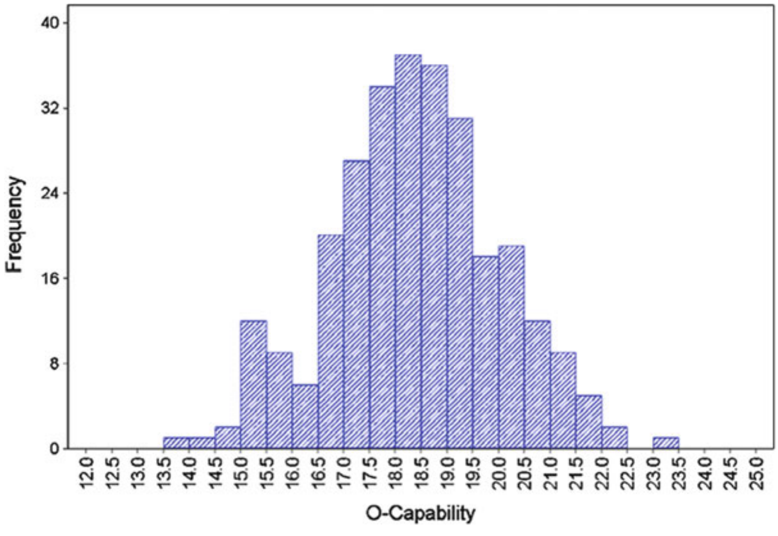

Fig. 20.18 Histogram of regular season *O-Capability* for post-season teams

season game. Thus, teams that achieve the post-season are typically above average offensively and defensively.

Table 20.5 presents descriptive statistics of regular season efficiency for all regular season teams and post-season teams. Figures 20.21 and 20.22 are

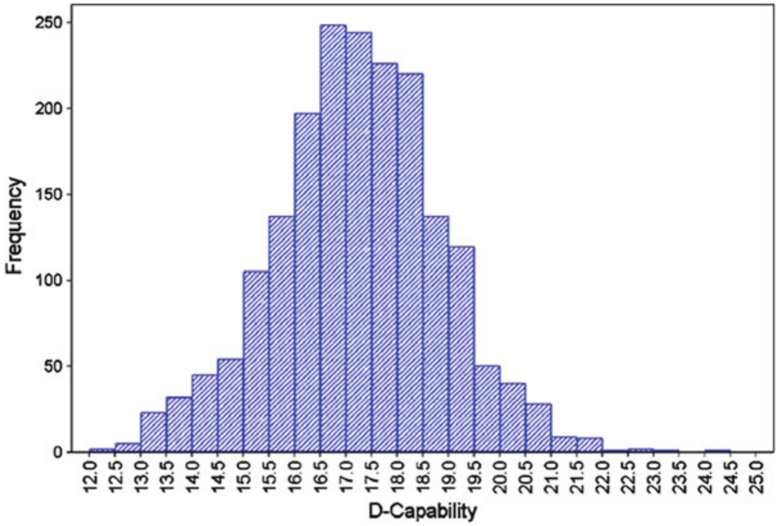

Fig. 20.19 Histogram of regular season *D-Capability* for all regular season teams

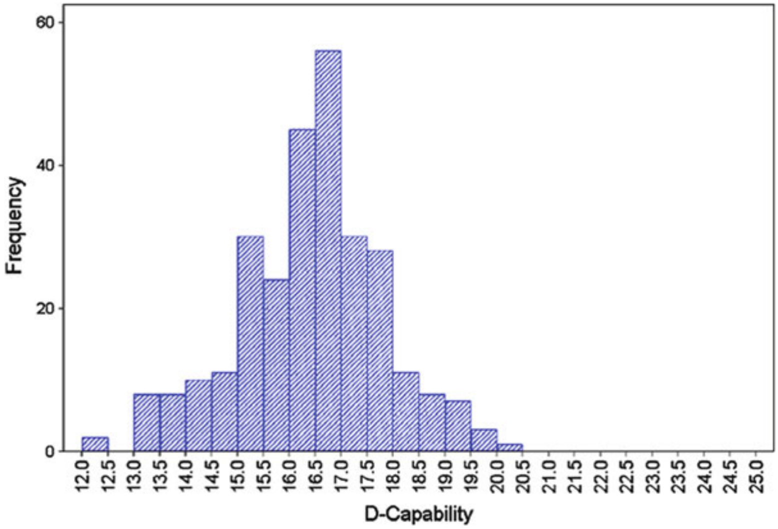

Fig. 20.20 Histogram of regular season *D-Capability* for post-season teams

histograms of *O-Efficiency* for all regular season teams and post-season teams, respectively. Figures 20.23 and 20.24 are histograms of *D-Efficiency* for all regular season teams and post-season teams, respectively. Figures 20.25 and 20.26 are histograms of *W-Efficiency* for all regular season teams and post-season teams,

Table 20.5 Descriptive statistics of regular season *O-Efficiency*, *D-Efficiency*, *W-Efficiency*, and *F-Efficiency* for all regular season and post-season teams

Variable	Teams	N	Mean	SD	Minimum	1st quartile	Median	3rd quartile	Maximum
Regular season	All	1,934	1.13	0.06	1	1.09	1.13	1.17	1.38
O-Efficiency	Post-season	282	1.09	0.05	1	1.06	1.10	1.12	1.22
Regular season	All	1,934	0.90	0.05	0.74	0.87	0.90	0.93	1
D-Efficiency	Post-season	282	0.92	0.04	0.78	0.89	0.92	0.95	1
Regular season	All	1,934	1.16	0.09	1	1.10	1.15	1.21	1.62
W-Efficiency	Post-season	282	1.09	0.04	1	1.06	1.09	1.12	1.23
Regular season	All	1,934	1.36	0.18	1	1.23	1.33	1.45	2.46
F-Efficiency	Post-season	282	1.17	0.06	1	1.13	1.17	1.21	1.33

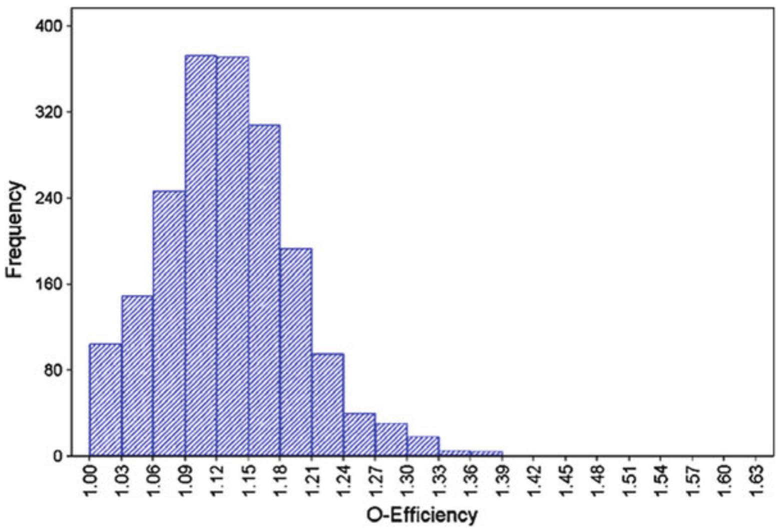

Fig. 20.21 Histogram of regular season *O-Efficiency* for all regular season teams

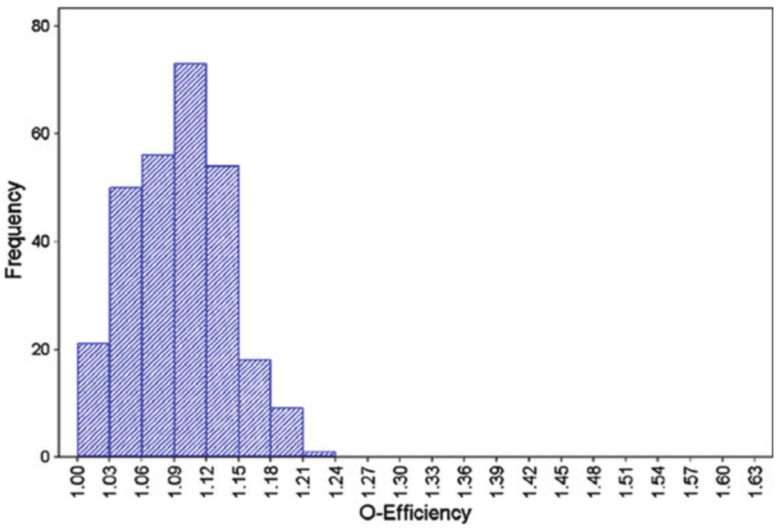

Fig. 20.22 Histogram of regular season *O-Efficiency* for post-season teams

respectively. Figures 20.27 and 20.28 are histograms of *F-Efficiency* for all regular season teams and post-season teams, respectively. On average, a regular season team should be able to increase its runs gained by 13 % (given its total bases gained), decrease its runs surrendered by 10 % (given its total bases surrendered), and win 16 % more games (given its runs gained and runs surrendered). Overall, a

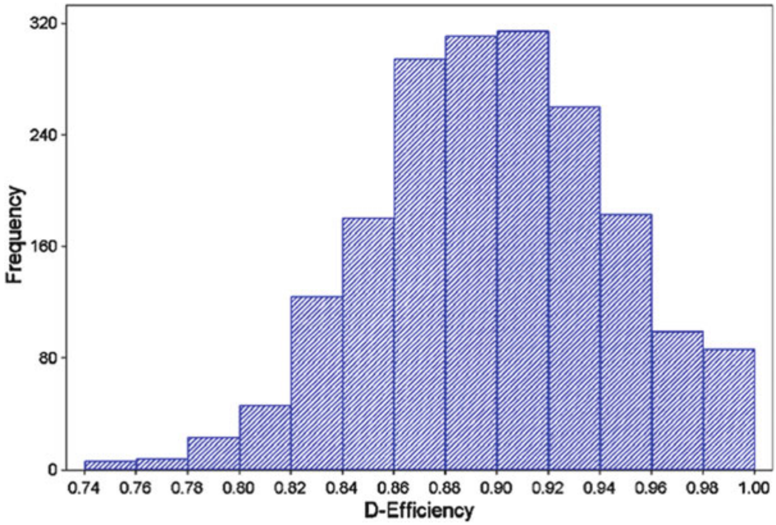

Fig. 20.23 Histogram of regular season *D-Efficiency* for all regular season teams

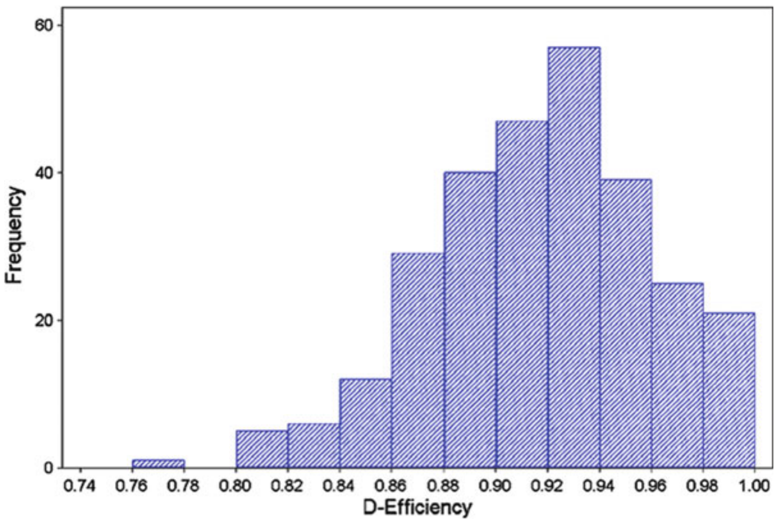

Fig. 20.24 Histogram of regular season *D-Efficiency* for post-season teams

typical regular season team should be able to win 36 % more games if it were efficient in the offense, defense, and integration sub-DMUs. Typical post-season teams demonstrate above average efficiency. On average, a post-season team should be able to increase its runs gained by 9 % (given its total bases gained),

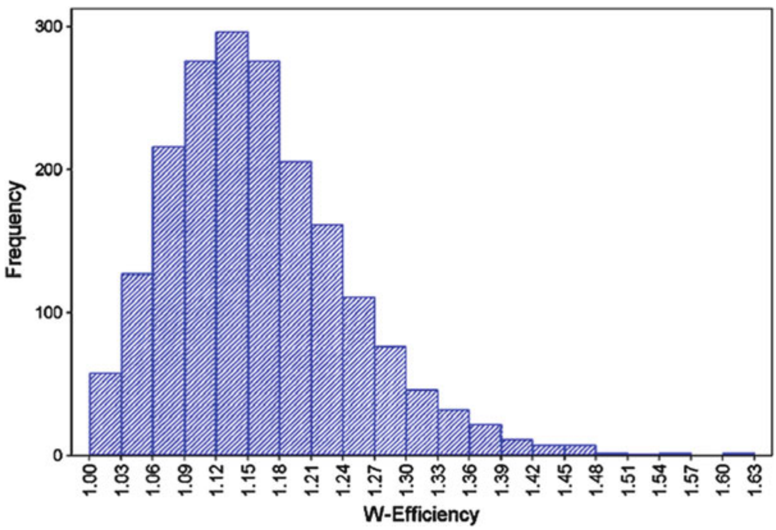

Fig. 20.25 Histogram of regular season *W-Efficiency* for all regular season teams

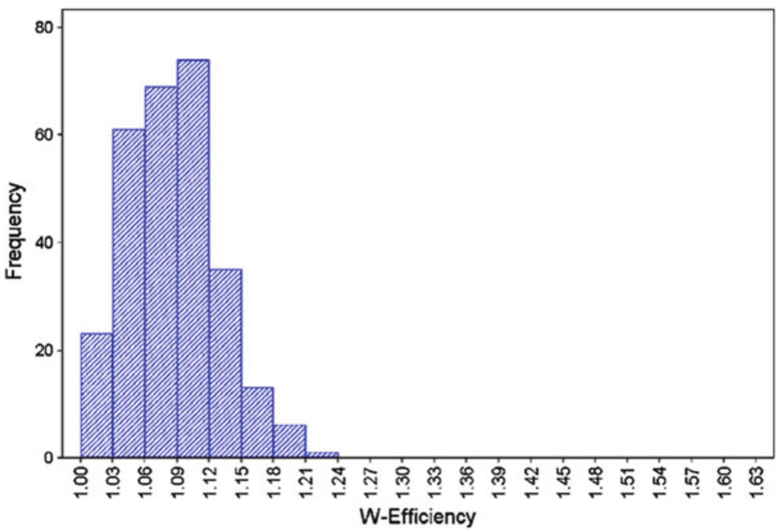

Fig. 20.26 Histogram of regular season *W-Efficiency* for post-season teams

decrease its runs surrendered by 8 % (given its total bases surrendered), and win 9 % more games (given its runs gained and runs surrendered). Overall, a typical post-season team should be able to win 17 % more games if it were efficient in the offense, defense, and integration sub-DMUs.

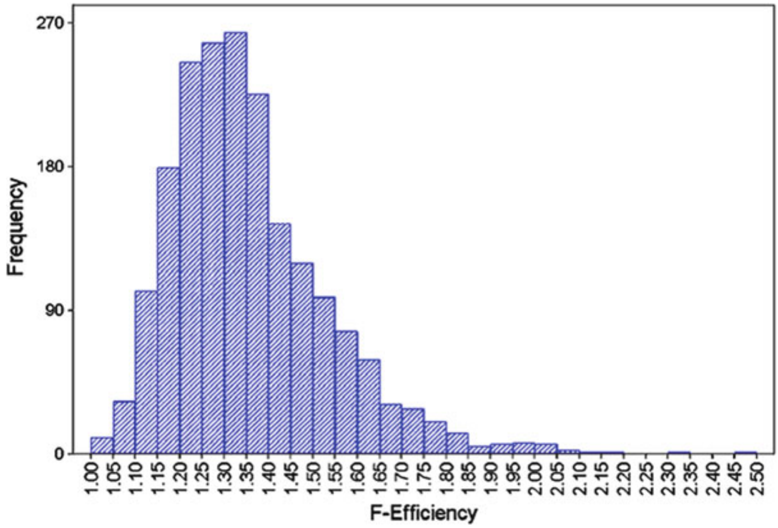

Fig. 20.27 Histogram of regular season *F-Efficiency* for all regular season teams

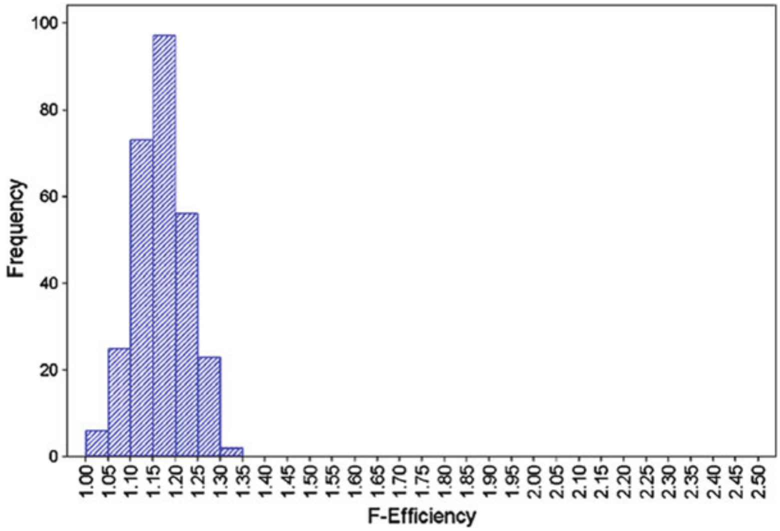

Fig. 20.28 Histogram of regular season *F-Efficiency* for post-season teams

Table 20.6 presents descriptive statistics of regular season effectiveness for all regular season teams and post-season teams and post-season effectiveness for all post-season teams. Figures 20.29 and 20.30 are histograms of regular season effectiveness for all regular season teams and postseason teams, respectively, and

Table 20.6 Descriptive statistics of regular season effectiveness for all regular season and post-season teams and post-season effectiveness for post-season teams

Variable	Teams	N	Mean	SD	Minimum	1st quartile	Median	3rd quartile	Maximum
Regular season *WPct*	All	1,934	0.50	0.08	0.23	0.44	0.50	0.56	0.75
	Post-season	282	0.61	0.04	0.51	0.58	0.60	0.63	0.75
Division series effectiveness	Post-season	56	0.58	0.33	0.11	0.30	0.60	0.88	1
League series effectiveness	Post-season	124	0.58	0.30	0.08	0.31	0.58	0.86	1
World series effectiveness	Post-season	192	0.57	0.29	0.05	0.34	0.58	0.81	1
Post-season effectiveness	Post-season	282	0.52	0.27	0.05	0.31	0.51	0.74	1

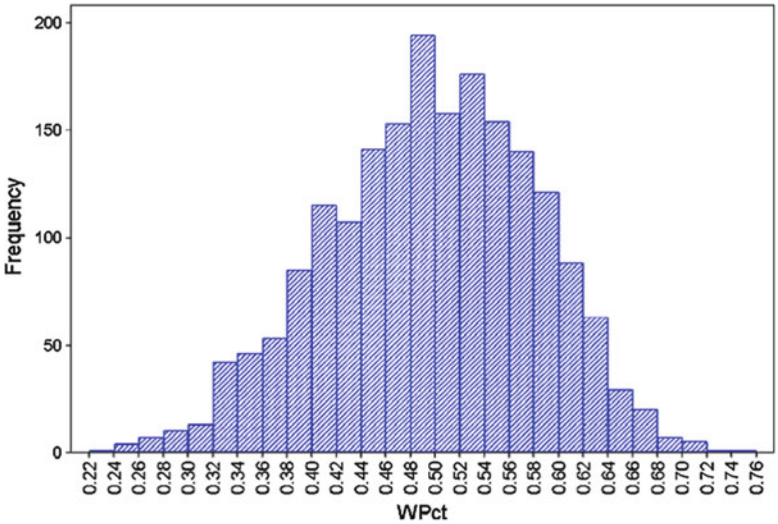

Fig. 20.29 Histogram of regular season effectiveness for all regular season teams

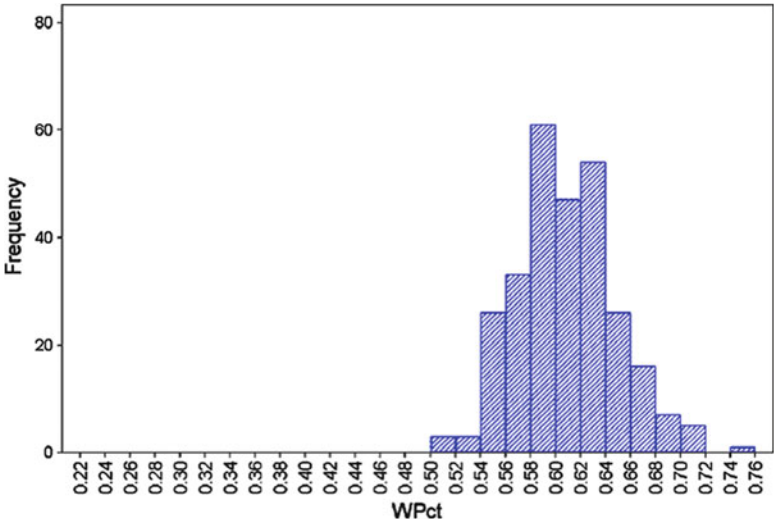

Fig. 20.30 Histogram of regular season effectiveness for post-season teams

Fig. 20.31 is a histogram of post-season effectiveness for post-season teams. We see that no team has won fewer than 23 % or more than 75 % of its regular season games. A typical post-season team wins 61 % of its regular season games and each post-season team has won at least 51 % of its regular season games.

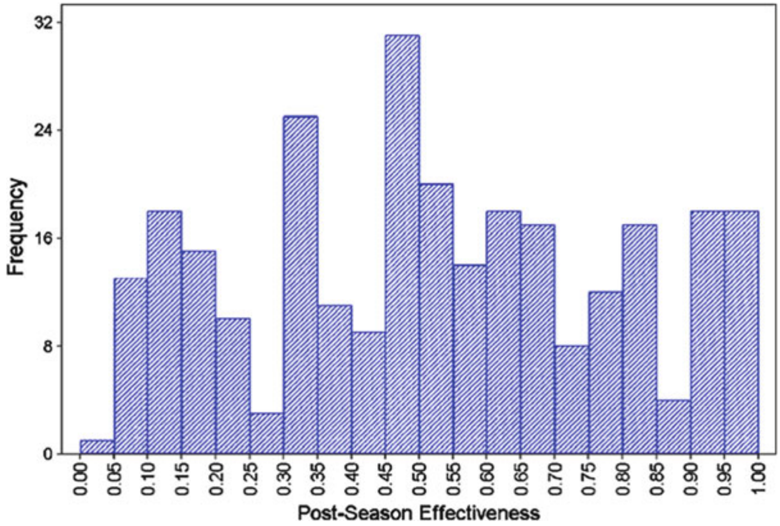

Fig. 20.31 Histogram of post-season effectiveness for post-season teams

Table 20.7 Results of hypothesis tests on post-season and non-post-season teams

Variable	Two-sample t test			Wilcoxon rank-sum test	
O-Capability	t = 13.23	DF = 1932	P < 0.00005	Z = 12.318	P < 0.00005
	F = 1.04	DF = 281,1651	P = 0.3371		
D-Capability	t = −10.37	DF = 423.4	P < 0.00005	Z = −9.518	P < 0.00005
	F = 1.37	DF = 1651,281	P = 0.0005		
O-Efficiency	t = −13.74	DF = 495.1	P < 0.00005	Z = −11.055	P < 0.00005
	F = 1.99	DF = 1651,281	P < 0.00005		
D-Efficiency	t = 8	DF = 406.2	P < 0.00005	Z = 7.623	P < 0.00005
	F = 1.21	DF = 1651,281	P = 0.0212		
W-Efficiency	t = −26.26	DF = 751.4	P < 0.00005	Z = −17.582	P < 0.00005
	F = 4.12	DF = 1651,281	P < 0.00005		
F-Efficiency	t = −41.07	DF = 1293.6	P < 0.00005	Z = −23.408	P < 0.00005
	F = 9.04	DF = 1651,281	P < 0.00005		
WPct	t = 42.97	DF = 672.7	P < 0.00005	Z = 24.134	P < 0.00005
	F = 3.47	DF = 1651,281	P < 0.00005		

Hypothesis Tests on Capability, Efficiency, and Effectiveness Measures

We perform a series of hypothesis tests to determine differences in capability, efficiency, and effectiveness between post-season and non-post-season teams. Table 20.7 presents the results of both a two-sample t-test and a Wilcoxon rank-sum test for each variable. Table 20.7 also shows the results of the F-tests to determine whether to assume equal or unequal variances when performing the t-tests. The results of the F-tests indicate that we should assume unequal variances

Table 20.8 Regression output for the regular season analysis

Weighted least squares linear regression of winning percentage					
Weighting variable: Games played					
Predictor variables	**Coefficient**	**Std error**	**T**	**P**	
Constant	1.36968	0.01867	73.36	0.0000	
O-Capability	0.03537	4.283E-04	82.57	0.0000	
D-Capability	−0.04247	3.907E-04	−108.71	0.0000	
O-Efficiency	−0.26566	0.00935	−28.42	0.0000	
D-Efficiency	−0.13465	0.00957	−14.06	0.0000	
W-Efficiency	−0.25583	0.00686	−37.28	0.0000	
R^2	0.9245	Resid. Mean Square (MSE)			0.08455
Adjusted R^2	0.9243	Standard deviation			0.29077
Source	DF	SS	MS	F	P
Regression	5	1,996.91	399.383	4,723.70	0.0000
Residual	1,928	163.01	0.085		
Total	1,933	2,159.92			

for all the t-tests except for the one involving *O-Capability*. We summarize the hypothesis tests for each variable below:

- *O-Capability*: Post-season teams on average gain more total bases than do non-post-season teams.
- *D-Capability*: Post-season teams on average surrender fewer total bases than do non-post-season teams.
- *O-Efficiency*: Post-season teams have on average lower inverse efficiency scores at the offense sub-DMU than do non-post-season teams.
- *D-Efficiency*: Post-season teams have on average higher efficiency scores at the defense sub-DMU than do non-post-season teams.
- *W-Efficiency*: Post-season teams have on average lower inverse efficiency scores at the integration sub-DMU than do non-post-season teams.
- *F-Efficiency*: Post-season teams have on average lower organizational inverse efficiency scores than do non-post-season teams.
- *WPct*: Post-season teams have on average higher regular season winning percentages than do non-post-season teams.

Regular Season Regression Analysis

The sample size for the regression model is 1934 regular season teams. We omitted *F-Efficiency* from the model because of its high colinearity with the other three efficiency scores. Table 20.8 shows the resulting regression model.

We observe that all five independent variables are highly statistically significant and that all five coefficients have the expected sign. Recall that *D-Capability* is a reverse quantity and that larger values of *O-Efficiency*, *D-Efficiency*, and *W-Efficiency* indicate greater potential to increase output and therefore signify

Table 20.9 Coefficient of partial determination and the R^2 contribution of each capability measure and each efficiency measure in the regular season analysis

Variable	Coefficient of partial determination	R^2 contribution
O-Capability	0.780	0.267
D-Capability	0.860	0.463
O-Efficiency	0.295	0.032
D-Efficiency	0.093	0.008
W-Efficiency	0.419	0.054

lower efficiency. The model explains over 92 % of the variation in *WPct*, indicating that omitted factors and random variation account for no more than 8 % of the variation in regular season effectiveness. Table 20.9 shows the coefficients of partial determination and the R^2 contribution of each independent variable.

The results show that capability contributes more to regular season effectiveness than does efficiency. Specifically, the coefficients of partial determination of *O-Capability* and *D-Capability* are 0.780 and 0.860, respectively, while those of *O-Efficiency*, *D-Efficiency*, and *W-Efficiency* are 0.295, 0.093, and 0.419, respectively. We observe a similar pattern in the R^2 contributions.

Defensive capability appears to be more important than offensive capability, as indicated by the higher coefficient of partial determination, higher R^2 contribution, and larger (absolute) regression coefficient for *D-Capability* relative to *O-Capability* ($t = 12.25$, $df = 3866$, $P < 0.001$). However, good management apparently can enhance offense more than it can enhance defense, as indicated by the higher coefficient of partial determination, higher R^2 contribution, and larger (absolute) regression coefficient for *O-Efficiency* relative to *D-Efficiency* ($t = 9.79$, $df = 3866$, $P < 0.001$). The coefficients of partial determination and the R^2 contributions suggest that *W-efficiency* contributes somewhat more to regular season effectiveness than does *O-Efficiency*, although the (absolute) regression coefficients of *W-Efficiency* and *O-Efficiency* are nearly equal.

Post-season Regression Analysis

The sample size for the regression model is 282 post-season teams. We find that a team's post-season performance is virtually unrelated to offensive and defensive capabilities and that only overall efficiency on the field (a combination of *O-Efficiency*, *D-Efficiency*, and *W-Efficiency*) has even the slightest relationship to post-season performance. Overall efficiency on the field can account for just over 1 % of post-season performance, suggesting that nearly 99 % of post-season success is attributable to chance and other unidentified factors.

20.5.2.5 Conclusions of the Study

In this section, we summarize our results by responding to each research question.

How much does team capability and managerial efficiency contribute to regular season effectiveness in MLB?

We conclude that both capability and efficiency are significant contributors to regular season effectiveness in MLB. However, capability is more important than efficiency. This supports our speculation that capability is more important than efficiency in industries where labor is highly paid. Moreover, we conclude that defensive capability contributes more to regular season effectiveness than does offensive capability. This supports an organizational strategy that places greater emphasis on defense (primarily pitching) relative to offense (primarily hitting).

Among the three efficiency measures, we conclude that the team's ability to win close games, as indicated by its *W-Efficiency*, has the greatest contribution to regular season effectiveness. This suggests that managers who employ effective strategies late in the game, such as pinch-hitting and relief pitching, can significantly influence the team's overall effectiveness.

We also find that the team's *O-Efficiency* has greater influence on its regular season effectiveness than does its *D-Efficiency*. We speculate that this may be because the offense typically has greater control over the tactics that increase *O-Efficiency* relative to the control that the defense has over the tactics that increase *D-Efficiency*. For example, the offense decides when to try to steal a base, when to attempt a hit-and-run play, and when a runner seeks to advance an extra base on a hit. There are few tactics that the defense can employ, such as pitching out and having the pitcher keep runners close to their bases, leaving the defense in a generally reactive position. Thus, the defense tends to rely more on capability – the ability of the pitcher and the catcher to prevent stolen bases and the throwing abilities of the outfielders – than on efficiency.

How much does team capability and managerial efficiency contribute to post-season effectiveness in MLB?

We conclude that regular season capabilities and efficiencies are poor predictors of post-season effectiveness. Thus, post-season success is overwhelmingly determined by chance in that even talented and well-managed teams have little relative advantage in post-season play. We believe that this is due primarily to two factors. First, opposing teams in the post-season are likely also to be talented and well managed, nullifying any relative advantage. Second, post-season series are short – either five or seven games in almost all cases – so that an inferior team maintains a significant chance of winning the series with the help of a few lucky bounces.

20.6 Conclusion

Data envelopment analysis has been extensively applied to measure the performance of individual athletes and teams in a variety of sports as well as to analyze nations competing in the Olympics. Most of the models presented in the literature are single-stage DEA models which treat the underlying process of converting inputs into outputs as a "black box." This approach is appropriate in many situations including when the purpose of the analysis is to rank decision making units (individual athletes, teams, or nations).

In other situations, analysts are interested in investigating the sources of inefficiency within the organization in order to improve organizational performance. For example, the owner of a sports team may be interested in evaluating the efficiency of various organizational sub-processes under the control of different administrators (general managers, talent scouts, on-field managers, or coaches) in order to make personnel decisions. To accomplish this, researchers have developed two-stage and network DEA methodologies.

In this chapter, we model an MLB team as comprised of a front office operation which consumes money in the form of player salaries to acquire offensive and defensive talent and an on-field operation which uses the talent to outscore opponents and win games. We present a network DEA methodology to measure performance of the front office operation (offense and defense), the on-field operation (offense, defense, and integration), and the overall team. We utilize the methodology in two industry-wide studies of Major League Baseball.

In the first study, we use a two-stage DEA model as part of a larger analysis to determine the minimum total player salary required for a team to be competitive, to count the number of teams that are noncompetitive due to low total player salary, to determine the hypercompetitive salary, to count the number of hypercompetitive teams, and to examine the relationship between market size, efficiency, and competitiveness. In order to address these issues, we need to classify the MLB teams as noncompetitive due to low total player salary, noncompetitive for other reasons, conditionally competitive, economically competitive, and hypercompetitive. The classification process utilizes the front office, on-field, and overall team efficiency scores obtained from the two-stage DEA model.

In the second study, we use a network DEA model as part of a larger analysis to explore the relative contributions of team capability and managerial efficiency to team effectiveness during the regular season and the post-season. In order to build the model for team effectiveness, we utilize the *O-Efficiency*, *D-Efficiency*, *W-Efficiency*, and *F-Efficiency* scores determined from the network DEA model.

We emphasize that each of these studies requires the results obtained from the two-stage and network DEA models in order to perform the analysis. A single-stage DEA model does not provide the in-depth information the analyst needs to address the research questions.

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