Success in Professional Baseball:

The Value of Above Average Position Players

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Abstract

In professional baseball, efficient spending is the key to success. Because modern player contracts are so costly, front offices must seek out the most valuable players. In addition, to reach the playoffs, teams need offensively above average players at some positions. Together, these facts lead to an interesting question of whether or not defensive position impacts the value of offensively above average players. To answer this question, reliable metrics of offensive ability must be employed and appropriately analyzed.

Through an analysis involving on-base percentage, park-adjusted linear weights, and weighted on-base average over the course of the 2010 through 2013 Major League Baseball (MLB) regular seasons, it was determined that above average players are more valuable at certain positions than at others. Ultimately, the specific results of this analysis provide practical financial guidance to baseball franchises by generally identifying the most valuable position players.

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Success and Player Position

One hundred seventy-one million dollars. In 2013, it bought the New York Yankees six more regular season losses and several days more of offseason vacation than the Tampa Bay Rays. One hundred seventy-one million dollars separated the payrolls of the Yankees and the Rays (STATS, LLC, and the Associated Press, 2013), yet the more expensive Yankees nevertheless managed to miss the playoffs, ending the season six games behind the Rays in the American League East. Two words too easily sum up this monumental failure: inefficient spending. To be fair, though the Yankees presented an easy target in 2013, they are certainly not the only MLB franchise frivolously spending money. Likewise, the Rays are not the only franchise displaying some semblance of fiscal responsibility. Especially within the last several years, many teams with a relatively enormous payroll failed to achieve a playoff berth while much more fiscally restrained teams played on into October. Despite the lack of a salary cap, it seems as though any team can compete. As Michael Lewis (2004) observed, financial stewardship is more important than financial wealth in professional baseball (p. XIII). The key to success in baseball is efficient spending.

Players are the main object of inefficient spending in baseball. Star players routinely garner contracts worth hundreds of millions of dollars, and even below-average players demand seven-figure salaries. Because every player a team wishes to sign costs so much, efficient spending requires that front offices only spend money on the most valuable players. This fact leads to a simple question: What makes a player valuable? Naturally, in order to answer this question, the game of baseball must be considered.

In baseball, players fundamentally contribute to their teams on offense and on defense. Therefore, it seems as though offensive ability and defensive ability both need to be taken into account when determining player value. For very accurate evaluations, this is indeed true, but for easier, yet still adequate evaluations, defensive ability can be disregarded (pitchers aside). Baseball analysts John Thorn, Pete Palmer, and David Reuther (1985) presented a theoretical breakdown of baseball which naturally split the game in half, 50% being offense and 50% being defense. They further broke down defense into pitching and fielding. To determine the percentage of baseball that could be attributed to fielding, they took the percentage of runs that are unearned (these are credited to fielders) and divided it by two (since defense is 50% of baseball). In their breakdown, Thorn et al. estimated that fielding accounted for about six percent of baseball (p. 178). When the same theoretical breakdown and techniques used by Thorn et al. were applied to the earned and unearned run totals in the 2013 MLB regular season (provided by Retrosheet.org (2013e) it could be concluded that fielding accounted for less than four percent of baseball in 2013. Based on this, offensive ability is much more influential to the value of a player than defensive ability, pitchers notwithstanding. Thus, the most valuable position players are almost always the best offensive players.

With this in mind, player evaluations are straightforward given a reliable metric of offensive ability. Better offensive players are more valuable. This observation leads to the conclusion that teams should simply look to sign the best offensive players available. Efficient spending would simply require teams to spend their money on the best offensive players at the best price. Although not entirely inadvisable, this conclusion completely ignores two important elements of baseball: success and player position.

The ultimate goal of every baseball franchise is to win the World Series. Nevertheless, a team will generally consider a season to be successful if they make the playoffs. Undeniably, a certain level of offensive production accompanies a playoff berth; in order for a team to have a successful season, they need some players who are offensively above average at their position. A truly exceptional team would field such players at every position. This situation, however, is near impossible in practice due to the enormous price tag that would be required. Therefore, a team essentially needs to decide at which positions to employ above average hitters. Although many teams doubtfully consider this reality, it leads to an interesting question: Are above average offensive players more valuable at certain positions than at others? If the answer is yes, then teams looking to efficiently spend should primarily hire players at the most valuable positions. If the answer is no, then efficient spending would simply require teams to sign the best available offensive player at the cheapest price. Either way, the answer to this question of positional value will surely provide teams with useful financial guidance.

Measuring Offensive Ability

In order to determine whether or not above average offensive players are more valuable at certain positions than at others, a way to measure offensive ability is needed. Traditionally, major league managers and ordinary baseball fans alike have evaluated offensive ability in two flawed ways: based on subjective qualities and based on inept statistics.

First, players have often been valued based on subjective qualities. A typical example of this is when scouts and managers judge a player based on physical observation and not necessarily on how the player has actually produced. In an interview with former Montreal Expos manager Omar Minaya, Josh Dubow (2002) received a response that epitomizes this situation:

> "I don't talk about on-base percentage"…"I'm old school. I'm not a stat guy. I'm a talent evaluator. The guys who taught me the game of baseball never talked about on-base percentage. Give me talent, and I'll give you on-base percentage" (p. B6)

This line of thinking is flawed in that it does not consider the objective production of a player revealed in statistics, but rather relies on subjective evaluations often based on how a scout or manager may *feel* about a player.

Second, players have often been evaluated by how good they are in some statistic that fails to reveal true offensive talent. Perhaps the best example of this is the popularity of the batting average. Batting averages appear in every major league box score, and fans routinely use batting averages to offensively rank players. The flaw with the batting average, as Eric Seidman (2008) explained, is that it fails to distinguish between singles, doubles, triples, and home runs. In essence, the batting average converts all hits into singles, treating all hits as equally valuable (p. 18). Obviously, a home run is worth far more than a single. Because it does not correctly value offensive events, batting average fails as an indicator of true offensive ability, and thus cannot be relied upon to accurately rank players.

In order to correctly appraise offensive ability, statistics which properly capture offensive ability need to be employed. Based on such statistics, accurate player rankings can be determined and above average players can be identified. To correctly measure offensive ability, a statistic needs to appropriately represent the events that are most offensively important, those events which contribute the most to run scoring, and therefore to winning. Hence, a statistic which strongly correlates to run production or winning is undoubtedly a good measure of true offensive ability.

On-Base Percentage

On-Base Percentage (OBP) is a conveniently simple statistic that accurately measures offensive skill. Jahn Hakes and Raymond Sauer (2006) presented a linear regression analysis which suggests a strong correlation between OBP and winning percentage (p. 175). Because it strongly correlates to winning percentages, OBP is a reliable offensive metric. Formula 1 is the formula used to calculate OBP (FanGraphs, 2014).

$$OBP = \frac{H+BB+HBP}{AB+BB+HBP+SF} \qquad (1)$$

In this formula, H denotes hits, BB denotes walks, HBP denotes hit-by-pitch, AB denotes at-bats, and SF denotes sacrifice flies. The numerator of OBP enumerates all of the times a particular player reaches base, while the denominator enumerates almost all of the plate appearances for that player. Notably, OBP does not include regular sacrifice hits because they are very situation-dependent and usually result from the decision of a manager. It is unfair to penalize a player for following the orders of his manager. OBP measures how effectively a batter gets on base and thereby avoids making an out, two essential elements of run production.

Linear Weights

On-Base Percentage is known as a traditional statistic, basically meaning that it has been officially recorded for the past several decades. Simplicity characterizes traditional statistics. Simplicity does not typically characterize sabermetrics. As explained by Gabriel Costa, Michael Huber, and John Saccoman (2008), sabermetrics is a term that combines the acronym for the Society of American Baseball Research (SABR) and “metric” to generally define the “search for objective knowledge about baseball.” Statistician Bill James both coined and defined the term (p. 1). Although generally defined here, sabermetrics are fundamentally statistics which aim to accurately describe baseball. Over the last few decades, sabermetricians have developed numerous offensive statistics which reliably capture the true offensive production of a player. One of these statistics is Linear Weights (LWTS).

Pete Palmer created the Linear Weights system and introduced it in the book *The Hidden Game of Baseball: A Revolutionary Approach to Baseball and its Statistics*. In this book, Thorn et al. (1985) presented a statistical study involving several offensive statistics, wherein Linear Weights proved to correlate most closely with run production (p. 58-59). Jim Albert and Jay Bennett (2003) further confirmed the reliability of LWTS by concluding that LWTS is the best of the additive models of offensive production and that it is a dependable metric for player evaluations (p. 241). LWTS is certainly a trustworthy metric of offensive production.

In baseball, the primary purpose of the offense is to score runs. Accordingly, the goal of every at bat is to create runs (James, 2001, p. 330). LWTS aims to record how well a player accomplished this goal. To do so, the LWTS system relies on run values, the value in runs of every offensive event. Using the run values of the various offensive events as weights, LWTS combines the statistics of a player (or players) in a linear fashion to total the number of runs that that player contributed. As a simple example, assume a single is worth 0.45 runs and a double is worth 0.75 runs. If a player hit 80 singles and 16 doubles in a season, they would have 0.45(80) + 0.75(16) = 48 LWTS. Of course, a more accurate LWTS calculation would include many other offensive events besides singles and doubles. Formula 2 is a more complete LWTS formulation:

$$LWTS = w_{1B} \times 1B + w_{2B} \times 2B + w_{3B} \times 3B + w_{HR} \times HR + w_{NIBB} \times NIBB + w_{HBP} \times HBP + w_{SB} \times SB + w_{CS} \times CS + w_{OUT} \times OUT \tag{2}$$

Here, 1B denotes singles, 2B denotes doubles, 3B denotes triples, HR denotes home runs, NIBB denotes unintentional walks, HBP denotes hit-by-pitch, SB denotes stolen bases, CS denotes caught stealing, OUT denotes outs, and the various w variables denote the respective weights for each of the offensive events. Other LWTS formulations include more offensive events such as reached base on error (RBOE), passed ball, and bunt, but as Lee Panas (2010) mentioned, the six main offensive events that account for a majority of scored runs are singles, doubles, triples, home runs, walks, and hit batsmen (p. 23). Formula 2 contains all of these events plus SB and CS, and is therefore a satisfactory LWTS formulation.

In order to determine the run values for the various offensive events, LWTS relies on historical play-by-play data. Following the general process of authors Tom Tango, Mitchel Lichtman, and Andrew Dolphin (2007), the calculation of the values begins with an understanding of base-out states (p. 16-29). A team can fill the bases in $2^3 = 8$ distinct ways. This is the result of two options, occupied or unoccupied, for each of the three bases. When combined with three possible out counts (zero, one, or two outs), the eight ways to fill the bases becomes twenty-four possible scenarios for a team at any at-bat in a game. These scenarios are called base-out states.

Historical data assigns run values to each of the base-out states. These run values represent how many runs are expected to score from each state on average, and are aptly called run expectancies (RE). In order to calculate these run expectancies, the number of runs scored from each particular state to the end of the inning in which they occurred is counted and divided by how many times that particular state occurred. For accuracy, the determination of these run expectancies is typically carried out over a large amount of play-by-play data. As an example, according to regular season play-by-play data provided by Retrosheet.org (2013c) and processed by Bevent.exe from Retrosheet.org (2013a) and RetrosheetMod.jar written by Quinn Detweiler (personal communication, 2013), the base-out state of bases loaded with one out occurred 1722 times in 2010, with 2613 runs scoring from that state to the end of each respective inning. Thus, in 2010, the run expectancy for that particular base-out state was 2613/1722 = 1.517 runs. Using similar calculations and the same play-by-play data, Table 1 provides the run expectancies for each of the base-out states in 2010 (X's denote a runner on that base).

Table 1

Run Expectancies by Base-Out State in 2010

1B	2B	3B	0 Outs	1 Out	2 Outs
-	-	-	0.492	0.262	0.104
X	-	-	0.878	0.514	0.233
-	X	-	1.104	0.681	0.324
-	-	X	1.384	0.935	0.348
X	X	-	1.433	0.890	0.456
X	-	X	1.801	1.115	0.481
-	X	X	1.976	1.393	0.594
X	X	X	2.376	1.517	0.786

Note. According to regular season play-by-play data provided by Retrosheet.org (2013c) and processed by Bevent.exe from Retrosheet.org (2013a) and RetrosheetMod.jar written by Quinn Detweiler (personal communication, 2013).

Notably, Table 1 displays intuitive results. States with fewer outs, states with more runners, and states with runners in scoring position logically should have higher run expectancies than states with fewer of these characteristics. Table 1 reveals all of these logical expectations.

The run value of each individual offensive event is based on the base-out state run expectancies. The double in 2010 will facilitate an explanation of how the LWTS system determines run values for each of the events. To begin, the number of times a double was hit in each of the base-out states is counted. Then, at each respective base-out state the number of runs scored to the end of the inning (REOI) following the double is counted and subsequently averaged over the total number of times a double occurred in that particular state (Avg. REOI). Table 2 contains all of this information for the double in 2010, based on play-by-play data from Retrosheet.org (2013c) which was processed by Bevent.exe from Retrosheet.org (2013a) and RetroSheetMod.jar by Quinn Detweiler (personal communication, 2013). For each base-out state, the last column of Table 2 shows the average number of runs that scored to the end of an inning following a double.

Table 2

Run Value Calculation of the Double in 2010 – Part 1

Base-Out State						
1B	2B	3B	Outs	# of Doubles	REOI	Avg. REOI
-	-	-	0	2099	2285	1.089
-	-	-	1	1448	962	0.664
-	-	-	2	1064	326	0.306
X	-	-	0	473	899	1.901
X	-	-	1	547	799	1.461
X	-	-	2	516	494	0.957
-	X	-	0	147	292	1.986
-	X	-	1	250	416	1.664
-	X	-	2	288	376	1.306
-	-	X	0	23	49	2.130
-	-	X	1	81	131	1.617
-	-	X	2	104	132	1.269
X	X	-	0	107	309	2.888
X	X	-	1	189	506	2.677
X	X	-	2	247	486	1.968
X	-	X	0	52	188	3.615
X	-	X	1	94	208	2.213
X	-	X	2	122	228	1.869
-	X	X	0	36	100	2.778
-	X	X	1	63	173	2.746
-	X	X	2	92	212	2.304
X	X	X	0	35	161	4.600
X	X	X	1	74	255	3.446
X	X	X	2	96	278	2.896

Note. Data for determining the LWTS run value of the double in 2010. REOI denotes runs to the end of the inning and Avg. REOI is the average number of runs scored to the end of the inning. According to regular season play-by-play data provided by Retrosheet.org (2013c) and processed by Bevent.exe from Retrosheet.org (2013a) and RetrosheetMod.jar written by Quinn Detweiler (personal communication, 2013).

Importantly, in each state the double did not account for all of these runs since each base-out state has an associated run expectancy, the average number of runs that are expected to score from that state just as a result of being in that state. In order to find the actual run value of the double at each base-out state, the run expectancy of the state must be subtracted from the Avg. REOI produced by the double. As an example, consider the base-out state of a runner on first with one out. In 2010, when a double was hit in this state, an average of 1.461 runs scored to the end of the inning. The double did not solely account for all of those 1.461 runs, however, because based on the run expectancies, 0.514 runs are estimated to score from that state regardless of the double. To find the true number of runs that can be attributed to the double, the 0.514 expected runs are subtracted from the 1.461 average runs that scored after the double, equaling 0.947 runs. Theoretically, the double raised the value of the runner on first with one out state by 0.947 runs, and is therefore worth 0.947 runs in that state. Using similar calculations, the true run value of the double can be determined for each base-out state. Table 3, an augmented version of Table 2, shows the real run values of the double for each base-out state in 2010. The overall, context-neutral run value of the double is simply a weighted average of the run values at each base-out state, weighted according to the number of doubles hit corresponding to each run value. In 2010, the overall run value of the double was 0.750 runs. Appendix A displays the run values for each of the offensive events in Formula 2 for each of the last four seasons.

It is important to note that the above method is not the most exact way of calculating run values. Tango et al. (2007) mentioned that a better way to compute the run value for a particular event is to award to the offensive event the difference between the run expectancies of the base-out state before the event and the base-out state directly following the event, plus any runs that score (p. 26). This method essentially changes the run values for each base-out state (from those recorded in Table 3), and therefore the weighted average which determines the overall run value of each event. This more

Table 3

Run Value Calculation of the Double in 2010 – Part 2

Base-Out State								
1B	2B	3B	Outs	# of Doubles	REOI	Avg. REOI	Start RE	Run Value
-	-	-	0	2099	2285	1.089	0.492	0.597
-	-	-	1	1448	962	0.664	0.262	0.402
-	-	-	2	1064	326	0.306	0.104	0.203
X	-	-	0	473	899	1.901	0.878	1.023
X	-	-	1	547	799	1.461	0.514	0.947
X	-	-	2	516	494	0.957	0.233	0.725
-	X	-	0	147	292	1.986	1.104	0.882
-	X	-	1	250	416	1.664	0.681	0.983
-	X	-	2	288	376	1.306	0.324	0.981
-	-	X	0	23	49	2.130	1.384	0.747
-	-	X	1	81	131	1.617	0.935	0.683
-	-	X	2	104	132	1.269	0.348	0.921
X	X	-	0	107	309	2.888	1.433	1.455
X	X	-	1	189	506	2.677	0.890	1.788
X	X	-	2	247	486	1.968	0.456	1.512
X	-	X	0	52	188	3.615	1.801	1.814
X	-	X	1	94	208	2.213	1.115	1.098
X	-	X	2	122	228	1.869	0.481	1.388
-	X	X	0	36	100	2.778	1.976	0.801
-	X	X	1	63	173	2.746	1.393	1.353
-	X	X	2	92	212	2.304	0.594	1.710
X	X	X	0	35	161	4.600	2.376	2.224
X	X	X	1	74	255	3.446	1.517	1.929
X	X	X	2	96	278	2.896	0.786	2.110

Note. Data for determining the LWTS run value of the double in 2010. REOI denotes runs to the end of the inning, Avg. REOI is the average number of runs scored to the end of the inning, Start RE is the appropriate run expectancy for each base-out state in 2010 (see Table 1), and Run Value is the run value of the double at the corresponding base-out state. According to regular season play-by-play data provided by Retrosheet.org (2013c) and processed by Bevent.exe from Retrosheet.org (2013a) and RetrosheetMod.jar written by Quinn Detweiler (personal communication, 2013).

precise method is extraordinarily complex (except for the home run), however, and will not result in significantly different run values for calculations carried out over large amounts of play-by-play data. Furthermore, a more accurate way to apply the LWTS run values is to apply them by situation, as opposed to determining an overall, context-neutral run value. For example, a double hit with the bases empty and no outs would be worth 0.597 runs and a double hit with a runner on first and one out would earn 0.947 runs in the context-specific approach, whereas both doubles would be worth 0.750 runs in the context-neutral approach. As Tom Tango (n.d.) revealed, however, the results of a context-specific application of LWTS do not differ enough from the context-neutral results of LWTS to warrant an extensive amount of additional calculations. Therefore, the context-neutral technique outlined above is adequate in determining LWTS run values.

Once all of the run values for the various offensive events are calculated, the value of the out must be set. After all, the out is an offensive event, albeit a detrimental one. Because it negatively impacts offense, the out has a negative run value in the LWTS system. Importantly, JT Jordan (2010) noted that weighting the out to make the league statistics produce zero LWTS is imperative in any LWTS computation (Transforming Linear Weights into a Rate section, para. 4). Setting the run value of the out so that the league statistics produce zero LWTS also conveniently establishes zero LWTS as the measure of an average player. A player who has a positive LWTS value is offensively above average, and a player who has a negative LWTS value is offensively below average. Notably, though some outs do offensively help teams (such as sacrifice flies), these outs are vastly outnumbered by the more generic ground out or fly out. Thus, the averaged run value of the out which produces zero league LWTS is a satisfactory run value.

Park-Adjusted Linear Weights

Although finding the run values of the offensive events and the out is tedious, the LWTS statistic as shown in Formula 2 is easy to calculate given the run values. Once applied to a set of counted statistics, say to the statistics of a player or team, a further modification can be made to LWTS values in order to refine them. In “The Sabermetric Manifesto”, David Grabiner (2011) stated that a good metric should not capture factors which a player cannot control, such as which ballpark they typically play in (General Principles section, para. 10). In professional baseball, ballparks greatly differ in numerous characteristics including dimension, altitude, and fence height. All of these variations combine to make some ballparks more conducive to offense than others. Surely, a ballpark with slightly shorter fences and smaller dimensions will yield more home runs than one with contrasting features. Players whose home park is hitter-friendly will undoubtedly benefit from their park and have better offensive statistics than they would at a pitcher-friendly park. In order to more precisely compare players, an adjustment for ballpark should be made to offensive statistics. Fortunately, it is not terribly difficult to adjust LWTS values for the home ballpark of a player or team.

In order to adjust LWTS values according to home ballpark, a park factor must be assigned to each park. Many different methods exist to determine park factors, but an easy one is an abbreviated version of a method explained by Thorn et al. (1985, p. 99-101). To begin, the total number of runs allowed by all home teams is divided by the total number of runs allowed by all away teams for a specified time period, such as a season. This number is labeled the home-road ratio for the league (HRL). Then, for each individual park, a similar ratio is determined for the home team; the number of runs allowed by that team at home is divided by the number of runs allowed by that team on the road to give the home-road ratio for that particular team (HRT). To find the park factor (PF) for a particular park, the home-road ratio for the home team is divided by the home-road ratio for the league, added to one, and divided by two.

$$PF = \frac{\frac{HRT}{HRL}+1}{2} \tag{3}$$

Park factors exceeding one indicate a hitter-friendly park, whereas park factors below one indicate a pitcher-friendly park. As an example, according to data provided by Retrosheet.org (2013d), home teams allowed 10316 runs in 2010, whereas away teams allowed 10992 runs. From these, HRL = 10316/10992 = 0.939. Continuing this example, to find the park factor for Citizen’s Bank Park, the home-road ratio for the Philadelphia Phillies must be determined. According to Retrosheet.org (2013f), the Phillies allowed 312 runs at home and 328 runs on the road in 2010. Thus, for the Phillies, HRT = 312/328 = 0.951. Therefore, the 2010 park factor for Citizen’s Bank Park was PF = [(0.951/0.939)+1]/2 = 1.007, indicating that Citizen’s Bank Park was hitter-friendly in 2010. To put this park factor in context, the highest park factor from the last four regular seasons was 1.240 (Coors Field, Colorado, 2012) and the lowest park factor from the last four seasons was 0.845 (Safeco Field, Seattle, 2012); thus, the 1.007 park factor for the 2010 Phillies was relatively inconsequential.

Using the park factors, LWTS values can be adjusted according to park, resulting in park-adjusted linear weights (PALWTS). In order to do this, the technique presented by Thorn et al. (1985) can be followed (p. 101). To start, the total number of runs scored in the league is divided by the total number of plate appearances (PA) in the league to determine the league average of runs scored per plate appearance (RPAL). Following this, an adapted version of the equation presented by Thorn et al. can be applied:

$$PALWTS = LWTS - RPAL \times PA \times (PF - 1) \tag{4}$$

Note that in this formula, PF and PA are based on the player or team whose LWTS value is being adjusted. For example, according to data provided by Retrosheet.org (2013d), RPAL equaled 0.117 in 2010. According to counted data from MLB.com (2013) and run values determined using the technique described in the LWTS section, the catcher position for the 2010 Philadelphia Phillies had a LWTS total of 12.257 over the course of 628 plate appearances. Using Formula 3 for the Phillies' catcher position, PALWTS = 12.257 - 0.117 × (1.007 - 1) × (628) = 11.760. Since the home field of the Phillies (Citizen's Bank Park) is a hitter-friendly park, the statistics for Phillies hitters should be decreased when adjusted for park, as is shown in the reduced PALWTS value above.

The formula for PALWTS can be best explained using the above example of the Philadelphia Phillies. Because Citizen's Bank Park had a PF of 1.007 in 2010, Philadelphia catchers are expected to hit approximately 0.7% better than the league. To find how many runs this 0.7% represents, the 0.7% is multiplied by the average number of runs expected to score based on plate appearances. Since the league average of runs scored per plate appearance was 0.117 in 2010, and the Phillies catchers had 628 PA, the expected number of runs scored for the catchers was 0.117 × 628 = 73.48 runs. Multiplying this by 0.7% gives the additional number of runs the Phillies catchers are expected to score as a result of playing half of their games in Citizen's Bank Park: 0.007 × 73.48 = 0.514 runs. Therefore, 0.514 runs are attributed to Citizen's Bank Park and subtracted from the unadjusted LWTS total to calculate PALWTS (the discrepancy is a result of rounding).

Weighted On-Base Average

LWTS and PALWTS are not the only statistics to use the run values calculated in the LWTS system. A sabermetric known as weighted on-base average (wOBA) also employs the LWTS run values, using them in the form of a rate statistic. Dave Cameron (2008) of FanGraphs.com, a reputable sabermetric website, asserted that wOBA is a reliable statistic that correctly values offensive events and is not dependent on context. In other words, weighted on-base average is a dependable measure of offensive ability.

Baseball statistician Tom Tango created wOBA and presented it in *The Book: Playing the Percentages in Baseball*. Essentially, wOBA aims to correct OBP. Although OBP strongly correlates to winning percentage and clearly communicates important information by revealing the rate at which a player reaches base, Tango et al. (2007) noted that OBP fails in that it treats every hit as a single. In order to correct this shortcoming of OBP, the LWTS run values are used to weight the various offensive events in the formula for wOBA. The formula for wOBA as written in *The Book* is as follows (p. 29-30):

$$wOBA = \frac{w_{NIBB} \times NIBB + w_{HBP} \times HBP + w_{1B} \times 1B + w_{RBOE} \times RBOE + w_{2B} \times 2B + w_{3B} \times 3B + w_{HR} \times HR}{PA} \quad (5)$$

In this formula, RBOE denotes reached base on error, the various w variables denote the respective weights of the offensive events, and the other abbreviations denote events as previously noted. Importantly, the weights for the offensive events in Formula 5 are not the exact LWTS run values. To calculate the weights for wOBA, the LWTS run values are first realigned relative to the out since the negative impact of the out is now accounted for in the division by plate appearances. To do this, the absolute value of the out is added to each of the LWTS run values. These adjusted weights are then used in Formula 5 on the counted statistics of the league to find the league wOBA. Finally, since wOBA is modeled from OBP, it is scaled with a constant factor so that the league wOBA is equal to the league OBP. Because the numerator of wOBA is linear in nature, the constant factor distributes to each of the individual weights, which is why the constant factor does not appear in Formula 5.

Answering the Objective Question of Positional Value

Through a statistical analysis of OBP, PALWTS, and wOBA, three accurate metrics of offensive ability, the objective question of whether or not offensively above average players are more valuable at certain positions than at others was addressed. In order to employ and analyze these three statistics in a way that would answer the objective question, several preliminary steps had to be taken.

Applying OBP, PALWTS, and wOBA to Player Statistics

To begin, OBP, PALWTS, and wOBA were applied to player statistics from the last four regular seasons of Major League Baseball (2010, 2011, 2012, and 2013). LWTS run values were calculated using regular season play-by-play data provided by Retrosheet.org (2013c) and processed by Bevent.exe from Retrosheet.org (2013a) and

RetrosheetMod.jar written by Quinn Detweiler (2013, personal communication). Additional data from Retrosheet.org (2013b) was used to calculate the park factors for PALWTS. OBP, PALWTS, and wOBA were determined for each position (excluding pitcher), for each team, during each of the last four regular seasons using counted player statistics from MLB.com (2013). All three of the statistics were calculated using Formulas 1 through 5, respectively, with one minor note being that the wOBA calculations did not include RBOE (relative to the total of hits, walks, and hit-by-pitches, very few players reach base on error, making this a relatively inconsequential exclusion). Importantly, the statistics were not applied to individual player statistics, but rather positional totals. At any given position for any given team during each of the last four regular seasons, all of the offensive statistics attributed to that specific position, team, and year were compiled. OBP, PALWTS, and wOBA were then determined in each case using the grouped positional statistics. Due to this fact, whenever a *player* is henceforth mentioned, a group of players is actually being referenced. In some cases, the grouped statistics predominately represented one player, but in many cases, the grouped statistics were comprised of substantial contributions from multiple players.

As a side note, it may seem as though the determination of OBP, PALWTS, and wOBA for composite positional statistics instead of for single players at each position misinterpreted the objective question of positional value. Indeed, grouped positional statistics answered a slightly modified version of the objective question. Instead of answering if above average individual players are more valuable at certain positions than at others, the composite statistics answered whether or not above average composite statistics are more valuable at certain positions than at others. Logically, the second question is a stronger version of the first. If above average composite statistics are more valuable at a certain position as opposed to others, then an above average player is clearly more valuable at that position as well, as this player is needed to provide part of the composite statistics. Therefore, the grouped statistics certainly answered whether or not offensively above average players are more valuable at certain positions than at others. It is also worth noting that the use of grouped statistics to determine positional value was practically mandatory due to injuries and player platooning, which greatly complicated the selection of a single "starting" player at each position.

Determining Player Ability

To determine the relative offensive level of players (composite statistics), and to identify which players were offensively above average, z-scores were used for OBP, PALWTS, and wOBA. For each of these three statistics, separate means and standard deviations were calculated for each year and position. Z-scores were then figured for each specific year, team, and position using the year and position-dependent means and standard deviations. In this way, catchers in 2010 were only offensively compared to catchers in 2010, first basemen in 2011 to first basemen in 2011, and so on. Significantly, Keith Woolner (Baseball Prospectus, 2006) pointed out that offensive ability differs across positions, with defensively difficult positions typically performing at a lower offensive level than less demanding defensive positions. Because of this, it was important to define the offensive ability of a player based on the average and standard deviation for their respective position, not based on the overall average and standard deviation of the league. In addition, since positional averages and standard deviations changed from year to year, player comparisons were exclusively made on a yearly basis.

Playoff Percentages

Ultimately, the z-scores were analyzed using the idea of a *playoff percentage*. In the notation of probability, the term *playoff percentage* refers to P{Team made the playoffs | Positional z-score corresponding to (OBP, PALWTS, or wOBA) was greater than x}×100%. For example, the playoff percentage corresponding to the OBP of catchers in 2010 at a z-score of 0.3 was 60%. This means that in 2010, 60% of teams whose respective catcher positions achieved an OBP z-score higher than 0.3 made the playoffs. Analogous playoff percentages corresponding to OBP, PALWTS, and wOBA were calculated for each position over the course of the last four years at every z-score from -3 to 3, incremented by 0.1. Because a successful year is generally defined as one in which a team reaches the playoffs, the playoff percentages essentially represent the success rate of teams with a given level of player at a given position.

In order to increase the sample sizes of the percentages, the various single-season playoff percentages were appropriately compiled to represent the last four regular seasons combined. Accordingly, the four-year playoff percentages represent the percentage of teams that made the playoffs over the course of the last four years, given a particular position and statistical z-score. Finally, to assist in analysis, the four-year playoff percentages corresponding to OBP, PALWTS, and wOBA were plotted against the normal cumulative probabilities associated with each of the respective z-scores. This was done due to the fact that a uniform change in z-score (in this case, 0.1) does not represent a uniform change in normal cumulative probability. Plotting the playoff percentages against the normal cumulative probabilities most accurately portrayed the trend of the playoff percentages as the production level increased. Lastly, because the most significant playoff percentages occurred between the z-scores of -2 and 2, the plots only display the playoff percentages at the normal cumulative probabilities associated with these z-scores. As an example, the plot for the catcher position is shown in Figure 1. Appendix B contains the four-year playoff percentage plots for each of the positions. These plots were the main object of the analysis of positional value.

Determining Positional Values Using the Playoff Percentage Plots

Two basic questions must be considered when determining the value of an offensively above average player at a particular position: “Does an above average player at this position give a team a better chance of making the playoffs than a below average player?” and “How much of a chance of succeeding does an above average offensive player at this position give a team?” More valuable positions will be those at which above average offensive players increase the success rate of teams, and those at which above average players give teams a high chance of succeeding, relative to the other positions. Naturally, positions with these characteristics are more valuable because they contribute more to success.

Historical positional values were ascertained by analyzing the playoff percentage plots. Two characteristics of the plots for each statistic correspond to the two questions which determine value: the overall trend of the playoff percentages (Did an above average player at this position give a team a better chance of making the playoffs than a below average player?) and the magnitude of the playoff percentages (How much of a chance of succeeding did an above average offensive player at this position give a

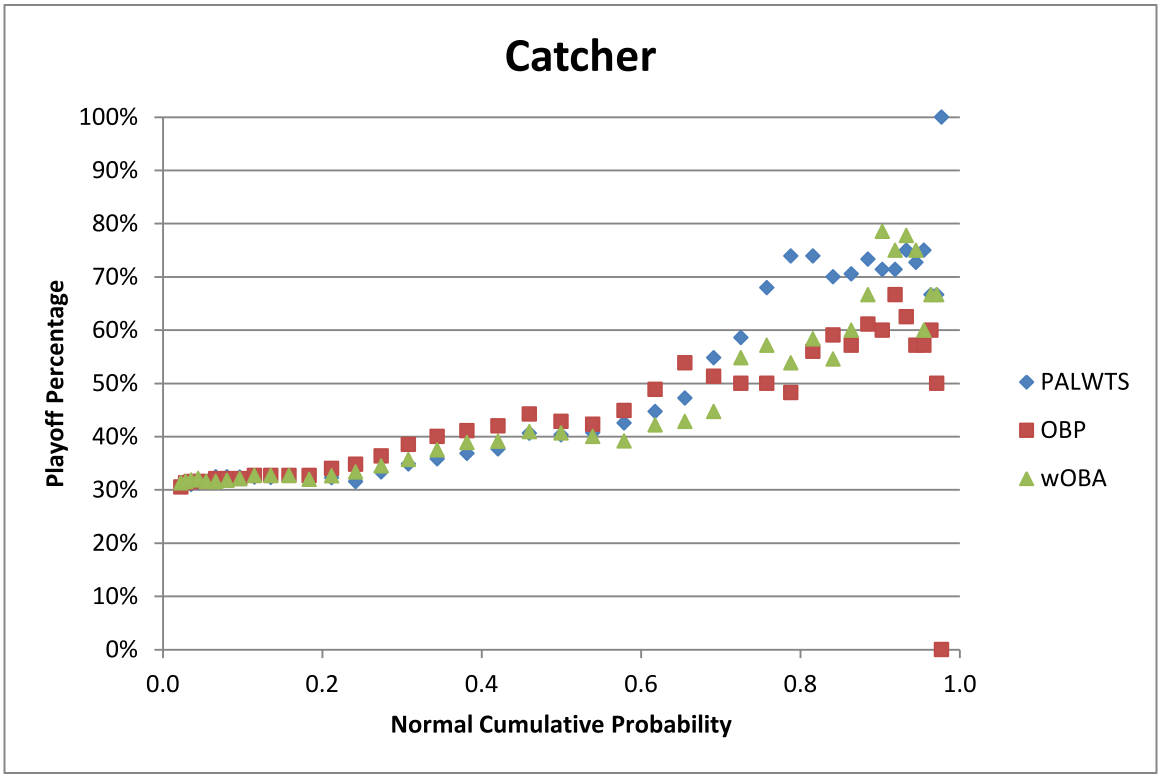

Figure 1. Four-year playoff percentage plot for the catcher position. PALWTS denotes park-adjusted linear weights, OBP denotes on-base percentage, and wOBA denotes weighted on-base average. PALWTS calculations were based on play-by-play data provided by Retrosheet.org (2013c) and processed by Bevent.exe from Retrosheet.org (2013a) and RetroSheetMod.jar by Quinn Detweiler (personal communication, 2013), park-specific data provided by Retrosheet.org (2013b), and counted player statistics from MLB.com (2013). OBP was calculated with counted player statistics from MLB.com (2013). wOBA calculations were based on play-by-play data provided by Retrosheet.org (2013c) and processed by Bevent.exe from Retrosheet.org (2013a) and RetroSheetMod.jar by Quinn Detweiler (personal communication, 2013), as well as counted player statistics from MLB.com (2013).

team?). Overall, if the playoff percentages for a particular position trended upwards as the normal cumulative probabilities increased, then that position had some value as the upward trend signified that above average players increased the chances that a team made the playoffs. Furthermore, relatively high playoff percentages at normal cumulative probabilities greater than 0.500 signified greater value as they showed that above average players at that position helped teams to reach the playoffs at a higher rate than at other positions. Importantly, playoff percentages at the very right of the plots often represented a very small number of teams, occasionally just one or two. Because of this, the "end behavior" of the plots was usually disregarded.

Lastly, before presenting the analysis of the four-year plots, it is important to note two things. First, although the playoff percentage plots helped to answer the objective question of positional value, they could not give precise answers, even with four years of data represented. Practically, this means that the four-year plots could not establish a single-file hierarchy of the positions according to the value of above average players at each position. Acknowledging this, the positions were more generally sorted into five categories signifying their relative values: very high value, high value, moderate value, low value, and very low value. Second, the following analysis of the four-year plots always reports the playoff percentages in sentence form (followed by the corresponding numerical playoff percentage in parentheses), and the specific percentages mentioned always occurred at z-scores greater than 0 (normal cumulative probabilities greater than 0.500) and therefore represented above average players.

Analysis: Positional values based on the last four regular seasons. During the last four years, offensively above average catchers showed very high value. The playoff percentages for OBP, PALWTS, and wOBA all trended upwards with a comparatively strong slope and the playoff percentages for all three statistics reached very high values relative to other positions. During the last four seasons, seventeen of the best twenty-three catchers in PALWTS made the playoffs (74% playoff percentage), eleven of the top eighteen catchers in OBP made the playoffs (61%), and eleven of the best fourteen catchers in wOBA achieved a playoff berth (79%). Above average catchers clearly exhibited very high value over the last four years.

Good first basemen had high offensive value over the last four years. PALWTS, OBP, and wOBA all had playoff percentages which generally rose as z-scores (and corresponding normal cumulative probabilities) increased. In addition, over the last four seasons, twelve of the best nineteen first basemen in PALWTS reached the playoffs (63% playoff percentage), seven of the top fourteen first basemen in OBP achieved a playoff berth (50%), and eight of the top fourteen first basemen in wOBA made the playoffs (57%). These numbers indicated that above average first basemen showed more than moderate value over the last four years, but that they did not have as much value as catchers. Therefore, first basemen had high value over the last four seasons.

Above average second basemen also showed high value over the last four seasons. The playoff percentages for all three statistics generally displayed an upward trend. Furthermore, over the course of the last four years, eight of the top fourteen second basemen in PALWTS made the playoffs (57%), eleven of the best nineteen second basemen in OBP reached the postseason (58%), and ten of the top eighteen second basemen in wOBA achieved a playoff berth (56%). Based on these playoff percentages and the increasing trend of the playoff percentages, second basemen had high value over the last four seasons.

Good shortstops had very low offensive value over the last four years. The playoff percentages for PALWTS, OBP, and wOBA all trended either level or downward between the z-scores of 0 and 1.5 (between normal cumulative probabilities of 0.5 and 0.933). In addition, since the 2010 season, only six of the best twenty-six shortstops in PALWTS helped their teams achieve a playoff berth (23%) while a meager five out of the top sixteen shortstops in OBP made the playoffs (31%), and only seven of the top twenty-six shortstops according to wOBA reached the postseason (27%). Keeping in mind that if one were to randomly select team names from a hat to determine playoff berths, a team would have had a 30% chance of making the playoffs during the last four years, it is clear that above average shortstops had very low offensive value.

Above average third basemen showed moderate value over the last four seasons. For all three statistics, the playoff percentages trended gradually upwards over most of the z-scores and reached moderate levels for each of the three statistics: nine of the top twenty third basemen according to PALWTS reached the playoffs (45%) and eight of the top seventeen third basemen in OBP and wOBA achieved playoff berths (47%). Thus, good offensive third basemen had moderate value over the last four years.

Like first and second basemen, left fielders had high offensive value over the last four seasons. The overall trend of the playoff percentages for all three statistics rose with a strong upward slope and then leveled off near a z-score of 1 (normal cumulative probability of 0.841). Before leveling off, the playoff percentages reached relatively high values. Thirteen of the best twenty left fielders in PALWTS reached the postseason (65%), fourteen of the best twenty-four left fielders in OBP achieved a playoff berth (58%), and twelve of the top twenty-two left fielders in wOBA made the playoffs (55%). These numbers indicated a high offensive value for left field.

Good offensive center fielders showed low offensive value over the last four years. The playoff percentages for PALWTS, OBP, and wOBA all trended downward over positive z-scores (normal cumulative probabilities exceeding 0.500). Furthermore, over the last four seasons, seven of the top nineteen center fielders according to PALWTS made the playoffs (37%), only five of the top eighteen center fielders in OBP reached the postseason (28%), and just six of the best nineteen center fielders in wOBA made the playoffs (32%). From these numbers, good offensive center fielders clearly had less than moderate value over the last four seasons.

Lastly, right fielders also had low offensive value over the last four seasons. All three of the statistics showed playoff percentages which very gradually rose but then stagnated near a z-score of 0.5 (normal cumulative probability of 0.691). Over the last four years, seven of the best eighteen right fielders in PALWTS achieved a playoff berth (39%), ten of the top twenty-six right fielders according to OBP made the playoffs (39%), and twelve of the best twenty-six right fielders in wOBA reached the postseason (46%). These percentages came close to those of moderately valued third basemen, but OBP and PALWTS revealed convincingly low playoff percentages for above average right fielders, giving good right fielders low offensive value over the last four years.

Table 4 collected the four-year positional values.

Notably, sabermetric analysis involves subjectivity, and so does not achieve the degree of certainty characteristic of mathematics (Costa, Huber, & Saccoman, 2009). In the case of the determination of positional values above (which clearly involved a certain degree of subjectivity), the observation of Costa et al. directly applies to the preciseness of Table 4. Unfortunately, four years of statistics could not define clear boundaries between any of the adjacent categories in Table 4. Nevertheless, Table 4 is quite significant as clear separations in positional value emerge when examining nonadjacent classes. For example, good first basemen undoubtedly showed more offensive value than good center fielders. Gaps in positional value further widen as comparisons involve positions which are increasingly far apart. In the most extreme

Table 4

Four-Year Positional Values

Very High Value	High Value	Moderate Value	Low Value	Very Low Value
Catcher	First Base	Third Base	Center Field	Shortstop
	Second Base		Right Field	
	Left Field			

Note. The value of offensively above average players at each of the positions (excluding pitcher). Based on the 2010, 2011, 2012, and 2013 regular seasons in Major League Baseball.

case, the offensive value of above average catchers far exceeded that of above average shortstops. Although not extremely precise, Table 4 does provide a fairly specific ranking of the positions according to their offensive importance over the last four years.

Applying the positional values. It is clear from the breakdown of the four-year positional values that above average players are more valuable at certain positions rather than others. In fact, Table 4 reveals that it is very possible to historically determine which particular positions are more offensively valuable than the others for above average players. The objective question of positional value has been satisfactorily answered by data from the last four regular seasons.

Returning to the discussion which raised the objective question, the applicability of the breakdown of positional values becomes quite clear. Based on the last four years, teams should primarily look to sign above average players at catcher, first base, second base, and left field. In addition, front offices should avoid devoting a large amount of resources to offensively above average shortstops and center fielders. Ultimately, by following the positional values of the last four years, teams will increase the efficiency of their spending by primarily signing the most valuable players.

Positional Value Shifts

The positional values as determined by the last four regular seasons certainly provide useful guidance to teams, but they are static. Logically, it is not unreasonable to suspect that the value of above average players at certain positions shifts over the course of time. Since the four-year data grouped all of the years together, it could not reveal any changes in the positional values. Of course, if positional values reliably change over time, front offices should accordingly adapt their hiring strategies to always sign the most valuable players.

Identifying Positional Value Shifts

In order to determine whether the positional values change over time, a comparison of two sets of seasons (each set being contiguous) is needed. Given a significant number of teams in each set of seasons, a drop in the playoff percentages from one set of seasons to another would indicate a loss in value for a particular position, and a rise in the playoff percentages would indicate a gain in value.

Unfortunately, four years of data only provides two pairs of seasons, which cannot give significant results due to the small number of teams involved in each pair of seasons. Regardless, as a preliminary analysis, the last four years were grouped in pairs (2010 with 2011 and 2012 with 2013) and the paired-year playoff percentages corresponding to PALWTS, OBP, and wOBA were plotted with each other for each position. These plots suggested that some of the positional values may have shifted. Appendix C contains the playoff percentage plots of the two-year paired data for the catcher and center field positions. From these plots, it appears that above average catchers may have lost value between the last two pairs of seasons, whereas center fielders perhaps gained offensive value. Of course, these findings are not concrete due to small sample sizes, but they do call for further investigation and research. In particular, an analysis comparing two groups of four seasons each would be adequate in determining whether or not positional value shifts occur, and if they do, which particular positions shifted in value. This analysis, however, is beyond the scope of this paper.

Conclusion

Although the analysis presented herein was to some degree subjective and to no degree mathematically rigorous, it nevertheless revealed intriguing information regarding the offensive value of above average players. A simple statistical examination of the past four seasons of play-by-play data provided a reasonably specific ranking of the positions according to their relative values. Surely, additional, more rigorous investigations will be helpful in further validating these findings.

Overall, it is clear that offensively above average players are more valuable at certain positions than at others. This conclusion has great practical relevance; historical value rankings can provide a useful guide to professional baseball franchises in making future personnel decisions. Ultimately, front offices who consider the positional values of above average players will effectively increase the efficiency of their spending, and consequently enhance their chance of success.

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Appendix A
LWTS Run Values by Year

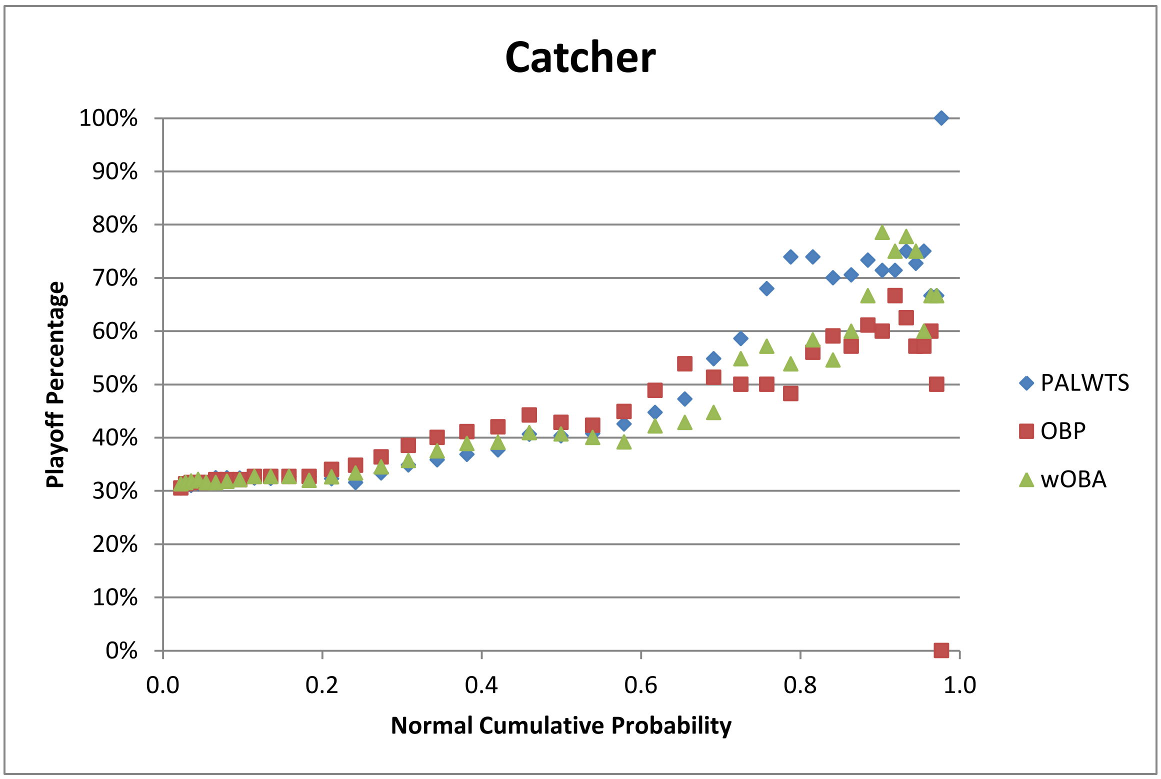
Event	2010	2011	2012	2013
1B	0.453	0.453	0.454	0.442
2B	0.750	0.751	0.736	0.759
3B	1.086	1.076	1.045	0.992
HR	1.405	1.391	1.393	1.371
NIBB	0.320	0.297	0.297	0.291
HBP	0.383	0.337	0.308	0.312
SB	0.220	0.143	0.169	0.172
CS	-0.437	-0.428	-0.426	-0.378
Out	-0.269	-0.257	-0.260	-0.253

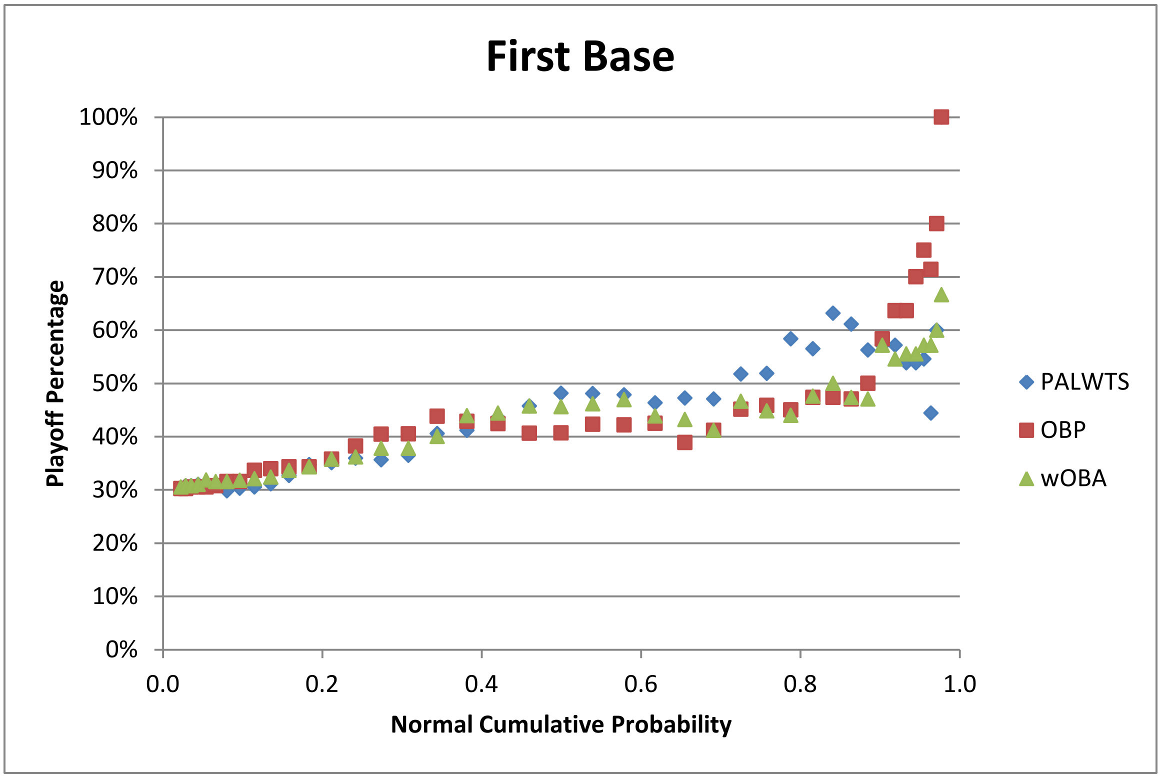
Note. 1B = Single, 2B = Double, 3B = Triple, HR = Home run, NIBB = Unintentional Walk, HBP = Hit by pitch, SB = Stolen base, CS = Caught Stealing. Based on regular season play-by-play data provided by Retrosheet.org (2013c) and processed by Bevent.exe from Retrosheet.org (2013a) and RetrosheetMod.jar written by Quinn Detweiler (personal communication, 2013).

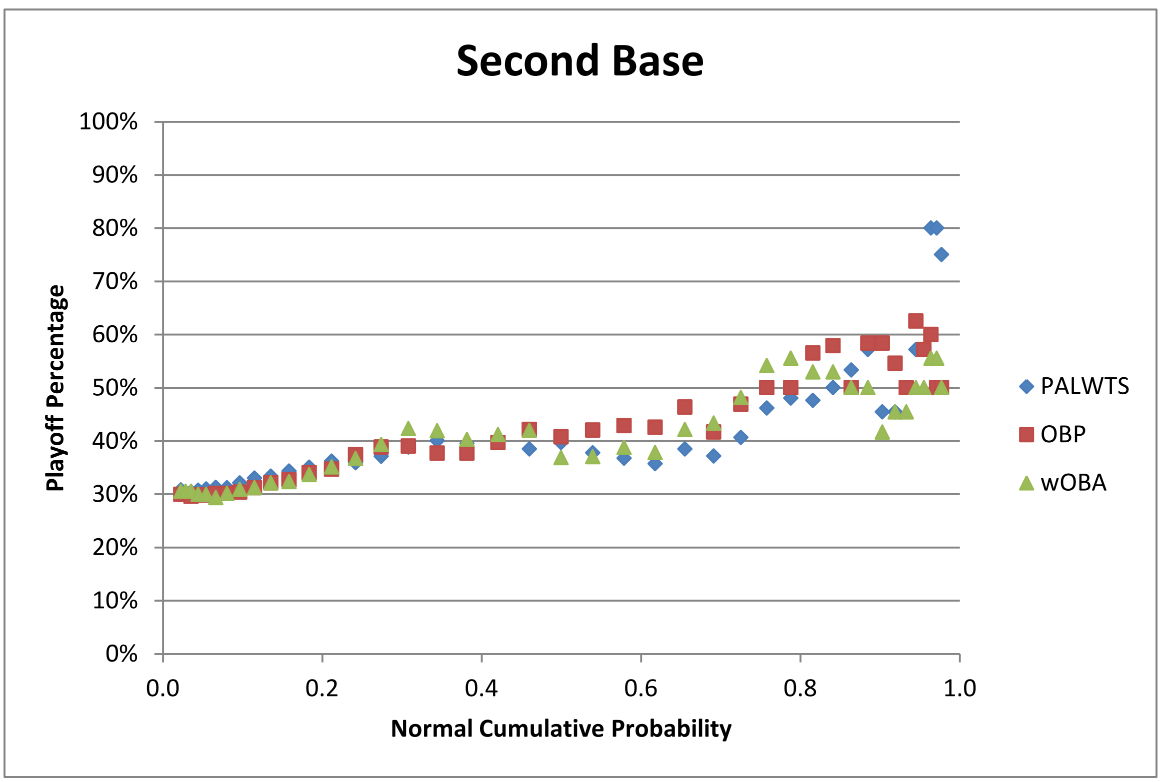
Appendix B
Four-Year Playoff Percentage Plots

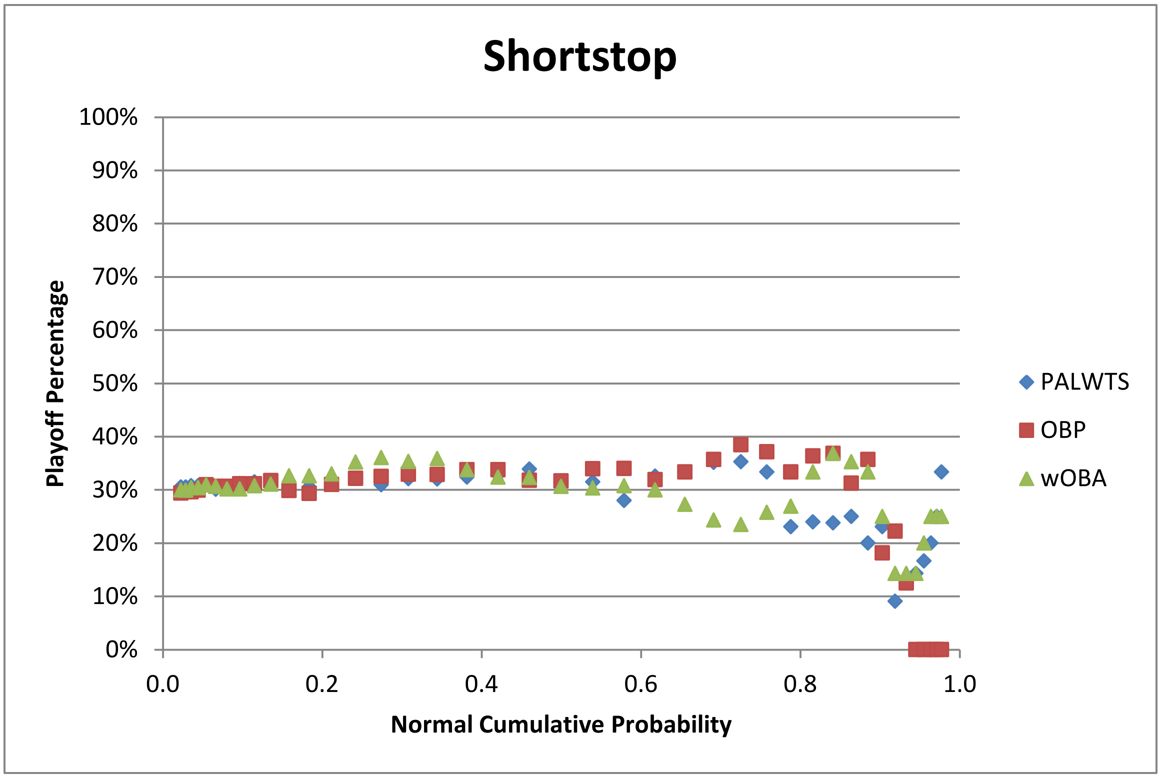
The following are the plots of the playoff percentages corresponding to park-adjusted linear weights (PALWTS), on-base percentage (OBP), and weighted on-base average (wOBA) for each position (excluding pitcher) over the course of the last four regular seasalberons in Major League Baseball (2010, 2011, 2012, and 2013).

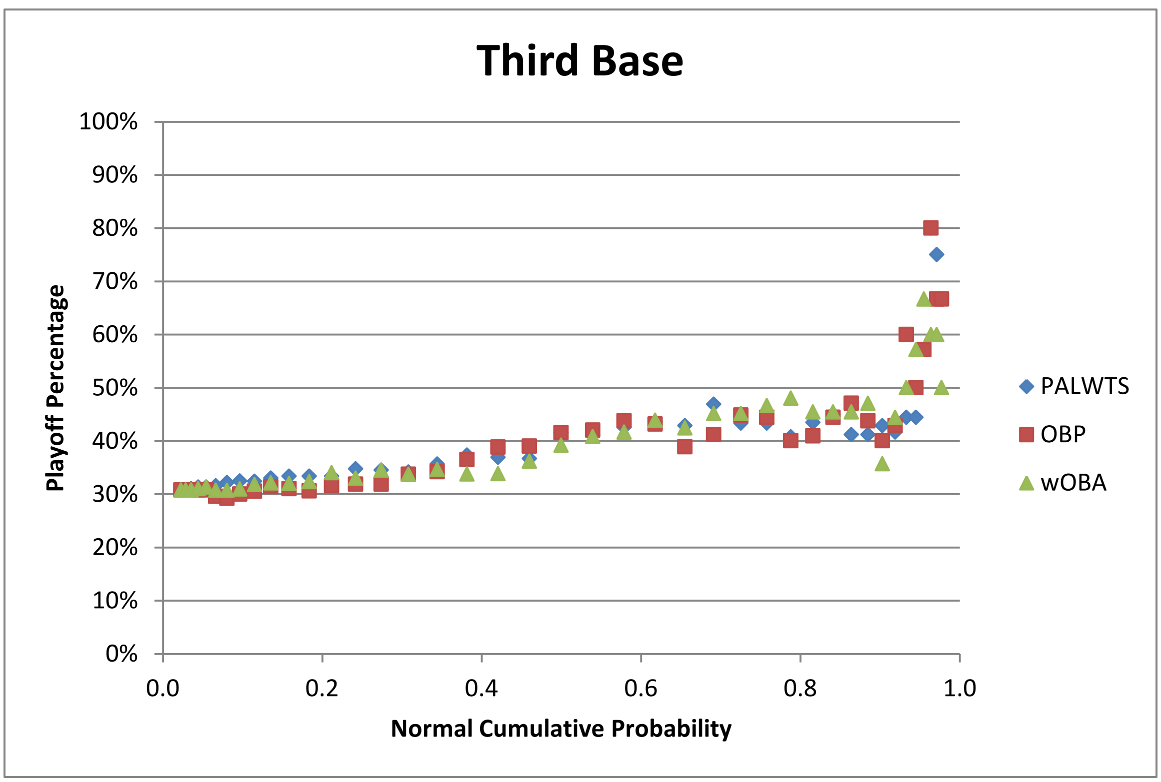
For each plot, the PALWTS calculations were based on play-by-play data provided by Retrosheet.org (2013c) and processed by Bevent.exe from Retrosheet.org (2013a) and RetroSheetMod.jar by Quinn Detweiler (personal communication, 2013), park-specific data provided by Retrosheet.org (2013b), and counted player statistics from MLB.com (2013). In addition, OBP was calculated with counted player statistics from MLB.com (2013). Finally, wOBA calculations were based on play-by-play data provided by Retrosheet.org (2013c) and processed by Bevent.exe from Retrosheet.org (2013a) and RetroSheetMod.jar by Quinn Detweiler (personal communication, 2013), as well as counted player statistics from MLB.com (2013).

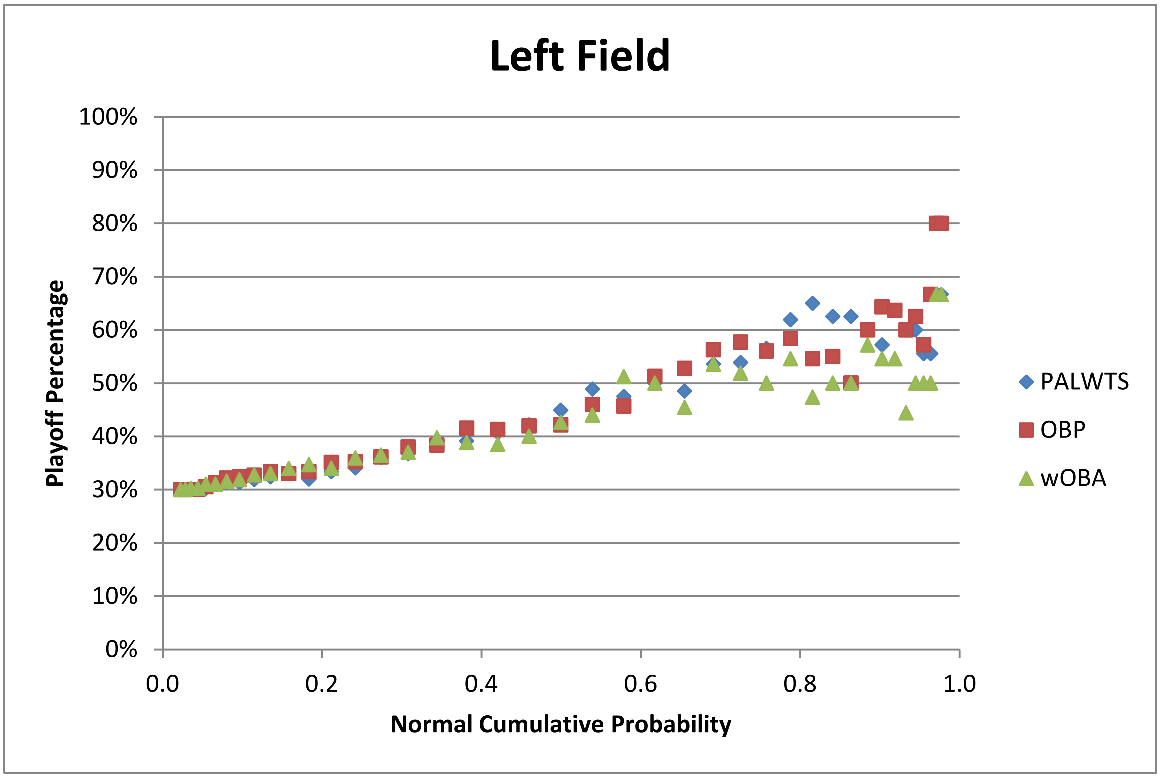


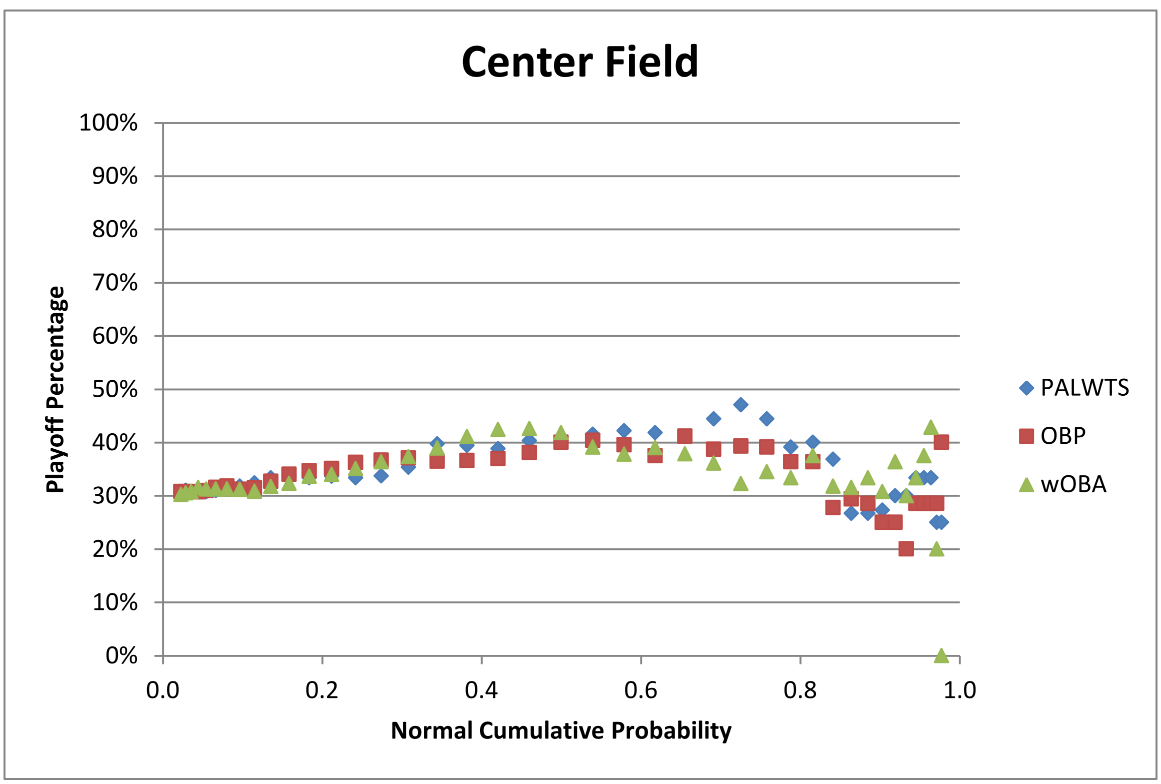

First Base
Playoff Percentage
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
0.0
0.2
0.4
0.6
0.8
1.0
Normal Cumulative Probability
PALWTS
OBP
wOBA


Second Base
Playoff Percentage
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
0.0
0.2
0.4
0.6
0.8
1.0
Normal Cumulative Probability
PALWTS
OBP
wOBA


Shortstop
Playoff Percentage
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
0.0
0.2
0.4
0.6
0.8
1.0
Normal Cumulative Probability
PALWTS
OBP
wOBA


Third Base
Playoff Percentage
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
0.0
0.2
0.4
0.6
0.8
1.0
Normal Cumulative Probability
PALWTS
OBP
wOBA


Left Field
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Playoff Percentage
0.0
0.2
0.4
0.6
0.8
1.0
Normal Cumulative Probability
PALWTS
OBP
wOBA


Center Field
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Playoff Percentage
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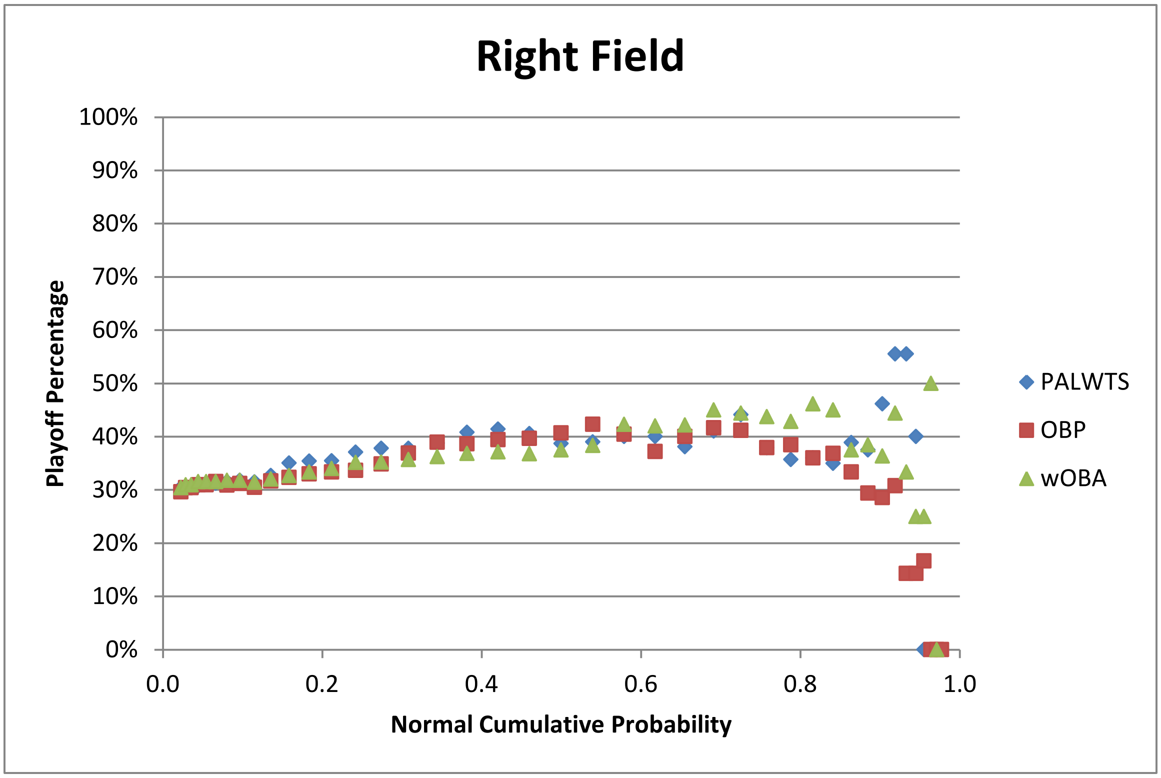
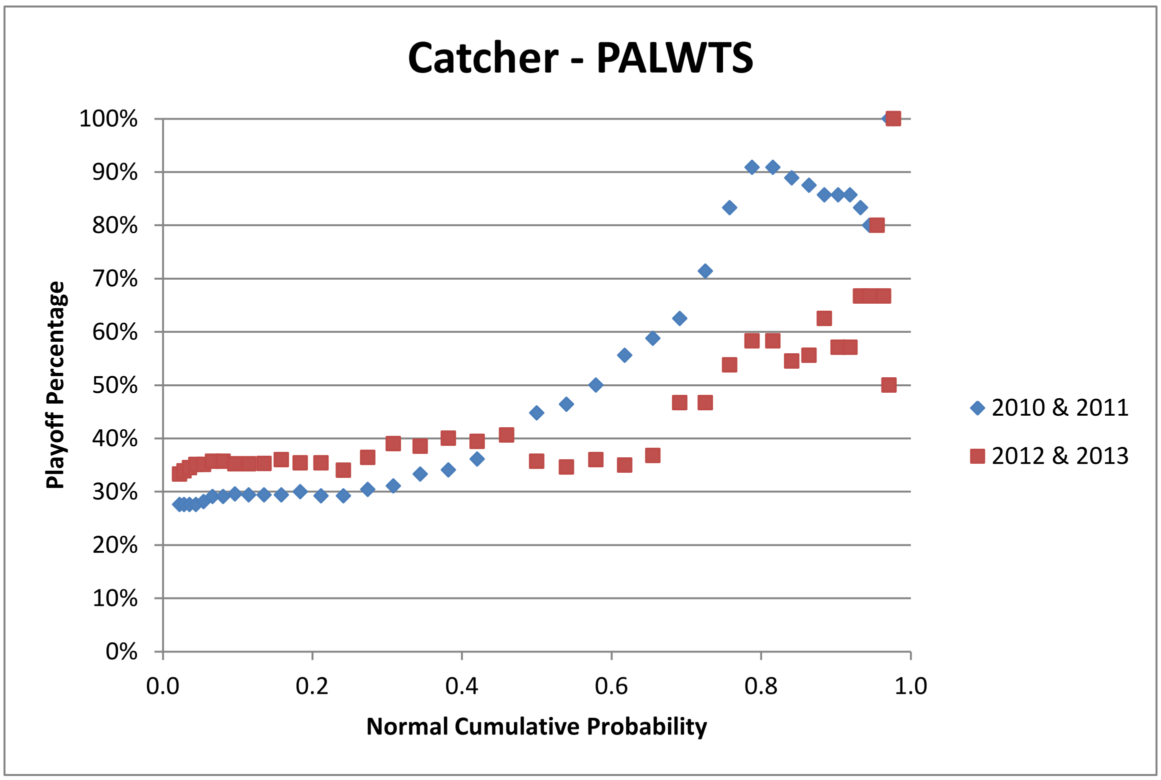
0.2
0.4
0.6
0.8
1.0
Normal Cumulative Probability
PALWTS
OBP
wOBA

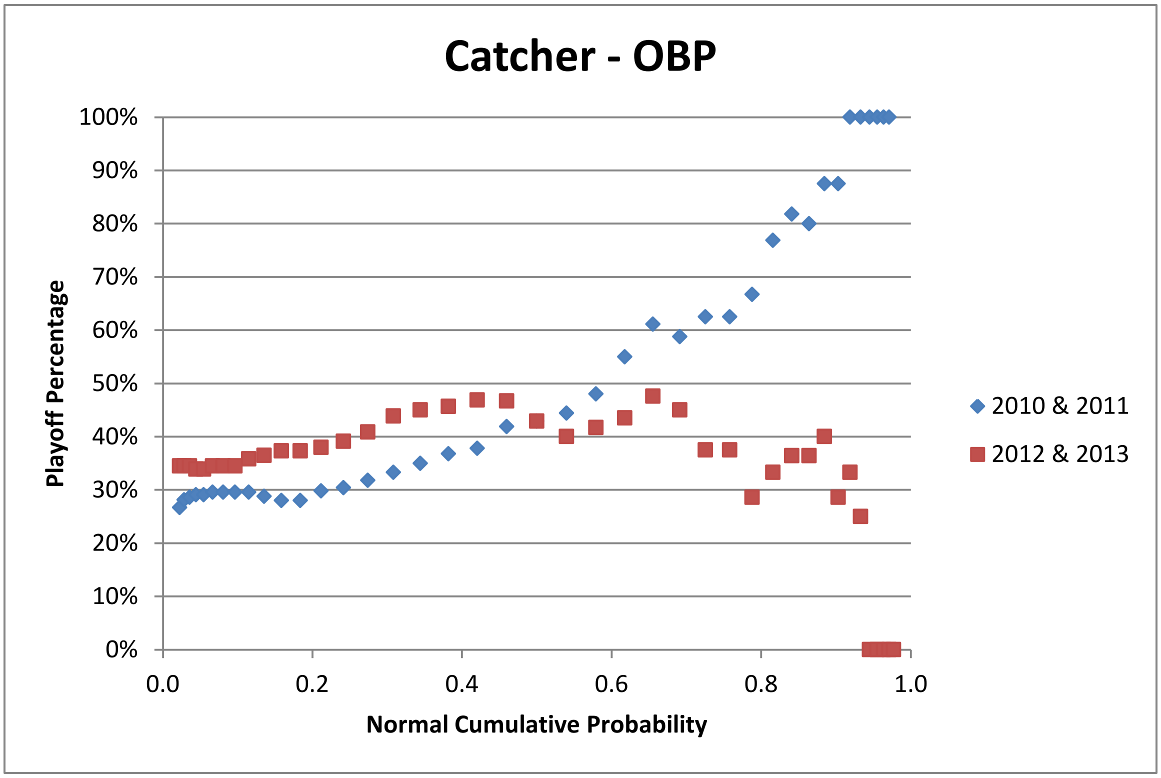

Right Field
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Playoff Percentage
0.0
0.2
0.4
0.6
0.8
1.0
Normal Cumulative Probability
PALWTS
OBP
wOBA

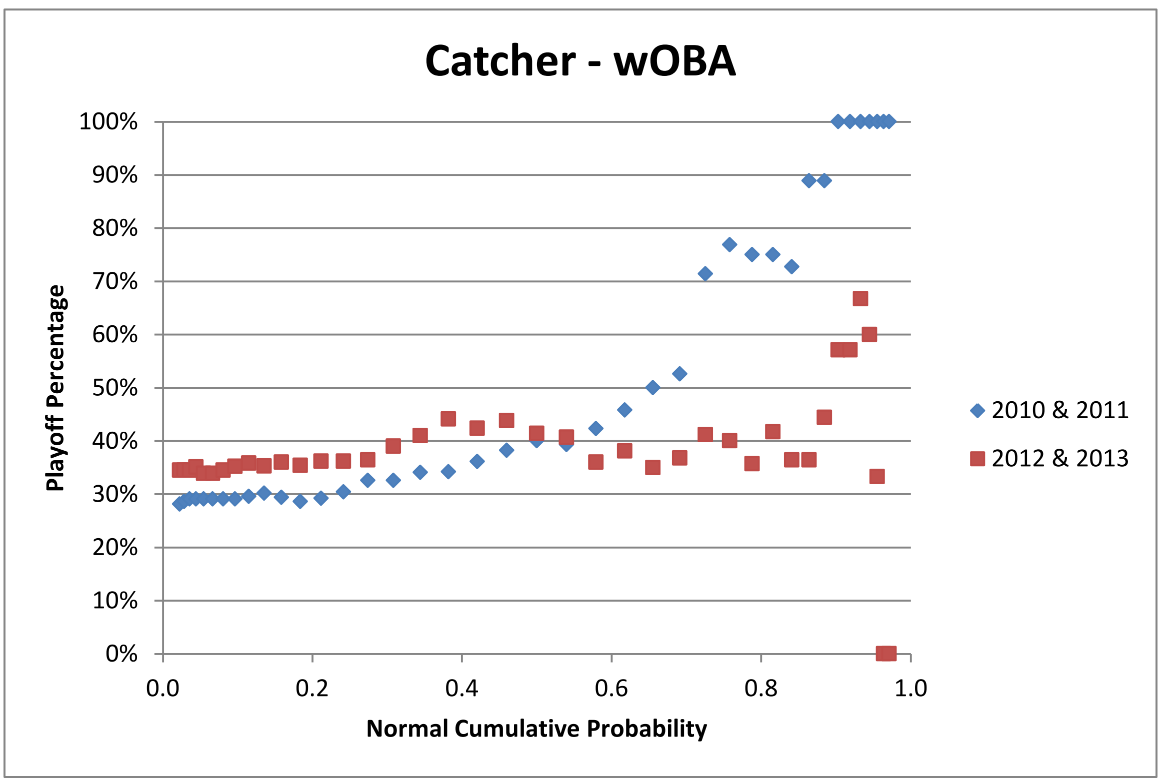
Appendix C
Paired Year Comparison Playoff Percentage Plots

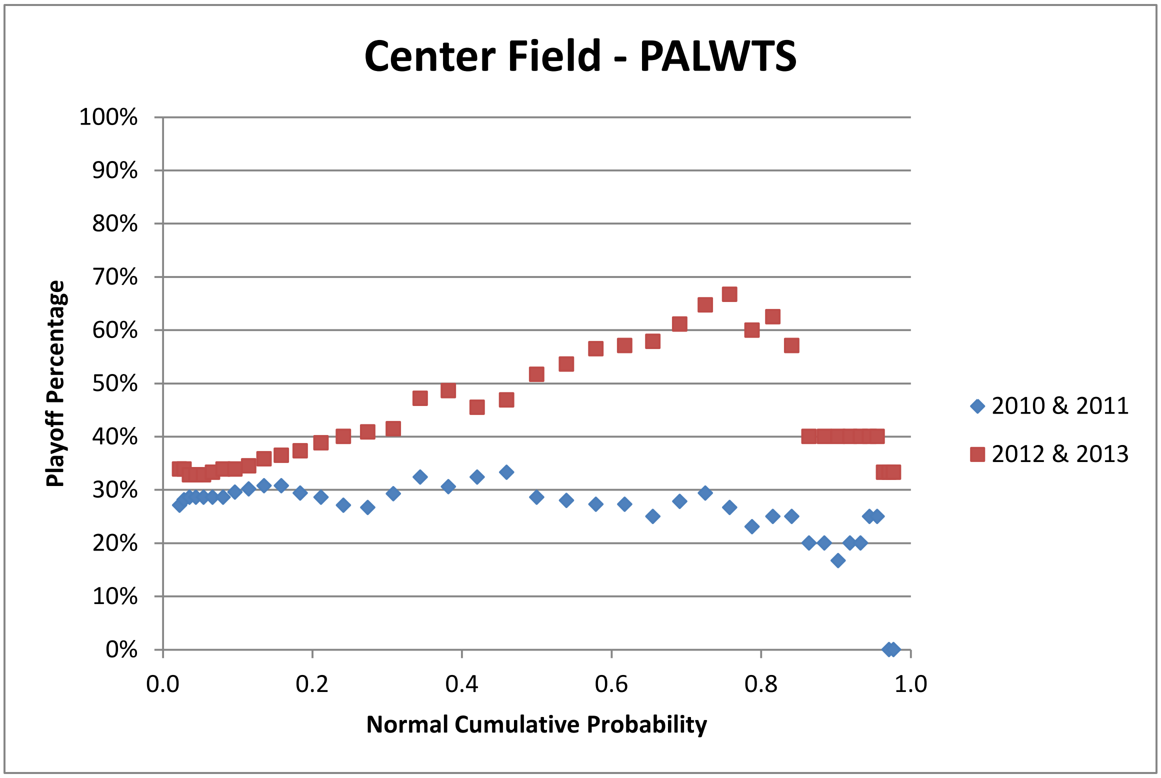
The following are plots of playoff percentages corresponding to park-adjusted linear weights (PALWTS), on-base percentage (OBP), and weighted on-base average (wOBA) over the course of the last four regular seasons of Major League Baseball, paired for comparison (2010 with 2011 and 2012 with 2013).

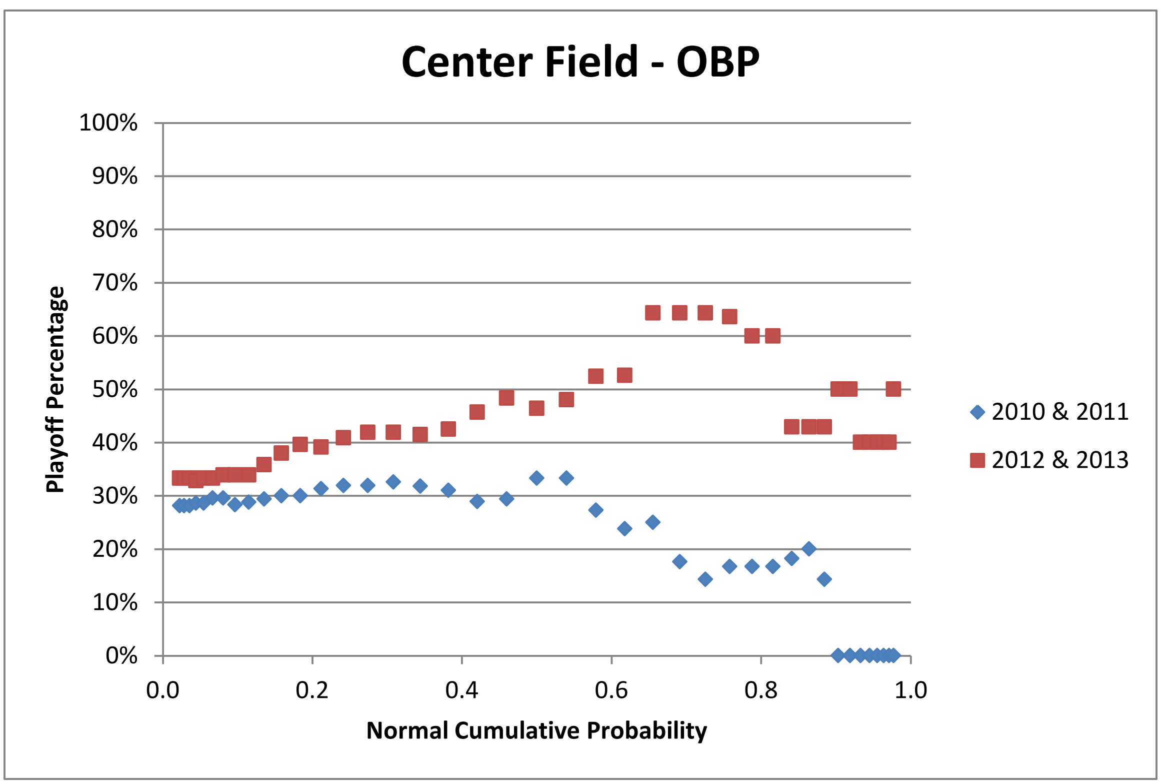
For each plot, the PALWTS calculations were based on play-by-play data provided by Retrosheet.org (2013c) and processed by Bevent.exe from Retrosheet.org (2013a) and RetroSheetMod.jar by Quinn Detweiler (personal communication, 2013), park-specific data provided by Retrosheet.org (2013b), and counted player statistics from MLB.com (2013). In addition, OBP was calculated with counted player statistics from MLB.com (2013). Finally, wOBA calculations were based on play-by-play data provided by Retrosheet.org (2013c) and processed by Bevent.exe from Retrosheet.org (2013a) and RetroSheetMod.jar by Quinn Detweiler (personal communication, 2013), as well as counted player statistics from MLB.com (2013).

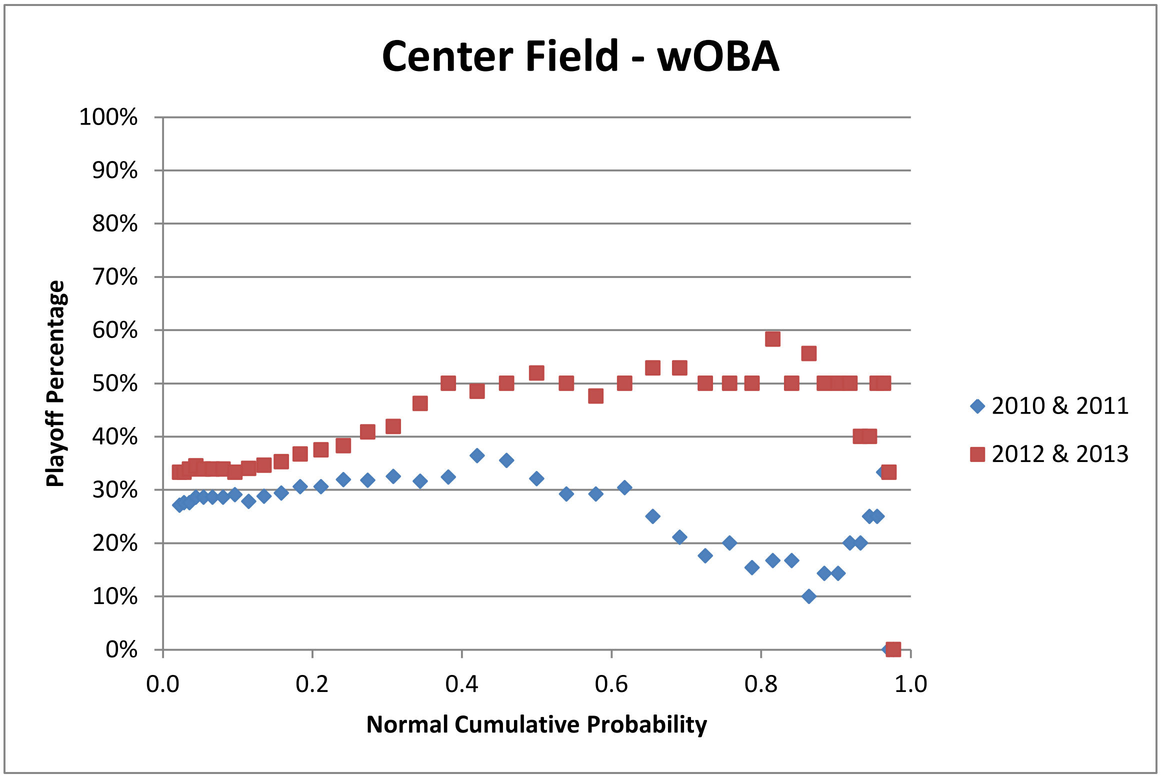



Catcher - OBP
Playoff Percentage
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
0.0
0.2
0.4
0.6
0.8
1.0
Normal Cumulative Probability
2010 & 2011
2012 & 2013


Catcher - wOBA
Playoff Percentage
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
0.0
0.2
0.4
0.6
0.8
1.0
Normal Cumulative Probability
2010 & 2011
2012 & 2013


Center Field - PALWTS
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Playoff Percentage
0.0
0.2
0.4
0.6
0.8
1.0
Normal Cumulative Probability
2010 & 2011
2012 & 2013


Center Field - OBP
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Playoff Percentage
0.0
0.2
0.4
0.6
0.8
1.0
Normal Cumulative Probability
2010 & 2011
2012 & 2013


Center Field - wOBA
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Playoff Percentage
0.0
0.2
0.4
0.6
0.8
1.0
Normal Cumulative Probability
2010 & 2011
2012 & 2013