By the Numbers

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Review

Baseball-Oriented Statistics Text Focuses on the Math

Ted Turocy

Jim Albert's new book, "Teaching Statistics Using Baseball," is a supplementary text aimed at teachers, rather than a guide for the sabermetrically-savvy BTN reader.

Teaching Statistics Using Baseball

by Jim Albert

The Mathematical Association of America, 304 pages, $45, June 2003, ISBN 0883857278

This new offering from the coauthor of *Curve Ball* presents a set of baseball-themed case studies and exercises suitable for use as additional or ancillary material for an introductory course in probability and statistics.

This book is part of the Mathematical Association of America's Classroom Resource Materials series, and as such, the choice of the word "teaching" as opposed to "learning" in the title appears to have been deliberate. The material is organized into nine chapters, each consisting of a sequence of case studies, with topics ranging from summarizing the distribution of team on-base percentages to Markov modeling of the progress of an inning. The case studies are not generally written to stand on their own in teaching a concept. For example, the case studies on least-squares regression do not present any of the relevant theory or formulas, focusing instead on the use and interpretation of regression analysis.

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The book excels in choosing examples which make good "sabermetric sense." For example, on-base percentage, rather than batting average, is the thematic statistic used in examples for the binomial and negative binomial distributions. The case studies for regression feature good discussions of evaluating offensive statistics in terms of their ability to predict run scoring, while the chapter on statistical inference focuses in large part on methodologies for understanding which situational hitting splits are, and are not, statistically significant.

Readers who enjoyed *Curve Ball* will find that many of the examples in that book reappear here, in expanded presentations suitable for beginning statistics students. These are augmented by a trove of exercises; nearly half the pages (by rough count) are devoted to practical exercises for mastering the relevant statistical concepts. These exercises are hands-on, focusing on computation and manipulation of actual datasets.

As a *By The Numbers* reader, should you pick this book up? Because of the focus of the text, only true completists among the sabermetrically-savvy would want to make this book a priority for their bookshelf. On the other hand, with its focus on basic concepts and statistical methodology, it could be ideal for readers who are interested in understanding more about what goes on in these pages, or are interested in undertaking research of their own, but whose last statistics course was a while ago, or fuzzy in their minds. (Or both!)

Ted Turocy, arbiter@econmail.tamu.edu ♦

Academic Research: More on Home Field Advantage

Charlie Pavitt

The author reviews two recent academic papers on home field advantage.

This is one of a series of reviews of sabermetric articles published in academic journals. It is part of a project of mine to collect and catalog sabermetric research, and I would appreciate learning of and receiving copies of any studies of which I am unaware. Please visit the Statistical Baseball Research Bibliography at its new location www.udel.edu/communication/pavitt/biblioexplan.htm . Use it for your research, and let me know what is missing.

Kevin G. Quinn, Paul B. Bursik, Christopher P. Borick, and Lisa Raethz, Do New Digs Mean More Wins? The Relationship Between a New Venue and a Professional Sports Team's Competitive Success, Journal of Sports Economics, August 2003, Volume 4 Number 3, pp. 167-182

Jack C. Watson II and Andrew J. Krantz III, Home Field Advantage: New Stadium Construction and Team Performance in Professional Sports, Perceptual and Motor Skills, December 2003, Volume 97 Number 3, pp. 794-796

Back in the February, 2003 issue of *BTN*, I reported on a study by Richard Pollard showing evidence of a slight decline in home winning percentage for teams that moved to a new ballpark in the same metropolitan area between 1988 and 2001, from .547 to .537. Given our ignorance of the causes of home field advantage, this was a helpful study, as it implies that familiarity with the home field is likely part of an explanation if teams do worse after moving to a less familiar park. Now we have two more studies of the same issue published close to simultaneously (yes, in the world of academe four months apart is close to simultaneous). Not surprisingly, none of these research groups appears aware of the others' work; what is more, not even one of the articles cited by Quinn et al. is also cited by either Watson/Krantz or Pollard, and only two are dually cited by both Watson/Krantz and Pollard, more evidence in support of the unfortunate fact that researchers in the social sciences usually ignore studies outside of their home discipline.

What is more, the findings of both Quinn et al. and Watson/Krantz are basically identical with one another and opposite of Pollard's. Watson and Krantz found the fourteen Major League Baseball teams that switched ballparks between 1950 and 1996 to increase their winning percentage from .523 before the move to .564 afterward, a statistically significant difference. These comparisons are somewhat messy, as, for example, a team that switched during the very end of that period would have far more data points before the move than after. Perhaps this unequal-sample-size problem cancelled out across all the moves in the data set, but it is impossible to say given the data presented. Further, it seems that Watson and Krantz included teams that moved between metropolitan areas in their analysis; again, the report is unclear on this. Quinn et al., in contrast, compared the seven years before the switch with the seven years after, and also compared the won-loss trajectory of teams that switched with that for teams that did not, in order to see if changes due to stadium switches are merely a function of the normal ups and downs in team fortune over the years. Despite the better method, they got analogous results; over the 1982 to 1996 period, MLB teams increased significantly from .498 before the switch to .541 after. Incidentally, neither research group found NFL or NBA teams to improve with new facilities; Quinn et al. found a marginally significant increase in the NHL (probability of less than .10), from .500 to .529.

Interestingly, Watson and Krantz's speculative explanations for their findings imply that home team familiarity with their new ballpark may be involved, the same explanation given by Pollard for his contradictory findings. Anyway, we are back on square one, and so again I quote myself; we still have no good idea what causes home field advantage.

Call For Help

I have been unable as yet to find copies of the first two volumes of the Journal of Sports Economics. If anyone in SABRland has access to this journal and can get me copies of sabermetric articles (not including those solely concerned with MLB finances), I would be most appreciative and happy to reimburse expenses.

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Do Hitters Get Their Expected RBIs?

Cyril Morong

Are some hitters "good RBI guys" in the sense that they are able to drive in more runners than you'd expect from a player with their same stats, and the same number of runners on base? In this study, the author compares players' actual RBIs to their expected, to see if any consistently exceed or fall short of expectations.

Taking into account the number and position of runners on base for a given hitter, do hitters get the number of RBIs that you'd expect?

For the most part, yes. If we assume that hitters hit about the same way with runners on base as they do otherwise, they generally get about the number of RBIs we would expect based on how many baserunners there are and what bases they are on.

To calculate a hitter's number of expected RBIs, I first computed how many times a man was on first base when he batted (regardless of whether the other bases were occupied), how many times a man was on second base, and how many times a man was on third base. Then I computed his single, double, triple and home run frequency, assuming he batted the same way with runners on base as he did for all of his at bats. Then, I computed, based on that, how many RBIs were expected for each of the bases.

For example, if there were 2000 runners on first during the period (the data is explained below), and the batter's home run frequency is 3%, then we would expect him to hit a home run and drive in the runner on first 60 times – which means 60 RBIs for that case ("home run driving in runner on first"). Then we also assume that he hits home runs 3% of the time when runners are on second base and third bases. We repeat for triples.

With singles and doubles, things are a little different. Of course, runners on second and third will score on a double, and a runner on third will score on a single. But I had to make assumptions about how often runners on first would score on a double and how often runners on second would score on a single. I assumed that 42.6% of runners scored from first on doubles and 63.4% scored from second. These were the major league averages for the years 1987-2000 that I got from John Jarvis's website (http://knology.net/~johnfjarvis/stats.html).

As an example, let's look at Jay Bell. Below is how many runners were on base when he batted, his hit frequencies, his expected RBIs in each case, and how many total RBIs we would have expected him to get (I had to adjust the at-bat numbers I found at the CNN/SI site; this is explained in the section entitled "Data" below). This only includes RBIs from hits; RBIs from sacrifice flies and walks with the bases loaded are not included.

	RBIs driving himself in	RBIs driving in runner on 1st	RBIs driving in runner on 2nd	RBIs driving in runner on 3rd	Total RBIs
AB where possible	7219 AB	1814 AB	1396 AB	708 AB	
1B hit (17.73% of AB)			156.93	125.54	282.47
2B hit (5.4% of AB)		41.75	75.42	38.25	155.42
3B hit (0.93% of AB)		16.84	12.96	6.57	36.37
HR hit (2.66% of AB)	192.02	48.25	37.13	18.83	296.23
Total RBIs	192.02	106.84	282.44	189.19	770.49

If Jay Bell had the same hit frequencies with runners on base as he did overall, we would expect him to get 770.49 RBIs.

Bell gets 192 expected RBIs from driving himself in from home runs since .0266*7219 = 192.02. He gets 156.93 expected RBIs from his singles driving in runners on 2nd, since 1396*.1773*.634 = 156.93. He gets 41.75 expected RBIs from runners on 1st driven in by doubles, since 1814*.054*.426 = 41.75. He gets 16.84 expected RBIs driving in runners on 1st with triples, since 1814*.0093 = 16.84. (I assumed that all runners score on triples, and that all runners on 3rd score on singles and all runners on 2nd score on doubles.)

Adding up all of the individual cases gives 770.49 expected RBIs. During the years 1987-2001, Jay Bell actually got 776 RBIs, with sacrifice flies and bases loaded walks excluded.

Below is a list of the 61 players who had 6000 or more plate appearances from the years 1987-2001 and who also had data listed at the CNN/SI site. The totals are per 600 at bats, or about a full season.

Name	Actual	Predicted	Difference
Tino Martinez	103.93	93.75	10.18
Jeff Bagwell	113.06	103.81	9.25
Frank Thomas	117.90	109.89	8.01
Wally Joyner	84.48	77.04	7.44
Robin Ventura	90.57	83.67	6.90
Dante Bichette	99.95	93.10	6.85
Harold Baines	94.28	87.51	6.77
Mark Grace	76.18	69.97	6.21
David Justice	103.19	96.99	6.21
B.J. Surhoff	75.98	70.02	5.96
Juan Gonzalez	123.21	117.78	5.43
Luis Gonzalez	87.50	82.46	5.05
John Olerud	87.83	83.08	4.76
Greg Vaughn	100.19	95.57	4.62
Paul O'Neill	94.80	90.19	4.60
Tony Gwynn	71.58	67.14	4.44
Travis Fryman	86.69	82.43	4.26
Gary Sheffield	98.15	94.06	4.08
Eric Karros	89.70	85.73	3.98
Jay Buhner	106.52	102.96	3.56
Bernie Williams	93.49	89.97	3.52
Barry Bonds	111.72	108.35	3.36
Ken Griffey Jr.	112.30	108.94	3.36
Mark McLemore	51.36	48.06	3.30
Kenny Lofton	55.16	51.87	3.29
Larry Walker	107.72	104.48	3.24
Jose Canseco	111.68	108.56	3.12
Andres Galarraga	102.89	99.77	3.12
Sammy Sosa	108.32	105.25	3.07
Ray Lankford	86.15	83.20	2.95
Delino DeShields	52.73	50.03	2.69
Will Clark	93.75	91.32	2.42
Todd Zeile	80.47	78.20	2.27

Name	Actual	Predicted	Difference
Mark McGwire	127.26	125.02	2.24
Matt Williams	99.05	96.96	2.10
Cal Ripken	79.41	77.61	1.81
Fred McGriff	100.76	99.09	1.67
Tim Raines	65.42	63.76	1.67
Edgar Martinez	97.80	96.44	1.36
Ken Caminiti	85.88	85.16	0.72
Jay Bell	64.50	64.04	0.46
Gregg Jefferies	66.30	65.95	0.36
Brady Anderson	63.65	63.36	0.30
Rafael Palmeiro	96.95	96.67	0.29
Chuck Knoblauch	51.53	51.75	-0.22
Tony Fernandez	60.07	60.45	-0.39
Ruben Sierra	89.29	89.83	-0.55
Ron Gant	86.37	87.04	-0.66
Roberto Alomar	71.11	71.86	-0.75
Marquis Grissom	60.58	61.59	-1.02
Bobby Bonilla	90.35	91.37	-1.02
Barry Larkin	68.58	70.52	-1.94
Devon White	64.56	66.50	-1.94
Steve Finley	66.49	68.46	-1.97
Dave Martinez	55.81	57.81	-2.00
Craig Biggio	59.81	61.86	-2.05
Omar Vizquel	47.01	49.76	-2.75
Rickey Henderson	55.40	58.45	-3.05
Benito Santiago	71.44	75.83	-4.39
Ellis Burks	93.29	99.86	-6.57
Wade Boggs	56.42	63.25	-6.83

Some observations:

47 of the 61 hitters (77%) were predicted to within 5 RBIs per 600 at bats. So this is reasonably accurate (the correlation between the actual RBIs and predicted RBIs is .987). But there are only 16 hitters who had fewer RBIs than expected. I expected about half the hitters to have more RBIs than expected, and half to have less. A few RBIs come from groundouts and I don't have data on those. But there are not many such cases.[1]

Maybe my list of 61 players tends to be populated by very good hitters (who else would last so long?). They tend to bat in the middle of the order and the runners who are on base might be faster than average since they would be the 1 and 2 hitters. Also, these hitters may have more than average power. Maybe their singles and doubles go farther (and travel faster) than average, making it easier for runners to score.

Notice that the players who are above expectations also seem to be power hitters who hit in the middle of the order. The players who are negative tend to be players who batted at the top or bottom of the order. If they were at the top of the order, it might be partly because of their speed. So they may get more singles and doubles as a result of speed and the runners who are on already may not score. Also, if they have below average power, maybe their doubles and singles don't go as far as they do for the power hitters, making it harder for runners to score.

[1] Using Retrosheet files, Cliff Otto found that there were about 36 groundball RBIs per team in major league baseball in 2003. That would work out to about 4 per lineup slot. If every player's expected RBIs per season were raised by 4, there would be a much more even balance between players who had more RBIs than expected and those who had fewer. Clem Comly, also using Retrosheet files, found that the average AL team in 1966 had about 25 groundball RBIs. His figure is lower than Otto's because he removed sacrafice hits, errors, and fielders choices where no out occurred. (Both references from e-mail correspondences with the author.)

But the bottom line is that the vast majority of hitters are predicted fairly well, and only one was off by more than 10 RBIs.

Alternate methods

The assumed runner advancement is for both leagues. I also tried using different figures for hitters from each league. For the AL, 64.5% of runners scored from second base on singles and 39.5% scored from first base on doubles. For the NL, these were 62.3% and 45.7%, respectively. For any players who did not get at least 80% of their at bats in one league, I used a weighted average. Then I not only used the league runner advance figures, but I also took into account the fact that, on average, batting average is higher with runners on base (and HR% is lower). The differences are not great. I also tried it with RBIs from walks. Interested readers may e-mail me for details on these alternative methods. The results are similar to those already mentioned here.

The Data

I came across a discrepancy in the CNN/SI data I used; their data appeared to be incorrect for all players. Take Rafael Palmeiro, for example. I added up the at-bats that CNN/SI reported for Rafael Palmeiro for each situation where runners might be on base:

```
Runner on 1B        1262
Runner on 2B         714
Runner on 3B         236
Runners on 1B, 2B    614
Runners on 1B, 3B    249
Runners on 2B, 3B    142
Bases Loaded         163
```

This adds up to 3380. But the discrepancy comes in where, in a separate line, they report that he had 3852 at-bats with runners on base, not 3380. With no runners on, they give him 4521. Adding this to 3852, you get 8373, the same total that he has in the Lee Sinins sabermetric encyclopedia (for 1987-2001). So the 3852, not the 3380, must be right.

Then I looked at how many runners on base at-bats were missing for Palmeiro. That would be 3852 - 3380 or 472. The 3852 is 13.96% higher than the 3380. I assumed that Palmeiro got those other 472 at bats and that the seven base situations came up with the same frequency as they did for the at-bats listed. So I raised the at-bats with a runner on first 13.96%, the at-bats with a runner second 13.96%, and so on. I did this for all the hitters and it raised the average RBI opportunities per at bat to 1.62 from 1.52. This is more consistent with other studies I have done. E-mail me for details.

If you went to the CNN/SI site to look for these discrepancies, you would not be able to find them. They no longer list all of the base out situations. They leave one out, the one with runners on first. So you can't check the total at bats from the seven on-base situations with the total given in the separate "runners on base" line. Since they had a discrepancy before, it might still exist and you could not detect it.

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Informal Peer Review

The following committee members have volunteered to be contacted by other members for informal peer review of articles.

Please contact any of our volunteers on an as-needed basis - that is, if you want someone to look over your manuscript in advance, these people are willing. Of course, I'll be doing a bit of that too, but, as much as I'd like to, I don't have time to contact every contributor with detailed comments on their work. (I will get back to you on more serious issues, like if I don't understand part of your method or results.)

If you'd like to be added to the list, send your name, e-mail address, and areas of expertise (don't worry if you don't have any - I certainly don't), and you'll see your name in print next issue.

Expertise in "Statistics" below means "real" statistics, as opposed to baseball statistics - confidence intervals, testing, sampling, and so on.

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Using Calculus to Relate Runs to Wins: Part II

Ralph Caola

How many extra runs does it take to create an additional win? In the previous issue, the author presented a theoretical formula to answer that question. Here, he compares those theoretical results to real-life MLB data.

Introduction

In part I of this article, in the last issue, I derived a formula for incremental differential runs per win. The main purpose of this article is to compare those theoretical results to actual data. For those who want to cut right to the chase, the results are shown in Table 2.

Incremental Differential Runs Per Win – Theoretical

Bill James' Pythagorean Theorem predicts winning percentage (W%) as a function of runs scored (Rs) and runs allowed (Ra). The formula is:

$$W\% = \frac{Rs^2}{Rs^2 + Ra^2}$$

The Pythagorean Theorem can be written in terms of differential runs (Rd) and total runs (Rt) using

`Rd = Rs – Ra` and `Rt = Rs + Ra`

Substituting these expressions into the Pythagorean Theorem yields

$$W\% = \frac{(Rt + Rd)^2}{(Rt + Rd)^2 + (Rt - Rd)^2} \qquad \text{(equation 1)}$$

Rt and Rd can be expressed either in runs, or in runs per game.

In the first article, I derived the formula for incremental differential runs per win (dRd/dW) from equation 1. Incremental differential runs per win is the number of extra differential runs a team needs to get one more win. The formula is

$$\frac{dRd}{dW} = \frac{\left(Rt^2 + Rd^2\right)^2}{Rt\left(Rt^2 - Rd^2\right)} \qquad \text{(equation 2)}$$

To use equation 2, Rt and Rd must be expressed in runs per game.

Procedure

The main purpose of this article is to determine how closely the results of equation 2 for incremental differential runs per win match actual data. The results of equation 2, I call *theoretical* incremental differential runs per win. The numbers derived from actual data, I call *empirical* incremental differential runs per win. To do this study, I used data for all team seasons from 1901-2003. The primary source was Sean Lahman's database. The methods I used to do the calculations follow.

Calculating Empirical Incremental Differential Runs Per Win

The first step is to calculate an empirical value for incremental differential runs per win. Ideally, the way to calculate an empirical value would be to sort all teams by wins, then calculate average Rd for each number of wins. Then, all you would need to do is calculate the difference between the average Rd for teams with n+1 wins and the average Rd for teams with n wins and you'd have the number of runs needed to get one more win. Unfortunately, there are not enough team seasons at each value of wins to calculate a representative average. Also, 81 wins, for example, has different meanings in a 154 game season and a 162 game season. So, I didn't sort by wins, I sorted by Pythagorean winning percentage.

The specific procedure follows:

1. I sorted teams by Pythagorean winning percentage. I sorted by Pythagorean winning percentage rather than actual winning percentage in order to eliminate the biases due to luck for good and bad teams.

2. I grouped the teams in .050 ranges of Pythagorean winning percentage: range 1 – 0.301-0.350, range 2 – 0.351-0.400, etc.

3. I calculated average actual winning percentage and average differential runs per game (Rd) for each range.

The results of these first three steps are shown in Table 1. The table also shows average Rt for various ranges of winning percentage. I needed to monitor Rt because, at any particular value of winning percentage, Rd depends upon Rt (see equation 1). Since Rt turned out to be nearly constant, it did not have a significant affect on Rd. When necessary, I used Rt = 8.8 runs per game in subsequent calculations.

Table 1 – Runs/Game data for teams by Pythagorean Winning Percentage

Range #	Pythagorean W%	Average Actual W%	Rt (R/G)	Ave Rd (R/G)
1	301-350	341	8.9	-1.54
2	351-400	388	8.8	-1.08
3	401-450	430	8.8	-0.65
4	451-500	478	8.8	-0.20
5	501-550	527	8.8	0.24
6	551-600	567	8.7	0.63
7	601-650	612	8.8	1.09
8	651-700	656	8.7	1.51

4. I calculated incremental differential runs per game by subtracting the average differential runs per game for adjacent winning percentage ranges. For example:

```
Range 1: 301-350, Rd = -1.54 R/G
Range 2: 351-400, Rd = -1.08 R/G
Incremental differential runs per game between ranges: -1.08 – (-1.54) = 0.46 R/G
```

5. I calculated incremental differential runs per win (dRd/dW) by dividing incremental differential runs per game, from step 4, by the difference between the average Pythagorean winning percentages for adjacent ranges. For example:

```
Range 1: 301-350, Average W% = 0.341
Range 2: 351-400, Average W% = 0.388
Difference between avg. W%'s, range 1-2: 0.388 – 0.341 = 0.047
Incremental differential runs per win (dRd/dW), between ranges: 0.46/0.047 = 9.8 R/G
```

Rd is in units of runs per game and winning percentage is in units of wins per game. So, dimensionally, when you divide Rd by W%, you're dividing runs per game by wins per game and the result is runs per win.

This result is shown in the first row, third column of Table 2.

This means, for teams with Pythagorean winning percentages between about 0.341 and 0.388, if Team A had one more Pythagorean win than Team B, Team A would, on average, have 9.8 more differential runs than Team B.

Calculating Theoretical Incremental Differential Runs Per Win

In calculating the empirical derivative, I determined the slope of the line connecting the midpoints of adjacent winning percentage ranges. At what point on the theoretical Rd vs. W% curve should I calculate the theoretical derivative?

I determined the best point would be midway between the two points used to calculate the empirical derivative. Why use the midpoint? Think of a smooth curve, like a parabola, whose first derivative increases monotonically as the x-value increases. (When the first derivative of a function changes monotonically, the function's second derivative is either always positive or always negative. This means the curve has no inflection points.) It is reasonable to assume, that, if you connect any two points on the curve with a straight line, the slope of that line and the slope of the line tangent to the curve at a point midway between the x-values of the first two points would be approximately equal. Therefore, I calculated the theoretical derivative corresponding to winning percentage range 1-2 at

```
Range 1: 301-350, Average W% = 0.341
Range 2: 351-400, Average W% = 0.388
W% = (0.388-0.341)/2 = 0.365
```

Using equation 1 with W% = 0.365 and Rt = 8.8 runs/game,

```
Rd = -1.21 runs per game.
```

Then, from equation 2 with Rd = -1.21 and Rt = 8.8 runs per game,

```
dRd/dW = 9.3 runs per win.
```

This result is shown in first row, fourth column of Table 2.

Table 2 – Comparison of Theoretical and Empirical Incremental Differential Runs per Win (pythagorean W%)

Ranges	Pythag. W%	Empirical dRd/dW(R/W)	Theoretical dRd/dW(R/W)	% Diff
1-2	325-375	9.8	9.3	-5
2-3	375-425	10.2	9.0	-12
3-4	425-475	9.4	8.9	-5
4-5	475-525	9.0	8.8	-2
5-6	525-575	9.8	8.9	-9
6-7	575-625	10.2	9.0	-12
7-8	625-675	9.8	9.3	-5

Table 3 – Runs/Game data for teams by Actual Winning Percentage

Range #	Actual W%	Average Actual W%	Rt (R/G)	Ave Rd (R/G)
1	251-350	323	8.9	-1.59
2	351-450	410	8.8	-0.78
3	451-550	501	8.7	0.02
4	551-650	590	8.7	0.77
5	651-750	678	8.9	1.59

Results - Comparing Empirical and Theoretical Values

As seen in table 2, the theoretical values of dRd/dW match the empirical data fairly well, but they all tend to be low. The average difference is 7%.

In Tables 3 and 4, I compared empirical and theoretical values as I did previously, but with two small changes. Instead of sorting by Pythagorean winning percentage, I sorted by actual winning percentage. Also I used wider ranges of winning percentage. Previously I had 50 point ranges starting at 0.300 and ending at 0.700. In Tables 3 and 4, I used 100 point ranges starting at 0.250 and ending at 0.750. The wider ranges seem to smooth out the variation in empirical values when Table 4 is compared to Table 2.

Table 4 – Comparison of Theoretical and Empirical Incremental Differential Runs per Win (actual W%)

Ranges	Actual W%	Empirical dRd/dW(R/W)	Theoretical dRd/dW(R/W)	% Diff
1-2	301-400	9.3	9.3	0
2-3	401-500	8.8	8.9	1
3-4	501-600	8.4	8.9	5
4-5	601-700	9.3	9.3	0

Here, the theoretical values of dRd/RW match the empirical data quite well. All the differences are 5% or less, and three are 1% or less.

Ralph Caola, RJCSB25@aol.com ♦

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Phil Birnbaum, Editor

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Analyzing Small Ball in the Postseason

Kevin Mello and Vijay Mehrotra

Joe Morgan has argued that bunting and stealing are an important strategy in postseason play because of the scarcity of runs. Here, the authors look at play-by-play data of World Series games to see if that's really the case.

Joe Morgan has repeatedly criticized the Oakland Athletics for not bunting and stealing in the postseason, on the grounds that with fewer runs being scored, teams need to be more aggressive. Does Joe Morgan know something the A's don't? The analysis that follows in this paper will show whether teams should change their strategy in the World Series. It will attempt to answer two significant questions:

- Do teams really score less in the postseason?
- If scoring really is lower in the postseason, should you bunt and steal more?

Postseason Scoring Analysis

The first test was to actually make sure that the postseason is lower scoring than the regular season. For the two World Series teams in all seasons from 1982 to 2002, I compared their average runs per game in the regular season to their average runs per game in the World Series. The results are in Table 1:

Table 1 – Run Scoring for teams in the World Series, regular season vs. World Series games

	NL team, regular season	NL team, World Series	% Change	AL team, regular season	AL team, World Series	% Change
2002	4.83	6.29	+30	5.25	5.86	+12
2001	5.05	5.29	+ 5	4.99	2.00	-60
2000	4.98	3.20	-36	5.38	3.00	-44
1999	5.19	2.25	-57	5.56	5.25	- 6
1998	4.62	3.25	-30	5.96	6.50	+ 9
1997	4.57	5.29	+16	5.36	6.29	+17
1996	4.77	4.33	- 9	5.38	3.00	-44
1995	3.98	3.83	- 4	5.19	3.16	-39
1993	5.41	6.00	+11	5.23	7.50	+43
1992	4.21	3.33	-21	4.81	2.83	-41
1991	4.62	4.14	-10	4.79	3.43	-28
1990	4.28	5.50	+28	4.52	2.00	-56
1989	4.31	3.50	-19	4.40	8.00	+82
1988	3.88	4.20	+ 8	4.94	2.20	-55
1987	4.93	3.71	-25	4.85	5.43	+12
1986	4.83	4.57	- 5	4.90	3.86	-21
1985	4.61	1.86	-60	4.24	4.00	- 6
1984	4.23	3.00	-29	5.12	4.60	-10
1983	4.30	1.80	-58	4.93	3.60	-27
1982	4.23	5.57	+32	5.50	4.71	-14
Average	4.59	4.05	-12	5.06	4.36	-14

The table clearly shows that in almost every year, teams in the World Series score fewer runs than they did in the regular season. There are a couple of years for which this is not true, but there is definitely a trend towards less scoring in the World Series. Also worth noting is that in the years that scoring goes down, it often goes down by a larger percentage than years when scoring increases. This is reflected in the totals, which show that for both leagues combined, scoring drops about 13% in the World Series.

To assess the value of strategies like the sacrifice bunt and steal, we use the model previously built by George Lindsey in 1964, and used by Pete Palmer in *The Hidden Game of Baseball* and numerous other studies since. The Lindsey model looks at each base-out situation and then from that point forward gives a prediction of the probability of scoring runs and the number of expected runs scored.

I built a table of run expectancies and run probabilities using Retrosheet play-by-play data for each World Series game from 1982-2002. For each base-out situation, I found the number of runs expected to score in the remainder of the inning, as well as the probability of scoring.

Table 2 shows the run expectations, and Table 3 the probabilities. Full data is presented in Table 8, at the end of the article.

Table 2 – Run Expectations, World Series Games, 1982-2002

Men on base	0 out	1 out	2 out
None	.48	.26	.09
1	.80	.54	.19
2	1.08	.62	.35
1,2	1.62	.92	.43
3	1.44	.92	.39
1,3	1.86	1.22	.40
2,3	1.81	1.81	.56
Loaded	2.35	1.33	.79

Bunting

To look at bunting strategy, we can use Table 2 to compare the run expectation before and after a bunt. For instance, with a runner on second and nobody out, the run expectation before the bunt is 1.08 runs, while after the successful bunt it is only 0.92. This suggests that bunting is not a good idea.

We can also compare the probabilities using Table 3. Before the bunt with a runner on second, the chance of scoring at least one run is 61%. After the bunt, it's only 44%.

A summary of run values for all bunting situations can be seen in Table 4; the probability analysis is Table 5.

It turns out that bunting is not very useful in most situations. Even a successful sacrifice bunt will lower your expected number of runs scored and your probability of scoring.

There is only one situation that this is not true, which is 1st and 2nd with zero outs. A successful bunt in this case will increase the run expectation, but the increase in percentage points is actually not even statistically significant. This means there is no true evidence that a bunt actually is beneficial even in this situation.

When my data is compared to the Lindsey and Palmer data, they are actually surprisingly similar. Palmer showed that a

Table 3 – Probability of scoring at least one run, World Series Games, 1982-2002

Men on base	0 out	1 out	2 out
None	.26	.16	.06
1	.39	.27	.12
2	.61	.39	.22
1,2	.67	.44	.25
3	.89	.67	.24
1,3	.88	.70	.23
2,3	.77	.75	.26
Loaded	.75	.64	.33

Table 4 – Run Values of Successful Bunts, World Series games 1982-2002

Situation	Run Expectation Before Bunt	Run Expectation After Successful Bunt	Value of Bunt (in Runs)
Runner on 1st, nobody out	.80	.62	- .18
Runner on 1st, one out	.54	.35	- .19
Runner on 2nd, nobody out	1.08	.92	- .16
Runner on 2nd, one out	.62	.39	- .23
1st and 2nd, nobody out	1.62	1.81	+ .19
1st and 2nd, one out	.92	.43	- .49

sacrifice also always reduces the expected number of runs scored and the probability of scoring. Stealing also was shown by Palmer to be of only marginal value.

This suggests that the World Series is similar to regular season games. This is important because this means that offensive strategy should be the same regardless of what part of the season a team is in. A team would have no reason to change their strategy just because they are in the postseason.

Table 5 – Probabilities of Successful Bunts, World Series games 1982-2002

Situation	Prob. of Scoring Before Bunt	Prob. of Scoring After Successful Bunt	Difference
Runner on 1st, nobody out	.39	.39	.00
Runner on 1st, one out	.27	.22	- .05
Runner on 2nd, nobody out	.61	.67	+ .06
Runner on 2nd, one out	.39	.24	- .15
1st and 2nd, nobody out	.67	.75	+ .08
1st and 2nd, one out	.44	.26	- .18

Another interesting point to take away from this table is that you actually lower your probability of scoring in most situations with a bunt. This means that even in a close late inning game when a team bunts to try and score just one run they are even decreasing their chances of scoring that one run by utilizing the bunt. The table shows that there is an increase in the probability of scoring with a runner on 2nd and no outs, but if you look at the expected runs table this situation will lead to a lower number of expected runs. This means a successful bunt in this situation will lead to scoring less in this situation, but may increase your chances of scoring a single run. The most logical situation to bunt is with runners on 1st and 2nd and no outs. In this situation a successful bunt will increase both the probability of scoring and the expected number of runs scored. The key here though is that the bunt must be successful for this to be at all worth it because you are only increasing your probability of scoring by about 8%. If you have a poor bunter up it would probably be smarter to just hit away instead of increasing your chances by such a small percentage.

Stealing

Steals are different from bunts in that if the steal is successful, you are getting a base without giving up an out, and it is clear from the tables that this fact will always increase your expected number of runs scored and your probability of scoring, sometimes to a great degree. Because a successful steal has only positive effects, the analysis of steals gives results in terms of a breakeven point. If you are not at least as successful as the breakeven percentage then you should not steal.

Table 6 shows the calculation of breakeven points on a Run Expectation basis, and Table 7 repeats the analysis for probabilities.

Table 6 – Breakeven Points for Steal Situations based on run expectations, World Series 1982-2002

Situation	Run Expectation before steal attempt	Run Expectation after successful steal	Run Expectation after Caught Stealing	Breakeven Point
Runner on 1st, nobody out	.80	1.08	.26	.66
Runner on 1st, 1 out	.54	.62	.09	.84
Runner on 1st, 2 outs	.19	.35	.00	.54
Runner on 2nd, nobody out	1.08	1.44	.26	.69
Runner on 2nd, 1 out	.62	.92	.09	.64
Runner on 2nd, 2 outs	.35	.39	.00	.88
1st and 2nd, nobody out	1.62	1.81	.62	.84
1st and 2nd, 1 out	.92	1.81	.35	.39
1st and 2nd, nobody out	.43	.56	.00	.77

The breakeven points for the expected number of runs scored are higher than for the probability of scoring because to score many runs in an inning getting caught stealing would be a huge detriment. This also means that when making a decision to steal it should be clear what your main goal is at that point of the game. If you're only trying to score one run, then the breakeven point is lower.

A better case can be made for stealing than for bunting. There are situations where it seems it does make sense to try to steal. While stealing is definitely more valuable than bunting, it is still important to steal in the right situation. There are some cases where stealing simply would not make sense, and even a successful steal would not be a huge impact to expected runs scored or the probability of scoring. Teams should

Table 7 – Breakeven Points for Steal Situations based on probabilities, World Series 1982-2002

Situation	Prob of scoring before steal attempt	Prob of scoring after successful steal	Prob of scoring after Caught Stealing	Breakeven Point
Runner on 1st, nobody out	.39	.61	.16	.51
Runner on 1st, 1 out	.27	.39	.06	.64
Runner on 1st, 2 outs	.12	.22	.00	.52
Runner on 2nd, nobody out	.61	.89	.16	.55
Runner on 2nd, 1 out	.39	.67	.06	.50
Runner on 2nd, 2 outs	.22	.24	.00	.93
1st and 2nd, nobody out	.67	.77	.39	.74
1st and 2nd, 1 out	.44	.75	.22	.42
1st and 2nd, nobody out	.25	.26	.00	.98

almost always steal with a runner on first and two outs. The other stealing situations would really depend on the situation of the game. If a team is trying to maximize the number of runs scored, it should probably not steal in these other situations, since the breakeven point is so much higher for expected runs scored than it is for the probability of scoring. But if a team is looking for one run and they have a fairly successful runner on the bases then it can be worth the gamble.

An interesting situation is first and second with one out; the numbers show this is actually a very good time to steal. However, the breakeven point in the table is probably too low. The run expectation chart has a run expectation for second-and-third-with-one-out at 1.81 runs, equal to the same situation but with zero outs. This is probably just random noise in the data, where World Series teams simply scored more runs in that situation by luck (note the high standard errors for these estimates in Table 8). The "correct" number is probably lower, which would make the breakeven point substantially higher.

Conclusions

This study examined the expected number of runs scored and the probability of scoring for teams in the World Series between 1982-2002. Regular season scoring was compared to runs scored during the postseason, and postseason scoring is definitely lower than regular season scoring. Pitching obviously dominates in the postseason, but interestingly this fact does not change how a team should play the game. Teams should not change their strategy to bunt and steal more, and in fact teams that do like to bunt and steal might want to reconsider this strategy.

The results of this study have made it clear that even in the World Series, teams that bunt are reducing their chances of scoring and decreasing their expected runs scored. In fact, they are helping the other team when they bunt. The bunt strategy has always been thought of as a way to add a crucial run for your team in a close game, but in fact a team would score more often by not bunting. This means that managers are hurting their team when they bunt, and decreasing their team's chance of winning the game. Stealing can still make sense in some situations during the game, but it should be evaluated to when a steal should take place.

However, one limitation to this study is that the situation may change depending on the skill of the hitter after a poor hitter. There is a possibility a bunt would make sense if a talented hitter follows a poor hitter, and the poor hitter bunts. A study could be done to see if it would make sense for a poor hitter or a pitcher to bunt if there is a talented hitter coming up next. This study did not take into account such line-up effects.

A final insight from this research is the fact that the postseason probabilities were very similar to Lindsey's, and Palmer's, regular season probabilities. This could suggest that when two great teams play each other they score as much as an average team. The final note then would be that a bunt simply does not help to beat a great pitcher, and in fact it helps the pitcher. The best way to beat good pitching is to hit away, and pick and choose your time to steal.

Table 8 – Full Situation Data for World Series Games, 1982-2002

Bases	Outs	Frequency	Relative Frequency	Expected Runs	Standard Error (Expected Runs)	Prob of Scoring
0	0	2157	23.57%	0.48	.021	26.29%
0	1	1556	17.00%	0.26	.019	15.81%
0	2	1215	13.28%	0.09	.011	6.09%
1	0	541	5.91%	0.80	.053	39.00%
1	1	649	7.09%	0.54	.043	27.27%
1	2	606	6.62%	0.19	.024	11.55%
2	0	158	1.73%	1.08	.094	61.39%
2	1	261	2.85%	0.62	.060	39.08%
2	2	347	3.79%	0.35	.043	22.19%
3	0	27	0.30%	1.44	.274	88.89%
3	1	93	1.02%	0.92	.101	66.67%
3	2	147	1.61%	0.39	.070	23.81%
1,2	0	121	1.32%	1.62	.148	66.94%
1,2	1	231	2.52%	0.92	.088	44.16%
1,2	2	309	3.38%	0.43	.051	25.24%
1,3	0	43	0.47%	1.86	.234	88.37%
1,3	1	123	1.34%	1.22	.118	69.92%
1,3	2	149	1.63%	0.40	.071	23.49%
2,3	0	26	0.28%	1.81	.338	76.92%
2,3	1	79	0.86%	1.81	.179	74.68%
2,3	2	89	0.97%	0.56	.114	25.84%
1,2,3	0	20	0.22%	2.35	.460	75.00%
1,2,3	1	92	1.01%	1.33	.150	64.13%
1,2,3	2	112	1.22%	0.79	.129	33.04%
Total		9151				

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