By the Numbers

Volume 19, Number 2 The Newsletter of the SABR Statistical Analysis Committee May, 2009

Review

Academic Research: Offense vs. Defense

Charlie Pavitt

The author reviews several academic studies that attempt to quantify offense and defense. Sadly, most of them fail because they use inappropriate measures of performance – with one exception.

Herbert F. Lewis, Kathleen A. Lock, and Thomas R. Sexton, Organizational Capability, Efficiency, and Effectiveness in Major League Baseball: 1901-2002, European Journal of Operational Research, 2009, Vol. 197, pp. 731-740

The existing academic research attempting to determine the relative impact of batting, pitching, and fielding in team performance has been miserable, due to the poor choice of individual performance measures. Akers and Buttross (Journal of Sports Behavior, 1988, Vol. 11 No. 2, pp. 99-112) used average and home runs to represent batting, strikeout/walk ratio to represent pitching (they foresaw DIPS analysis by noting that ERA is dependent on fielding whereas K/BB ratio is not), fielding average, and career won-loss and years of experience representing managing. Featherstone and Studenmund (*Research Quarterly,* 1974, Vol. 45 No. 1, pp. 80-85) tried ERA, HR, BA, and fielding percentage. Humphrey, Morgeson, and Mannor (*Journal of Applied Psychology,* 2009, Vol. 94 No. 1, pp. 48-61) employed the average of on-base and fielding percentage (!) for position players and the average of on-base percentage against and innings pitched (!!) for pitchers. Jones (*Organizational Behavior and Human Performance,* 1974, Vol. 11, pp. 426-451) chose RBI to stand for batting and ERA for pitching, as such just using poor stand-ins for runs scored. Clearly unaware of any indicator other than fielding percentage, Jones claimed that "fielding is of so high and uniform a caliber that it plays little role in the determination of final standing" (p. 438). Smart and Wolfe (*European Sport Management Quarterly,* 2003, Vol. 3 No. 3, pp. 165-188) attempted team ERA relative to league average to represent defense (purposely passing on fielding as too hard to measure), Furtado's extrapolated runs to represent offense, and two measures of managing, one representing specific managers' experience and past record and the other team managerial turnover. Although often accounting for huge amounts of variance in team winning percentage, most of the chosen indices are on totally different scales and their combination makes no sense. Their conclusions about the relative importance of the factors cannot be trusted; for example, Akers and Buttress found manager career won-loss to account for more variance than K/BB, and concluded that managing is more important than pitching. Gee, maybe if a manager is lucky (unlucky) enough to oversee a team with good (poor) pitching, their career record will be good (poor) no matter their personal skill.

In this issue

Lewis, Lock, and Sexton (2009) do a far better job of this task than those just mentioned. Their goal is to measure both a team's capability (ability to score and prevent runs) and efficiency (ability to spread the runs scored and prevented so as to win as much as possible; in other words, in close games rather than wasting them in blow-outs. Their measure of "offensive capability" consists of total bases plus walks plus a guesstimate of opposition errors, divided by games played, resulting in an attempt at bases per game. Their index for "defensive capability" consists of the exact converse; total bases plus walks given up plus own errors divided by games played. This is the first time in this literature that the indices corresponded in a sensible way. Efficiency for offense, defense, and their combination was measured by comparing their actual distribution to the ideal.

Their authors' analysis was based on all seasons from 1900 through 2002 excepting strike seasons. In total, defensive capability accounted for 46.3 percent of variance, offensive capability for 26.7 percent, offensive efficiency for 3.2 percent, defensive efficiency for .8 percent, and the combination of the latter two ("winning efficiency") for 5.4 percent. In addition, Lewis et al. noted that an ideally efficient use of bases gained would increase average run production by 13 percent, of bases given up decrease runs given up by 10 percent, and the best combination of runs scored and given up improve the team by 16 games.

Lewis et al. also examined World Series over the same period of time. Teams making it were not surprisingly more efficient than average. Interestingly, their equations accounted for a grand total of one percent of variance in World Series performance. In other words, at-most-seven-game-series are just not predictable this way.

There is still a good bit of work to do in this regard. Defensive capability has to be divided into pitching versus fielding through some method of representing DIPS and defensive efficiency record. But, for the first time, we have an academic study in this area that can be taken seriously.

Charlie Pavitt, chazzq@UDel.Edu ♦

"By the Numbers" mailing list

SABR members who have joined the Statistical Analysis Committee will receive e-mail notification of new issues of BTN, as well as other news concerning this publication.

The easiest way to join the committee is to visit http://members.sabr.org, click on "my SABR," then "committees and regionals," then "add new" committee. Add the Statistical Analysis Committee, and you're done. You will be informed when new issues are available for downloading from the internet.

If you would like more information, send an e-mail to Neal Traven, at beisbol@alumni.pitt.edu. If you don't have internet access, we will send you BTN by mail; write to Neal at 4317 Dayton Ave. N. #201, Seattle, WA, 98103-7154.

Submissions

Phil Birnbaum, Editor

Submissions to *By the Numbers* are, of course, encouraged. Articles should be concise (though not necessarily short), and pertain to statistical analysis of baseball. Letters to the Editor, original research, opinions, summaries of existing research, criticism, and reviews of other work are all welcome.

Articles should be submitted in electronic form, preferably by e-mail. I can read most word processor formats. If you send charts, please send them in word processor form rather than in spreadsheet. Unless you specify otherwise, I may send your work to others for comment (i.e., informal peer review).

I usually edit for spelling and grammar. If you can (and I understand it isn't always possible), try to format your article roughly the same way BTN does.

I will acknowledge all articles upon receipt, and will try, within a reasonable time, to let you know if your submission is accepted.

Send submissions to Phil Birnbaum, at birnbaum@sympatico.ca .

Book Review: "Mathletics"

Phil Birnbaum

The author revies the recent book "Mathletics," a review of the state of the sabermetric art in various sports.

"Mathletics," by Wayne Winston, is a fine book. It's meant as an introduction to the sabermetrics of baseball, football, and basketball, with a little bit of math/Excel textbook built in. It's not perfect, but it suits its purpose very well, and it's probably the first book I'd suggest for anyone who wants a quick overview of what sabermetrics is all about in practical terms.

One of the things that I think makes the book work well is that it's not full of itself. It doesn't make grand pronouncements about how it's a revolution in thinking about sports, or how its breakthroughs are going to change the game. It just gets to work, with clear explanations of the various findings in sabermetrics. Every subject gets its own chapter, and the chapters are generally exactly as long as they need to get the point across. The discussion of Joe DiMaggio's hitting streak takes eight pages, but the Park Factors chapter is only three, because, really, that's all it takes to explain park factor.

About a third of the book is devoted to each of the three sports. Readers here will be interested mostly in the baseball section, and I'd say the selection of subjects is pretty decent. The first few chapters deal with the oldest, most established results -- Pythagoras, linear weights, and runs created. There's a chapter on the various fielding evaluation methods, on streakiness, and on the "win probability added" method of evaluating offense. DIPS gets its own chapter, in the context of evaluating pitchers. There's even a chapter on replacement value, although, strangely, Winston discusses it only in the context of win probability, rather than methods that don't involve timing of events.

For the most part, it's a matter of personal opinion what topics in sabermetrics are more important and what topics are less important, and, since this is Winston's book and not mine, you should take my recommendations with a grain of salt. But my main complaint is that I wish there had been a discussion of random chance in the statistical record, and regression to the mean. Throughout the book, no mention is made of the fact that most extreme values of sports statistics are biased away from the mean, although I think there are a few casual mentions of small sample sizes. (But even as I write this, other topics occur to me ... Hall of Fame induction standards, for instance, and baseball draft findings.)

On the football side, there are discussions of quarterback rating methods, an analysis of NCAA overtime strategies, and NFL overtime probabilities. There's a chapter on the paradox of the passing premium, and one on fourth-down decision-making. All this stuff seems like solid summaries to me, at least from what I've learned about football strategy from research blogs like Brian Burke's.[1]

Most of the baseball and football material was already familar to me, as was about half the material in the basketball section (formulas for ranking players, a summary of the research on referee racism, etc.). But there was a bunch of basketball stuff I hadn't seen before, or didn't know much about. Again, some of that might be because I don't follow basketball research that closely. But I'm sure some of the stuff is original, as Winston works as a consultant to the NBA's Dallas Mavericks. I found the "plus-minus" chapters to be the most interesting (and they're also the longest), but, after reading them, I still wasn't quite sure how much of the results were real, and how much were just noise due to small sample sizes.

The plus-minus system tries to figure out a player's value by how his team does when he's on the floor. The problem with that, of course, is that the player's rating will be biased by the teammates he plays with: a crappy player might look good if he plays with Kevin Garnett all the time. The system tries to factor that out, by keeping track of all the teammates and opposition players on the floor at the same time, and finding a set of ratings that most consistently predicts outcomes based on those other nine players. (Winston uses a feature of Microsoft Excel called "Excel Solver" for this; I'm not sure how it would differ from an ordinary least-squares regression.)

The results are impressive, but there aren't any confidence intervals, or even simple intuitive measures of how reliable the results might be. I really like the plus-minus method in theory, but I've always wondered about how much you can trust its answers, and Winston doesn't really tell us here. The question is especially relevant because Winston goes on to try to figure out the "chemistry" of various lineups. For instance, suppose you have five players who are +1 each, but, when they're on the court together, the team winds up +15 instead of the expected +5. Winston would say that those five players complement each other somehow and perform exceptionally well together. I'd ask, could it just be

[1] http://www.advancednflstats.com/

random?

Another interesting study in the book, which I think is original to Winston, is a measure of which draft positions give you the best value per dollar (similar to the Massey/Thaler study[2] of the NFL draft). It turns out that the 1-10 choices are by far the most lucrative, but that 6-10 slightly outperforms 1-5 after adjusting for salaries. There are only five years in Winston's study, though, and he tells us that the 6-10s are "pumped up by the phenomenal success of #10 picks Paul Pierce, Jason Terry, Joe Johnson, and Caron Butler."

Finally, there's a fourth section of the book, which discusses topics that aren't specific to a single sport. Gambling probabilities are covered, along with team rating methods, competitive balance, and other such things.

As I said, I really like the book and its method of presentation ... but I have to say I don't agree with everything in it, and I think there are things in it that are just plain wrong. Winston spends two chapters trying to evaluate how play has improved over the decades ("Would Ted Williams Hit .406 Today?"), but I don't think the computations work. The method, as has been done by many others, is to look at all players who played two consecutive years, and see how their performance changed from one year to the next. If their performance dropped by (say) two points, you conclude that the league improved by two points between those two seasons.

As I have argued elsewhere,[3] I think that method doesn't measure league improvement -- I think it measures the difference between player performance in the first year of their career, as compared to the last year of their career. So I think Winston's conclusion, that Ted Williams would have hit .344 in 2005, is completely without basis.

Another problem is the chapter on parity. Winston regresses NFL team's performance this season on its performance last season, and gets an r-squared of .12. He does the same thing for the NBA, and gets an r-squared of .32. He therefore concludes that the NFL has more parity, and it must be because of the salary cap, the draft, and the fact that contracts in the NFL are not guaranteed.

Those might all be factors, but, as has been pointed out many times in various online discussions, the main reason is that NFL teams play 16 games, while NBA teams play 82 games. Even if the other factors affecting year-to-year performance were exactly the same, the correlation would be lower in the NFL just because random chance is a much higher proportion of performance in a 16-game season than in an 82-game season.

Winston also revisits the question of whether payroll can buy wins. He finds that there's a reasonable correlation between team pay and performance in baseball, but low or negative correlations in the NBA and NFL. That, he speculates, is because it's much easier to evaluate the statistics to figure out if a baseball player is good, than to figure out the relative skill of a football player or basketball player. Under that theory, NBA and NFL teams just aren't very good at figuring out who's valuable and who's not.

That doesn't sound plausible to me, that teams could be that blind. Most of the effect, I think, is that because the NBA and NFL both have a salary cap, the distribution of team payroll is very narrow. Therefore, most of the variation is luck, which means the r-squared is going to be lower.

That is: the r-squared is not an absolute measure of the relationship between pay and performance -- it's a *relative* measure, relative to the other sources of variance. In any given year, there will be a high correlation between my salary and the total salary of people in my house -- but a lower correlation between my salary and the total salary of people in the country. The R-squared depends heavily on the size of the *other* factors that contribute to variance. In the NBA and NFL, those factors are much larger than the (compressed) payroll. In MLB, however, you have teams that spend $200 million, and teams that spend $60 million. That means a lot more of the observed difference between teams is payroll-related.

One last way to look at this: in Rotisserie League Baseball, there is a high correlation between player salary and performance: Albert Pujols goes for a lot more rotisserie dollars than Eric Hinske. But if you do a correlation between team pay and performance, you'll get a very low number, because all teams pay around $260!

Winston would do better to regress individual player performance on individual player salaries. If he did that, he'd find that there is indeed a strong link between pay and performance, but that the salary cap means it doesn't apply at the team level.

------

[2] My review of the Massey/Thaler study is at http://sabermetricresearch.blogspot.com/2006/12/do-nfl-teams-overvalue-high-draft-picks.html .

[3] http://sabermetricresearch.blogspot.com/2006/08/can-we-measure-player-improvement-over.html

I should also mention a few picky things that could be improved. There are some silly errors that could have been fixed with a little more reviewing. For instance, in Chapter 1, Winston notes that in July, 2005, the Washington Nationals were 50-32 despite having allowed more runs than they scored. According to Pythagoras, based on their runs scored and allowed, they should have been around .500. "Sure enough," the book says, "the poor Nationals finished 81-81."

But, of course, that doesn't follow. Perhaps the Nationals should have finished .500 in their remaining 80 games, but that should have brought them to 90-72, not 81-81 -- you can't go back and reverse the games that already happened. That's just a little oversight that should have been caught, and could be misleading to someone who's reading about Pythagoras for the first time.

Another thing I found is that some of the Excel charts were a little off-putting. That's my opinion, which is not necessarily better than Winston's own editorial judgment (and, after all, it is his book, and part of its mandate is teaching a bit of Excel). But at least a little better formatting would have helped. In particular, numbers in cells should be rounded to the appropriate number of decimals; a chart showing the "mean strength" of the Buffalo Bills to be 3.107639211 is obviously a little too exact.

And I hate the term "Mathletics" as a substitute for sabermetrics. Hate, hate, hate. Hate.

Another strength of the book is its bibliography. Even before getting to it, at the back of the book, it's obvious that the author is quite well read in the current state of the sabermetric art; almost every source I can think of is sourced somewhere in the text. The bibliography expands on the text references, with a listing of somewhere around 100 articles and websites, with full opinionated descriptions of what's in them. (Disclaimer: Winston says some very kind things about my own site ... thanks!)

The only omission I found -- and it's a big one -- is that "The Book" blog[4] isn't included. In my opinion, that should be among the first places sabermetricians go to learn what's new in the field (especially in baseball). Tom Tango, one of the blog owners, is very thorough in identifying which new research is worthy and which isn't, and I'm disappointed Winston didn't include that particular blog. However, "The Book" itself is listed, with a nicely favorable review and a link to Tango's own website (if not the book's).

I think of "Mathletics" as a bit of a sabermetric Wikipedia between hard covers. Despite some shortcomings that I've described here, it's the only concise, current, beginner's description of sabermetric findings that I can think of. My preference would be to see it expanded a bit. I'd love for it to have a section on hockey -- there's lots of stuff we know thanks to Alan Ryder[5], Gabriel Desjardins[6], Tyler Dellow[7], and others[8] -- and there are lots of other topics in the other three sports that could be added. I'd also prefer if more of the Excel stuff was left out of the book and placed on the author's website[9] (where the full spreadsheets can be found.)

But, as I said, it's Winston's book, not mine, and until he appoints me paid editor, I should appreciate it for what it is, which is a book that fills what I think is an important untapped need. Even as it stands, it's now the first book I'd recommend to any beginner who wants a quick overview of the state of sabermetric knowledge.

Note: A version of this review previously appeared on the author's blog.

Phil Birnbaum, birnbaum@sympatico.ca ♦

4 http://insidethebook.com/ee/
5 http://www.hockeyanalytics.com/
6 http://www.behindthenethockey.com/
7 http://www.mc79hockey.com/
8 Such as, for instance, http://puckprospectus.com/ .
9 http://waynewinston.com/wordpress/?page_id=13

Which Batter Had the Greatest "Eye"?

Tom Hanrahan

Which batter had the best "eye," in the sense of knowing how work a walk? Here, the author gives a method for answering that question, by adjusting career walk totals for a player's power (to adjust for the fact that sluggers get pitched around).

Methods

How do we go about measuring who had the best "eye" at the plate? Like anything, we could go for counting stats; those who posit that Hank Aaron is the best career hitter can point out that he has the most total bases and most RBI. However, many would argue that rate stats are more telling, and of course no one can top Ruth's lifetime SLG and OPS. For "best eye", it's easy to lookup the career leaders in walks and see that Barry Bonds had far more walks than anyone else (Rickey is #2). But it's also true that Ted Williams walked more per at-bat than Bonds.

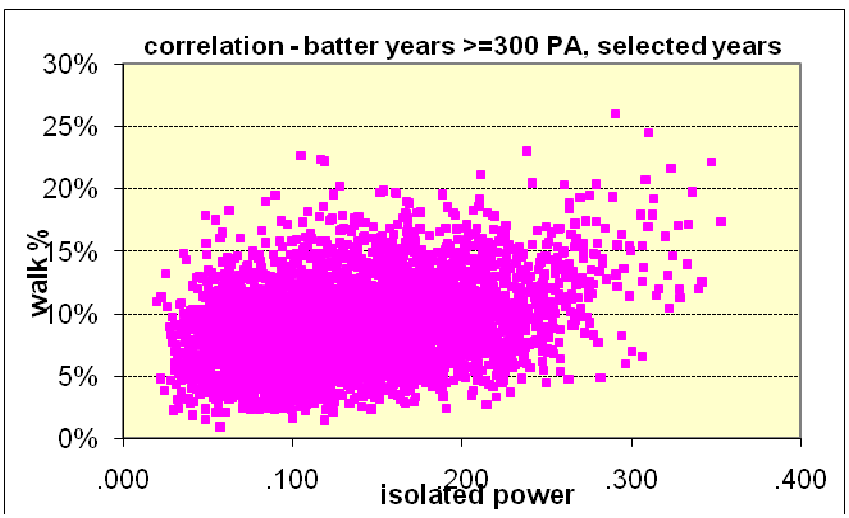
What other factors might go into this analysis? League norms, certainly – in 1949, when Teddy Ballgame was walked 162 times, the average team drew four-and-a-half walks per game. He likely would have been given a free pass much less often in the NL of 1968, when walks were below three per game!

The obvious elephant in the room here is the fairly obvious tendency for pitchers to throw more carefully to dangerous batters; does anyone think that Bonds started walking 200 times a year late in his career because his eye got so much better with age and experience (um… no)? So, we need to quantify and account somehow for this tendency.

Correlating walks with power

I took 20 years of MLB data: 1953-56, 1965-72, and 1981-88. I found all batters who had at least 300 PA in any year, which resulted in over 3700 player-seasons. I ran a linear regression on the data set, with walk rate (BB/PA)[1] as the independent variable, and various other hitting rates as the dependent variables. I found that walk rate (somewhat surprisingly) did not correlate positively with batting average. However, there was a strong correlation with isolated power (extra bases per at-bat). See figure 1.

Figure 1: walks vs. power



There is a lot of scatter here, which basically means that the ability to draw walks goes well beyond how much power a player has; but the relationship is certainly there. Of the total variation in walk rate, 12% (the r^2 value) can be explained by ISO. In

[1] I actually used BB/(AB+BB) instead of BB/PA. I did not think it right to include sacrifice bunts and HBP in the denominator, since neither represent the ability or inability to work a walk.

coming up with a "best fit", I found that the regression line fit better with a square function; the actual equation was BB/PA = .076 + .656 * ISO^2. This means that a player with ZERO power drew walks, on average in those years, 7.6% of the time up. But a Ruthian slugger with an ISO of .350 would have walked at a 15.6% rate. If this regression line were extended to absurd proportions (not recommended!), a batter with a .740 ISO would be walked every time he came up; which probably isn't too far from reality.

Adjustments for league and park norms

All right, so we can adjust a player's walk rate by accounting for his power. Would this bring us to the "right" answer? I would say no, because we have not yet accounted for differences in leagues, as mentioned previously. One way to do this would be to find the league-average walk rate for every season, and adjust the player's walk rate either linearly or proportionately. It's possible that some parks even have 'walk effects', which are not as well documented as effects on runs scored and home runs. All of the above leads me to conclude that making these adjustments, while prudent, involves a LOT of work, and even then may be very imperfect.

Fortunately, others have already cut swaths through the forest and paved smooth paths here, performing the arduous task of calibrating every batter's stats to a standard environment.

1. At Baseball-reference.com ("bb-ref"), anyone can look up raw players stats and 'transform' them into stats for a 'neutralized' run environment. An explanation is given at http://www.baseball-reference.com/about/equiv_stats.shtml.

2. At Baseballprospectus.com ("BP"), when looking up the records for individual players, they also have a 'translated stats' section, which shows how the player would have done in a modern run environment. Unlike baseball-reference.com, this translation also includes a league-strength adjustment, so that a player in a weaker league (such as 1914-15 Federal League, the brief Union Association, the original AA of 1871, and the WWII seasons) is not shown to be dominant over more modern counterparts.

While league-strength adjustments can be controversial, in this case I believe there are good reasons to use BP's numbers. First, it does normalize players across the past 130 years. Secondly, the adjustments each system uses are different; BP tends to more liberally add home runs and take away triples from the dead-ball totals, so they more closely approximate the modern game. Because of this additional realism, I will use BP's data here.[2]

"Peak" vs "Prime" vs "Career"

When discussing who was the best at anything, the debate ensues over whether it is meant who was the best when they were at their best, versus who had the most career value. Let's call this Sandy Koufax vs. Don Sutton. Most skills wax and wane as a player ages. Fortunately, in the field of drawing walks, batters' skills appear to be fairly constant over time. A study by Tom Tango (data posted at http://www.tangotiger.net/agepatterns.txt) showed that batters' walk rates actually increase somewhat all the way through about age 37 (whereas most other skills peak at age 27 or earlier); but the differences are not large – a typical batter tends to draw walks about 10% more frequently in his 30s than in his late 20s. Therefore, with this fairly 'flat' curve of skill, I feel very comfortable in using career rate stats as the basic metric.

Show me the data

I took the batters who had the highest career walk rates in MLB history, and who drew at least 800 walks in their careers. To these, I added others who had high walk rates and very little power, as well as one historically notable player, Rickey Henderson. I found each player's BP page, and recorded their "translated" stat lines of at bats, walks, and isolated power. Lastly, I used the regression formula found previously to compute an *adjusted walk rate*; this is the ranking metric. It means, in English, the rate of walks the batter would have drawn, over his career, in a 1990s run scoring environment, in a neutral hitter's park, *if* he had hit for an average amount of power.

Table 1 shows the batters, ordered by their career walk rate (UNadjusted). Some notes:

[2] One frustrating item in using BP's data is that it changes on occasion, as the web site holders make small 'tweaks' to the formulae used. This means that it is possible that one day someone may read this article and be unable to reproduce the numbers quoted in these tables as 'translated stats'.

Table 1 – Adjustments for players with highest walk rates

	Walks	AB	Walk Rate	Isolated Power (ISO)	Walk rate translated for era	ISO translated for era	Walk rate after all adjustments (era and ISO)
T Williams	2021	7706	.208	.290	.180	.327	.125
B Bonds	2558	9847	.206	.334	.202	.337	.142
M Bishop	1153	4494	.204	.095	.193	.104	.201
B Ruth	2062	8398	.197	.348	.190	.401	.100
E Stanky	996	4301	.188	.080	.176	.104	.184
F Fain	904	3930	.187	.106	.153	.135	.156
G Tenace	984	4390	.183	.188	.181	.265	.150
R Cullenbine	853	3879	.180	.156	.164	.204	.152
E Yost	1614	7346	.180	.117	.153	.142	.155
M Mantle	1733	8102	.176	.259	.192	.299	.148
J McGraw	836	3924	.176	.077	.186	.135	.189
M McGwire	1317	6187	.176	.325	.202	.373	.126
R Henderson	2190	10961	.167	.140	.162	.190	.153
R Thomas	1042	5296	.164	.043	.188	.092	.197
M Huggins	1003	5558	.153	.049	.162	.090	.172
T Hartsel	837	4848	.147	.094	.185	.168	.181

Barry Bonds, who decimated the record for career walks previously held by Rickey Henderson, would have had a walk rate much lower, since his tremendous amount of power likely caused many of his walks, as well as his keen eye.

Ted Williams, long noted for his ability to lay off a ever-so-slightly-imperfect pitch, played in a high-walk environment. The AL of 1950 was a league full of power pitchers who didn't always throw strikes. So, Ted's translated walk rate is lower. The same goes for Eddie "walking man" Yost.

Babe Ruth of course hit for far more power than any other MLB player. In the modern game, his isolated power might have been a truly eye-popping .401; no wonder he was walked so often.

The highest *translated* walk rates belong to the modern big boppers, Bonds and McGwire.

The last 3 players listed in table 1 each played in a low-walk environment: the dead-ball era, when pitchers had no good reason to pitch around anyone. So, their adjusted walk rates are higher than their raw rates. These three are –

- Roy Thomas: Early 20th century outfielder for the Philadelphia Phillies. He led the league in walks five years in a row. In that span, he never drove in more than 33 men in a season. It makes you wonder why opposing pitchers didn't simply lob fat pitches over the middle.
- Topsy Hartsel: Same years, same city, different league, put up many of the same stats for the Athletics, but with more pop in his bat.
- Miller Huggins: Four-time walks leader between 1905 and 1914. Never hit more than 19 doubles in a season, and his high in home runs came as rookie, when he hit…. two (!).

Re-ranking the hitters in table 1 by best *translated* (for a normal environment, from the BP stats) walk rate shows the leaders are:

```
.202 Barry Bonds
.202 Mark McGwire
.193 Max Bishop
.192 Mickey Mantle
.190 Babe Ruth
.188 Roy Thomas
.186 John McGraw
.184 Topsy Hartsel
.181 Gene Tenace
.180 Ted Williams
```

Bonds and Ruth; yeah, we know those guys. Possibly the two most feared sluggers who ever played. Big Mack and the Mick, same story. But who are these guys named Thomas (not Frank!) and Bishop?

The next step is to adjust for the players' (isolated) power. I have used the regression relationship shown earlier to produce the equation for adjusted walk rate:

Adjusted walk rate = translated walk rate + .015 – translated ISO^2 * .656

This was done by using a league-average walk rate of .091 (.076+.015).

Table 2 is a ranking of Best Eye Hitters – those who would have walked the most often, given they had average power.

Table 2 – Players with highest adjusted walk rates

Hitter	Actual walk rate	Walk rate translated for era	ISO translated for era	Walk rate after all adjustments (era and ISO)
M Bishop	.204	.193	.104	**.201**
R Thomas	.164	.188	.092	**.197**
J McGraw	.176	.186	.135	**.189**
E Stanky	.188	.176	.104	**.184**
T Hartsel	.147	.185	.168	**.181**
M Huggins	.153	.162	.090	**.172**
F Fain	.187	.153	.135	**.156**
E Yost	.180	.153	.142	**.155**
R Henderson	.167	.162	.190	**.153**

Conclusions

We can see from these tables that the real power hitters who historically drew the most walks were actually walking as much out of respect for their power as their great eyes. Oh, it's true that Bonds and Williams had very good plate discipline; just not historically GREAT plate discipline. Babe Ruth probably had no better than average plate discipline – his walks drawn were mostly a facet of being a man among boys as he created a new kind of game, where power ruled.

The real king of the strike zone was the man whose nickname was…. "Camera Eye". Max Bishop, the man who scored 1153 runs in his major league career, which only lasted 1338 games. He finished in the top four in walks drawn in the AL *nine years in a row*, despite being an otherwise below-average hitter. A modern-day Max Bishop with 'average' power hitting leadoff might walk 140 times per year while accumulating 570 official at-bats.

He had the best batting eye. Ever.

Max Bishop, career statistics per 162 games played

AB	R	H	2B	3B	HR	RBI	BB	K	AVG	OBP	SLG
544	117	147	20	4	5	46	140	55	.271	.423	.366

Tom Hanrahan, Han60Man@aol.com ♦

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.

Member	E-mail	Expertise
Shelly Appleton	slappleton@sbcglobal.net	Statistics
Ben Baumer	bbaumer@nymets.com	Statistics
Chris Beauchamp	cbeaucha@asinc.ca	Statistics
Jim Box	jim.box@duke.edu	Statistics
Keith Carlson	kcsqrd@charter.net	General
Dan Evans	devans@seattlemariners.com	General
Rob Fabrizzio	rfabrizzio@bigfoot.com	Statistics
Larry Grasso	l.grasso@juno.com	Statistics
Tom Hanrahan	Han60Man@aol.com	Statistics
John Heer	jheer@walterhav.com	Proofreading
Dan Heisman	danheisman@comcast.net	General
Bill Johnson	firebee02@hotmail.com	Statistics
Mark E. Johnson	maejohns@yahoo.com	General
David Kaplan	dkaplan@education.wisc.edu	Statistics (regression)
Keith Karcher	karcherk@earthlink.net	Statistics
Chris Leach	chrisleach@yahoo.com	General
Chris Long	clong@padres.com	Statistics
John Matthew IV	john.matthew@rogers.com	Apostrophes
Nicholas Miceli	nsmiceli@yahoo.com	Statistics
John Stryker	john.stryker@gmail.com	General
Tom Thress	TomThress@aol.com	Statistics (regression)
Joel Tscherne	Joel@tscherne.org	General
Dick Unruh	runruhjr@iw.net	Proofreading
Steve Wang	scwang@fas.harvard.edu	Statistics