

Statistical Fallacies in Sports

Scientists like to poke fun at sports experts for their lack of understanding of simple scientific concepts. We nerds take some satisfaction in knowing something or doing something better than the tremendously gifted athletes that play sports. While we can't field a ground ball in the hole, we know that ground balls don't pick up speed as they travel on artificial turf. We know that despite the talents of some pitchers, they can't increase the mass of a baseball by throwing a "heavy ball." We yell at the television when the announcer quotes a turnover *ratio* of +7 or a winning *percentage* of 0.500. We know that Michael Jordan cannot float an extra instant in the air, a baseball hitting a fence that is 400 feet away actually would have traveled *farther* than 400 feet, and we snicker at reports such as the following in the Associated Press (St. Louis Cardinal vs. Pittsburgh Pirates, April 26):

"Luna, who went 2-for-5 and raised his average to .432, had his fourth straight multihit game for the Cardinals, who have won six of seven overall."

These mistakes run from mathematical to physical. There are not a lack of statistical mistakes in sports. They may not be as blatantly obvious as the above examples, but they may actually be more harmful in their effect. In this column I present my top 5 list of statistical concepts that are misunderstood in the sports world—I'll call them fallacies. Interestingly, the fallacies are the same that are made in many other walks of life—including science. I lead a dual life as a statistician who writes and studies sports, but also a statistician who consults in medical and scientific applications. Many of the misunderstandings I deal with in medical applications are the same as those in sports. The beauty of sports is that these concepts are so clear, concise, repeatable, and enjoyable to discuss. In this article I present examples from the world of sports, but also touch on examples from the scientific community where the same principles are not well understood.

Variation

This first concept is the most obvious: Variation. The fallacy is the lack of understanding of simple random variation. There is healthy natural variation in sports and frequently this is not well understood. To understand variation it is important to understand the distinction between intrinsic ability and performance. When a basketball player has made 30 free throws in 40 attempts in a season, that player's free throw percentage for the season is 75%. This represents "data" that was observed—a player's performance is data. The player has a true

ability to make a free throw, which is determined by their skill and “mother nature.” This true ability of a player to make a free throw is something that is unknown. I refer to this as their “intrinsic ability.” We don’t know Shaquille O’Neal’s true intrinsic ability to make a free throw, but we observe many attempts, which provide information about his true intrinsic ability. This distinction between the intrinsic ability and the data is not always made in sports. When one team beats another team it is foreign in sports to think that there was some probability that each team would win.

It is common in sports is to attach a reason to randomness. These “effects” or “phenomena” gain a sports life. The most dubious effect I hear about in sports is “chemistry.” When a team’s performance is different from that expected the reason is usually chemistry—good or bad. Suppose a Major League Baseball (MLB) team has a true intrinsic ability to win of 0.500. Over the 162-game season they will win an average of 81 games. The standard deviation of the number of wins is 6.4 games. This “average deviation,” due to pure randomness, is more than 6 games. More than 30% of the time a true 0.500-team will win more than 87 games or less than 75 games. A team winning 87 or more games is usually in the playoff chase, while a team winning 75 or less games is an also ran, finishing double digit games out of a playoff position. A team that was expected to be around a 0.500 team but wins 75 games will complain of poor chemistry, while the team winning 87 will talk about the great team chemistry—it is nothing but trying to explain variation.

A non-pitcher starting baseball player will have about 500 at bats in a season. The most common measure of a hitter’s success is his batting average, the number of hits divided by number of at bats. Suppose a player has a true intrinsic probability of 0.3 of getting a hit in an at bat. After 500 at bats the player’s expected batting average is 0.300, with a standard deviation of 0.020. The average deviation for a player with a true ability of 0.300 means 20 points on their observed batting average. In MLB a player who bats 0.280 is thought of very differently from a hitter batting 0.320. A true 0.300-hitter will be expected to vary by these 20 points—purely due to randomness.

On *ESPN.com* (Nov. 30, 2005) writer Greg Garber wrote an article about the National Football League’s (NFL) “truisms and untruths,” with the following headline: “There are a bunch of cliches and truisms tied to the NFL. After crunching some numbers, we figured out which ones are deadly sins... and which are myths.” (sports.espn.go.com/nfl/news/story?id=2241116) Garber’s Myth #3 is: “No. 1 conference seed advances to Super Bowl”. Garber claims this is a myth as *only* 50% of conference No. 1 seeds advance to the Super Bowl. The NFL playoffs consist of two six-team brackets with the winner of each bracket advancing to the Super Bowl. The top two seeds in each bracket get a bye. Garber points out that the Pittsburgh Steelers lost

two home conference finals in four years, “Two losses at home in the conference game final in four years— not quite an advantage for the top seed. In the previous five years only half of the 10 No. 1 seeds have advanced to the Super Bowl. The 50 percent ratio applied to the 1990’s as well.” In order for the conference No. 1 seed to advance to the Super Bowl they have to win two home games against very strong competition. There is variability in sport, and beating two good playoff teams (being the one to advance from 6 playoff teams), even at home, is not easy. If the No. 1 seed has a 70% chance of winning each game individually they would have *only* a 49% chance of advancing to the Super Bowl. I saw the headline that 50% of No. 1 seeds advanced and thought that was large! This means the other 5 playoff teams share a 50% probability of advancing to the Super Bowl. There is so much more variability in sports than people realize.

Ask someone to write down a sequence of 30 coin flips (heads and tails) from a fair coin. Then have them flip a fair coin 30 times and record the results. You will find that picking which one is which is usually easy—the sequence with the longest run of heads or tails is very likely the flip of the real coin. When asked to generate random sequences we tend to underestimate the amount of natural variability. What happens in sports is that we see natural variability—but it looks too strange—and thus we create reasons and effects for why something happened, when in actuality it was pure randomness. This is not a meaningless consequence, because people use these effects and myths to make decisions, thinking they are “predictive” or “descriptive” of the truth, when they don’t exist and don’t predict—a mirage.

Multiplicities

As more data becomes available to analyze and digest the conclusions may become worse. For example, in baseball, the individual player’s statistics are broken down in to many subcategories, called “splits.” On *ESPN.com*, for Albert Pujols’ 2005 season the following subclassifications for his at bats are reported: dome stadium, open air stadium, vs. left-hand pitcher, vs. right-hand pitcher, at home, on road, during day, at night, on grass fields, on turf fields, each month April through October, before All-Star game, after All-Star game, against each of 20 different teams he faced, in each of the 16 stadiums he played, first time facing a pitcher in a game, second time, third time, and fourth or more times, against finesse pitchers, power pitchers, groundball pitchers, and flyball pitchers, as a pinch-hitter, as a first baseman, for each of the 12 different possible counts, after each of the 11 possible counts (ignores 0-0), while batting second, third, fifth, sixth, or ninth in the batting order, and seventeen different combinations of runners on base and number of outs. In total there are 111 different “splits” presented.

Albert Pujols is one of the best hitters in baseball and in his short career has performed as well as anyone in history. He had 195 hits in 591 at bats, for a batting average of 0.330 (with 41 home runs). Pujols' hits, at bats, and batting average against each of the 20 teams he faced in 2005 are presented in Table 1. He batted a paltry 0.167 against the Nationals and a whopping 0.444 against the Rockies. What did the Nationals know or execute that the Rockies did not? This topic could be addressed routinely while watching a baseball game or listening to the experts. The experts and players would discuss something that the pitchers for the Nationals did and that the Rockies did not do. I do not think that Pujols was better or worse against one team than the other. Sure, I believe that some pitching staffs are better than others and thus Pujols is not an intrinsic 0.330-hitter against all teams—but this variability across teams is probably “ten to twenty points,” not hundreds of points. The statistical issue is that if you split data up in to many different “splits” there is bound to be a great deal of variability. If you then separate the strange cases and present them individually they seem amazing, but this ignores the multiplicities present. It is not at all suprising that Pujols hit 0.167 against a team or 0.444 against a team. If you put it on the Washington Nationals broadcast that Pujols batted 0.167 againsts them it seems amazing. There is no reason for this other than variability caused by splitting the data. The batting performance variation in the splits does not imply that Pujols was intrinsically different in any of these splits. I would guess he was virtually the same hitter against the Nationals as he was against the Rockies.

To demonstrate the variability caused by splitting the data I simulated a full 2005 season for Pujols using the same number of at bats he had against each team. I assume his true probability of getting a hit in any at bat is 0.330, against every team. I then repeated this season 10,000 times and in Table 1 present the average lowest and highest batting averages (and every position in between in the table). The same team was not always in the same position, but the order of the averages is preserved for comparison. The mean lowest batting average in the 10,000 simulated trials is 0.139. Given Albert Pujols at bats against each team, if he were intrinsically a 0.330-hitter in every at bat, against every team he faced, on average the team he performed the worst against would have resulted in an average of 0.139. The mean highest batting average is expected to be 0.538. Thus looking at his observed batting averages against teams, with a spread from 0.167 to 0.444 is actually smaller than you would expect just from pure randomness and multiplicity!

You could have split Pujols' at bats by the 3rd letter of the pitcher's last name and you would see a good deal of variability—this is expected. The mistake is believing that the variable that was split is truly different, just from the data. It is expected that strange things will happen, but it is not predictive of future performance nor descriptive of intrinsic truth. This problem

is perhaps the biggest mistake made in medical practice. Many clinical trials are conducted and the results are analyzed breaking up the results in to many “splits.” This may be patient demographics, such as gender, race, age, etc, or it may be disease subclasses or drug interactions. The results are broken down in many splits and then those splits that come out looking good are then thought to be “real.”

I believe this is why so many “false” trials report different causes of cancer. If you conduct a study where you record 100 different patient demographics and compare to the cancer rates you will find some extreme data. If Pujols’ data were cancer rates, we would hear that the Nationals are protective against cancer and the Rockies cause cancer. A new trial conducted to verify that the Nationals are protective—costing possibly hundreds of millions of dollars would be conducted and would find that the Nationals do not prevent cancer. Many pharmaceuticals are tested and found to not be effective for all patients, but in certain subclasses appear to be effective. The human mind is so creative it can create biological explanations for anything, regardless of how false. Future trials are run, where patients are agreeing to be randomized for the purpose of scientific study, resources are being used and the future trial finds no effect in the subgroup.

Expert baseball color commentators, using their creative mind, can create a baseball reason for Pujols hitting 0.167 against the Nationals and 0.444 against the Rockies—regardless of how false.

Regression to the Mean

This next concept may be the reason I become a statistician. This concept manifested itself many times in sports when I was a kid. As a 10-year-old in 1977 I was a big fan of the “Big Red Machine”—the Cincinnati Reds 1970’s baseball team. Approximately half way through the season their left fielder, George Foster, had 31 home runs. Doubling his midseason total (which I was just sophisticated enough to do) implied he was on pace for 62 home runs. In an unsophisticated way I believed it was at least a 50-50 proposition that he would. My father bet me a week’s allowance that not only would he not hit 62 (which would have been a single season record), but that he would not hit 54 or more home runs. He finished the season with 52 home runs. This was not an isolated occurrence—it happened many times. The Edmonton Oilers hockey team was on pace to break the record for the most wins in a season in the mid 1980’s. I followed the NHL closely and thought they had the team to win the most games ever—they fell short. Eric Dickerson in his rookie season was on pace to break the single season rushing record

and he fell short.

I always wondered why this happened, why players on pace to break records almost always fell short. The regression-to-the-mean effect was explained to me, but I didn't understand it until I started playing Strat-O-Matic baseball, a dice simulation baseball game. Cards would be made which, based on dice rolls, would report the result of an at bat. The cards were constructed to match what was done in a particular season. So, if a player batted 0.320 in a season they would give the player a 0.320 chance of getting a hit. If a player hit 50 home runs in 500 at bats the player would have a 1 in 10 chance of hitting a home run in an at bat.

I played many simulated games with these cards and found that amazing things happened—things which never happened in real MLB baseball. Players would hit five home runs in a game, or would hit more than 61 home runs in a season. A player would bat over 0.400 in a season—which has not happened since 1941. The reason this happened was simple. The cards were based on the performance of the previous season, and not on the true intrinsic ability of the players. Due to random variation some players would perform well above their true intrinsic ability. With over 300 regular hitters in MLB, just from chance some players will perform well above their intrinsic skill. Strat-O-Matic cards treat their intrinsic skill to be exactly how they performed. When games would be simulated, due to random chance they would perform well above their assumed skill—which was already much higher than their real intrinsic skill. This created simulated performances that were far too extreme—they never happened. It hit me pretty clearly—the player's with the best performance really were not that good, they just performed by chance (they were good players having great seasons).

Much like the multiplicities issue, where the data is broken in to many splits, here there are many players. They each will have natural variation. The variation will spread their performance out from their true intrinsic abilities. It is simple, and obvious, but very powerful: Variation spreads out performance. During a season, the extreme values (Highest batting average, best winning percentage, most yards rushing) are more extreme than the true intrinsic abilities. Projecting a player to continue their pace is faulty because they are unlikely to be as good as their pace. This is especially true when the player is on pace for a record. A record means that no player in history has performed that well—nobody is that good. In statistics this is referred to as the “regression effect.” It refers to the tendency for values far from the middle of a population returning to the middle, to “regress” to the middle.

When George Foster was on pace to break Roger Maris' season home run record of 61, he was not really a 62-home run hitter. His pace was the best of the season and the best in history. It is much more likely he was a good home run hitter that was performing well due to pure random variation. This is why, seemingly, in every season a player is on-pace to break

a record, but almost always falls short. The mistake is that people attach “reasons” to this pure randomness. The reason is simple—pure random variation. But the reasons we get from sports players and experts is that the pressure and media scrutiny gets to the player. Everyone is trying really hard to stop the player and so they concentrate on him more. The idea that the player was not as good as their performance is foreign.

In a simple example of the regression effect, Figure 1 shows the scores from the first two days of the 2006 Masters golf tournament. There are 90 players shown (I added slight variation to each observation so that the duplicate scores could be seen). The line shown is the regression line fitting the second day based on knowing the first day score. The line demonstrates the regression effect. The slope is quite a bit smaller than 1. If the slope were 1 then the estimated number of shots in the second round would change by one shot for each one extra shot in the first round. The slope of the regression line is 0.228, which means that for every shot change in the first round there is an estimated change of 0.228 shots in the second round.

The estimated score for a player that shot 80 in the first round is 75.12, while the estimated score for a player who shot 70 in the first round is 72.84. The mean score in the second round was 73.97. Players who shot less than the average in the first round are believed to be better than average, but not as good as they shot. Likewise a player shooting worse than average in the first round is expected to shoot worse than average in the second round, but not quite as bad. Suppose I would offer to “think good thoughts” for all players shooting worse than average in the first round in exchange for money. These players on average improve by 3.37 shots. This is certainly not unique to the Masters—this happens in every golf tournament. I could make a fortune thinking good thoughts about players to improve their scores.

Players and experts within the golf world attach an effect to this as well—it is pressure. Those that play well in the first round feel the pressure and play worse the second day (they increase by an average of 1.21 shots). Those players playing poorly in the first round can play loose because they have much less at stake now that they are out of contention. Of course there is no such effect, it is simply the regression effect. The players who played poorly are not as bad as they played and the players that played well are not as good as they played. This regression effect is ubiquitous in sports. In fact, golf teaching professionals benefit from it. Golfers who are playing poorly go see their instructor and then start to play better. The lesson could have no effect and the player is likely to improve. I think this is a huge part of the exploding golf club industry. When a golfer of any level is playing poorly they try new clubs and when they start to play better they believe it was the club causing them to play better.

Sports Illustrated ran an article (with a cover story) titled “The Slump: Solving the Biggest Mystery in Sports” (June 7, 2004, Vol. 100, No. 23). In this article they analyze baseball

slumps—when a player performs well below their typical level. The article focuses on Derek Jeter’s poor start to the 2004 season. He had an 0-32 stretch in April and was hitting 0.220 through May 31 (214 at bats), despite being a career 0.313 hitter. When looked at individually this is a very surprising start, with a probability of only 0.0017 that this could happen. Surely something has happened to Derek Jeter—some “effect” has grabbed him.

They point out that he was hitting 0.189 through May 25th. This of course brings up the multiplicities misunderstandings as well—they are going to present the worst looking numbers as a side note, looking through all the different days. They would not say he was hitting 0.221 through May 25th. The 0.189 is surprising, but it suffers from multiplicities and the regression-to-the-mean effect. Randomness spreads the performance out from the true intrinsic abilities and separating out the player who is performing the worst looks really surprising, but in the context of 300 players it is not at all surprising. The article states: “Even great hitters aren’t immune to slumps. How does a player like Derek Jeter suddenly lose his way at the plate—and how does he find his way back?” The answer is very likely that he never lost his way, he was always a 0.313 hitter and through random variation performed far below his ability.

In a telling statement of the regression effect, the article quotes the following fact: “This season has produced even more proof that no one is immune [to the slump]. Career 0.300 hitters Jeter, Chipper Jones of the Atlanta Braves and Jose Vidro of the Montreal Expos—who ranked seventh, 12th and 18th respectively, in career batting average among active players entering this season—all were hitting worse than 0.250 at week’s end.” In the context of the top 25 active players, having three of them performing 50 points below their career average is not surprising at all—it would be surprising if this didn’t happen! When Jeter pulled out of his “slump” I am sure he thanked his batting coach and claimed that he helped pull him out of his slump. I’m guessing a batting coach helps, but the regression effect is as much responsible—he was never a 0.220-hitter, the data just came out that way.

Many jinxes and effects are simply regression-to-the-mean. The well known sophomore jinx is simply the regression effect. The very best freshmen tend to not play as well in their sophomore seasons. The rookie of the year jinx is the same idea—players play worse in their second year after winning the rookie of the year. This is simply a regression-to-the-mean effect. The player was likely not as good as he performed in his rookie year. When his behavior returns to the true intrinsic value this is seen as a decline in performance. There is no jinx, just regression-to-the-mean.

This effect is ubiquitous outside of sports as well. Besides helping golf professionals it helps doctors, veterinarians, and psychologists. Not to diminish the unquestionable positive effect these professionals have, they tend to see people (or animals) that are doing worse than usual.

Many of these subjects would likely have gotten better with no intervention by the professional. In clinical trials there is a concept called the “placebo effect.” This happens when subjects enter a clinical trial and are given a placebo. These subjects tend to get better. They improve. It is said that this is because they are in a clinical trial and are getting better care and think maybe they are being treated with a new treatment and thus do better. This is many times purely a regression-to-the-mean effect. These subjects are in the trial because they are doing poorly. They have to meet clinical trial entry criteria, which generally guarantee they are far from the mean. Maybe they have high blood pressure or high cholesterol. These quantities vary in a subject, and since they enter the trial they are likely in the tail of the population. These subjects would likely get better without a placebo. The placebo did not have an effect, being in a clinical trial did not have an effect, and thinking you might have gotten the treatment did not have an effect—the subjects improved on their own or had intrinsic values that were not as poor as was originally measured.

Conditioning Fallacies and Law of Small Numbers

Most people understand the “Law of Large Numbers.” Casually, it says that in the long run people will perform to their true ability. If a basketball player has an intrinsic ability of 75% to make a free throw as the number of free throw attempts gets very large the percent of successes will converge to 75%. The key to this statement is “very large.” The mathematical arguments address very large as “going to infinity.” Sports personalities understand this idea, but misunderstand what large means—thinking ten is “large.” It is common to hear a baseball announcer say that a player who has zero hits in their four at bats (referred to as 0-for-4), as being “due.” What they mean by this statement is that the player may be an intrinsic 0.300-hitter and in the long-run they will hit 0.300, so they are more likely to get a hit in their next at bat. There is a notion that there is natural “adjustment” in the process, that intrinsically the probability of success changes in order to get a final success probability of 0.300.

In the previous section I discussed the Sports Illustrated article focusing on Derek Jeter’s slump. Through his first 214 at bats Derek Jeter had 47 hits for his 0.220 batting average. Does this mean he is going to change in such a way that he is better than his career 0.313 average (in 2004) in order to hit 0.313 for the season (I assume Jeter is intrinsically a 0.313 hitter, but understand that this is a statistical guess). The law of large numbers doesn’t say this at all. It says that he is expected to hit 0.313 for the remainder of the season. If he batted a million more times and had 313,000 hits his batting average would be $313047/1000214 = 0.313$. He wouldn’t

need to be a better hitter in his next million at bats to make up for his 0.220 average, only to perform as expected and things will converge to the true intrinsic value. In the 2004 season Jeter finished the season with 141 hits in 429 at bats (0.328 average) to finish the season with a 0.292 batting average. Interestingly, at the time of writing this article, in the 2006 season Jeter has 36 hits in his first 91 at bats for a 0.396 batting average.

In the 2004 season the law of large numbers did not change Derek Jeter to make him a better intrinsic hitter so that at season's end he would hit 0.313. This "effect" is believed though—that Jeter was due—he would eventually "snap" out of his slump and be better than 0.313—you can hear the commentator saying "I wouldn't want to face Jeter when he finally breaks out of his slump.". The article alludes to this belief, "Jeter, however, showed last week how stars with long track records of success can get well soon. Entering the Yankees' May 26 game against the Baltimore Orioles, Jeter, who hit 0.324 in 2003, was batting 0.189 after 190 at bats. Suddenly, facing the Orioles and the Tampa Bay Devil Rays, he pounded out 11 hits in his next 24 at bats, raising his average 31 points in five days, to 0.220. To hit .300 for the season—assuming he maintained his rate of at bats—Jeter would need to hit .335 the rest of the way."

I rarely hear the following, the opposite notion of being due, "This player is scorching hot, going 7 for his last 11, so let's pitch to him because he is due to make an out." But I do hear an opposite rationale for the same idea. Tom Kelly, the Minnesota Twins former manager, when asked why he pinch hit for the relatively weak hitting Steve Lombardozzi when a home run was needed, after he had homered earlier in the game, responded (paraphrasing) "How likely is it that Steve Lombardozzi would homer two times in one game?" This of course is silly—he didn't have to homer twice, but only once. The first home run had already happened. I refer to this as the conditioning fallacy. When I teach an introductory statistics course I ask the students what they would bet on if they saw a coin flipped eight straight times and each time it was heads? I got every answer imaginable, but the most common was tails, because the likelihood of nine straight heads is very small. These are the same people who bring bombs on their planes when they fly, because the chance of two people having a bomb on a plane is nearly zero.

Being Casual About Causation

All of the previous misunderstandings are based on a lack of understanding of natural variation. In this section I discuss a fallacy that has nothing to do with variation. It seems every football game I watch, early in the game one expert will ask another: "What is the key for Team A to beat Team B?" The response is almost always, "They have to run the ball. If Team

A runs the ball 25 times or more they will win this game.” They then quote some ominous statistics, such as Team A being 13-1 when their running back gets 25 or more carries. This relationship between the statistics and the numbers is real—it isn’t a lack of understanding of the variability, it is not understanding the direction of the causation. Running the ball does not cause winning, but winning causes running the ball. Teams that get a lead try to run the ball frequently because it keeps the clock running and decreases the time for the opponent to catch up. The opponent is losing and thus throws the ball more, both for time conservation, but also to gain yardage in bigger chunks—it is a risk reward strategy. The term you hear in statistics circles is that “correlation does not imply causation.” There is clearly a correlation between running the ball and winning, but the data does not tell you which way the causation goes, or if it exists at all.

I excitedly read the article on *ESPN.com*, by Garber, referencing his NFL statistical study, as good analyses of football data are rare (the additional of this article doesn’t change this). He created a list of five “sins” and five “myths”. Sin #3 is “Allowing a 100-yard Runner.” A team allowing a 100-yard runner loses 75% of the time. There is no misunderstanding of the variability, I believe the 75% is very close to the truth—yes, at the end of the game if you allowed a 100-yard rusher you probably lost. This is not a function of the team running well against you—it is a function of the team running *often* against you. The article quotes many anecdotal results: During weeks 6-9 of the 2004 season teams with a 100-yard rusher were 32-1. In 2004, the Patriots running back Corey Dillon cleared 100 yards nine times during the regular season. New England won eight of those nine games; only a four-interception game by Tom Bradycost them a 29-28 decision at Miami (multiplicities anyone?).

There is nothing controversial in these numbers, but there is also nothing interesting about them. What this tells me is—you better get the lead and then run the ball. This does not mean you should run the ball a lot or effectively. Interesting, Myth #2 is: “Highest average per carry wins.” The claim is that this is a myth because the team with the highest per carry average only wins 55% of their games. So, running effectively is not the end-all statistic, but running a lot is? The combination of these tells me to run the ball a lot for a lot of yards, but average yards per carry doesn’t matter? Of course this statement itself suffers from the causal fallacy! Teams that are behind tend to throw the ball frequently. The defense tries to defend the pass, not worrying too much about the run. Likely the team that is behind will run infrequently but effectively when they occasionally run. But, they will lose more often than not, because they were trailing (meaning they were probably not as good and must overcome a deficit).

Myth #4 is “A 300-yard passer usually wins”. Teams with 300-yard passers win 46% of the time. This is for exactly the same reason—teams needing to throw the ball a lot are trailing.

The writer claims that the big powerhouse offenses with big time passers are overrated. This is silly—teams winning 17-3 after the first quarter do not throw for 300 yards! This reasoning follows with Sin #1: “Trailing after the first quarter”. Teams trailing after the first quarter lose 75% of the time. The writer seems shocked by this statistic: “Teams that found themselves trailing after the first quarter lost a staggering 75 percent of their games in '03-04.” Staggering? I was kinda surprised it wasn't larger than this. A team trailing after the first quarter is fighting three battles. First they are probably the inferior team, they have to score more points than the opponent, and they have a fairly short time to do it. This Sin #1 ties the whole story together and really makes these four sins and myths “true,” but scientifically silly.

Team	At Bats	Hits	Average	Simulated
Nationals	18	3	0.167	0.140
Red Sox	11	2	0.182	0.189
Giants	19	5	0.263	0.219
Marlins	26	7	0.269	0.241
Yankees	11	3	0.273	0.258
Phillies	24	7	0.292	0.273
Cubs	60	18	0.300	0.286
Astros	63	19	0.302	0.299
Mets	22	7	0.318	0.311
Pirates	57	19	0.333	0.322
Devil Rays	12	4	0.333	0.334
Reds	65	22	0.338	0.345
Diamondbacks	23	8	0.348	0.357
Dodgers	28	10	0.357	0.370
Brewers	53	20	0.377	0.384
Padres	26	10	0.385	0.399
Braves	22	9	0.409	0.419
Royals	12	5	0.417	0.442
Blue Jays	12	5	0.417	0.476
Rockies	27	12	0.444	0.538

Table 1: The breakdown of Albert Pujols' 2005 season by opponent. The teams are listed in order of Pujols' batting average. The "Simulated" column refers to the mean average for the teams in that ranking assuming Pujols' has an intrinsic 0.330 average against every team.

2006 Masters First Two Rounds

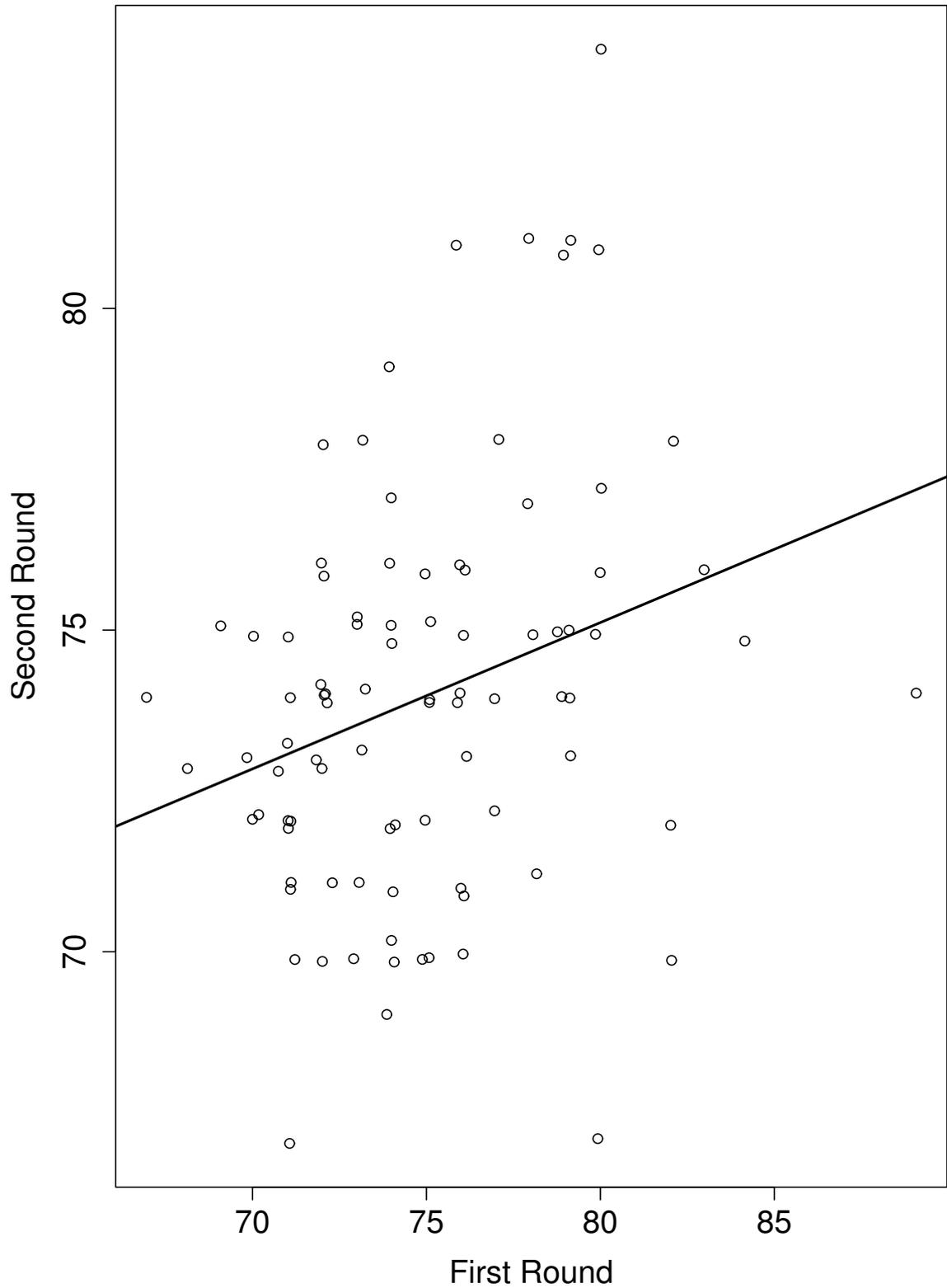


Figure 1: The first and second round scores for the 90 golfers in the 2006 Masters gold Tournament.