# CLUTCH PITCHING IN BASEBALL: DOES IT EXIST?

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**INTRODUCTION**

Steeped in legend and lore, baseball is a fascinating game. Unlike most other sports, there is no clock in baseball. The game cannot end until the winning team has retired 27 batters. It is also the only sport where the defense has control of the ball. More specifically, the game cannot move forward until the pitcher makes a pitch. This makes pitching, which is a main component of baseball defense, a planned action. In other sports, the defense reacts to the offense. In baseball, the offense reacts to the pitcher. This makes the position of pitcher the most important on the field.

Baseball is also the sport of choice for mathematicians, statisticians, and economists. Ever since Henry Chadwick invented the box score in the late $19^{th}$ century, numbers have been pivotal to the discussion and analysis of baseball feats and accomplishments.

Over the years, fans have made countless observations about the game, laying claim to theories about almost every aspect of the game. One of these observations says that certain players seem to increase their level of performance when the game is on the line. A player with this ability has come to be called a ‘clutch’ player. Baseball broadcasters talk almost incessantly about clutch hitters and clutch pitchers, but until recently there had been no studies to determine if these observations were valid.

Recent research into the theory of clutch hitting has provided split results. While the original studies found no evidence of the phenomenon, more recent research tends to conclude that it does exist, albeit at levels far below what a casual observer might claim. Much less research has been completed on theory of clutch pitching. The idea here is that a pitcher has the ability to perform at a higher level at pivotal moments, leading to more wins than he would be expected to earn based on statistics averaged over all games and situations. Also, a clutch pitcher would have an abnormally high winning percentage in important, late season games.

It is believed that because it is reactionary, hitting is not an activity that lends itself to clutch performance. Although there is some evidence that points to the existence of clutch hitting, the phenomenon has been proven to be limited at best. On the contrary, pitching is a planned action, and as such, may very well be suited to fit the theory.

In order to assess the existence of clutch, we must first understand that pitchers come in two distinct varieties. Starting pitchers start games, pitch every fifth day, and throw up to nine innings at a time. Relievers, on the other hand, come into the middle of games, may throw many days in a row, and sometimes face as few as one batter. They often come into games in clutch situations. Therefore, relievers as a population must be clutch. If a reliever is not clutch, he will surely lose his job. Starting pitchers have no such restriction. A large chunk of a starting pitcher's innings come in non-clutch situations. Because of this, we will only be looking at starting pitchers, as they should show us a greater discrepancy in terms of clutch ability.

Since consistent data is only available starting in 1974, this study will look at all starting pitchers (defined as any pitcher who started at least twenty games in at least one season or at least 200 games over the course of his career) from 1974-2006. There will be three measures of clutch pitching to consider. First, we will determine if a pitcher performs better than usual during crucial in game situations. Next, we will see if any pitchers have the ability to win more games than their other statistics would predict. Finally, we'll see if some pitchers show an improved ability to win games during a pennant race.  Hopefully, some or all of these measures will indicate the existence of clutch pitching in baseball.

**LITERATURE REVIEW**

The body of literature dealing with clutch pitching in baseball can be considered limited at best. Some research has been done in the area, but none has been rigorous and most studies have included relatively small sample sizes. In general, these studies have been rather informal.

Conversely, much time has been spent researching the possibility of clutch hitting. Sabermetricians have delved into this topic time and time again, often coming away with no more information than when they started. Book chapters, formal research papers, and informal studies have attempted to answer this question for decades. Over the years, the consensus on the topic has morphed. While the naked eye says that clutch hitting is as real as the ocean is wet, early research indicated that the phenomenon was but a hoax. More recent research has changed that belief, instead indicating that clutch hitting does exist, albeit in small amounts.

Along with Pete Palmer, Cramer (1977) argued that although some players exhibited the ability to produce more wins points (a statistic describing how much a player's performance contributes to team wins) than their basic batting statistics would indicate, their inability to reproduce these numbers from year to year indicates that these differences can be explained away by luck, not skill. He argued that so called "clutch hitters" in one year were not necessarily "clutch hitters" the next, meaning that they were never clutch hitters to begin with. To do this, he simply regressed what he considered to be a hitter's clutch statistics in one year with those same statistics from the next year.

Albert (2001) took another look at clutch hitting, this time looking more specifically at situational statistics, and came to a similar conclusion. They too dismissed the idea of clutch hitting.

This was the common consensus among baseball statisticians until James (2004) made arguments as to why many common ideas about the game are inherently flawed. In this paper, James makes the claim that Cramer's conclusions are simply incorrect. His theory is that Cramer's methodology was wrong. He argues that Cramer's tests do not disprove clutch hitting. Instead, he claims that Palmer's methods could not detect consistent clutch hitting, even if the phenomenon did exist.

But although this theory is currently the consensus among most knowledgeable fans, it has been disproved by Phil Birnbaum. (Birnbaum, 2005) In this article, Birnbaum proves that Cramer's original test would find any consistencies in clutch hitting. By repeating Cramer's study for several more pairs of years, and then comparing the results of those studies to large sample-sized simulations, Birnbaum was able to deduce that Cramer's test would have found consistencies if hitters were capable of performing just fifteen batting average points better in the clutch. The difference here is that Birnbaum, instead of using only one set of data, containing two years of statistics, used many years of data. He also ran computer simulations, using fictional clutch players. His test found these clutch players to be clutch, thus proving its effectiveness. The final conclusions of Birnbaum's study is that although Cramer's test cannot explicitly disprove clutch hitting, the results are powerful enough to make the claim that if the phenomenon is real, it exists at a level small enough to be considered unimportant and undetectable.

Yet other researchers have found some evidence of clutch hitting. Silver (2006) rates hitters based on a clutch measure he developed. Using a statistic that measures the difference between the wins a player adds to his team based on how he has performed in various game situations and the expected number of wins his performance seems to indicate based on average game situations, Silver found some evidence of clutch. Some hitters were clutch, while others were not. More in depth analysis, however, revealed that most of this was simply due to luck. He determined that 70% of a player's production is due to skill, 28% is due to luck, and just 2% is a factor of clutch ability. But he does show some evidence of clutch hitting.

With all of this detailed analysis on clutch hitting, it is odd that so little research has focused on the theory of clutch pitching. Although some researchers have looked into the theory, none have used large samples and none have used more than one measure to evaluate "clutch." In fact, only one measure of clutch pitching has ever been researched in any formal study.

Some informal studies have looked at Earned Run Average (ERA) compared to predicted ERA.(Levin, 2006) This method is inherently flawed, as the statistic ERA is a poor measure of pitching performance. It relies heavily on defense and the ever changing, random rate of Batting Average on Balls In Play (BABIP). Even the best pitchers have years with high ERAs. Because of this, these studies have little to no value.

The more formal studies of clutch pitching have all focused on wins versus expected wins. This is a completely valid method of measuring clutch, and is in fact one of the ideas I plan to investigate. However, all of these studies have used small sample sizes or flawed methodologies.

Palmer (1985) examines the correlation between wins and expected wins. Palmer's study defines expected wins as the number of runs a pitcher gives up in a season and compares it to the average number of runs his team scored in his innings pitched based on his team's total runs scored during the season. This is incorrect. It has been shown in recent years that the number of runs a particular team scores for one pitcher is not necessarily the same for another pitcher. Due to randomness, some pitchers receive good run support while others do not.

This study does have a large sample size. It uses all pitchers between 1900 and 1983 who had accumulated at least 150 career decisions. There were 529 pitchers in the study. Based on the idea that the data is normal and 95% of all data should reside within two standard deviations of the mean, Palmer expected 26 pitchers to win more than two standard deviations more games than they actually did. His sample found 21 of these pitchers, of which 6 were relievers. Theory would also have expected one pitcher to lie outside three standard deviations of the mean. Two did. Both Bert Blyleven and Red Ruffing won far fewer games than expected.

Palmer's results showed that most pitchers' actual wins were remarkably close to their expected wins. He took this to mean that clutch pitchers do not exist. I believe that this conclusion is flawed. Along with the fact that the run support data was incomplete, as some of the run support data was unavailable and therefore extrapolated from available data, and incorrect, Palmer's conclusions seem unreasonably one sided. Tom Seaton gave up 614 lifetime runs while getting 621 runs of support. Based on Palmer's equation, Seaton should have won 80 games and lost 78. However, he won 93 and lost just 65. If this does not indicate an ability to pitch in the clutch, than I do not know what does.

There are several other flawed studies looking at a pitchers' ability to pitch in the clutch. Using American League pitchers from 2000-20003 that compiled at least 50 decisions, Morong (2003) used a sample size of just 47 pitchers. He than calculated their expected winning percentage using their run support and runs allowed. His model had an r-squared of .816, indicating that 81.6% of his results could be explained by the model.

Morong concluded that clutch pitchers do not exist. However, there were two pitchers who won almost seven games more than expected over the course of just four seasons. Morong states that 39 of the 47 pitchers won within 4 games of their expected totals. This does not point to a lack of clutch pitching, as Morong states. Instead, it simply indicates that the model works. If many pitchers were winning many more or many less games than expected, we could no longer use his formula for expected wins. The fact that only two pitchers won nearly seven more games than expected instead points towards validating the idea of clutch pitching.

Morong explains that Roger Clemens probably won so many more games than expected due to the dominant Yankees bullpen, but he gives no explanation as to why Eric Milton posted just as many more wins over expected wins.

Morong's study goes on to study the 70 pitchers who threw at least 3000 innings between 1920 and 1990. He again dismisses the idea of clutch pitching, but this time acknowledges the shortcomings of his data, noting that some of the least clutch pitchers seem to have been the aces of their staffs. These pitchers would generally be matched up against the aces of the other teams, leading to lower run support than Morong's data indicates.

Morong completes his study by looking at 59 pitchers between 1991 and 2000. Again, most pitchers came within one win per year of their expected wins, but two won over one and a quarter games more per year than expected. This is not a small number and should not be overlooked. One win can be the difference between the pennant and a lazy October.

Morong's conclusions state that pitchers do not win more games than expected. This infers that they have no ability to pitch to the score. According to Morong, pitchers do not have the ability to hold the opponent to 1 run when his team scores 2, while managing to allow only 6 when his team scores 7. Spira (2001 agrees. Spira again attempts to compare actual wins with expected wins using Bill James' Pythagorean Theorem for predicting winning percentage. The theorem simply states that expected wins equals runs scored squared divided by the sum of runs scored squared and runs allowed squared.

Spira claims to have followed the career of several pitchers with the reputation of being extremely clutch or extremely un-clutch. His findings indicate that pitchers generally tend to win about as many games as they are expected to win. He observed that those pitchers deemed clutch were not clutch at all. It was all an illusion. In reality, those pitchers perceived as clutch simply received a high level of run support and threw a lot of innings.

His conclusions all seem logical. The only problem is that Morong only looked at a handful of pitchers. And although he acknowledges that "none of this proves that there are no pitchers who 'pitch to the score'," he does claim that his study provides evidence that the theory of clutch pitching may be flawed.

The entire theory behind clutch pitching is much more logical than that behind clutch hitting. It is believed that clutch hitting exists because people remember a player getting hits in important situations. The theory behind clutch pitching is a little more detailed.

People do remember pitchers winning tightly contested games, but the physical exertion of pitching is also different from that of hitting. Hitting is reactive. A hitter must react to the pitch. On the contrary, pitching is a completely controlled action. Bill James, the godfather of sabermetrics himself, has been quoted as saying, "Pitching is planned. Hitting is reactive. It's much harder to plan a reaction than to execute a plan." (Levin, 2006)

A pitcher can put as little or as much energy into a given pitch as he wants. Bradbury & Drinen (2004) make the claim that, "…each pitcher has a finite stock of energy from which he can allocate his pitching effort. From this stock the pitcher can vary effort from batter to batter. In baseball, the speed of the pitch is the main determinant of effort; thus, the more speed used per batter, the faster the pitcher depletes his stock of effort." This implies that a clutch pitcher knows when to use his stock more efficiently than a pitcher who is not clutch. Bradbury and Drinen quote Major League manager Tony La Russa as saying, "If you have a veteran pitcher who may know what he's doing out there, he may throw 140 pitches – but of the 140, he's only maxing out on 40…but when the slop is flying, he'll reach back and make his best pitch."

So although much research has pointed towards the idea that clutch pitching does not exist, this research has been fatally flawed. These studies have used small sample sizes and poor methodologies. And although many sabermetricians are still skeptical towards the idea of clutch pitching, the validity of the theory is gaining ground. James (2004) succinctly sums up the current stance on clutch pitching. “Sabermetrics has traditionally discounted the existence of this ability at *any* level. I would know argue that it may exist.”

## DATA DESCRIPTION

The data for this project originated from three separate sources. The yearly and career statistics for every pitcher came from the Lahman (1996-2007) database. This database includes the basic statistics for every hitter and pitcher from 1871- 2006. The database was broken down into several smaller databases, of which I used two. I used the database containing yearly statistics for every pitcher from 1871-2006, as well as the database containing career statistics for the same pitchers. These two databases have made it possible to compare a pitcher's statistics in a specific situation to his statistics in any given year or throughout his career as a whole.

In order to most accurately assess the theory of clutch pitching in baseball, it was necessary to make a clear decision as to what pitchers would be included in the study. There are two distinct roles that a pitcher can have. He can either be a starting pitcher or a relief pitcher. There is the role of the 'spot starter', a reliever who is occasionally called up to start a game, but for our purposes we will consider this type of pitcher to be a relief pitcher. These two types of pitchers are completely different animals. Starting pitchers generally pitch every fifth day. The start the game, as their title infers, and usually go many innings. A reliever, on the other hand, comes into the game later. He may pitch to as few as one batter and is generally counted on to succeed in important situations. By this logic, relievers should be clutch by nature. A relief pitcher who is not clutch will not get key outs and will not keep his job. Because of this, we will only be looking at starting pitchers. In order to allow for as many pitchers as possible to remain in the study, we defined a starting pitcher to be any pitcher who started twenty or more games in at least one season or any pitcher who managed to accumulate 200 starts throughout his career.

Also, because some of the data is limited due to lack of in-game data, our pitchers will range from 1974-2006. This leaves 865 pitchers in the Lahman database.

This database contains the first and last name of every pitcher, as well as a unique player id that differentiates between different players with the same name. The database also includes information on twenty-three different pitching statistics. Several of these are pertinent.

As all true sabermetricians understand, a pitcher can only control a few things. He can control his number of walks issued (BB), strikeouts(K), and home runs allowed (HR). All other statistics are at least somewhat dependant on luck. A pitcher's earned run average(ERA), generally considered the best indicator of a pitcher's skill, is dependant on opponents' batting average. This, it turns out, is not completely under the pitcher's control. The batting average of balls in play (BABIP) has been shown to be random. (Keri, 2006, p. 54) Also, ERA is at least partly a function of the defensive skill of the team playing behind the pitcher. Therefore, we will not consider ERA to be a quality indicator of a pitcher's skill, instead looking at walks, strikeouts, and home runs.

Another pertinent piece of data from the Lahman data set is wins (W). This simply describes the number of wins a pitcher earns. A win is awarded to any pitcher who pitches at least 5 innings and leaves the game while his team is ahead. His team must not relinquish the lead and go on to win the game. This statistic will later be compared to expected wins to determine if pitchers have any ability to win more games than their other statistics, namely runs allowed (R) and run support indicate.

With a few manipulations, the data in the Lahman database can give us a lot of information about the effectiveness of a pitcher. From the basic statistics hits (H), walks, hit by pitch (HBP), and innings pitched we can generate a close approximation of plate appearances (PA). Granted, plate appearances usually also include sacrifices, but this number is generally so small that it would only slightly increase the figure. Also, since we will later generate this statistic the same way using another database, the fact that we don't use sacrifices here can be disregarded.

This statistic of plate appearances allows us to calculate some important rate numbers. These rate statistics will make it possible to compare a pitcher's career numbers to his numbers during specific clutch situations. By dividing a pitcher's strikeouts by his plate appearances, we can determine a strikeout rate. This statistic is called krate and describes how many strikeouts a particular pitcher earns per batter faced. By doing the same calculation with home runs, hrrate is created. This statistic describes how many home runs a pitcher gives up per batter faced. The rate statistic bbrate indicates how many walks a pitcher issues per batter faced. It is again simply walks divided by plate appearances. Our final core statistic is on base average (oba). It is simply the number of hits plus the number of walks plus the number of hit by pitches, all divided by plate appearances.

The second source used for this project is www.baseball-reference.com. A free source of online baseball data, www.baseball-reference.com also has the statistics of every player to have played in the Major Leagues. Using the qualifying pitchers from the Lahman database, I went through and collected 'clutch splits,' compiling the numbers into a separate database.

The website included eight ‘clutch splits.’ One of these is ‘2 outs, RISP,’ which indicates a situation in which there are two outs in an inning with runners in scoring position, considered second and third base. Another of the clutch stats from www.baseball-express.com is ‘Late and Close.’ This situation is defined as situations, “in the 7th or later with the batting team tied, ahead by one, or the tying run at least on deck.” (baseball-express) The third clutch situation is ‘tie game.’ This simply describes situations in which the game is tied. The rest of the situations describe games within 1, 2, 3, and 4 runs. For this study, we dropped the statistics for those situations in which the game was within 2, 3, and 4 runs.

Each of these clutch situations contains 24 different pitching variables. Several of these are useful. Again, walks, homeruns, and strikeouts will be important. We can generate the same rate statistics as were generated with the Lahman database.

When these two databases are merged, we are left with a new database containing home run rates, strikeout rates, walk rates, and on base averages for all 865 pitchers both during their careers as well as during these specific situations. From this, the clutch statistics can be formed.

These clutch statistics include clutchkrate, clutchhrrate, clutchbbrate, and clutchoba. Clutchkrate is a measure of how many more batters per plate appearance a pitcher strikes out during the clutch scenarios than he does over the course of his career. Clutchhrrate measures how many fewer home runs per plate appearance a pitcher gives up in the clutch situations than he does during his career in general. Clutchbbrate measures how many fewer walks per plate appearance a pitcher issues in the clutch than he usually does. Clutchoba simply describes how much less likely a pitcher is to allow a batter to reach base safely during the clutch situations than he is over his career.

But these raw clutch statistics do not tell us much about a particular pitcher's ability to perform in the clutch. In order to do this we must see if his performance in the clutch is particularly more impressive than the average pitcher's clutch performance. By taking this clutch statistic and dividing by the standard deviation, we can determine how far from the mean a particular pitcher's clutch ability is. These statistics are named sdabovebbrate, sdabovehrrate, sdabovekrate, and sdaboveoba. From this we can begin to analyze the data.

The third source of data comes from STATS LLC, a company that provides statistics for large websites. As I found out, they will also provide statistics for smaller accounts.

The data from STATS LLC originally came in 66 different data files. The data was split up by year, with one file each for run support data and monthly split data. The run support data contained 33 variables for each player, including of course the player's name. Among these variables, we only need month, wins, and losses.

In order to generate a winning percentage in pennant races, it was imperative to have monthly data. I determined what seasons and what teams were in a pennant race by defining a pennant race as any time a team finished the regular season winning their division by 4 or less games, or any time a team finished within 4 games of winning the division. From these situations I used the data for September, the last month of the regular season, to determine how a pitcher performed in pennant races. In the final data set, we created a statistic called decisions, which is simply wins plus losses. This allowed us to create a statistic for winning percentage. By subtracting a pitcher's winning percentage from his winning percentage during a pennant race, we were able to determine how much better a pitcher performed during pennant races.

The other STATS LLC data set included the pertinent data of run support. Along with the player's name and player id, these data files included run support and average run support for each pitcher. From this data we eventually created expected wins.

There were several methods used to create expected wins. First, we looked at Bill James' Pythagorean Theorem for expected winning percentage. (Morong, 2003) This theorem estimates winning percentage for any given team, but we can use it to do the same for any given pitcher. Simply stated, it is runs scored squared divided by the sum of runs scored squared and runs allowed squared. By multiplying this decimal by decisions, we have expected wins. We later adjusted this estimation of expected wins by changing the power that runs scored and run support are raised to from 2 to 1.83, as this power has proven to be more accurate.

But these estimations were off, as will be explained later, so instead we regressed wins on runs scored and run support to create a more accurate definition of expected wins.

**ANALYSIS AND RESULTS**

In terms of pitching in clutch situations, we have some very interesting results. Looking at the results for sdabovebbrate, sdabovekrate, sdabovehrrate, and sdaboveoba, we are able to begin to analyze this data. Looking at Figure 1, Figure 2, and Figure 3, we can see that the statistics for clutchoba, clutchhrrate, and clutchkratethese statistics are distributed approximately normally. The only exception is Figure 4, which shows clutchbbrate. This histogram shows that in clutch situations, most pitchers tend to walk more batters. We'll explain this phenomenon later.

Because the data is distributed normally, it is expected that in each of these categories over 99% of all pitchers lie within three standard deviations from the mean. This implies that for every one hundred pitchers, it would not be abnormal to find one pitcher to lie outside three standard deviations from the mean. There are four different clutch categories and four different rates, giving each pitcher 16 chances to lie outside this range. With 865 pitchers, we would expect to find about 138 instances of these statistics lying outside three standard deviations from the mean. But since we are only concerned with clutch pitchers and have no need to look at 'unclutch' pitchers, we should only expect to find 69 instances.

In reality, we have 85 instances of pitchers with statistics lying at least three standard deviations from the mean. (Figure 5) But this does not seem to be strong enough evidence to claim that nearly one out of every seven and a half pitchers is clutch. Instead, let us delve deeper.

These 85 instances of clutch pitching include 15 pitchers who have statistics lying more than three standard deviations away from the mean in more than one split or in more than one rate. (Figure 6)

Each of these pitchers posted a clutch rate in at least two different splits or in at least two different rates. Some of the most notable of these clutch pitchers exhibited clutch ability in three or more different rates. Miguel Asencio, for example, has a sdaboveoba in late and close situations of 8.89229, a sdabovehrrate of 3.379168with 2 outs and runners in scoring position, and a sdabovekrate of 4.561497in situations that are late and close. He exhibits the ability to strike out more batters, give up fewer home runs, and allow fewer batters to get on base in clutch situations.

In late and close situations, John Koronka has shown a tremendous ability to increase his performance. In these situations Cain has an sdabovebbrate, sdaboveoba, and sdabovehrrate of 3.643294, 6.624362, 3.763057 respectively. He shows an indubitable ability to improve his performance when the game is on the line.

Mike O'Connor shows the ability to increase all four of his pitching rates in the clutch. In late and close situations, O'Connor has a sdabovebbrate of 4.188656, a sdaboveoba of 12.85332, and a sdabovehrrate of 4.145116. In situations with runners in scoring position and 2 outs, he posted a sdabovekrate of 3.119765. O'Conner clearly shows the ability to up all aspects of his game in the clutch.

Some other pitchers show the ability to improve a certain aspect of their performance over several different situations. In situations in which the game is tied, there are two outs with runners in scoring position, or the game is within one run, Tim

Conroy has the ability to increase his strikeout rate. In these situations, his sdabovekrate is 4.090293, 4.844224, 3.961539 respectively.

These 15 pitchers are all clutch in that they have the ability to increase their performances when the game is on the line. In the situation of O'Connor, for example, it is nearly impossible that his results are mere luck. If we consider the fact that the likelihood of a pitcher randomly having a krate greater than three standard deviations from the mean is approximately one in two hundred, we can calculate the probability that O'Connor's situation is luck. In order to find out the probability that this is luck, we must raise 1/200 to the fourth power, as O'Connor had a sdabovekrate greater than three standard deviations above the mean in all four clutch categories. This gives us a probability of 1 in 1,600,000,000. But there were 865 pitchers, so the probability that at least one pitcher exhibited this ability is 865 in 1,600,000,000, or 0.000000540625. There were four different rates, though, giving each pitcher four chances. This increases the probability to 0.0000021625. To claim that this situation is random would only be foolish.

The rest of the pitchers in Figure 6 all had at least two instances of clutch pitching. We can say with 90% confidence that these pitchers are clutch. For those with three or four instances of clutch, we can be confident at the 99% confidence level.

But I think what is most interesting to look at is the fact that certain rates are easier to better in clutch situations. Again looking at Figure 6, we can see that more pitchers have the ability to strike out more batters in the clutch than any other measure of pitching skill. This is simple to explain. In these tight game situations, a pitcher may simply use more energy for each pitch than he would if the game were not on the line. A pitcher may try to strike a batter out by throwing with more velocity or by breaking off an especially sharp curveball.

On the other hand, we can see that the ability to walk fewer batters is very difficult to improve in clutch situations. This is also easily explained. In all clutch situations excluding those with the bases loaded, a walk is not nearly as detrimental as a hit. A walk simply puts one more runner on base. With first base empty, it may even be beneficial, setting up a potential double play. A hit, meanwhile, will most likely score a run. In this situation, a pitcher throws his pitches more carefully, making sure not to make mistakes over the plate where the batter can drive the ball. He is less afraid to walk the batter.

The ability to win more games than expected also produced some interesting results. James' Pythagorean Theorem proved to be ineffective at predicting expected wins. Although the theory does work for teams, it clearly does not work for pitchers. When we looked at the histogram of clutchwins, which was simply wins minus expected wins, we saw that pitchers tended to lose more games than expected. (Figure 7) At first glance, this is disturbing, but after some thought, the reason for this problem becomes apparent. Each time a pitcher leaves a game with a lead, he is in position to earn a win. But each times his bullpen gives back that lead, the pitcher loses his win, as well as a decision. Because of this, each lead a bullpen blows reduces his wins by 1, while only reducing his expected wins by one times his expected winning percentage. Over time, this will lead to fewer wins than expected wins. This also applies to James' theory when we used the power of 1.83 instead of 2.

In order to correct for this, we had to change our methods of creating expected wins. We did this by regressing wins on runs scored and run support. The regression came out to be: Wins = -1.057292 + .0063384 x runs scored + .1148752 x run support The coefficients were all significant. It may seem odd that the coefficient for runs scored is positive, but this is easily reconciled. When we realize that a pitcher wins more games when he pitches more games, and that pitching more games inevitably leads to more runs being scored, we can understand how the coefficient on runs scored is positive. When we look at the histogram of these expected wins (Figure 8) we see that this time, wins minus expected wins looks more normal.

Using this version of expected wins, we get some very interesting and telling results. Using wins minus expected wins to generate clutch wins, and dividing this statistic by the standard deviation, we can see which pitchers were the most clutch in any given season. (Figure 9) The nine best clutch seasons were all at least three standard deviations from the mean, and include such star pitchers as Roger Clemens, Orel Hershiser, Dwight Gooden, and Jim Palmer. In all nine of these instances, the pitcher won at least eight games more than expected.

But what is even more interesting is the results we get for the most clutch pitchers over the course of a career. Looking at Figure 9, we can see that out of the over 800 pitchers in this study, only four can be considered clutch with 99% confidence. These pitchers are Bob Welch, Nolan Ryan, Roger Clemens, and Greg Maddux. If we round, a fifth pitcher makes the list. His name is Pedro Martinez. These are clearly some of the best pitchers since 1974. Granted, all of these pitchers had many starts, giving them more opportunities to win more games than expected. But if they were not clutch pitchers, they wouldn't win more games than expected, and these starts would not amount to any clutch wins.

If we look at the numbers for clutch wins per decision, we see that the most clutch pitchers tend to simply be pitchers who started very few games.  The fact that they won many more games per decision than expected is simply a result of luck.  But if you look at the top career clutch pitchers, we see that they each have extremely positive clutch wins per decision statistics.  Greg Maddux has a clutch wins per decision above standard deviation of 1.45.  Roger Clemens ranks at 1.42.  Nolan Ryan, Bob Welch, and Pedro Martinez have clutch wins per decision above standard deviations of 1.2, 1.62, and 1.82 respectively.

It is clear to see that pitchers do have the ability to win more games than expected.  They can pitch to the score in order to help their teams win.

But this regression does not account for the quality of a particular pitcher's team's bullpen.  This is important, as a bad bullpen will give up a high percentage of inherited runners and give back a considerable number of leads.  A good bullpen will do the opposite, stranding many runners and protecting a high percentage of wins. We do not have any good statistics to measure each team's bullpen, but we are able to account for the quality of said bullpens by creating dummies for each team-year.  By doing this, we can account for how much each team-year contributes to a pitcher's expected wins.

Using this regression, we again find very interesting results.  Looking at histograms for fullregclutchwins and career_fullregclutchwins, our statistics for clutch wins and career clutch wins using this more complete regression, we see that both are approximately normal. (Figures 10 and 11) Because of this, we can say that all pitchers whose clutch win statistics lie outside three standard deviations from the mean are clutch.

Figures 12 and 13 again show us that our results are impressive. Jim Palmer, Pedro Martinez, Dwight Gooden, Orel Hershiser, Mike Mussina, and Randy Johnson are just some of the notable names on the list of pitchers with the most clutch seasons. Looking at those pitchers who have the most career wins minus expected wins, we see an even more impressive list. The four most clutch pitchers of all time, according to this model, are all current or future Hall of Famers. They are Greg Maddux, Randy Johnson, Pedro Martinez, and Roger Clemens.

Our results with respect to the ability to perform better in the heat of a pennant race are a bit cloudier. When looking at a histogram for clutch wins during a pennant race (Figure 14) we can see that it is not normally distributed. The same goes for career pennant race clutch wins. (Figure 15) This is due to relatively small samples in our monthly data. Esteban Loaiza, the pitcher with the most career clutch wins during a pennant race, for example, only has 18 career decisions during a pennant race. Comparing this to his 228 career decisions, we can see that the sample of decisions during a pennant race is small, giving us an inaccurate winning percentage and therefore inaccurate statistics for performance in pennant races. Because of this, we cannot determine if a pitcher's performance in these important games is a matter of skill or simply a product of luck over the span of a few games.

Sadly, this means that we cannot make any claims about pitchers' abilities to win "the big game." Originally, this was the reason we chose not to compare a pitcher's regular season to his postseason performance. However, it turns out that we do not have large enough samples to compare a pitcher’s normal performance to his performance during pennant races.

**CONCLUSIONS**

Out of 865 pitchers, 15 exhibit the ability to consistently improve their performance in clutch situations. This doesn't, however, mean that approximately one in every 57.7 starting pitchers can be deemed 'clutch.' Instead, we can say that given our definition of clutch performance in pressure situations, we get results that make sense. Given this definition, and the fact that each of the 30 Major League teams generally employs five starting pitchers, we should see approximately three starters per year with the ability to raise their performance to another level in key in game situations.

If we perform a simple test, we can conclude with over 90% confidence that each pitcher with two instances of clutch performance is in fact clutch by our definition. We can also conclude with over 99% confidence that each pitcher with three instances of clutch performance is indeed truly clutch by our definition. For those with four or more instances, it is almost impossible to believe that the pitcher is anything but clutch.

As for our question regarding the ability to win more games than expected, we can again say that, given our definition, we have come up with reasonable results that make sense. We have 11 pitchers that we can say with 95% certainty had the ability to win more games than expected over the course of their careers. Of these, we can say with 99% certainty that four are clutch, using our definition. (Figure 16) These pitchers are, in order of least to most clutch, Dwight Gooden, Bobby Ojeda, Ron Guidry, Al Leiter, Curt Schilling, Nolan Ryan, Mike Mussina, Greg Maddux , Randy Johnson, Pedro Martinez, and Roger Clemens. Of these nine pitchers, Ryan is a Hall of Famer. Maddux, Johnson, Martinez, and Clemens are all future Hall of Famers.

In terms of the existence of the ability to win more games than expected, we can say a few things. First, it exists. That is clear. Also, we can say that it's not a common ability. Only 11 in 865 pitchers exhibit the ability. (Figure 17) That's just barely over 1% of all pitchers. Of those that do, all are excellent pitchers. Apparently a poor pitcher does not have the same ability to "pitch to the score" that a good pitcher does. Maybe, in reality, this is what separates pitchers. Roger Clemens has won over fifty more games than expected. If not for these games, would we consider these pitchers to be so great? Pitching to the score is skill, just like a good fastball or impeccable control. By mastering this skill, it is possible for a pitcher to win many more games than expected.

Our last measure of clutch, the ability to increase one's performance during a pennant race, proved not to be provable. The samples for the pennant race data were simply too small. We could not make any distinct observations about the difference between a pitcher's normal winning percentage and that during a pennant race.

What we can say is this: pitcher's can pitch to the score and they can pitch to the situation. But are these two abilities correlated? When we run a correlation between career clutch wins and the average standard deviation above the mean for our four clutch situations, we see that they are hardly correlated at all. In fact, the figure we get is .0068. When we regress one on the other, our r squared and adjusted r squared values both round to .000. These two abilities are clearly not correlated.

This is not a problem. In fact, it is what we should expect. The two situations are completely different. A pitcher may have runners in scoring position with less than two with his team leading by 6 runs. In this situation, a pitcher could give up a few runs and still win the ballgame, but his situational clutch statistics would be hurt. When we think about it, these two statistics have no reason to be correlated at all, and the fact that they're not correlated only proves their accuracy.

When we started, we set out to answer three distinct questions about clutch pitching. Do pitchers have the ability to increase performance in tough situation? Can they "pitch to the score" and win more games than expected? And, do pitchers posses the ability to win a higher percentage of important games? One of these questions remains. We cannot make any claims about the ability of pitchers to win a higher percentage of games during pennant races. But two of these questions have been answered. Pitchers can pitch to the situation. They can "make the big pitch" and increase their performance during tough, in game scenarios. They can also "pitch to the score" and win more games than expected.

The results aren't perfect, but I think they'd make Bill James smile.

**REFERENCE LIST**


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www.baseball-reference.com

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**DO FILES**

```
* merge clutch and career data

clear

set mem 250000


set more off

insheet using _clutch.txt


save _clutch.dta, replace

collapse g , by(playerid)

drop g

sort playerid

save _playerids.dta, replace

clear

insheet using _career.txt

rename sho sh

sort playerid

merge playerid using _playerids.dta

keep if _merge==3

drop _merge

append using  _clutch.dta

sort playerid split

save _clutch_career.dta, replace
```

```
/*
foreach x in year split g pa ab r h b v12 hr bb ibb so hbp sh sf roe gdp sb cs pk ba obp slg
/*
*/	ops babip {

rename `x' cl_`x'
}
*



set more on

save _clutch_career.dta, replace




clear

insheet using careerandclutchdata.txt

gen pacareer = ip*3 + h + bb + hbp

replace pa = pacareer if pa>=.

gen hrrate = hr/pa

gen bbrate = bb/pa

gen krate = so/pa

gen oba = [h + bb + hbp]/ pa

gen hrratenorm = hr/pacareer

gen bbratenorm = bb/pacareer

gen kratenorm = so/pacareer

gen obanorm = [h + bb + hbp]/ pacareer

sort split
```

```
drop if split=="Within 2 R"
drop if split=="Within 3 R"
drop if split=="Within 4 R"
drop if split=="Margin > 4 R"

sort playerid split

save _clutch_career.dta, replace




clear

set mem 500000

set more off

insheet using _realclutch.txt

gen clutchbbrate = bbratenorm - bbrate

gen clutchkrate = krate - kratenorm

gen clutchoba = obanorm - obp

gen clutchhrrate = hrratenorm - hrrate

replace clutchbbrate=. if abs(clutchbbrate)<=0

replace clutchkrate=. if abs(clutchkrate)<=0

replace clutchhrrate=. if abs(clutchhrrate)<=0

sum clutchbbrate

sum clutchhrrate

sum clutchkrate

sum clutchoba


gen sdabovebbrate = clutchbbrate/.0232096
```

```
gen sdabovekrate = clutchkrate/.0196327

gen sdaboveoba = clutchoba/.0248694

gen sdabovehrrate = clutchhrrate/.0078158

gen overallsdabove = (sdabovebbrate + sdabovekrate + sdaboveoba + sdabove hrrate)/4

save situationalclutch.dta,replace

set more off

clear

set mem 30000

use merged_yearly_runsupport.dta

keep if _merge==3

sort player_id

drop if player_id==6692

replace player_id=5165  if _yearly=="harrigr01"

replace player_id=6469  if _yearly=="harrigr02"

replace player_id=6214  if _yearly=="robinje02"

replace player_id=5744  if _yearly=="robinje01"


keep _yearly_  player_id

sort _yearly_
by _yearly_: gen marker=1 if _n==1

keep if marker==1

drop marker

rename _yearly v2
```

```
sort v2

save player_id_matches.dta, replace



clear

insheet using _pennantrace.txt

sort v2

merge v2 using player_id_matches.dta


rename v1 year
rename v2 playerid
rename v3 namelast
rename v4 namefirst
rename v5 stint
rename v6 team
rename v7 lg
rename v8 w
rename v9 l
rename v10 g
rename v11 gs
rename v12 cg
rename v13 sho
rename v14 sv
rename v15 ip
rename v16 h
rename v17 r
rename v18 er
rename v19 hr
rename v20 bb
rename v21 so
rename v22 baopp
rename v23 era
rename v24 ibb
rename v25 wp
rename v26 hbp
rename v27 bk
rename v28 bfp
rename v29 gf
rename v30 ipouts
```

```
rename v31 cumulative_starts
rename v32 career_starts
rename v33 gs20
rename v34 gs20_counter
rename v35 gs20_keeper

drop _merge

sort player_id year

save pennant_race_with_matched_ids.dta, replace



clear

forvalues x=1974/2006 {

clear

insheet using NatBallenberg_Monthly`x'.txt

gen year=`x'

save monthly_`x', replace


}

clear

use monthly_1974

forvalues x=1975/2006 {

append using monthly_`x'


}


keep if month=="September"


save september_stats.dta, replace
```

```
sort player_id year
merge player_id year using pennant_race_with_matched_ids.dta
keep if _merge==3
drop _merge
drop namelast
drop namefirst
drop stint
drop team
drop lg
drop w
drop l
drop g
drop gs
drop cg
drop sho
drop sv
drop ip
drop h
drop r
drop er
drop hr
drop bb
drop so
```

```
drop baopp

drop era

drop ibb

drop wp

drop hbp

drop bk

drop bfp

drop gf

drop ipouts

drop cumulative_starts

drop career_starts

drop gs20

drop gs20_counter

drop gs20_keeper

drop season

sort player_id year

save merged_yearly_monthly.dta, replace

clear

use merged_yearly_runsupport.dta

keep if _merge==3

drop _merge

sort player_id year

merge player_id year using merged_yearly_monthly.dta
```

```
save merged_yearly_runsupport_monthly.dta, replace




clear

set mem 30000

use merged_yearly_runsupport_monthly.dta

drop if gs <10

drop if _yearly_=="brownke01"

gen exwinpct = (run_support *run_support)/(run_support * run_support + r * r)

gen decisions = w + l

gen exwins = exwinpct * decisions

gen clutchwins = w - exwins

sum clutchwins

gen clutchwinsstd = clutchwins/1.577931

sort _yearly_ year

by _yearly_: gen cumulative_clutchwins=sum(clutchwins)
by _yearly_: gen career_clutchwins=cumulative_clutchwins[_N]

regress w r run_support

gen exwinsregress = -1.057292 + .0063384 * r + .1148752 * run_support

gen clutchwinsregress = w - exwinsregress

sum clutchwinsregress

gen clutchwinsregressstd = clutchwinsregress/2.79842

sort _yearly_ year
```

```
by _yearly_: gen cumulative_clutchwinsregress=sum(clutchwinsregress)
by _yearly_: gen career_clutchwinsregress =cumulative_clutchwinsregress[_N]

sort _yearly_ year

by _yearly_: gen cumulative_decisions=sum(decisions)
by _yearly_: gen career_decisions=cumulative_decisions[_N]



gen clutchwinsperdecision = career_clutchwinsregress / career_decisions

sum clutchwinsperdecision

gen clutchwinsperdecisionstd = clutchwinsperdecision/.0762853

sum career_clutchwinsregress

gen career_clutchwinsregressstd = career_clutchwinsregress/13.30102

gen jamesianexwinpct = (run_support^1.83)/(run_support^1.83 + r^1.83)

gen jamesianexwins = jamesianexwinpct * decisions

gen jamesianclutchwins = w - jamesianexwins

sum jamesianclutchwins

gen jamesianclutchwinsstd = jamesianclutchwins /1.533554

sort _yearly_ year

by _yearly_: gen cumulative_jamesianclutchwins=sum(jamesianclutchwins)
by _yearly_: gen career_jamesianclutchwins=cumulative_jamesianclutchwins[_N]

gen regseasonwinpct = w / decisions

gen pracedecisions = wins + losses

gen pracewinpct = wins/pracedecisions

gen praceclutch = regseasonwinpct - pracewinpct

sum praceclutch

gen praceclutchstd = praceclutch/.2864015
```

```
gen praceclutchwins = praceclutch * pracedecisions

sort _yearly_ year

by _yearly_: gen cumulative_praceclutchwins=sum(praceclutchwins)
by _yearly_: gen career_praceclutchwins=cumulative_praceclutchwins[_N]



regress career_clutchwinsregress career_praceclutchwins

sort _yearly_ year

save clutchstats.dta,replace


use situationalclutch.dta

use situationalclutch.dta

*creates Figure 1*
hist sdaboveoba

*creates Figure 2*
hist sdabovehrrate

*creates Figure 3*
hist sdabovekrate

*creates Figure 4*
hist sdabovebbrate

*In order to create Figure 5 I sorted each of the variables
*sdabovekrate, sdabovebbrate, sdabovehrrate, and sdaboveoba.  I
*copy and pasted each player who had values on any of these
*statistics of greater than 3.*

*To create Figure 6 I went through Figure E and copy and pasted
*each instance where a pitcher exhibited at least two instances
*of clutch performance.*

use clutchstats.dta

*creates Figure 7*
hist clutchwins
```

```
*creates Figure 8*
hist clutchwinsregress

*To create Figure 9, I sorted clutchwinsregressstd
*and than copy and pasted each pitcher whose value
*on clutchwinsregressstd was greater than or equal to 3*

*creates Figure 10*
hist fullregclutchwins

*creates Figure 11*
hist career_fullregclutchwins

use fullregression.dta

*To creates Figure 12 I sorted fullregclutchwinsstd and than*
*copy and pasted each pitcher whose value was greater than
*or equal to 3*

*To creates Figure 13 I sorted career_fullregclutchwinsstd and than*
*copy and pasted each pitcher whose value was greater than
*or equal to 3**

use clutchstats.dta

*In order to create Figure 14 I sorted career_clutchwinsregressstd
*and than copy and pasted each pitcher whose value
* on career_clutchwinsregressstd was greater than or equal to 3*

*creates Figure 15*
hist praceclutchwins

*creates Figure 16*
hist career_praceclutchwins

use fullregression.dta

*To create Figure 17 I sorted career_clutchwinsregressstd
*and than copy and pasted each pitcher whose value
*on career_clutchwinsregressstd was greater than or equal to 2*
```

**DATA APPENDIX**

Variable name: *hrrate*
Number of non-missing observations: 4329
Percentage of non-missing observations: 100%
Variable description: home-runs given up per plate appearance
Source variable: none
Modifications to source variable: none

Variable name: *krate*
Number of non-missing observations: 4329
Percentage of non-missing observations: 100%
Variable description: strikeouts per plate appearance
Source variable: none
Modifications to source variable: none

Variable name: *bbrate*
Number of non-missing observations: 4329
Percentage of non-missing observations: 100%
Variable description: walks issued per plate appearance
Source variable: none
Modifications to source variable: none

Variable name: *oba*
Number of non-missing observations: 4329
Percentage of non-missing observations: 100%
Variable description: on-base average against
Source variable: none
Modifications to source variable: none

Variable name: *hrratenorm*
Number of non-missing observations: 4329
Percentage of non-missing observations: 100%
Variable description: home-runs given up per plate appearance over the course of a given pitcher's career
Source variable: none
Modifications to source variable: none

Variable name: *kratenorm*
Number of non-missing observations: 4329
Percentage of non-missing observations: 100%

Variable description: strikeouts per plate appearance over the course of a given pitcher's career
Source variable: none
Modifications to source variable: none

Variable name: *bbratenorm*
Number of non-missing observations: 4329
Percentage of non-missing observations: 100%
Variable description: walks issued per plate appearance over the course of a given pitcher's career
Source variable: none
Modifications to source variable: none

Variable name: *obp*
Number of non-missing observations: 3464
Percentage of non-missing observations: 80%
Variable description: on-base percentage against during clutch situations
Source variable: obp
Modifications to source variable: none

Variable name: *clutchkrate*
Number of non-missing observations: 3464
Percentage of non-missing observations: 80%
Variable description: how many more strikeouts per plate appearance a pitcher earns during clutch situations as compared to said pitcher's career strikeout rate
Source variable: none
Modifications to source variable: none

Variable name: *clutchhrrate*
Number of non-missing observations: 3464
Percentage of non-missing observations: 80%
Variable description: how many less homeruns per plate appearance a pitcher gives up during clutch situations as compared to said pitcher's career home run rate
Source variable: none
Modifications to source variable: none

Variable name: *clutchbbrate*
Number of non-missing observations: 3464
Percentage of non-missing observations: 80%
Variable description: how many less walks per plate appearance a pitcher issues during clutch situations as compared to said pitcher's career walk rate

Source variable: none
Modifications to source variable: none

Variable name: *clutchoba*
Number of non-missing observations: 3464
Percentage of non-missing observations: 80%
Variable description: how much lower a pitcher's on base average against is during clutch situations as compared to his on base average against over the course of said pitcher's career.
Source variable: none
Modifications to source variable: none

Variable name: *sdabovebbrate*
Number of non-missing observations: 3464
Percentage of non-missing observations: 80%
Variable description: the number of standard deviations a pitcher's clutchbbrate lies above the mean
Source variable: none
Modifications to source variable: none

Variable name: *sdabovehrrate*
Number of non-missing observations: 3464
Percentage of non-missing observations: 80%
Variable description: the number of standard deviations a pitcher's clutchhrrate lies above the mean
Source variable: none
Modifications to source variable: none

Variable name: *sdabovekrate*
Number of non-missing observations: 3464
Percentage of non-missing observations: 80%
Variable description: the number of standard deviations a pitcher's clutchkrate lies above the mean
Source variable: none
Modifications to source variable: none

Variable name: *sdaboveoba*
Number of non-missing observations: 3464
Percentage of non-missing observations: 80%
Variable description: the number of standard deviations a pitcher's clutchoba lies above the mean

Source variable: none
Modifications to source variable: none

Variable name: *h*
Number of non-missing observations: 4329
Percentage of non-missing observations:  100%
Variable description: hits given up
Source variable: H
Modifications to source variable: none

Variable name: *bb*
Number of non-missing observations: 4329
Percentage of non-missing observations: 100%
Variable description:  walks issued
Source variable: BB
Modifications to source variable: none

Variable name: *hbp*
Number of non-missing observations: 4329
Percentage of non-missing observations: 100%
Variable description: the number of batters a pitcher hit
Source variable: HBP
Modifications to source variable: none

Variable name: *hr*
Number of non-missing observations: 4329
Percentage of non-missing observations: 100%
Variable description: home runs allowed
Source variable: HR
Modifications to source variable: none

Variable name: *k*
Number of non-missing observations: 4329
Percentage of non-missing observations: 100%
Variable description: the numbers of batters a pitcher struck out
Source variable: K
Modifications to source variable: none

Variable name: *w*
Number of non-missing observations: 865
Percentage of non-missing observations: 19.9%

Variable description: the number of games a pitcher won
Source variable: W
Modifications to source variable: none

Variable name: *r*
Number of non-missing observations: 865
Percentage of non-missing observations: 19.9%
Variable description: the number of runs a pitcher allowed
Source variable: R
Modifications to source variable: none

Variable name: *w*
Number of non-missing observations: 4516
Percentage of non-missing observations: 100%
Variable description: the number of wins a pitcher earned
Source variable: W
Modifications to source variable: none

Variable name: *l*
Number of non-missing observations: 4516
Percentage of non-missing observations: 100%
Variable description: the number of losses a pitcher earned
Source variable: L
Modifications to source variable: none

Variable name: *r*
Number of non-missing observations: 4516
Percentage of non-missing observations: 100%
Variable description: the number of runs a pitcher allowed
Source variable: R
Modifications to source variable: none

Variable name: *run_support*
Number of non-missing observations: 4516
Percentage of non-missing observations: 100%
Variable description: the number of runs a pitcher's team scored while he was on the mound
Source variable: run_support
Modifications to source variable: none

Variable name: *month*
Number of non-missing observations: 885
Percentage of non-missing observations: 19.6%
Variable description: the month of the year
Source variable: month
Modifications to source variable: none

Variable name: *wins*
Number of non-missing observations: 885
Percentage of non-missing observations: 19.6%
Variable description: the number of wins a pitcher earned during September of a given year
Source variable: wins
Modifications to source variable: none

Variable name: *losses*
Number of non-missing observations: 885
Percentage of non-missing observations: 19.6%
Variable description: the number of losses a pitcher earned during September of a given year
Source variable: losses
Modifications to source variable: none

Variable name: *exwinpct*
Number of non-missing observations: 4516
Percentage of non-missing observations: 100%
Variable description: the expected winning percentage of a pitcher based on the Pythagorean Theorem for expected winning percentage
Source variable: none
Modifications to source variable: none

Variable name: *decisions*
Number of non-missing observations: 4516
Percentage of non-missing observations: 100%
Variable description: the number of wins plus the number of losses a pitcher earned
Source variable: none
Modifications to source variable: none

Variable name: *exwins*
Number of non-missing observations: 4516
Percentage of non-missing observations: 100%

Variable description: the number of games a pitcher is expected to win using the Pythagorean Theorem for expected winning percentage
Source variable: none
Modifications to source variable: none

Variable name: *clutchwins*
Number of non-missing observations: 4516
Percentage of non-missing observations: 100%
Variable description: the number of wins a pitcher earned minus the number of wins a pitcher is expected to win using the Pythagorean Theorem
Source variable: none
Modifications to source variable: none

Variable name: *exwinregress*
Number of non-missing observations: 4516
Percentage of non-missing observations: 100%
Variable description: the number of wins a pitcher is expected to win using the regression
Source variable: none
Modifications to source variable: none

Variable name: *clutchwinsregress*
Number of non-missing observations: 4516
Percentage of non-missing observations: 100%
Variable description: the number of wins a pitcher earns minus the number of wins he's expected to earn using the regression
Source variable: none
Modifications to source variable: none

Variable name: *clutchwinsregressstd*
Number of non-missing observations: 4516
Percentage of non-missing observations: 100%
Variable description: clutchwinsregress converted to z-scores
Source variable: none
Modifications to source variable: none

Variable name: *career_clutchwinsregress*
Number of non-missing observations: 4516
Percentage of non-missing observations: 100%
Variable description: the number of career wins a pitcher earns minus the number of career wins he is expected to earn using the regression
Source variable: none

Modifications to source variable: none

Variable name: *clutchwinsperdecision*
Number of non-missing observations: 4516
Percentage of non-missing observations: 100%
Variable description: the number of clutch wins, using the regression model, that a pitcher earns per decision over the course of his career
Source variable: none
Modifications to source variable: none

Variable name: *career_clutchwinsregressstd*
Number of non-missing observations: 4516
Percentage of non-missing observations: 100%
Variable description: career_clutchwinsregress converted to z-scores
Source variable: none
Modifications to source variable: none

Variable name: *regseasonwinpct*
Number of non-missing observations: 4516
Percentage of non-missing observations: 100%
Variable description: the number of wins a pitcher earns divided by his total decisions
Source variable: none
Modifications to source variable: none

Variable name: *pracedecisions*
Number of non-missing observations: 885
Percentage of non-missing observations: 19.6%
Variable description: the number of decisions a pitcher has during a pennant race, defined as September during those years where his team either won its division by four games or less, or ended up coming within four games of winning the division
Source variable: none
Modifications to source variable: none

Variable name: *pracewinpct*
Number of non-missing observations: 885
Percentage of non-missing observations: 19.6%
Variable description: the winning percentage of a pitcher during a pennant race
Source variable: none
Modifications to source variable: none

Variable name: *praceclutchwins*
Number of non-missing observations: 885
Percentage of non-missing observations: 19.6%
Variable description: the number of wins a pitcher earns in a pennant race minus the number he would be expected to win given his regular season winning percentage and his number of decisions during the pennant race
Source variable: none
Modifications to source variable: none

Variable name: *fullregclutchwins*
Number of non-missing observations: 4516
Percentage of non-missing observations: 100%
Variable description: the number of wins minus expected wins using the full regression
Source variable: none
Modifications to source variable: none

Variable name: *fullregclutchwinsstd*
Number of non-missing observations: 4516
Percentage of non-missing observations: 100%
Variable description: fullregclutchwins converted to z-scores
Source variable: none
Modifications to source variable: none

Variable name: *career_fullregclutchwins*
Number of non-missing observations: 4516
Percentage of non-missing observations: 100%
Variable description: the number of career wins minus expected wins using the full regression
Source variable: none
Modifications to source variable: none

Variable name: *career_fullregclutchwinsstd*
Number of non-missing observations: 4516
Percentage of non-missing observations: 100%
Variable description: career_fullregclutchwins converted to z-scores
Source variable: none
Modifications to source variable: none

**FIGURES**

Figure 1: Clutch OBA

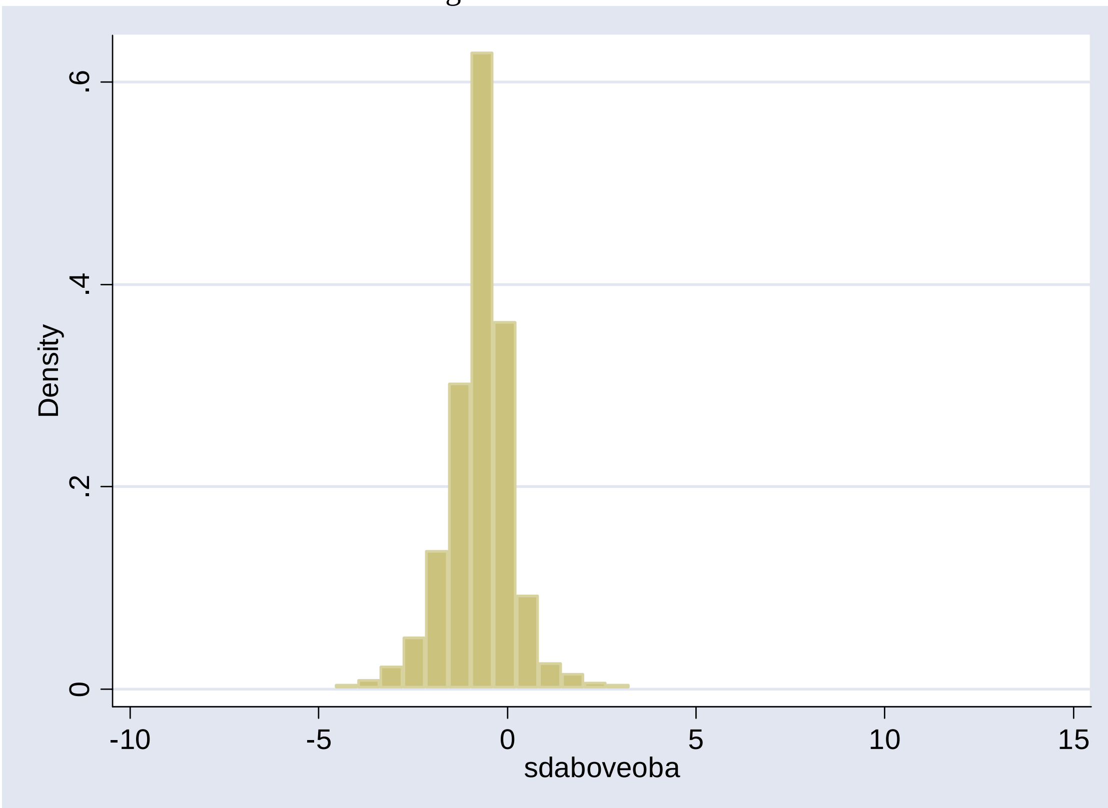


Figure 2: Clutch HR Rate

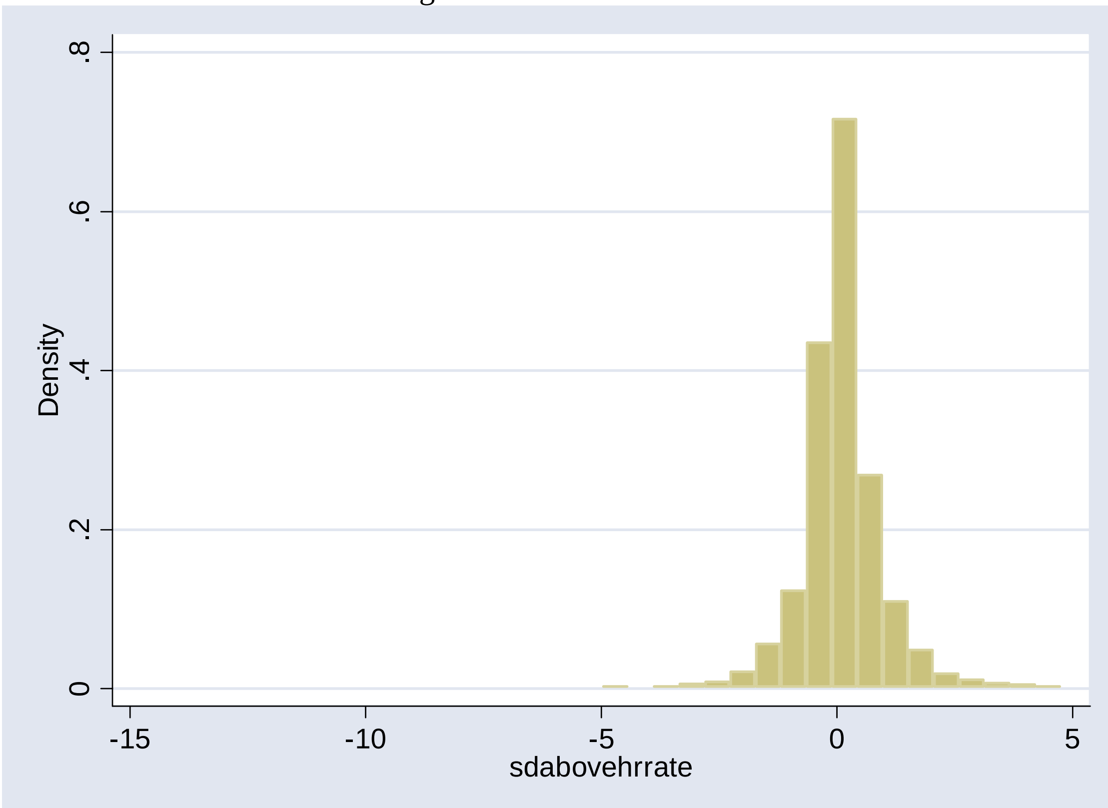


Figure 3:  Clutch K Rate

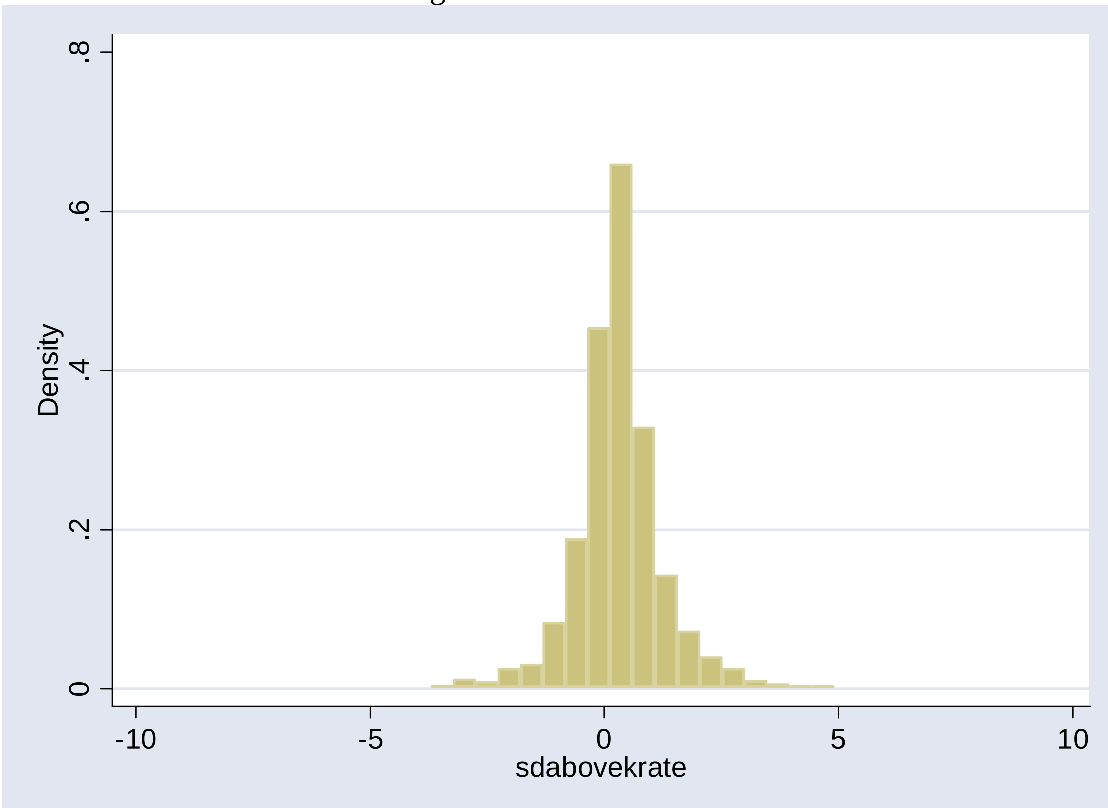
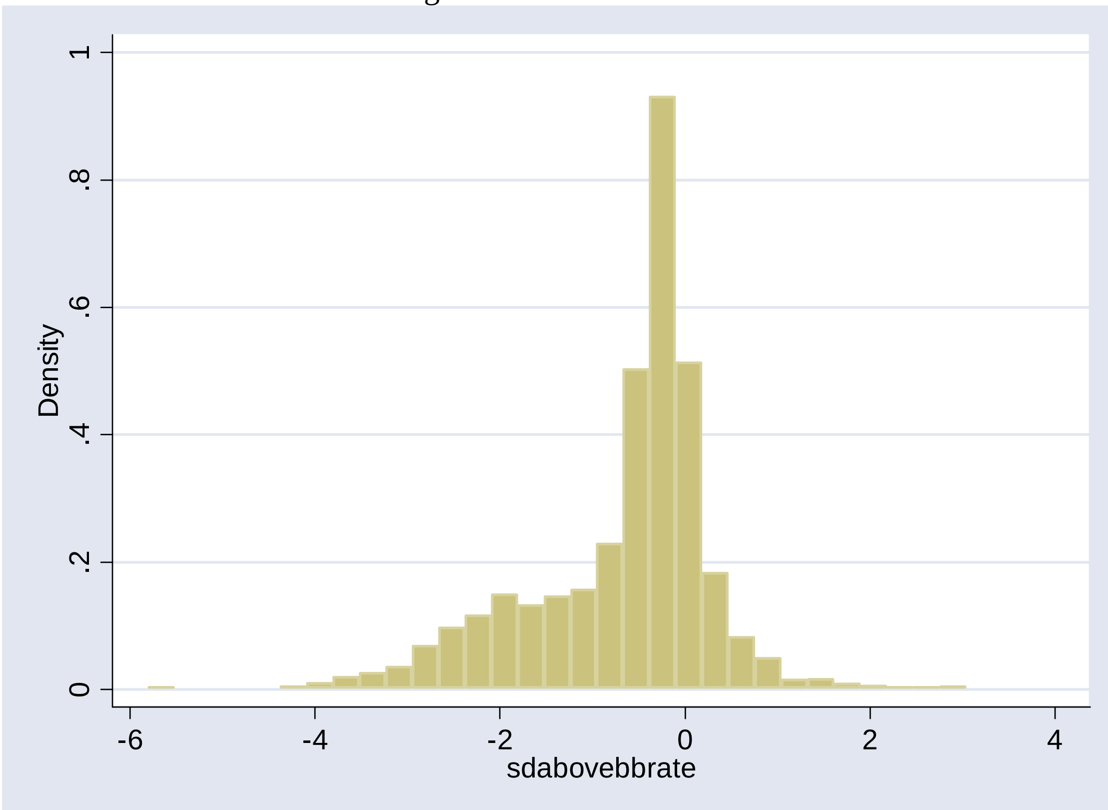


Figure 4: Clutch BB Rate



# Figure 5: Clutch Situational Pitching

| namelast | namefirst | split | sdabovebbrate | sdabovekrate | sdaboveoba | sdabovehrrate |
|---|---|---|---|---|---|---|
| Ankiel | Rick | Late & Close | | 3.57747 | | |
| Armstrong | Jack | Late & Close | | | | 3.724443 |
| Asencio | Miguel | 2 outs, RISP | | | | 3.379168 |
| Asencio | Miguel | Late & Close | | 4.561497 | | |
| Asencio | Miguel | Late & Close | | | 8.89229 | |
| Backe | Brandon | Late & Close | | 4.991962 | | |
| Barnes | Brian | 2 outs, RISP | | 3.694754 | | |
| Bedard | Erik | Late & Close | | 3.477734 | | |
| Bedard | Erik | Late & Close | | | 5.426242 | |
| Beech | Matt | 2 outs, RISP | | 3.425342 | | |
| Beech | Matt | 2 outs, RISP | | | | 3.100489 |
| Birkbeck | Mike | Late & Close | | | 3.821609 | |
| Bomback | Mark | Late & Close | | | | 3.046355 |
| Brazelton | Dewon | Late & Close | | | | 4.168914 |
| Butler | Bill | 2 outs, RISP | | 4.11545 | | |
| Cain | Matt | Late & Close | | | 4.778269 | |
| Cary | Chuck | Late & Close | | | | 3.579928 |
| Chacin | Gustavo | 2 outs, RISP | | 3.095112 | | |
| Claussen | Brandon | Late & Close | | 6.277578 | | |
| Combs | Pat | Late & Close | | | 5.736009 | |
| Comer | Steve | 2 outs, RISP | | 4.563921 | | |
| Comer | Steve | Late & Close | | | 5.668642 | |
| Comer | Steve | Within 1 R | | 3.71032 | | |
| Conroy | Tim | 2 outs, RISP | | 4.844224 | | |
| Conroy | Tim | Tie Game | | 4.090293 | | |
| Conroy | Tim | Within 1 R | | 3.961539 | | |
| Coppinger | Rocky | Late & Close | | | | 3.176719 |
| Davis | Lance | Late & Close | | | | 3.212096 |
| Deshaies | Jim | 2 outs, RISP | | 3.11352 | | |
| Durbin | Chad | Late & Close | | 4.998793 | | |
| Foppert | Jesse | Late & Close | | | | 4.054697 |
| Francis | Jeff | Late & Close | | | | 3.522084 |
| Gagne | Eric | Late & Close | | 5.47924 | | |
| Garcia | Ramon | 2 outs, RISP | | 3.10017 | | |
| Garvin | Jerry | 2 outs, RISP | | 4.315641 | | |
| Garvin | Jerry | Late & Close | | 5.320006 | | |
| Gobble | Jimmy | Late & Close | | 3.291549 | | |
| Gossage | Rich | Late & Close | | 3.05527 | | |
| Green | Tyler | Late & Close | | | | 3.428427 |
| Greinke | Zack | Late & Close | | 3.15166 | | |
| Hennessey | Brad | Late & Close | | | | 3.254766 |
| Hernandez | Carlos | 2 outs, RISP | | 4.647282 | | |
| Hernandez | Carlos | Late & Close | | 6.836812 | | |
| Hernandez | Carlos | Late & Close | | | | 3.753474 |
| Hitchcock | Sterling | Late & Close | | | | 3.62032 |
| Ishii | Kazuhisa | Late & Close | | | | 3.483559 |
| Jackson | Darrell | Late & Close | | 3.110407 | | |
| Jensen | Ryan | Late & Close | | 3.466497 | | |
| Jones | Jimmy | Late & Close | | | 3.105346 | |
| Koronka | John | Late & Close | 3.643294 | | | |
| Koronka | John | Late & Close | | | 6.624362 | |
| Koronka | John | Late & Close | | | | 3.763057 |
| Lerch | Randy | 2 outs, RISP | | 3.879104 | | |
| Lewis | Colby | Late & Close | | 3.108976 | | |
| Maroth | Mike | Late & Close | | | | 3.852043 |
| Marquis | Jason | Late & Close | | | 3.028742 | |
| Marshall | Sean | 2 outs, RISP | | | | 4.450216 |
| Marshall | Sean | Late & Close | | | | 4.450216 |
| Martinez | Pedro | 2 outs, RISP | | 3.293797 | | |
| Nied | David | Late & Close | | | 6.799661 | |
| Nied | David | Late & Close | | | | 3.032422 |
| Nolasco | Ricky | 2 outs, RISP | | | | 4.074708 |
| Nomo | Hideo | 2 outs, RISP | | 3.772893 | | |
| O'Connor | Mike | 2 outs, RISP | | 3.119765 | | |
| O'Connor | Mike | Late & Close | 4.188656 | | | |
| O'Connor | Mike | Late & Close | | | 12.85332 | |
| O'Connor | Mike | Late & Close | | | | 4.145116 |
| Olsen | Scott | 2 outs, RISP | | 6.105274 | | |
| Oquist | Mike | Late & Close | | | | 3.659894 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Perez | Oliver | Late & Close | | | | 3.472888 |
| Prokopec | Luke | 2 outs, RISP | | 3.926399 | | |
| Prokopec | Luke | 2 outs, RISP | | | | 4.781059 |
| Rodriguez | Wandy | 2 outs, RISP | | | | 3.800404 |
| Snell | Ian | Late & Close | | | 3.112479 | |
| Snell | Ian | Late & Close | | | | 4.245208 |
| Snyder | John | Late & Close | 3.476884 | | | |
| Snyder | John | Late & Close | | | 5.99532 | |
| Stein | Blake | 2 outs, RISP | | 3.132728 | | |
| Taylor | Wade | Late & Close | | 3.555227 | | |
| Thormodsgard | Paul | 2 outs, RISP | | | | 3.348307 |
| Verlander | Justin | 2 outs, RISP | | | | 3.250403 |
| Waechter | Doug | 2 outs, RISP | | | | 4.316449 |
| Wolf | Randy | 2 outs, RISP | | 4.297361 | | |
| Wortham | Rich | 2 outs, RISP | | 3.440021 | | |

# Figure 6:  Clutch Situational Pitchers (multiple instances)

| namelast | namefirst | split | sdabovebbrate | sdabovekrate | sdaboveoba | sdabovehrrate |
|---|---|---|---|---|---|---|
| Asencio | Miguel | 2 outs, RISP | | | | 3.379168 |
| Asencio | Miguel | Late & Close | | 4.561497 | | |
| Asencio | Miguel | Late & Close | | | 8.89229 | |
| Bedard | Erik | Late & Close | | 3.477734 | | |
| Bedard | Erik | Late & Close | | | 5.426242 | |
| Beech | Matt | 2 outs, RISP | | 3.425342 | | |
| Beech | Matt | 2 outs, RISP | | | | 3.100489 |
| Comer | Steve | 2 outs, RISP | | 4.563921 | | |
| Comer | Steve | Late & Close | | | 5.668642 | |
| Comer | Steve | Within 1 R | | 3.71032 | | |
| Conroy | Tim | 2 outs, RISP | | 4.844224 | | |
| Conroy | Tim | Tie Game | | 4.090293 | | |
| Conroy | Tim | Within 1 R | | 3.961539 | | |
| Garvin | Jerry | 2 outs, RISP | | 4.315641 | | |
| Garvin | Jerry | Late & Close | | 5.320006 | | |
| Hernandez | Carlos | 2 outs, RISP | | 4.647282 | | |
| Hernandez | Carlos | Late & Close | | 6.836812 | | |
| Hernandez | Carlos | Late & Close | | | | 3.753474 |
| Koronka | John | Late & Close | 3.643294 | | | |
| Koronka | John | Late & Close | | | 6.624362 | |
| Koronka | John | Late & Close | | | | 3.763057 |
| Marshall | Sean | 2 outs, RISP | | | | 4.450216 |
| Marshall | Sean | Late & Close | | | | 4.450216 |
| Nied | David | Late & Close | | | 6.799661 | |
| Nied | David | Late & Close | | | | 3.032422 |
| O'Connor | Mike | 2 outs, RISP | | 3.119765 | | |
| O'Connor | Mike | Late & Close | 4.188656 | | | |
| O'Connor | Mike | Late & Close | | | 12.85332 | |
| O'Connor | Mike | Late & Close | | | | 4.145116 |
| Prokopec | Luke | 2 outs, RISP | | 3.926399 | | |
| Prokopec | Luke | 2 outs, RISP | | | | 4.781059 |
| Snell | Ian | Late & Close | | | 3.112479 | |
| Snell | Ian | Late & Close | | | | 4.245208 |
| Snyder | John | Late & Close | 3.476884 | | | |
| Snyder | John | Late & Close | | | 5.99532 | |

Figure 7: Clutch Wins Using Pythagorean Model

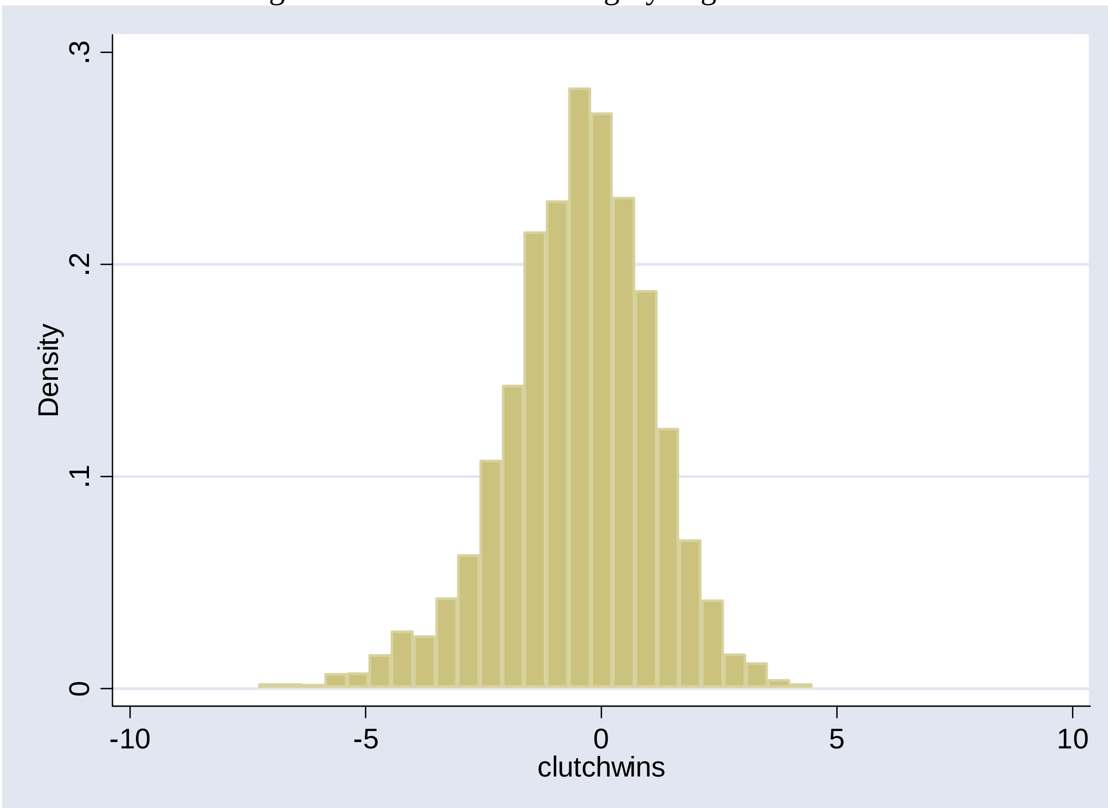


Figure 8:  Clutch Wins Using Regression

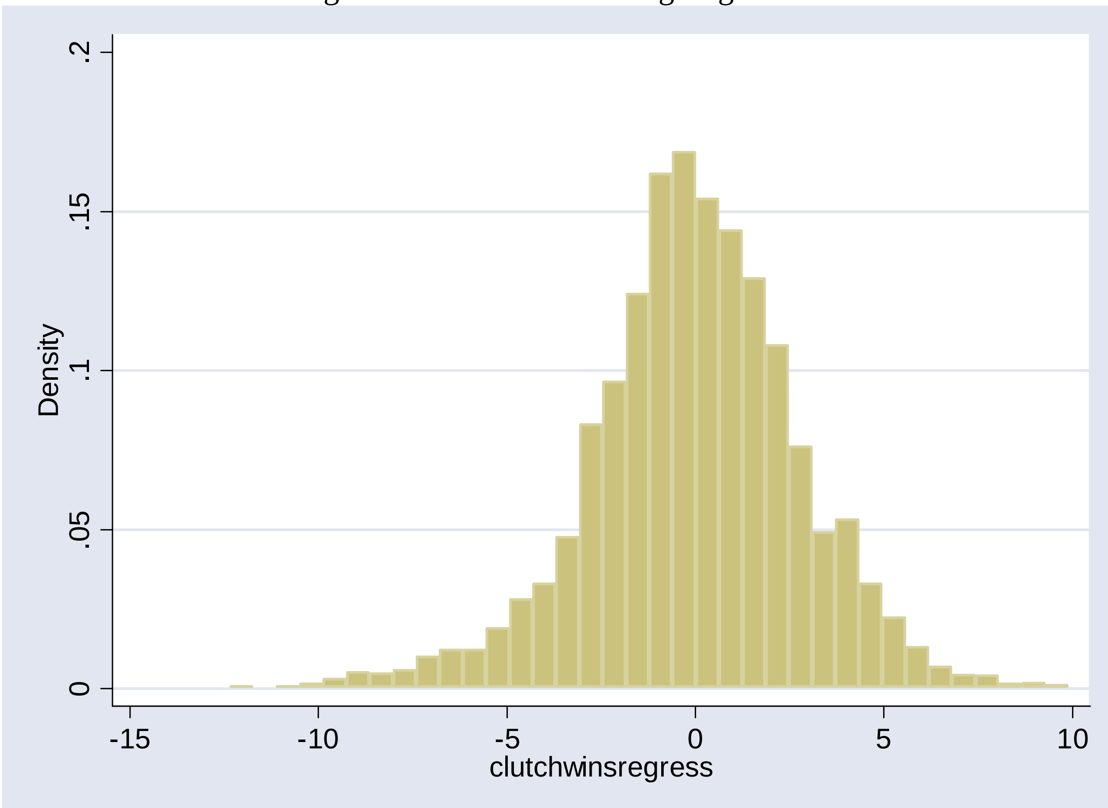


Figure 9: Best Clutch Win Seasons

| year | namelast | namefirst | clutchwinsregress | clutchwinsregressstd |
|---|---|---|---|---|
| 1990 | Clemens | Roger | 8.587554 | 3.068715 |
| 1976 | Garland | Wayne | 8.711736 | 3.113091 |
| 1989 | Gordon | Tom | 8.787229 | 3.140068 |
| 1976 | Palmer | Jim | 8.86184 | 3.16673 |
| 1985 | Gooden | Dwight | 8.881256 | 3.173668 |
| 1990 | Harris | Greg | 9.121578 | 3.259546 |
| 1990 | Welch | Bob | 9.566305 | 3.418467 |
| 1979 | Niekro | Joe | 9.80838 | 3.504971 |
| 1988 | Hershiser | Orel | 9.92444 | 3.546444 |

Figure 10: Clutch wins using full regression

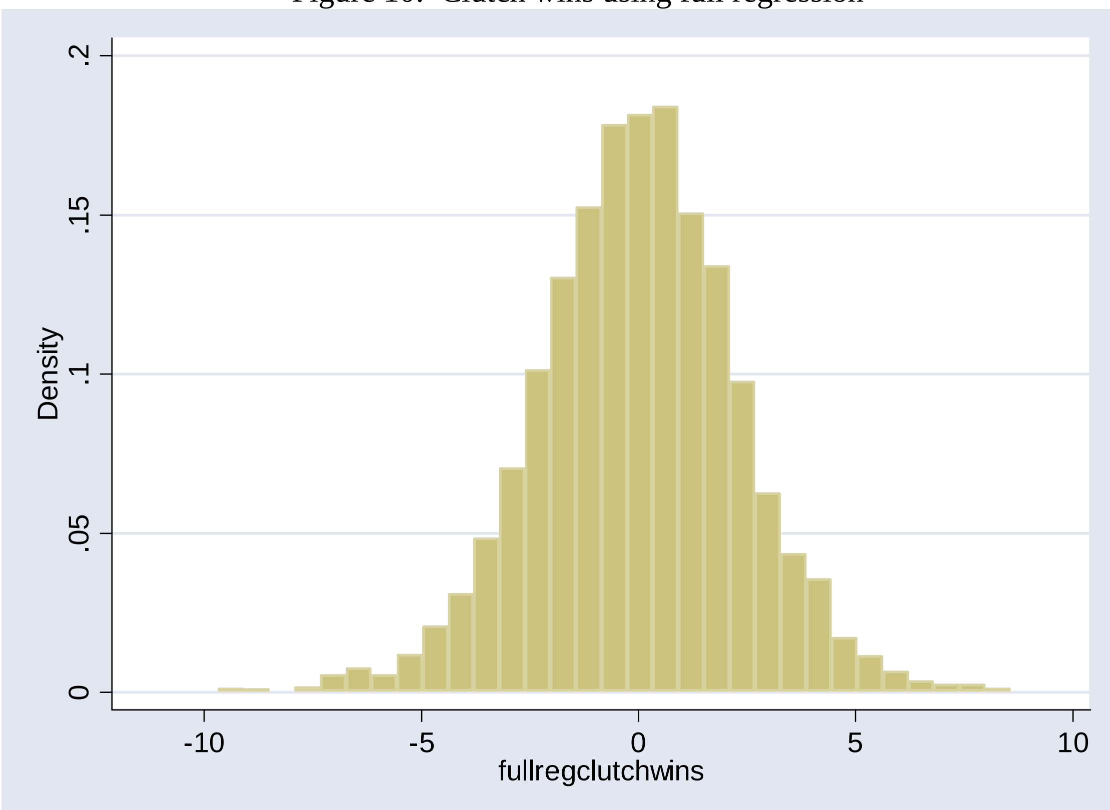


Figure 11: Career clutch wins using full regression

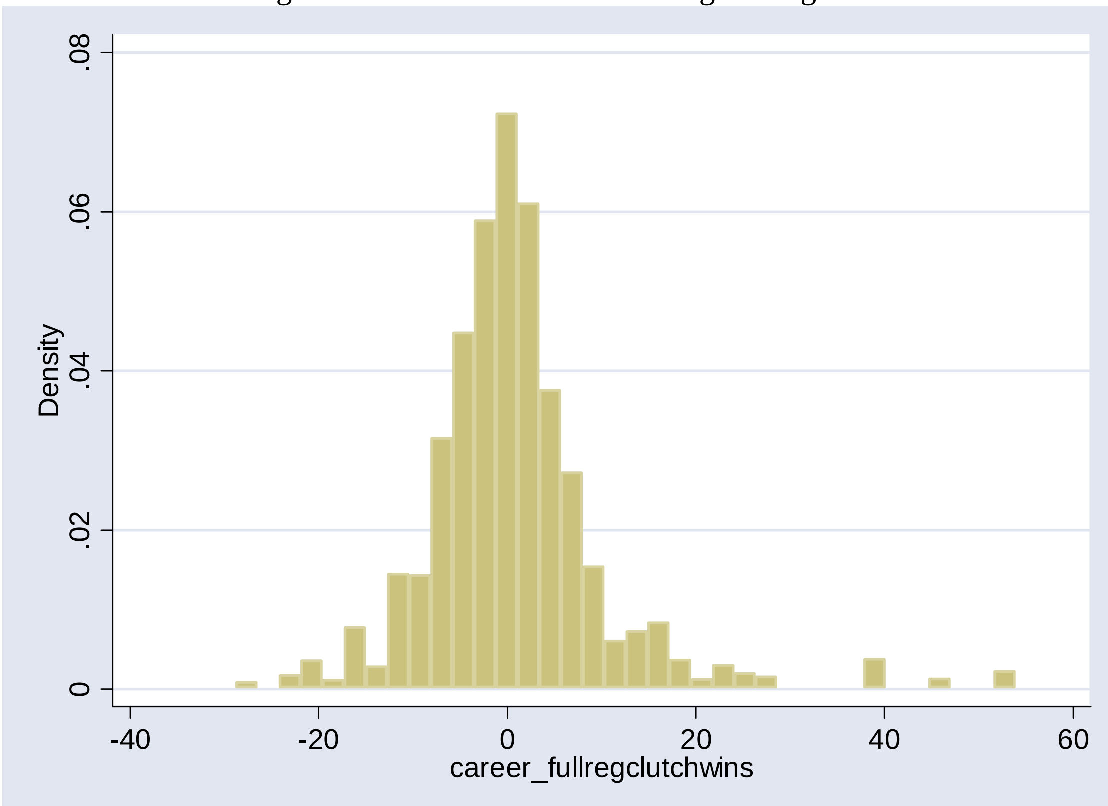



Figure 12: Best Clutch Win Seasons Using Full Regression:

| year | namelast | namefirst | fullregclutchwins | fullregclutchwinsstd |
|---|---|---|---|---|
| 1976 | Palmer | Jim | 7.015023 | 3.013428 |
| 1976 | Garland | Wayne | 7.019381 | 3.0153 |
| 1995 | Schourek | Pete | 7.297817 | 3.134907 |
| 1999 | Martinez | Pedro | 7.3151 | 3.142332 |
| 1991 | Moore | Mike | 7.451245 | 3.200815 |
| 1995 | Johnson | Randy | 7.458171 | 3.20379 |
| 1988 | Hershiser | Orel | 7.517007 | 3.229064 |
| 1989 | Gordon | Tom | 7.532933 | 3.235906 |
| 1985 | Gooden | Dwight | 7.669672 | 3.294644 |
| 1977 | Reuschel | Rick | 7.859871 | 3.376348 |
| 2000 | Martinez | Pedro | 8.157965 | 3.504399 |
| 1990 | Harris | Greg | 8.169421 | 3.509321 |
| 1995 | Mussina | Mike | 8.484981 | 3.644875 |

Figure 13: Best Career Clutch Pitchers Using Full Regression (99%)

| namelast | namefirst | career_fullregclutchwins | career_fullregclutchwinsstd |
|---|---|---|---|
| Maddux | Greg | 38.09032 | 3.970608 |
| Johnson | Randy | 39.20716 | 4.087029 |
| Martinez | Pedro | 45.07692 | 4.698905 |
| Clemens | Roger | 54.01146 | 5.630258 |

Figure 14: Most Clutch Pitchers Based on Career Clutch Wins (99%)

| namelast | namefirst | career_clutchwinsregress | career_clutchwinsregressstd |
|---|---|---|---|
| Martinez | Pedro | 39.26326 | 2.951899 |
| Welch | Bob | 42.93239 | 3.227752 |
| Ryan | Nolan | 43.77231 | 3.290899 |
| Clemens | Roger | 56.9694 | 4.283085 |
| Maddux | Greg | 58.73995 | 4.416199 |

Figure 15: Clutch Wins During a Pennant Race

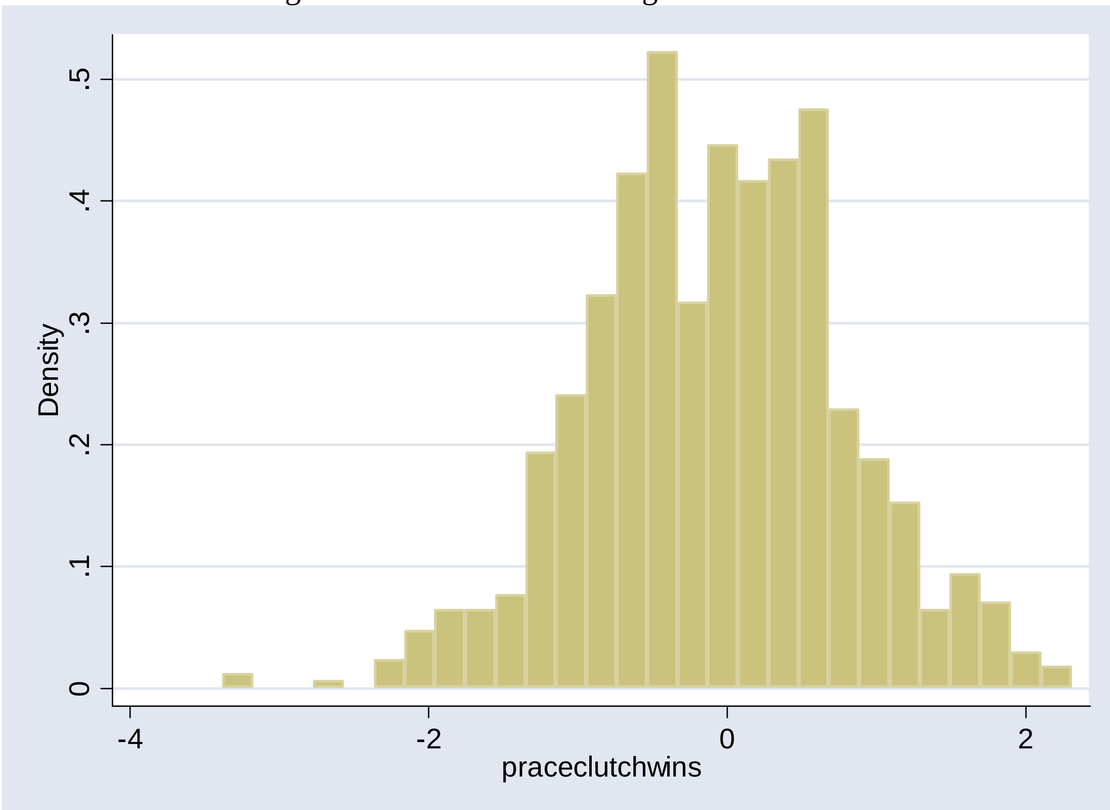


Figure 16: Career Clutch Wins During a Pennant Race

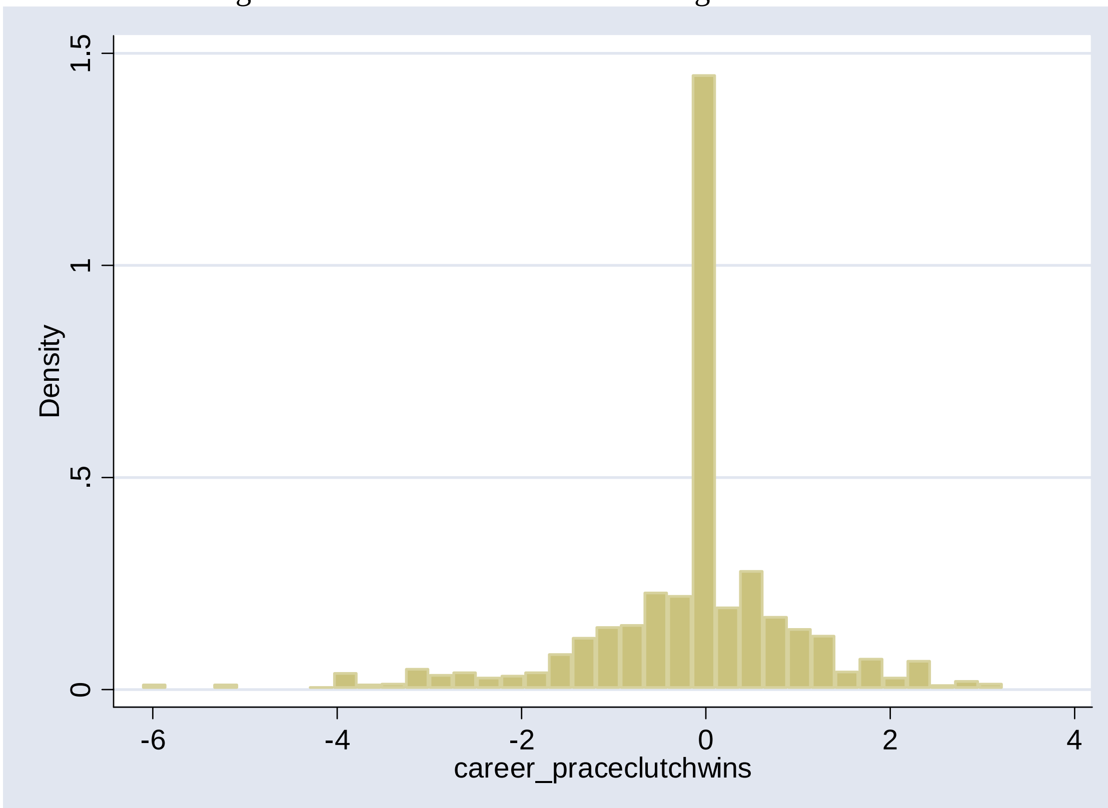


Figure 17: Most Career Clutch Pitchers Using Full Regression (95% confidence)

| namelast | namefirst | career_fullregclutchwins | career_fullregclutchwinsstd |
|---|---|---|---|
| Gooden | Dwight | 19.30105 | 2.011978 |
| Ojeda | Bobby | 19.39791 | 2.022075 |
| Guidry | Ron | 21.56063 | 2.247522 |
| Leiter | Al | 22.41991 | 2.337095 |
| Schilling | Curt | 23.54721 | 2.454607 |
| Ryan | Nolan | 24.28135 | 2.531134 |
| Mussina | Mike | 26.48086 | 2.760415 |
| Maddux | Greg | 38.09032 | 3.970608 |
| Johnson | Randy | 39.20716 | 4.087029 |
| Martinez | Pedro | 45.07692 | 4.698905 |
| Clemens | Roger | 54.01146 | 5.630258 |