The Elusive Realm of Pitch Framing

Elliott Evans

June 11, 2015

Abstract

Before PITCHf/x was installed in Major League ballparks before the 2007 regular season, it was thought that a catcher could only contribute so many things defensively to his team. A catcher could be successful at throwing out runners attempting to steal and may even be superior at calling a game. With the advent of this new pitch analysis system, however, analysts are attempting to find new value in catchers where it was thought not to exist: pitch framing ability. It is the distinct skill of taking a pitch outside the strike zone and framing it for a called strike. The purposes of this study are to examine the nature of this skill and, more specifically, (1) determine if pitch framing is a predictable skill, (2) find appropriate metrics for measurement, (3) quantify the value of this skill, and (4) definitely say who the best and worst pitch framers are. This was accomplished by parsing through both PITCHf/x and event databases to record pitches caught by catchers, taking note of pitches outside the strike zone that were called for strikes, along with pitches inside the strike zone called for balls.

1 Introduction

In 2005, Keith Woolner wrote[1] " ...the further we look into catcher performance, the fewer places the elusive realm of catcher influence has to hide," in reference to his conclusion that catchers cannot contribute in defensive ability aside from controlling the running game. Ten years later, with more sophisticated data collection systems, statisticians have begun to shed light on this once-elusive realm.

When Mike Fast (now an analyst for the analytics-minded Houston Astros) presented his 2011 Baseball Prospectus article, *Spinning Yarn*[2], on the specifics of pitch framing, he unleashed a new way of recognizing value in catchers. Not only did it appear that some catchers were able to get extra strikes called more frequently than other catchers, but that these extra strikes might be worth a considerable amount of runs over a season.

To date, it is questionable as to whether or not Major League organizations are looking at pitch framing data. When the Tampa Bay Rays signed the offensively inept 36 year-old catcher Jose Molina, and subsequently kept him for his 37 and 38 year-old seasons, some analysts suspected it was due to Jose Molina's exceptional pitch framing ability. Fans, however, have been kept mostly in the dark. The nature of pitch framing and its data are unknown to most fans who lack a knowledge of advanced baseball analytics. Sites for casual fans like ESPN.com and MLB.com and even sites for the analytically minded like FanGraphs and Baseball-Reference lack pitch framing data.

This study will attempt to make the realm of pitch framing even less elusive than it has become in recent years. The 5-year span of 2009-2013 is studied, with every pitch (with some exceptions, explained more fully in §2.1) caught by every catcher recorded from that span. Every pitch outside of the strike zone called for a strike (here, called a "good frame") and every pitch inside the strike zone called for a ball (called a "bad frame") is recorded. From this raw data, four main objectives will be completed: (1) determining the predictability of pitch framing, (2) finding reliable metrics, (3) quantifying the value of this skill, and (4) determining the best and worst pitch framers. This will be accomplished by determing the value of framed pitches in outs saved, then associating this value with runs, and finally, wins.

2 Methods

2.1 Data Collection

Two separate MySQL databases were created from the SQL dump files at baseballheatmaps.com: a retrosheet database of event data ($\approx$ 8.6 million observations) and a PITCHf/x database of pitch data ($\approx$ 5.8 million observations). Because the PITCHf/x database does not associate catchers with atbats (it records only the batter and pitcher), each pitch of every atbat in the PITCHf/x database had to be associated with an event from the retrosheet database, at which point the catcher would be associated with those pitches.

At the time of this study, the 2014 season had not been included in the SQL dump files used, so this season was excluded and only the 2009-2013 seasons were used. Pitchers whose retrosheet recorded names were different than their PITCHf/x recorded names (e.g. Tommy Milone v. Tom Milone) did not have their pitches recorded. This only happened for a handful of pitchers and should not have a substantial effect on rate statistics for catchers who caught several thousands of pitches in a given year. The following raw data was recorded for catchers:

- EliasID: the official player ID assigned to a catcher from the Elias Sports Bureau
- First Name, Last Name
- Team Name
- Number of Pitches Caught
- Good Frames: the number of pitches outside the strike zone a catcher had called for a strike
- Bad Frames: the number of pitches inside the strike zone a catcher had called for a ball

Note that the strike zone was definitively determined by PITCHf/x, where the width of the strike zone is the front of home plate, and the height of the strike zone is a function of the batter's height.

2.2 Translating Pitch Frames to Outs

To determine the value of a pitch frame in outs saved, one must be thinking at the count level. The true value in a ball turned into a strike is the added benefit in pitching to a count that more favors the pitcher. If we think in terms of a certain pitch count, i-j, for $\mathrm{i} \in \{0, 1, 2, 3\}$ and $\mathrm{j} \in \{0, 1, 2\}$, then the added benefit of a good frame is the expected outs saved from the count i-(j+1) relative to the count (i+1)-j. In other words, on a 1-1 count, the value of a good frame is the expected outs from a 1-2 count minus the expected outs from a 2-1 count. Thus, estimates for the expected number of outs driven by each pitch count must be calculated. For each count from 2009-2013, the subsequent number of outs generated was recorded, allowing for estimates of out expectations at each count. These count-level out expectations for 2009-2013 are displayed in Figure 1.

These expectations should agree with intuition. The count with the highest out expectation is 0-2, at 0.795. This is the best pitcher's count, in which batters have the least success. The counts with the three greatest out expectations are all of the two-strike counts. The count with the smallest out expectation is the 3-0 count, at 0.255 outs.

From this analysis, the estimated expected value of a pitch frame for a given count in outs saved, $\hat{\mathbb{E}}_{\mathrm{outs}}(\text{Good Frame}|\text{Count i-j})$, is the difference in estimated expected values between the value of count i-(j+1) and the value of count (i-1)-j. For the rest of the study, we will let $\hat{\mathbb{E}}_{\mathrm{Y}}(\mathrm{X})$ denote the estimated value of X in terms of Y. More formally,

$$\hat{\mathbb{E}}_{\mathrm{outs}}(\text{Good Frame}|\text{Count i-j}) = \hat{\mathbb{E}}_{\mathrm{outs}}(\text{Count i-(j+1)}) - \hat{\mathbb{E}}_{\mathrm{outs}}(\text{Count (i+1)-j})$$

Let us define the value above to be $\Delta Count_{\text{i-j}}$. For example, $\Delta Count_{1-1} = 0.768 - 0.615 = 0.153$ is the estimated out value of a good frame on a 1-1 count. For the case where i = 3

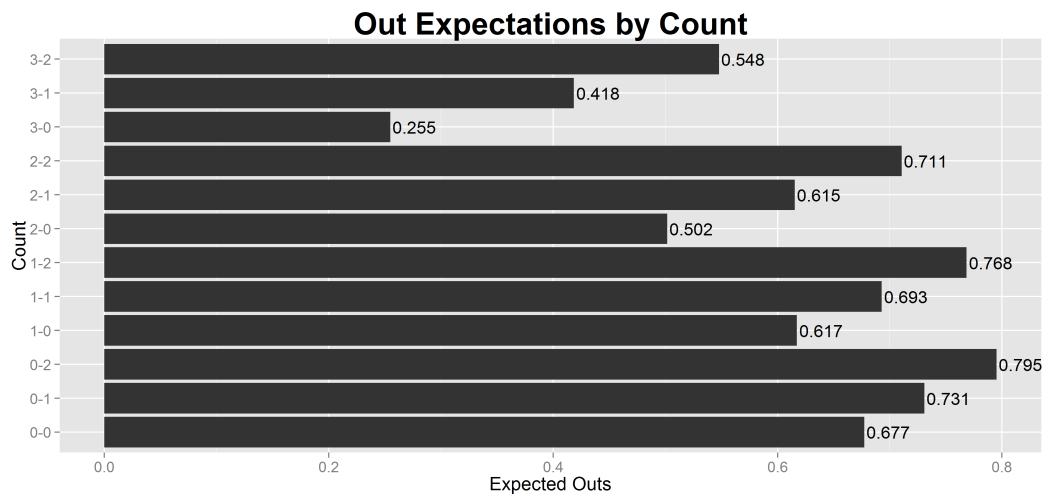

Figure 1: The expected number of outs generated by each pitch count.

(i.e. a 3-ball count), we write $\hat{\mathbb{E}}_{\text{outs}}(\text{Count (i+1)-j}) = 0$, since a 4-ball count is a walk, equating to 0 outs. Similarly, for the case where j = 2 (i.e. a 2-strike count), we write $\hat{\mathbb{E}}_{\text{outs}}(\text{Count i-(j+1) }) = 1$, since a 3-strike count is a strikeout, equating to 1 out. Then an estimate for the value of a good frame in outs saved is

$$\hat{\mathbb{E}}_{\text{outs}}(\text{Good Frame}) = \sum_{\substack{\text{i}\in\{0,1,2,3\}\\ \text{j}\in\{0,1,2\}}} \hat{\mathbb{P}}(\text{Count i-j})\Delta Count_{\text{i-j}},$$

where $\hat{\mathbb{P}}(\text{Count i-j})$ is the estimated probability of observing count i-j. Note that $\hat{\mathbb{E}}_{\text{outs}}(\text{Bad Frame}) = -\hat{\mathbb{E}}_{\text{outs}}(\text{Good Frame})$. Using this methodology, we obtain the following estimates, along with their estimated standard errors ($\hat{\text{SE}}$) and confidence intervals:

Year	$\hat{\mathbb{E}}_{\text{outs}}$(Good Frame)	$\hat{\text{SE}}$	Approximate 95% C.I.
2009	0.256	0.0039	(0.248, 0.264)
2010	0.252	0.0039	(0.244, 0.260)
2011	0.250	0.0039	(0.242, 0.258)
2012	0.247	0.0039	(0.239, 0.255)
2013	0.247	0.0039	(0.239, 0.255)
2009-2013	0.250	0.0017	(0.247, 0.253)

Table 1: Out expectations for the years 2009-2013.

These measurements were used to associate good frames and bad frames with their approximate values in outs.

2.3 Outs to Runs

Converting pitch frames to outs is just the first step. From there, outs must be converted to runs. A good frame will be associated with outs saved, which will then be associated with runs saved. A bad frame is valued in terms of outs made and runs lost. Firstly, it is useful to note that a base-out state in baseball is any combination of runners on base and the number of outs. For instance, one of the twenty-four base-out states is runners at the corners with one out. Another is bases empty with no outs.

To measure the value of any event in baseball, it is common to measure the change in run expectation to the end of the inning caused by the event. For instance, if a base-out state approximates an expected 0.5 runs scored by the conclusion of the inning and an out made creates a new base-out state that approximates 0.3 runs scored by the end of the inning (without scoring any new runs), then that out could be said to have been worth $0.3 - 0.5 = -0.2$ runs. Letting $\hat{\mathbb{E}}_{\text{runs}}(X)$ denote the estimated run value of X, the expected run value of an event is

$$\begin{aligned}\hat{\mathbb{E}}_{\text{runs}}(\text{Event}) = \hat{\mathbb{E}}_{\text{runs}}(&\text{base-out state after event}) - \hat{\mathbb{E}}_{\text{runs}}(\text{base-out state before event}) \\ &+ (\text{runs scored on event})\end{aligned}$$

The run expectations for base-out states for each year were determined from the expected runs matrices at Baseball Prospectus. Using the equation above for every out from 2009-2013, gives the following estimates:

Year	$\hat{\mathbb{E}}_{\text{runs}}(\text{Out})$	$\hat{\text{SE}}$	Approximate 95% C.I.
2009	0.271	0.0079	(0.256, 0.286)
2010	0.260	0.0079	(0.245, 0.276)
2011	0.252	0.0079	(0.237, 0.268)
2012	0.253	0.0079	(0.238, 0.268)
2013	0.254	0.0079	(0.247, 0.270)
2009-2013	0.258	0.0035	(0.251, 0.265)

Table 2: Run expectations for the years 2009-2013.

This leads to the estimate that a good frame in 2009 was worth $0.256 \cdot 0.271 = 0.069$ runs saved and on average, a good frame was worth $0.250 \cdot 0.258 = .065$ runs saved. The estimated run values of a good frame from 2009-2013 are presented in figure 2.

2.4 Runs to Wins

A team's Pythagorean Expectation, created by Bill James, is a way to relate runs scored (RS) and runs allowed (RA) to wins (W), giving us a useful estimate ($\hat{\text{W}}$):

$$\hat{\text{W}} = \text{G}\frac{\text{RS}^2}{\text{RS}^2 + \text{RA}^2}$$

Differentiating $\hat{\text{W}}$ with respect to RS gives the approximate change in wins for every run scored, holding RA constant:

$$\frac{d\hat{\text{W}}}{d\text{RS}} = \frac{2 \cdot \text{G} \cdot \text{RA}^2 \cdot \text{RS}}{(\text{RS}^2 + \text{RA}^2)^2}$$

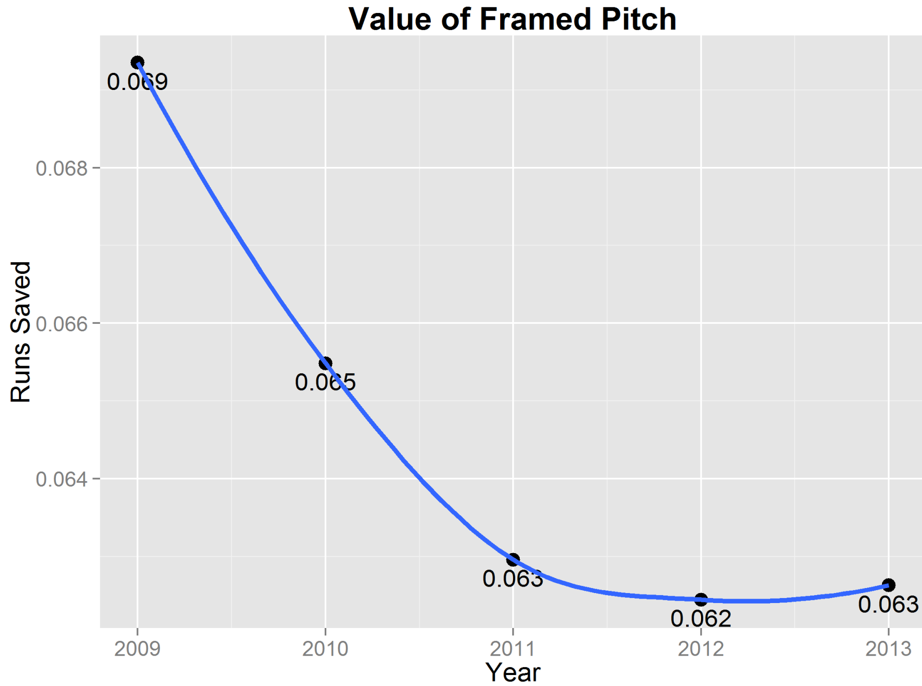

Figure 2: The value of a successful good frame over time, in runs saved.

Then the inverse of the function above gives the approximate number of runs for an extra win:

$$\hat{\mathbb{E}}_{\text{runs}}(\text{Win}) = \frac{(\text{RS}^2 + \text{RA}^2)^2}{2 \cdot \text{G} \cdot \text{RA}^2 \cdot \text{RS}}$$

Applying this equation to every team for a given year allows us to estimate the value of a win in runs for that year. Table 3 gives these estimates.

This leads us to the estimate that a good frame in 2009 was worth about $.069/9.382 \approx 0.007$ wins, or about 7 thousandths of a win. The same can be said for the 2009-2013 average value of a good frame. This gives us a reasonable way of relating pitches framed to wins.

Year	$\hat{\mathbb{E}}_{\text{runs}}(\text{Win})$	$\hat{\text{SE}}$	Approximate 95% C.I.
2009	9.382	0.310	(8.774, 9.990)
2010	8.987	0.310	(8.379, 9.595)
2011	8.750	0.310	(8.142, 9.358)
2012	8.819	0.310	(8.211, 9.427)
2013	8.560	0.310	(7.952, 9.168)
2009-2013	8.900	0.139	(8.628, 9.172)

Table 3: Run expectations for the years 2009-2013.

2.5 Metrics

The primary rate statistics for measuring pitch framing ability in this study will be presented as "GF/100" and "BF/100", or "Good Frames per 100 Pitches Caught" and "Bad Frames per 100 Pitches Caught", respectively. These should reflect the rates at which catchers turn balls into strikes and vice versa.

Using the estimates from §2.2-§2.4, we will also present two metrics of value:

- PfrRAA: Pitch Framing Runs Above Average. This gives the value of a catcher's pitch framing ability by taking the difference of his runs saved from good frames and his runs allowed from bad frames, relative to a catcher who had average GF/100 and BF/100 rates (determined by the year) and the same number of pitches caught.

- PfrWAA: Pitch Framing Wins Above Average. This gives the value of a catcher's pitch framing ability by taking the difference of his wins gained from good frames and his wins lost from bad frames, relative to a catcher who had average GF/100 and BF/100 rates (determined by the year) and the same number of pitches caught.

3 Results

3.1 Rate Metrics

3.1.1 GF/100

Among seasons of catchers from 2009-2013 with 5,000 or more pitches caught (≈33 or more games), the mean GF/100 was 5.95 and the standard deviation 0.701.

Using catchers with at least 4,500 pitches (≈30 games) caught each year from 2009 to 2013 (of which there were 19), the proportion of the variation in GF/100 due to variation between catchers was 0.648. The proportion of the variation in GF/100 due to year-to-year variation of individual catchers was .352. Figure 3 shows the distribution of GF/100 for catching seasons of at least 5,000 pitches caught. The histogram reveals an approximately normal distribution:

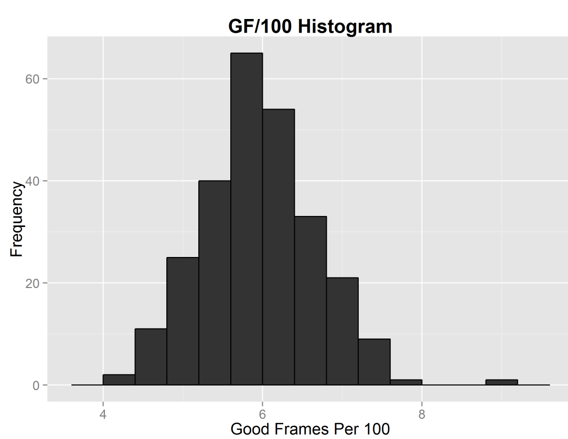

Figure 3: The distribution of GF/100.

Table 4 presents the best and worst pitch framing seasons (in terms of GF/100) from 2009-2013:

	First	Last	Year	Team	GF/100
Best					
1.	Jose	Molina	2009	Yankees	8.90
2.	David	Ross	2009	Braves	7.75
3.	Jose	Molina	2010	Blue Jays	7.60
4.	Jonathan	Lucroy	2010	Brewers	7.55
5.	Dioner	Navarro	2010	Rays	7.43
	First	Last	Year	Team	GF/100
Worst					
1.	Rob	Johnson	2010	Mariners	4.19
2.	Lou	Marson	2012	Indians	4.30
3.	John	Jaso	2013	Athletics	4.48
4.	Matt	Treanor	2011	- - -	4.49
5.	Ryan	Doumit	2011	Pirates	4.54

(a) Seasonal 2009-2013 Rates

	First	Last	GF/100
Best			
1.	Jose	Molina	7.47
2.	Jonathan	Lucroy	7.14
3.	David	Ross	7.11
4.	Ivan	Rodriguez	6.72
5.	Brian	McCann	6.68
	First	Last	GF/100
Worst			
1.	Lou	Marson	4.87
2.	Ryan	Doumit	4.88
3.	John	Jaso	5.07
4.	Gerald	Laird	5.08
5.	Rob	Johnson	5.19

(b) Aggregate 2009-2013 Rates

Table 4: The best and worst pitch framers by GF/100 from (a) catching seasons of 5,000+ pitches caught and (b) catchers with an aggregate 2009-2013 total of 25,000+ pitches caught

We notice that Jose Molina appears on this list several times among the best pitch framers. He actually owns four of the ten best GF/100 seasons, and Jonathan Lucroy owns two of them. We also notice that two players in the best of Table 4 are also in the best of Table 5 (Jonathan Lucroy and Brian McCann), meaning both catchers had higher rates of extra strikes called, but also had lower rates of extra balls called.

3.1.2 BF/100

Among seasons of catchers from 2009-2013 with 5,000 or more pitches caught (≈33 or more games), the mean BF/100 was 1.66 and the standard deviation 0.428.

Using the same pool of catchers as in §3.1.1, the proportion of the variation in BF/100 due to variation between catchers was 0.653. The proportion of the variation in BF/100 due to year-to-year variation of individual catchers was 0.347. Figure 4 shows the distribution of BF/100 for catching seasons of at least 5,000 pitches caught. The distribution reveals an approximate skew-right distribution.

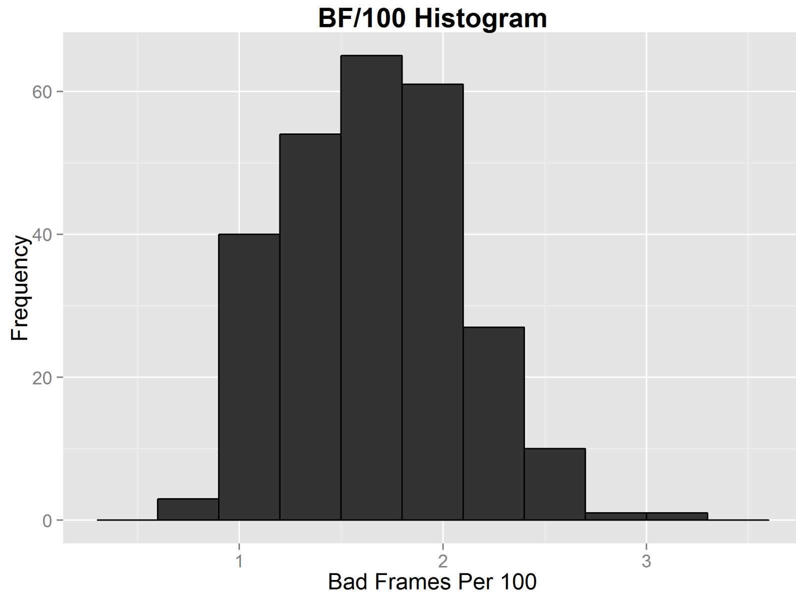

Figure 4: The distribution of BF/100.

The best and worst pitch framing seasons (in terms of BF/100) from 2009-2013 are given in table 5:

	First	Last	Year	Team	BF/100
Best					
1.	Yasmani	Grandal	2012	Padres	0.781
2.	Brian	McCann	2012	Braves	0.834
3.	Buster	Posey	2012	Giants	0.858
4.	Hank	Conger	2013	Angels	0.907
5.	Yadier	Molina	2013	Cardinals	0.912
	First	Last	Year	Team	BF/100
Worst					
1.	Ryan	Doumit	2009	Pirates	3.08
2.	Rob	Johnson	2009	Mariners	2.70
3.	Kenji	Johjima	2009	Mariners	2.67
4.	Matt	Treanor	2011	- - -	2.67
5.	Raul	Chavez	2009	Blue Jays	2.62

(a) Seasonal 2009-2013 Rates

	First	Last	BF/100
Best			
1.	Buster	Posey	0.987
2.	Jonathan	Lucroy	1.01
3.	Miguel	Montero	1.06
4.	Brian	McCann	1.07
5.	David	Ross	1.10
	First	Last	BF/100
Worst			
1.	Jason	Varitek	2.44
2.	Rob	Johnson	2.35
3.	Ryan	Doumit	2.34
4.	Gerald	Laird	2.12
5.	Nick	Hundley	2.05

(b) Aggregate 2009-2013 Rates

Table 5: The best and worst pitch framers by BF/100 from (a) catching seasons of 5,000+ pitches caught and (b) catchers with an aggregate 2009-2013 total of 25,000+ pitches caught

We see that catchers like Buster Posey and Brian McCann excel at limiting extra balls called while players like Ryan Doumit and Gerald Laird are among the worst.

3.2 Value Metrics

3.2.1 PfrRAA

Among all catching seasons with no minimum number of pitches caught, we observe the mean PfrRAA to be approximately 0 (as the metric is designed) and the standard deviation to be 4.52. However, the standard deviation of PfrRAA is dragged down by many catchers who have caught few pitches and, therefore, find their PfrRAA to be close to zero. The following is a plot showing the standard deviations of PfrRAA when we set different minimums for pitches caught:

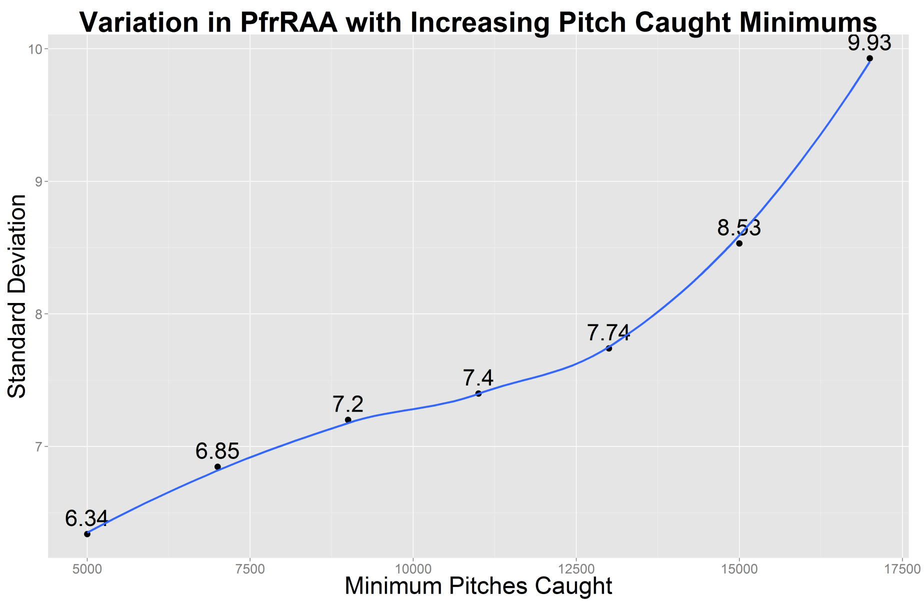

Figure 5: The standard deviation of PfrRAA when pitch caught minimums are changed

We see that while the standard deviation of PfrRAA when considering every seasonal observation, regardless of pitches caught, is 4.52, it may be more useful to consider full-time, or even regular back-up catchers, when the standard deviation is closer to 7.50.

The best and worst pitch framers by PfrRAA are given in Table 6, the first table on pg. 11.

3.2.2 PfrWAA

Among all catching seasons with no minimum number of pitches caught, the mean PfrWAA is approximately 0, as it is with PfrRAA. Without a pitch caught minimum, the standard deviation is 0.51. However, the pattern of increasing PfrWAA standard deviation with increasing pitch caught minimums is similar to that of PfrRAA. Thus, it may be useful to note that for full-time or regular back-up catchers, the standard deviation is closer to 0.85.

The best and worst pitch framers by PfrWAA are similar to PfrRAA, with the main difference being that some orders are different due to the varying seasonal run environments. These players are presented in table 7, the second table on pg. 11.

	First	Last	Year	Team	PfrRAA
Best					
1.	Brian	McCann	2009	Braves	23.6
2.	Jonathan	Lucroy	2011	Brewers	22.4
3.	Brian	McCann	2010	Braves	15.7
4.	Brian	McCann	2011	Braves	15.5
5.	Russell	Martin	2012	Yankees	14.4
	First	Last	Year	Team	PfrRAA
Worst					
1.	Gerald	Laird	2009	Tigers	-18.5
2.	Ryan	Doumit	2009	Pirates	-15.9
3.	Kurt	Suzuki	2009	Athletics	-14.5
4.	Jason	Kendall	2010	Royals	-13.0
5.	Matt	Treanor	2011	- - -	-12.7

(a) Seasonal 2009-2013 Rates

	First	Last	PfrRAA
Best			
1.	Brian	McCann	69.5
2.	Jonathan	Lucroy	63.0
3.	Jose	Molina	50.0
4.	Russell	Martin	44.0
5.	Ryan	Hanigan	37.8
	First	Last	PfrRAA
Worst			
1.	Ryan	Doumit	-48.6
2.	Gerald	Laird	-35.0
3.	Lou	Marson	-28.3
4.	John	Buck	-27.9
5.	Rob	Johnson	-25.7

(b) Aggregate 2009-2013 Rates

Table 6: The best and worst pitch framers by PfrRAA from (a) catching seasons of 5,000+ pitches caught and (b) catchers with an aggregate 2009-2013 total of 25,000+ pitches caught

	First	Last	Year	Team	PfrWAA
Best					
1.	Jonathan	Lucroy	2011	Brewers	2.56
2.	Brian	McCann	2009	Braves	2.52
3.	Brian	McCann	2011	Braves	1.77
4.	Brian	McCann	2010	Braves	1.74
5.	Jonathan	Lucroy	2013	Brewers	1.66
	First	Last	Year	Team	PfrWAA
Worst					
1.	Gerald	Laird	2009	Tigers	-1.97
2.	Ryan	Doumit	2009	Pirates	-1.69
3.	Kurt	Suzuki	2009	Athletics	-1.54
4.	Jason	Kendall	2010	Royals	-1.45
5.	Matt	Treanor	2011	- - -	-1.45

(a) Seasonal 2009-2013 Rates

	First	Last	PfrWAA
Best			
1.	Brian	McCann	7.81
2.	Jonathan	Lucroy	7.08
3.	Jose	Molina	5.62
4.	Russell	Martin	4.95
5.	Ryan	Hanigan	4.24
	First	Last	PfrWAA
Worst			
1.	Ryan	Doumit	-5.46
2.	Gerald	Laird	-3.93
3.	Lou	Marson	-3.18
4.	John	Buck	-3.14
5.	Rob	Johnson	-2.88

(b) Aggregate 2009-2013 Rates

Table 7: The best and worst pitch framers by PfrWAA from (a) catching seasons of 5,000+ pitches caught and (b) catchers with an aggregate 2009-2013 total of 25,000+ pitches caught

Like the results from PfrRAA, the catchers who earn their teams the most wins through pitch framing are Lucroy, McCann, and Molina, who were all worth over 5 wins above average from 2009-2013. Again, we see that Doumit and Laird contribute negatively.

4 Conclusions

These results imply that pitch framing is, indeed, a predictable skill, but not in the way we may have thought. About 65% of the variation in GF/100 is due to variation between catchers and we find a similar result for BF/100. These are traits that are not volatile over several years. In general, if a catcher is an excellent or terrible pitch framer one year, he will probably be an excellent or terrible pitch framer the subsequent year. This is important, as we do not observe this kind of consistency in other statistics like BABIP or ERA.

However, there is not much correlation between GF/100 and BF/100. In fact, the correlation between GF/100 and BF/100 for catching seasons of at least 5,000 pitches caught is only -0.337. There is also little evidence that exceptional pitch framers have both high rates of extra strikes and low rates of extra balls. Among these same catching seasons that had GF/100 rates of at least 7, the correlation between GF/100 and BF/100 is only -0.073. It appears that we can divide pitch framing into two *separate* skills: limiting extra balls (i.e. maintaining a low BF/100) and gaining extra strikes (i.e. maintaining a high GF/100). From the observed results, there is no real reason to suggest that these skills are related. While this may seem counterintuitive, it simply implies that the mechanics of pitch framing may be more complicated than we think. Overall, the consistency of both skills implies that these rates are appropriate measures of pitch framing skill. Since PfrRAA and PfrWAA are based on seasonal run environments in conjunction with GF/100 and BF/100 rates, our value statistics should also prove to be fairly reliable estimates.

In general, a successful pitch frame is worth about seven-hundredths of a run and about seven-thousandths of win. While pitch framing was worth slightly more in 2009 (0.069 runs), a pitch framed in 2011-2013 was worth about 0.063 runs. A great pitch framer will get about 8 good frames per 100 pitches, an average pitch framer around 6, and a terrible one around 4. In general, great pitch framers earn their team an extra 15 or more runs above average through their pitch framing skills, while the worst catchers lose their team 15 or more runs. Similarly, the best catchers are worth 2 wins above average from their pitch framing abilities while the worst are worth around -1.5 wins.

Pitch framing from 2009-2013 was dominated by four catchers: Jonathan Lucroy, Brian McCann, Russell Martin, and Jose Molina. These four had respective aggregate PfrWAA values of 7.08, 7.81, 4.95, and 5.62. What's especially impressive is that Jose Molina was worth so much when he played so infrequently. From 2009-2013, Molina broke 100 games played only once, in 2012. However, he consistently maintained some of the highest GF/100 rates in baseball, topping out at 8.90 GF/100 in 2009. The worst pitch framers were Ryan Doumit and Gerald Laird. Not only did these two have very low GF/100 rates at 4.88 and 5.08, respectively, but they also had very high BF/100 rates at 2.34 and 2.12, respectively. Over our five year span of interest, Doumit lost his team about five-and-a-half games from his pitch framing, and Laird lost his teams about four.

While collecting and analyzing pitch framing data can be challenging, it reveals a completely different aspect of the game of baseball. Many fans, and many ex-players, who claim to be students of the game, often suggest they can see everything that happens on a baseball field with their two eyes. This causes them to disregard statistics and anything else that might seem difficult to understand. Without digging deeper, however, it is impossible to see everything. In watching a whole season of baseball, a fan may never be able to recognize the difference between Brian McCann and Ryan Doumit behind the plate. While the act of pitch framing may be subtle, the 118 difference in runs between McCann and Doumit is not. Hopefully, as pitch framing analysis becomes more mainstream and the data more accessible to the average fan, the once-elusive realm of pitch framing will be elusive no longer.

References

[1] Click, James, Clay DavenPort, Neil Demause, Steven Goldman, Jonah Keri, Dayn Perry, Nate Silver, and Keith Woolner. ”Is Mike Matheny a Catching Genius?” Baseball Between the Numbers. New York: Basic, 2006. 110. Print.

[2] Fast, Mike. ”Spinning Yarn: Removing the Mask Encore Presentation.” Baseball Prospectus. Baseball Prospectus, 24 Sept. 2011. Web.