2016

2015 MLB Season in Review Using Pitch Quantification and the QOP1 Metric

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The 2015 MLB Season in Review
Using Pitch Quantification and the QOP1 Metric

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1. Introduction

The purpose of this paper is to provide SABR with the work we would like to present, should we be selected as presenters at the 2016 SABR Analytics Conference. Our subject is Quality of Pitch (QOP). QOP is a statistic calculated from the trajectory, location, and speed of a single pitch (see Appendix 1 for how QOP is calculated). QOP was introduced at last year's SABR Analytics Conference (2015), after which the primary question received from analysts was, "How does QOP compare with conventional MLB statistics?" Section 2 answers this question. Having provided evidence for the validity of QOP, the meat of the presentation would be Sections 3, which explores the following questions:

1. Which MLB players threw the highest quality pitches in 2015?
2. Can QOP data project ERA in 2016? Which MLB players have the highest probability of posting a decrease or increase in ERA in 2016?
3. Did quality deteriorate for pitches delivered from the stretch position with runners on base vs. the wind up?
4. Which MLB players were able to deliver quality pitches in pressure situations with runners in scoring position or in full count situations?
5. Which MLB pitchers produced the highest economic value to their team based on their QOP average and contract?
6. Can pitch quantification be used to quantify batters? Is there a correlation between QOP and batting average by pitch type?
7. Can QOP help prevent injuries to pitchers?

It should be noted at the outset that this work is ongoing. This draft reflects our latest results, but there are places in the paper which would be refined or added to, as noted in Section 3, should we be selected for presentation.

2. Comparing QOP with Conventional MLB Statistics

The purpose of this section is to provide evidence to that QOP "works", that is, it can be shown to rationally compare with conventional statistics. This section provides some key summaries of our

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Technical Report, *Pitch Quantification Part 1: Between-Pitcher Comparisons of QOP with Conventional Statistics*.

Since QOP provides a number for every pitch, we can look at either an average or the individual pitch values. To distinguish these, we let **QOPV** refer to a set of individual pitch values and **QOPA** refer to their average. While QOPV is normally on a -10 to 10 scale, there are no theoretical limits to the endpoints, since it is a regression model. Some particularly bad pitches score negative numbers, and a few exceptional pitches score over 10 (the model has rated five pitches at or above 10 since 2008). Naturally, QOPA in MLB typically falls in the 3 to 6 range, depending on the subject. A quality MLB pitch is considered over 5.

2.1 QOPV by Pitch Classification

Our first dataset consists of n=9990 pitches thrown in 2014. A random subset was used instead of the entire dataset for simplicity and robustness. Each of the three analyses shown below was replicated, with the same results, on two additional samples of around 10,000 pitches -- one from 2014 and another from 2013. Figure 1 shows boxplots of QOPV for each pitch designation. The rankings all make sense. The blue boxes are the 'bad' pitches: *Pitchout, Intentional Ball, Hit By Pitch, Ball in Dirt*, and *Balls*. It is clear that the bulk of these pitches are well below the quality of the others. The green boxes are the different strikes. The pink boxes are those in which the batter made contact with the ball, but did not

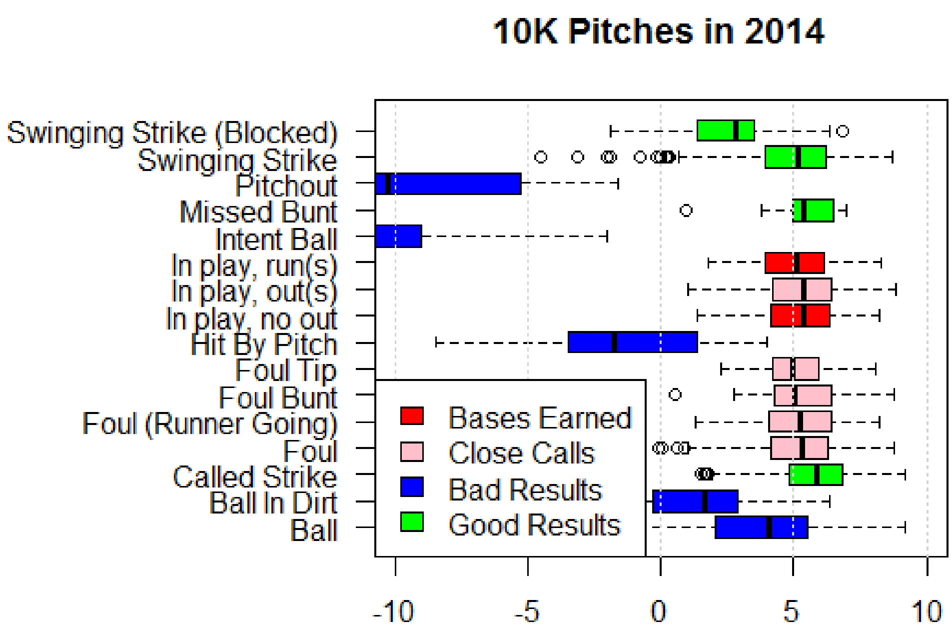

Figure 1. Boxplots of QOPV by pitch classification. Each box shows the range of QOPV for its pitch type. A box contains the middle 50% of the data, for that pitch type, with the dark line in the middle at the median. The remaining 50% of the data is

split evenly on each side. The colored labels are from the perspective of the pitcher. The bulk of the Bad Results (blue) are below the quality of the others. The green Called Strikes have the statistically significant highest QOPV.

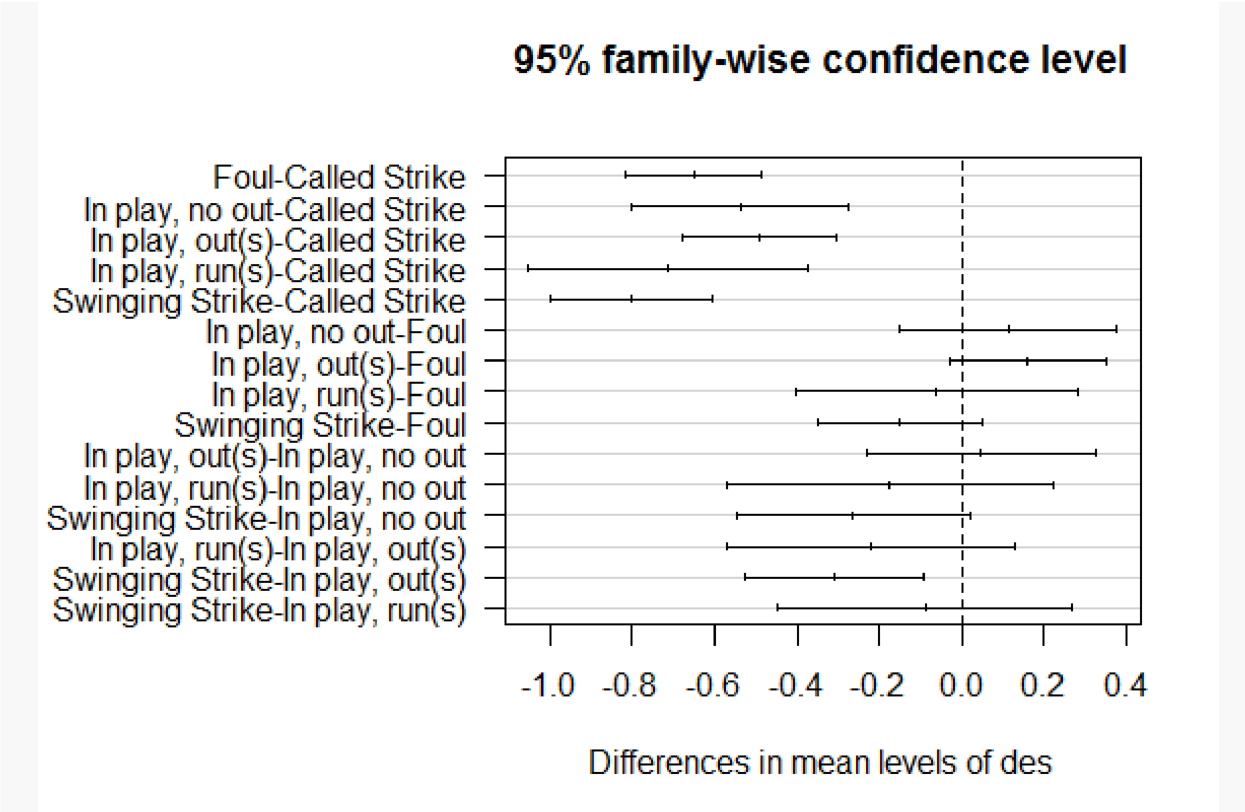

Figure 2. Confidence intervals of the difference between pitch designations for the Tukey HSD hypothesis tests. Each bar represents the 95% confidence interval for the difference in QOPA between the two pitch designations. If the interval overlaps zero, there is no statistically significant difference. All of the differences with Called Strike are below zero, meaning Called Strike has higher QOPA than the categories compared.

get any bases. The red boxes are those where bases were made. The results in Figure 2 (ANOVA F = 39.07, p-value < 2×10^{-16}) show that QOPA for *Called Strikes* are significantly higher than the *In play* pitches as well as *Fouls* and *Swinging strikes*. The differences in QOPA for the other categories are not distinguishable.

2.2 QOPV Compared with Annual Statistics

One of the benefits of QOP is that it offers a numeric value for every pitch. The richness of this information, however, makes it difficult to compare with annual statistics like ERA, FIP, BABIP, and OPS. When such comparisons are made they do not reveal much, presumably due to the loss of information caused by averaging over so many pitches. As an example, Table 1 shows the correlations between QOPA and ERA, FIP, SR, and WR for 2013.[1] One reason for the low correlation is that QOPA is *batter independent*. For example, we can have a well executed pitch (high QOPV), with a hit by a good batter. This counts neutral for FIP, SR & WR. Conversely, we can have a poorly executed pitch (low QOPV), with a hit. This counts neutral for FIP, SR & WR. These two features will "average out" in QOPA, to some extent.

	QOPA	ERA	FIP	SR	WR
QOPA	1.000	-0.114	-0.126	-0.060	-0.123
ERA	-0.114*	1.000	0.640	-0.333	0.215
FIP	-0.126*	0.640	1.000	-0.559	0.419
SR	-0.060	-0.333	-0.559	1.000	-0.066
WR	-0.123*	0.215	0.419	-0.066	1.000

Table 1. Correlation coefficients of QOPA vs. pitching statistics. There is a weak correlation between QOPA and the pitching statistics. Spearman's correlation was used. An * by correlation in the QOP column indicates the correlation is statistically significantly different than zero (p-value < 0.01). The expected sign depends on the nature of the statistic, e.g. it is negatively correlated with FIP. It should be positively correlated with the strikeout rate (SR), but it is not, although it should be noted that that correlation is statistically equivalent to zero.

2.3 QOPA Compared with Number of Bases Per Hit

Comparing QOPV with raw results – the number of bases run on a hit by a batter (**Bases**) –is a direct comparison with the quality of the batting performance. In theory, we would expect high QOPV pitches to have the lowest Base and low QOPV pitches to have the highest Base, on average. This analysis uses the 2015 regular season data from April to July (the time it was conducted). Since we are looking at the rarest and most valuable data – the pitches which resulted in hits that the batter got on base (including home runs), this limits us to only 26011 of the 438807 pitches recorded by PITCHf/x in this time frame.

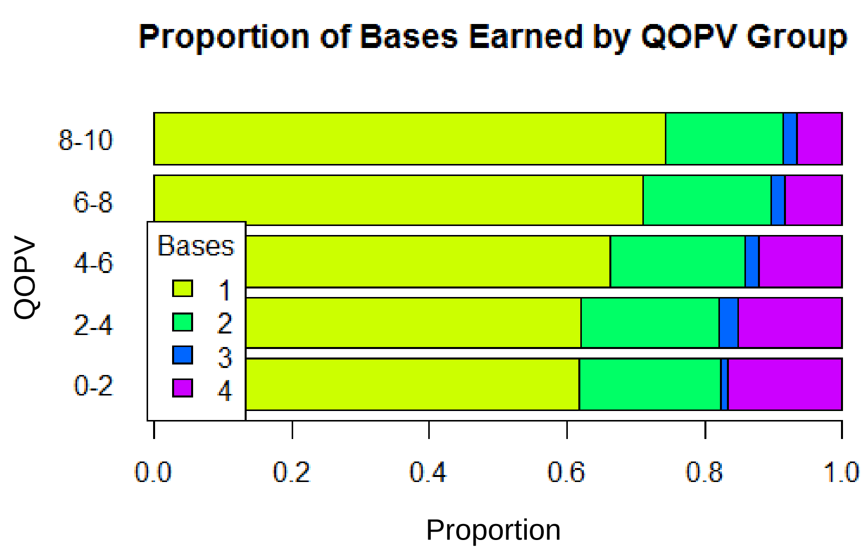

Figure 3. Proportion of bases run by QOPV group. Each bar represents 100%, which is divided between the proportion of hits which resulted in 1,2,3, or 4 bases. The higher the QOPV, the lower the bases.

To begin, Figure 4 shows the proportion of Bases by groups of QOPV. Notice that the QOPV 8-10 pitches have 6.6% home runs and 74.4% singles. By comparison, QOPV 0-2 pitches have 16.7% home runs and 61.8% singles. Thus, the highest QOPV pitches which were hit achieved the lowest results while the lowest QOPV pitches which were hit achieved the highest results. The proportions follow this consistent pattern for the other QOPV groups as well. The data of Figure 4 was submitted to a chi-squared test of independence (X^2 = 221.6, df=12, p-value < 2×10^{-16}). The results are highly statistically significant, meaning that the pattern of higher QOPV resulting in fewer bases is strong in the population. The same pattern holds, with p-value < 2×10^{-16}, for all seasons from 2008 to 2014.

Looking at the data differently, we can quantify the relationship between QOPV and Bases. Figure 5 shows a boxplot for each number of bases. The super-imposed regression line covers the median of each box with a negative slope. In particular, starting from 5.58 QOPV, as the number of bases increases by one, the QOPV drops 0.16 points, on average (p-value < 2×10^{-16}). The correlation between QOPA and Bases is as strong as possible (-1 using Spearman's correlation, -0.98 using Pearson's, with QOPAs 5.42, 5.28, 5.19, 4.94 for Bases 1,2,3,4).

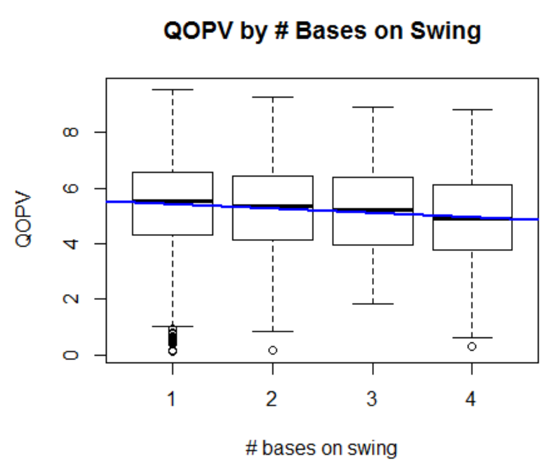

Figure 4. Boxplots of QOPV by Bases. The Linear regression line super-imposed shows a negative trend with very strong correlation between QOPA and bases (Spearman's correlation = -1.00).

Figure 6 is telling. Each row is the current pitches for the 2015 season of a particular designation. The designations are in the conceptual order of Called Strike, hit balls (In Play-Out(s), In Play-Run-No-Out, Fouls), missed balls (Missed Bunt, Swinging Strikes), and out of zone pitches (Balls, Pitchout, Hit by Pitch). The Called Strike has the highest proportion of 8-10 QOPV and the lowest proportion of 0-2 QOPV. Conversely, the Out of Zone Pitches have the lowest proportion of 8-10 QOPV and the highest proportion of 0-2 QOPV. The other categories and proportions lie in between these extremes. The table differences are highly statistically significant (chi-square test of independence p-value < 2×10^{-16}). The same pattern holds for each season from 2008 to 2014.

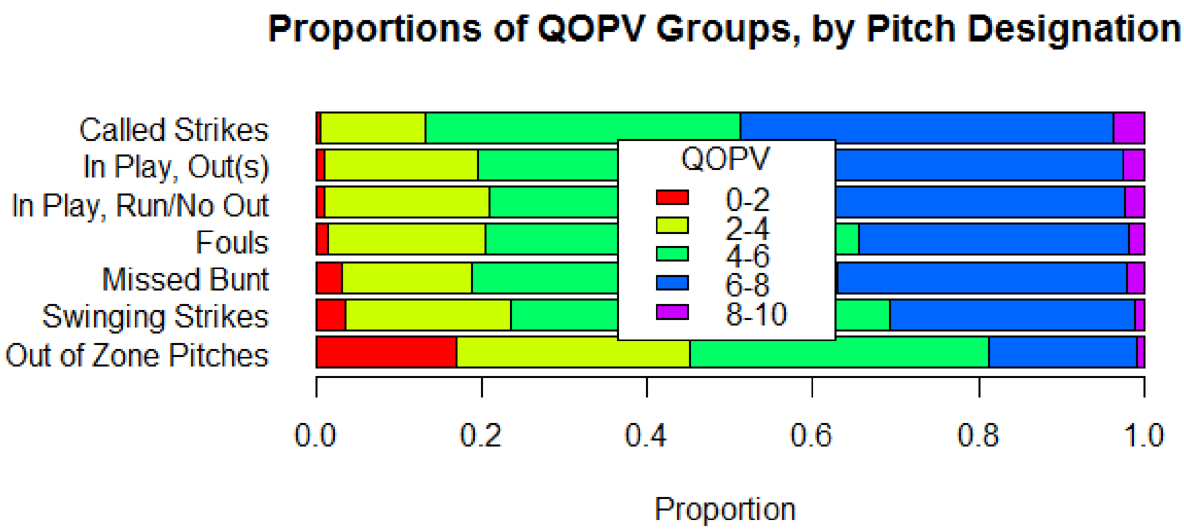

Figure 5. Barplot of proportions of QOPV by pitch designation for 2015. The 8-10 QOPV has the highest proportion of Called Strikes and the lowest proportion of Out of Zone Pitches (Balls, Pitchout, Hit by Pitch). Conversely, the 0-2 QOPV has the highest proportion Out of Zone Pitches and the lowest proportion of Called Strikes.

3. Exploring the 2015 MLB Season with QOP

Now we come to the primary content of our research: insights gleaned from QOP about the 2015 MLB season, as well as MLB pitching in general. While the previous section contained more explanation, since the techniques employed were less conventional, for this section we have chosen to use bullet points. There is one subsection for each of the seven questions. Each consists of mostly tables of players ranked by various QOP-based statistics, with salient observations. This accords with what our slide presentation would be like, should we be given the opportunity. Lastly, note that we wrote the seven questions prior to researching the answers. If we were given a chance to revise the abstract, we would make some minor modifications to the question wording.

3.1 Which MLB players threw the highest quality pitches in 2015?

qopv Rank	Pitcher	Pitch Type	MPH	qopv	Pitch Result
1	Steve Cishek	SI	91.5	9.90	Foul
2	Blake Treinen	SI	98.0	9.78	Ball
3	Justin Wilson	FF	97.5	9.76	Foul
4	Enny Romero	FF	98.5	9.69	Ball
5	Mat Latos	FT	93.5	9.68	Called Strike
6	Jim Johnson	FT	94.2	9.66	In play, out(s)
7	Zachary Britton	FT	98.2	9.61	Swinging Strike
8	Darren O'Day	FF	88.5	9.58	In play, out(s)
9	Nick Hagadone	FF	93.6	9.57	In play, no out
10	Steve Cishek	SI	91.5	9.55	Ball

Table 3.1. Pitchers ranked by QOPV.

- 90% of the top ten quality pitches from 2015 resulted in no batter reaching base
- Top ten quality pitches by pitch type have also been calculated and are available

3.2 Can QOP data project ERA in 2016? Which MLB players have the highest probability of posting a decrease or increase in ERA in 2016?

The task of projecting ERA turned out to be much more difficult than we anticipated when we wrote the abstract. It turns out that ERA is not even correlated with itself from one year to the next (see Appendix 2)!

Simply looking through data, however, we observed that some pitchers with high QOPA, who should have good conventional pitching statistics, also had high ERA, which seemed out of place. We studied this phenomenon and found it could be used to successfully **retrodict**[2] whether a pitcher's ERA would go down in the subsequent season. In Appendix 2, we provide five years' worth of retrodiction data from 2008 to 2013 to show that 85.5% of pitchers with ERA>5 and QOPA>5 had their ERA drop the following year, most of which were substantial. Tables 3.2a and 3.2b, below show our projections for 2016 using this approach.

qopa Rank	Pitcher	qopa	ERA	NP	IP
1	Enny Romero	5.50	5.10	598	30.0
2	Ivan Nova	5.39	5.07	1528	94.0
3	Ross Detwiler	5.33	7.25	1165	58.1
4	Bruce Rondon	5.28	5.81	553	31.0
5	Brad Hand	5.26	5.30	1546	93.1
6	Matt Garza	5.25	5.63	2380	148.2
7	Aaron Brooks	5.14	6.67	884	55.1
8	Christian Friedrich	5.12	5.25	967	58.1
9	Esmil Rogers	5.11	6.27	577	33.0

Table 3.2a. Pitchers with QOPA>5 and ERA>5. Pitchers have a minimum of 500 pitches (NP) and 30 innings pitched (IP).

- We project the nine pitchers in Table 3.2a will post a decrease in ERA in 2016.

qopa Rank	Pitcher	qopa	ERA	NP	IP
1	Huston Street	3.71	3.18	1008	62.1
2	Koji Uehara	3.83	2.23	629	40.1
3	Sergio Romo	3.87	2.98	873	57.1
4	C.J. Wilson	3.90	3.89	2109	132.0
5	Robbie Ross	3.91	3.86	1000	60.2
6	Joshua Fields	3.94	3.55	848	50.2
7	Shawn Kelley	3.95	2.45	780	51.1
8	Erasmo Ramirez	3.95	3.75	2406	163.1
9	Tsuyoshi Wada	3.96	3.62	528	32.1

Table 3.2b. Pitchers with QOPA<4 and ERA<4. Pitchers have a minimum of 500 pitches (NP) and 30 innings pitched (IP).

- We project the nine pitchers in Table 3.2b will post an increase in ERA in 2016.

3.3 Did quality deteriorate for pitches delivered from the stretch position with runners on base vs. the wind up?

	No BR	BR/1st	BR/2nd	BR/3rd	BR/1st&2nd	BR/1st&3rd	BR/2nd&3rd	BR/1st&2nd&3rd
2015	4.68	4.67	4.57	4.52	4.65	4.59	4.50	4.61
2014	4.69	4.66	4.56	4.48	4.63	4.56	4.48	4.65
2013	4.69	4.66	4.59	4.55	4.64	4.58	4.54	4.66
2012	4.70	4.66	4.57	4.54	4.64	4.60	4.51	4.66
2011	4.62	4.59	4.51	4.45	4.57	4.51	4.48	4.55
2010	4.61	4.56	4.46	4.41	4.55	4.49	4.39	4.52
2009	4.66	4.61	4.51	4.43	4.58	4.51	4.43	4.56
2008	4.63	4.59	4.51	4.48	4.57	4.53	4.41	4.57

Table 2.3a. League-wide QOPA by year with men on base from 2008-2015.

- Pitches with a runner on third base or with runners on second and third base posted the lowest pitch quality calculations the past eight seasons (2008-2015).
- Pitches with no runners on base posted the highest pitch quality calculations the past eight seasons (2008-2015).

2015 qopa	*0-0	*0-1	*0-2	*1-0	*1-1	*1-2	*2-0	*2-1	*2-2	*3-0	*3-1	*3-2
0 out	4.75	4.55	3.47	4.83	4.70	4.07	4.87	4.83	4.50	4.82	4.86	4.74
1 out	4.81	4.56	3.53	4.85	4.71	4.08	4.89	4.85	4.53	4.85	4.94	4.80
2 out	4.88	4.59	3.50	4.99	4.79	4.10	5.17	5.06	4.66	5.37	5.37	5.27
*Count												

Table 3.3b. League-wide QOPA for 2015 by Pitch Count and Outs.

- Pitch quality increased with each out recorded in all pitch counts except 0-2 situations (noted in blue in Table 3.3b - when pitchers typically entice the batter to chase a poor quality pitch).
- Pitch quality increases in “3 ball” counts as pitchers attempt to avoid walking the batter.

3.4 Which MLB players were able to deliver quality pitches in pressure situations with runners in scoring position or in full count situations?

qopa Rank	Pitcher	qopa	ERA	NP
1	Darren O'Day	5.89	1.52	270
2	Blake Treinen	5.74	3.86	258
3	Jeurys Familia	5.72	1.85	319
4	Justin Wilson	5.61	3.10	261
5	Mat Latos	5.56	4.95	410
6	James Paxton	5.53	3.90	256
7	Jim Johnson	5.53	4.46	283
8	Tommy Hunter	5.53	4.18	256
9	Ryan Madson	5.52	2.13	253
10	Joe Smith	5.41	3.58	256

**Runners in Scoring Position - Minimum 200 Pitches

Table 3.4. Top 10 QOPAs for pitches with runners in scoring position. Only QOPV for pitches with runners on second or third base were used for QOPA. Only pitchers with over 200 such pitches are included. ERA shown is for entire 2015 season.

- The pitchers listed vary from other lists, giving insight into which pitchers are able to deliver under pressure.
- QOPA could be used similarly to explore other pressure situations.

3.5 Which MLB pitchers produced the highest economic value to their team based on their QOP average and contract?

qopa $ Rank	Pitcher	qopa	ERA	NP	IP	2015 Contract	2015 Salary	$ per qopa	
1	Enny Romero	5.50	5.10	598	30.0	$507,500	$174,713	$31,766.00	per 1.0 qopa
2	Kevin Gausman	5.29	4.25	1873	112.1	$522,000	$231,049	$43,676.56	per 1.0 qopa
3	Cody Anderson	5.27	3.05	1289	91.1	$507,500	$296,734	$56,306.26	per 1.0 qopa
4	Noah Syndergaard	5.27	3.24	2372	150.0	$507,500	$410,437	$77,881.78	per 1.0 qopa
5	Blake Treinen	5.79	3.86	1007	67.2	$512,800	$462,360	$79,854.92	per 1.0 qopa
6	Jeurys Familia	5.77	1.85	1168	78.0	$523,925	$523,925	$90,801.56	per 1.0 qopa
7	James Paxton	5.65	3.90	1106	67.0	$519,000	$519,000	$91,858.41	per 1.0 qopa
8	Jeremy Jeffress	5.39	2.65	1049	68.0	$510,500	$510,500	$94,712.43	per 1.0 qopa
9	Brad Hand	5.26	5.30	1546	93.1	$520,000	$520,000	$98,859.32	per 1.0 qopa
10	Kyle Gibson	5.35	3.84	3211	194.2	$537,500	$537,500	$100,467.28	per 1.0 qopa

Table 3.5. High economic value pitchers of 2015. Contract is $ contracted for whole season, whereas if only a part of season was played, the salary differs. Only pitchers with over 500 pitches and 30 innings are included.

- This approach, or variations thereof (e.g. incorporating NP) can provide information to teams seeking bargain pitchers.

3.6 Can pitch quantification be used to quantify batters? Is there a correlation between QOP and batting average by pitch type?

Rank	Batter	AVG	qopaPH	Hits	qopaPH Rank
1	Miguel Cabrera	0.338	5.51	145	83
2	Dee Gordon	0.333	5.31	205	232
3	Bryce Harper	0.330	5.36	172	182
4	Paul Goldschmidt	0.321	5.31	182	230
5	Xander Bogaerts	0.320	5.20	196	305
6	Buster Posey	0.318	5.40	177	149
7	A.J. Pollock	0.315	5.24	192	282
8	Yunel Escobar	0.314	5.35	168	191
9	Joey Votto	0.314	5.52	171	78
10	Jose Altuve	0.313	5.28	200	253
11	David Peralta	0.312	5.64	144	30
12	Michael Brantley	0.310	5.38	164	170
13	Lorenzo Cain	0.307	5.51	169	82
14	Ben Revere	0.306	5.70	181	11
15	Prince Fielder	0.305	5.16	187	328
16	Ender Inciarte	0.303	5.20	159	310
17	Jason Kipnis	0.303	5.53	171	71
18	Nelson Cruz	0.302	5.31	178	223
19	DJ LeMahieu	0.301	5.30	170	235
20	Christian Yelich	0.300	5.28	143	255

Table 3.6. Top 20 batters of 2015 with QOPA of pitches hit. qopaPH is the average of the QOPV of only the pitches hit by the batters. Over 500 pitches per batter were required for inclusion.

- QOPA for Pitches Hit (qopaPH) results in a higher pitch quality average versus the season average since they are calculated from pitches thrown around the strike zone which consistently result in swings by the hitter.

- Quality per hit ranking (qopaPH) indicates that high average batters can hit low quality pitches (out of the strike zone or over the middle of the plate) on a consistent basis. (Note that the reason for the lower quality can be determined by examining the components of the qopaPH).

3.7 Can QOP help prevent injuries to pitchers?

In our 2015 SABR presentation we showed that there was a statistically significant decline in QOP (and not MPH) for Josh Beckett leading up to his injury. This QOP metric can also be used to monitor player recovery from injuries such as Tommy John Surgery.

Pitcher	Pitch Type	2015 qopa	2014 qopa	2013 qopa	2012 qopa	2011 qopa	2010 qopa
Stephen Strasburg	All	4.84	5.21	4.93	5.11	5.22	5.04
	FB	4.98	5.29	5.06	5.25	5.15	5.07
	OS	4.60	5.08	4.71	4.85	5.40	5.00
Matt Harvey	All	5.20	NA	5.02	4.85		
	FB	5.43	NA	5.10	4.97		
	OS	4.83	NA	4.90	4.62		
Jose Fernandez	All	4.72	4.70	4.85			
	FB	4.91	4.75	4.78			
	OS	4.48	4.66	4.94			

Table 3.7a. QOPA for three high profile pitchers with Tommy John surgery. FB are fastball and OS are off-speed pitches.

- Tommy John Surgery Dates
    - Stephen Strasburg: Sept. 3, 2010
    - Matt Harvey: Oct. 13, 2013
    - Jose Fernandez: May 16, 2014.
- The three pitchers list above possess the highest combination of historical pitch quality, contract value, and pitching success of Tommy John surgery patients since 2010.
- Table 3.7a shows that post-injury pitch quality may deteriorate for off-speed pitches and not fastballs. Further detail by pitch type is shown in Table 3.7b.

Player	Year		Total	CH	CU	FF	FT	SL
Stephen Strasburg	2015	qopa	4.84	4.40	4.74	5.07	4.46	4.00
		NP	2041	279	454	1103	191	14
	2014	qopa	5.21	4.91	5.30	5.34	5.20	4.92
		NP	3371	687	567	1371	695	51
	2013	qopa	4.93	4.21	5.07	4.97	5.42	
		NP	2844	461	650	1393	340	
	2012	qopa	5.11	4.48	5.16	5.18	5.52	
		NP	2615	421	496	1345	353	
	2011	qopa	5.22	5.32	5.47	5.07	5.37	
		NP	328	41	44	173	70	
	2010	qopa	5.04	4.43	5.36	5.00	5.22	
		NP	1064	169	271	425	199	
Matt Harvey	2015	qopa	5.20	5.19	4.58	5.40	5.50	4.73
		NP	2705	330	312	1071	576	416
	2014	qopa	NA					
		NP	NA					
	2013	qopa	5.02	4.98	4.97	5.09	5.46	4.80
		NP	2720	307	355	1475	68	515
	2012	qopa	4.85	4.98	4.12	4.93	6.47	4.71
		NP	978	118	104	626	14	116
Jose Fernandez	2015	qopa	4.72	4.51	4.47	4.93	4.75	
		NP	992	128	314	477	73	
	2014	qopa	4.70	4.78	4.62	4.84	3.93	
		NP	781	76	288	375	42	
	2013	qopa	4.85	4.52	5.05	4.82	4.52	
		NP	2604	222	884	1319	179	

Table 3.7b. QOPA for three high profile pitchers with Tommy John surgery. CH, CU, FF, FT, and SL are change-up, curveball, four-seam fastball, two-seam fastball, and sliders, respectively.

- In 2016, the following pitchers will be monitored: Brandon McCarthy, Yu Darvish, Homer Bailey.

4. Conclusion

Quality of Pitch (QOP) is a new patent pending metric for calculating pitch quality. The preceding results show how it can be used to add insight to MLB. This metric is not intended to calculate “Pitcher” quality, because there are many other factors involved in pitch results. We believe that when pitch quality is combined with pitch deception, pitch sequence, and batter performance, then the final result of the pitch is determined. We believe that increased pitch quality combined with the proper pitch context (pitch count, inning, situation, etc.) will determine pitch results.

Appendix 1: How QOP is Calculated

The formula for QOP is a multiple regression model with the following form (see Figure A1 for a graphical representation of components):

$$QOP = \beta_1{*}rise + \beta_2{*}break.point + \beta_3{*}vert.break + \beta_4{*}horiz.break + \beta_5{*}location + \beta_6{*}MPH$$

where

1. **rise**: the number of feet the ball rises vertically to the maximum height
2. **break.point**: the horizontal distance (in feet) from the release point to the maximum height
3. **vert.break**: the number of vertical feet from the maximum ball height to the point it crosses the plate
4. **horiz.break:** the number of horizontal feet, at home plate, from the "straight line" crossing point of the ball to the actual crossing point
5. **location**: a measurement of how easy the pitch is to hit, on average, based upon the location in the strike zone (the higher the value, the easier to hit)
6. **MPH:** pitch speed

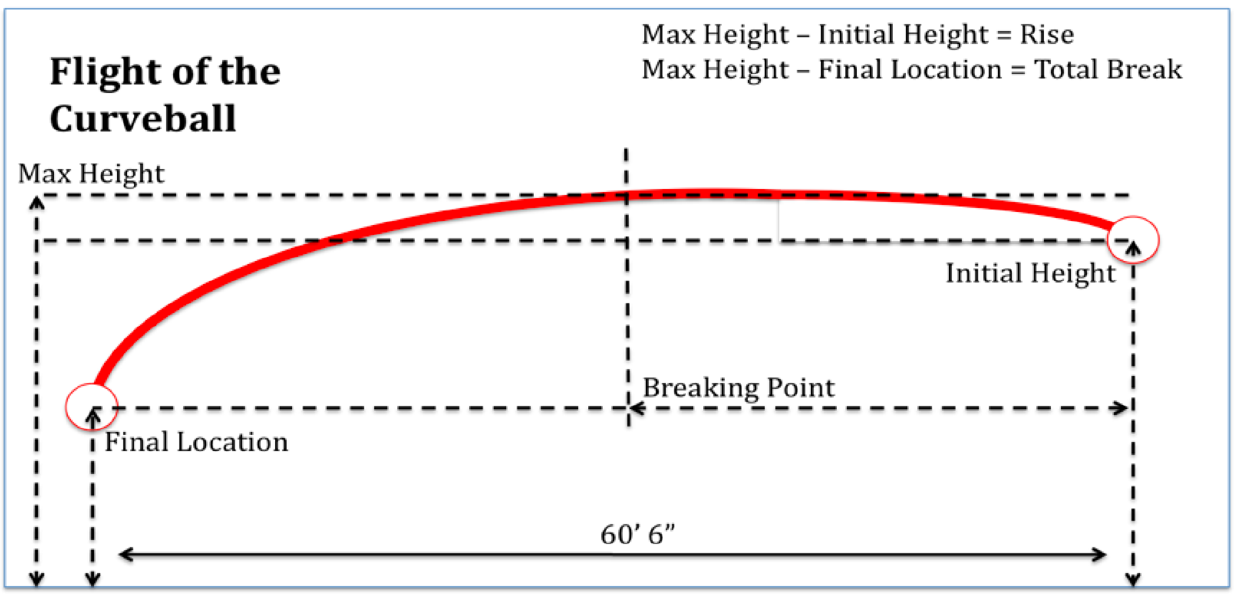

Figure A1. Curveball trajectory diagram. The trajectory components of a pitch used to develop the initial QOP model. In the model shown, the parameters were derived from the pitch measurements using a low-tech method. The current model uses PITCHf/x data.

The *rise* and *location* coefficients are negative, while the *break.point, vert.break, horiz.break*, and *MPH* are all positive. This makes sense, because a rising pitch and bad location make for a low quality pitch whereas a big break and fast speed make for a good quality pitch. Under extensive model testing, there were no quadratic relationships or interactions found. It is noteworthy that this is a zero intercept model. The model fit is excellent with a p-value < 10^{-5} for all coefficients (except *rise*, which is 0.005), and adjusted R^2 = 0.957. All QOP work has been done in R[3] and the model output is in Table A1. Unfortunately, the patent pending model is proprietary and the coefficients cannot be released at this time.

```
# Residuals:
#   Min      1Q  Median      3Q     Max
# -2.1066 -0.4282 -0.0656  0.3274  3.3782
#
# Coefficients:
#            Std. Error t value  Pr(>|t|)
#   rise        0.69040  -2.809  0.00519 **
#   break.point 0.01837  12.956  < 2e-16 ***
#   vert.break  0.01964  50.342  < 2e-16 ***
#   loc         0.01537 -65.053  < 2e-16 ***
#   horiz.break 0.08130   4.050  6.1e-05 ***
#   ---
# Residual standard error: 0.6724 on 419 degrees of freedom
# Multiple R-squared:  0.9578,  Adjusted R-squared:  0.9573
# F-statistic:  1903 on 5 and 419 DF,  p-value: < 2.2e-16
```

Table A1. Statistical software output for QOP model. It may be noticed that MPH does not appear in the output. This is because we combine this trajectory and location parameter model with MPH separately.

Appendix 2: Statistics Behind the ERA Projections

The purpose of this appendix is to document our statistic that 85.5% of pitchers with QOPA>5 and ERA>5 will post a lower ERA in the following season. The data is used is about 2/3 of MLB pitchers per season[4]. The data run from 2008 to 2013, giving the ability to use performance from 2008 to 2012 to retrodict performance from 2009 to 2013, which is five seasons. Our reasoning is as follows: if pitchers are pitching high quality pitches during a season, but this goes unrecognized for some reason in their

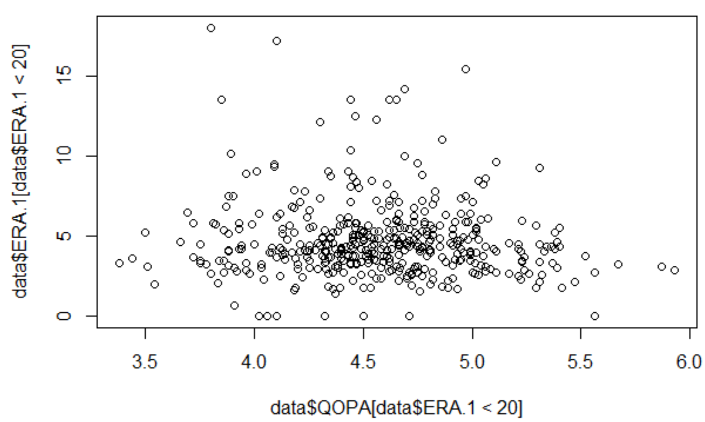

Figure A2.1 Scatterplot of ERA from 2012 with 2013. Note that ERA>=20 is not shown. It is clear that there is no correlation. Similar results hold for other years.

ERA, then on average their ERA should come into alignment with their true pitching ability which was previously observed in their QOPA. This implies looking at the ERA of only the subset of pitchers with poor ERA and good QOPA.

The ERA data are in Table A2.1. An example of the full statistics for one of the retrodictions from 2010 to 2011 is in Table A2.3. For the ERA data, Table A2.1 shows that, averaged over all seasons, for players with an ERA of 4.5 or higher in one season, if they also have a high QOPA (>4, 4.5, 5, or 5.5), then we can retrodict with around 75.9 to 83.4% accuracy that their ERA will go down in the subsequent season. The higher the QOPA, the higher the accuracy, although the fewer the players which meet this criteria. We list our predictions for the 2016 season, based on the 2015 data in sub-section 3.2. The margin of error for such predictions is from 3 to 10%, depending on the number of pitchers.

QOPA	ERA	08-09		09-10		10-11		11-12		12-13		Overall	
		n	p	n	p	n	p	n	p	n	p	N	p
4	4.5	164	0.713	156	0.737	124	0.766	108	0.796	122	0.811	674	0.759
4.5	4.5	102	0.706	87	0.782	68	0.809	60	0.817	84	0.821	401	0.781
5	4.5	20	0.850	16	0.750	13	0.846	12	0.750	24	0.875	85	0.824
5.5	4.5	2	1.000	0	NA	0	NA	1	1.000	3	0.667	6	0.834
4	5	118	0.788	115	0.765	81	0.753	78	0.833	92	0.837	484	0.793
4.5	5	74	0.730	61	0.787	46	0.804	45	0.822	60	0.867	286	0.797
5	5	14	0.786	7	0.714	10	1.000	9	0.778	15	0.933	55	0.855
5.5	5	0	NA	0	NA	0	NA	1	1.000	2	1.000	3	1.000

Table A2.1. Retrodicting next year's ERA with this year's QOPA and ERA. n is the number of pitchers that meet the QOPA and ERA criteria; p is the proportion of the n pitchers whose ERA was lower the following year. The first row of the table reads as follows: For the 2008 MLB season, there were 164 pitchers with an ERA of 4.5 or higher who also had a QOPA of 4 or higher. Of these 164 pitchers, 71.3% had their ERA go down in 2009. The 09-10 columns read similarly with the 2009 season data retrodicting the 2010 results, and so on. To illustrate, the data behind QOPA>5, ERA>5 for 2010-2011 (numbers in red) is shown in Table 5. Note: As described above, the number of pitchers (n) is given out of about 2/3 of all MLB pitchers, NOT all MLB pitchers.

	08-09	09-10	10-11	11-12	12-13	Overall
ERA	0.555	0.501	0.495	0.581	0.513	0.530

Table A2.2. Baseline ERA drop percentages. The first entry, 0.555, means that 55.5% of the pitchers' ERA (all pitchers in dataset) from 2008 dropped in the 2009 season. The other columns are interpreted similarly.

In order to evaluate the retrodiction rates in Table A2.1, we need to know the baseline rates. These overall rates are 53.0% (see Table A2.2), which is a little better than fifty-fifty[5]. Thus, using QOPA to retrodict ERA substantially increases the success rate. Upon inspection, the statistics in Table A2.1 make rational sense. Although not every statistic for every season is monotonic[6], they mostly are and all of the overall statistics are. This means that the results are consistent, implying that the statistics are reliable and would be likely to have a consistent prediction record. Such predictions can be done simply, without human bias, and may be used to identify undervalued potential.

Tom Tango challenged the objectivity of our retrodiction set of pitchers who have high ERA, saying that regression towards the mean would result in a higher than average percentage improvement. We agree that our retrodiction set is "biased" in this sense – but that is precisely the point – to select a set of pitchers for whom it is very likely that their ERA will drop. The way we did it was combining ERA with QOPA. We even showed the actual percentage of ERAs that did drop in Table A2.2. The opposite results, namely LOW ERAs with LOW QOPA, should also be able to be used to predict which low ERA pitchers will go up the following year. If our work is selected for presentation, we will complete that analysis and generate the statistic for the presentation.

	2010						2011					
Pitcher	**QOPA**	**ERA**	**SR**	**WR**	**HitR**	**n**	**QOPA**	**ERA**	**SR**	**WR**	**HitR**	**n**
Aaron Harang	5.47	5.32	0.163	0.075	0.276	2045	5.00	3.64	0.172	0.081	0.243	3103
Blake Wood	5.13	5.07	0.141	0.1	0.245	881	5.11	3.75	0.205	0.106	0.218	1218
Chad Qualls	5.25	5.57	0.165	0.066	0.264	1087	5.13	3.51	0.141	0.065	0.239	1237
Chris Jakubauskas	5.26	27	0	0	0.5	12	5.19	5.72	0.157	0.088	0.281	1297
Felipe Paulino	5.15	5.11	0.202	0.112	0.231	1614	4.78	4.11	0.224	0.09	0.232	2410
Kyle Lohse	5.01	6.55	0.125	0.081	0.299	1704	5.03	3.39	0.143	0.054	0.23	3033
Nick Blackburn	5.28	5.42	0.098	0.058	0.28	2275	5.38	4.49	0.113	0.081	0.273	2445
Sandy Rosario	5.29	54	0	0.083	0.75	41	4.57	2.45	0.111	0.111	0.278	65
Tyson Ross	5.05	5.49	0.189	0.118	0.231	706	5.24	2.75	0.166	0.09	0.228	538
Waldis Joaquin	5.45	9.64	0.074	0.259	0.222	135	5.92	4.26	0.111	0.111	0.222	101

Table A2.3. Example of pitching statistics for the 2010 retrodicting 2011 results. This table shows the ten players from 2010 who had QOPA>5 and ERA>5, along with their performance in 2011. SR = strikeout rate; WR = walk rate; HitR = hit rate; n = number of pitches for the season. For this year, the retrodiction accuracy was 100%, as all ERAs went down, most by a large margin.

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[1] Our source for conventional statistics is Sean Lahman's (http://www.seanlahman.com/baseball-archive/) database in R, which at the time of writing only has conventional statistics through 2013 (https://cran.r-project.org/web/packages/Lahman/index.html). The name formats between PITCHf/x data and the Lahman data vary somewhat. Using regular expressions, we were was able to match about 2/3 of the pitchers and batters. The discrepancies are typically names with abbreviations, like A.J. Burnett. Therefore, in all results shown using conventional statistics, the players that did not make the list are missing for presumably random reasons.

[2] A retrodiction is a prediction, but it is based on data which has already occurred, not data which is yet to occur. For example, we used 2008 data to "predict" what happened in 2009 – and then we checked whether it was accurate or not. In order to distinguish between whether the data was known or unknown, statisticians use the term retrodiction.

[3] www.r-project.org

[4] See Endnote 1.

[5] Why are the ERA and FIP rates not at 50%? It may be due to a few one or more of the following factors: (i) low ERA pitchers retiring, who may otherwise contribute an ERA increase (remove negative results), (ii) high ERA rookie pitchers entering the dataset who improve their ERA (add positive results) . Both factors would push the percentages above the random rate of 50%.

[6] Continuously increasing or continuously decreasing. E.g. Number of pitches in a season is monotonic, because it will either stay the same or go up, it cannot go down. Batting average is not monotonic, because it can go up or down over time.