Understanding The Effects of a Stolen Base Threat on Pitcher Pitch Quality

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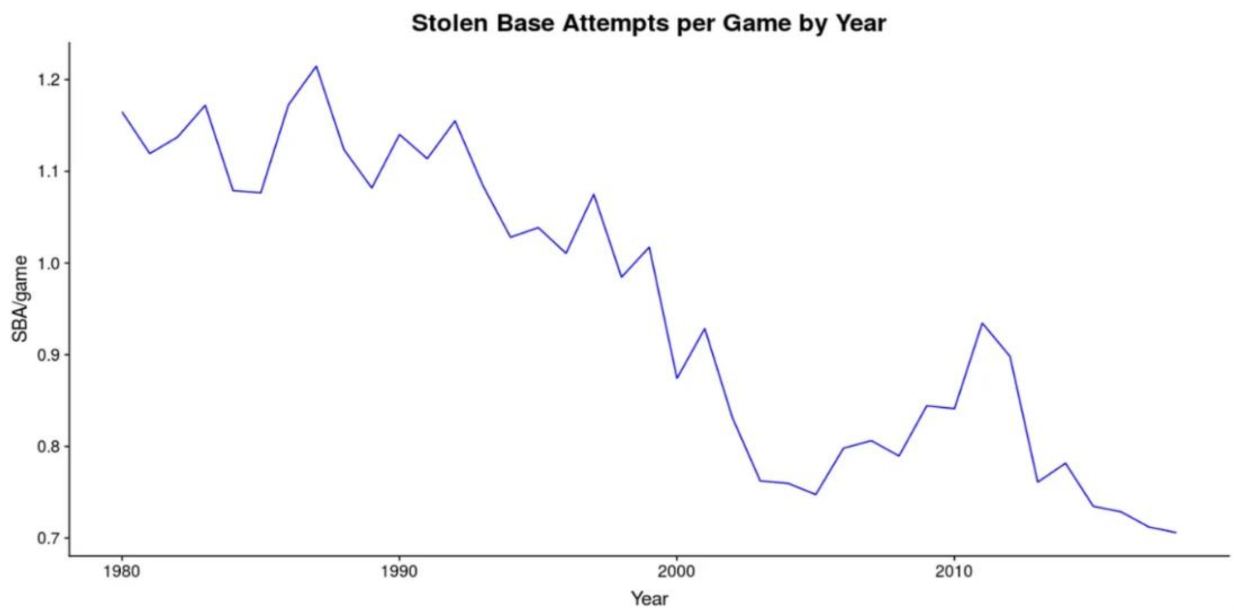
Abstract

The goal of this research paper is to determine whether characteristics of the base runner, such as their speed and stolen base tally, has any influence on the pitcher's pitch quality. The author analyzes the effects of the threat of a stolen base on the quality of a pitcher's pitch using Major League Baseball (MLB) play-by-play data from the 2011 through 2021 seasons. The author finds evidence that pitcher pitch quality decreases slightly in stolen base situations and that that effect is greatest for when there is a runner on first only and when it is a one run game. These effects are also present as you increase the base runner speed in late game situations only and are even greater as you increase the number of stolen bases in all situations. In the 7th inning or later and a one run game situation, speed becomes more influential than stolen bases in affecting pitch quality, which the author concludes that pitchers may feel more "pressure" from the runner despite them not being an active base stealer.

Introduction

The stolen base has become a dying part of baseball over the last decade. What used to be an essential component to any winning baseball club has been essentially disregarded nowadays. Analytically-minded front offices have proven that the stolen base is not worth the risk. Teams have concluded that in order for a stolen base attempt to be warranted, the player attempting to steal the bag must be successful at least 80% of the time. As a result, we have witnessed the average number of stolen base attempts per game decrease drastically these past 10 seasons.



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Some have argued however that the residual effects of a stolen base are not accurately captured in each attempt. A stolen base doesn't simply result in an additional base for the batting team, but can cause disruptive effects as it relates to the success of a pitcher. Pitcher's may get so caught up in the potential of a stolen base being attempted that they rush their release or aren't able to generate as much spin as they'd like to. Ultimately, there is potential for an increased likelihood of a stolen base creating a pressurized environment that ultimately puts a pitcher off his game and forces them to lose quality in their pitches.

Understanding these effects can be analyzed in the controlled setting of a runner on first, runner on second, or runner on first and second- three popular stolen base situations. By looking at the characteristics of those base runners such as their speed or their stolen base rate, we may be able to determine whether these effects influence a pitcher's pitch quality. Other settings, like inning and difference in score, will also be examined to see if these effects are greater when more is on the line i.e. when pressure effects are greater. The idea is that if this hypothesis is true, if pitcher’s do typically experience a decrease in the quality of their pitches in the event of a potential stolen base attempt, then teams should be attempting more stolen bases to create a better environment for the batter as they would see worse quality pitches during their at-bat.

Literature Review

Stolen base creation and prevention is something that has been analyzed in baseball extensively over the years. Offensive strategies have been developed to maximize the probability a stolen base attempt is successful. The three components of a stolen base; the runner, catcher, and pitcher, have been examined in these settings to understand the effect each has on any given stolen base attempt. The general understanding of the responsibility for the result of a successful stolen base is very biased. The prevention of a stolen base typically relies heavily on the catcher, however, when breaking a stolen base down we can see how the difference between a successful and unsuccessful attempt can be influenced by the most minute change from any one of the components. These influences can range from the quality of the pitch and the pitch type to the position of the fielder and how fast they get to the bag. The stolen base setting is a fascinating setting to study because of the pressure it applies to each of the three players, especially the pitcher and their pitch quality.

The quality of a pitcher's pitches is one of the main components of baseball that researchers have investigated over the last few decades. Initially, baseball analysts used out-based statistics to study the effects of a pitcher's pitches against batters. That analysis focused too heavily on things the pitchers couldn't control so thus researchers began to look at pitching-independent stats like FIP and per-nine stats. These stats only took into account outcomes that were influenced by the batter and pitcher rather than ones in which the defense had an effect. With the introduction of TrackMan and other pitch-tracking data companies, analysts began using that information to evaluate pitchers on their pitch locations, velocity, movement, and spin rate to get an independent understanding of the effectiveness of a pitcher's arsenal.

Defensive strategies have been implemented in baseball to help prevent offensive scoring. Positioning is the main feature of that strategy and the increase in shift percentages across the league is evidence of that idea. Positioning is not only important in decreasing the probability of a hit by the batter, but by the probability of a successful stolen base by the runner as well. In order for a stolen base to be prevented three things need to go right- the pitcher, the catcher, and the fielder all need to do their jobs.

A. Pitch Performance

The concept of pitch quality was made popular most recently by Eno Sarris (2022) who developed a Stuff+ metric that integrates various pitch quality characteristics to help evaluate pitcher pitch performance through an XGBoost model. Sarris uses these aspects of a pitcher's arsenal to generate a final, single-number statistic that determines the success of a pitcher's pitch.

His goal as he mentions is to independently measure pitch output and identify pitch success independent of the result the pitch may produce. He finds that the most important features, velocity difference between pitches and depth of pitch (horizontal and vertical movement), are most indicative of a quality pitch. Other independent researchers have taken similar approaches using other models than the XGBoost used by Sarris. One to note is Jason Wilson's (2017) QOP which combines various pitch features into a single number that calculates the quality of a pitch on a scale from 0 to 10. Wilson then takes these pitch success numbers and analyzes them with run expectancies in given situations. By doing comparative analysis in "high-pressure" situations, he finds that his quality of pitch metric displays a significant drop off in the quality of pitches in moments of stress. "The QOPA drops with men on base, with the lowest QOPA in the "pressure situations" of runners on third base and on second and third bases" (Wilson, 2017).

Another strategy for developing a pitch quality metric was done through a K-Nearest Neighbors approach which finds the 100 most similar pitches to X, averages the actual run values of those 100 similar pitches, and calls that the "expected run value" of pitch X. This idea developed by Moore (2020) uses run expectancy as a baseline and isolates pitch success through comparing what did happen in terms of runs scored versus what should've happened. With the shift in pitch characteristics becoming increasingly popular, researchers began analyzing the relationship between certain variables and how they work together. Andrews, Castillo, Steinhoff, and Walker (2021) analyzed how a pitcher's break and velocity worked with each other and discovered a positive, moderately strong correlation between velocity and pitch quality (correlation = 0.664 for four-seam and 0.586 for two-seam). Their research also finds no real evidence of a strong correlation between velocity and break, which suggest that pitchers looking to improve the quality of their fastballs can do so by improving either break or velocity “without worrying about erosion in the other pitch facet”.

The work done by P. Swartz, T. Swartz, Grosskopf, and Bingham (2016) uses pitch effects data to understand the relationship between pitch count and pitch performance and finds evidence to suggest that pitchers are at their best between pitch 20 and 70 and then experience a notable decline after that. Pitches after a count of 70 they suggest be due to fatigue or a possible third or fourth time through the batting order while pitches 0 to 20 they identify as the pitcher having to settle in and adjust to what pitches and patterns are working that night. Pitch sequencing is something that has been studied extensively by researchers. Identifying which combination of pitches to throw in a situation can be useful for the pitcher but the batter as well. Identifying possible edges in what the batter can expect in the next pitch is exactly what Prasad (2021) and Bloom (2014) try to do. Prasad uses a gaussian mixture model to predict the next pitch of an at-bat and also finds evidence to support pitchers using “set-up” and “knockout” pitches to help deceive the batter and get an out. His research also not only looks into what pitch will be coming next but where to expect it as well- the first analysis to include both pitch location and type. Following Prasad’s analysis, Lee (2022) uses his approach to develop a similar method that also predicts both the pitch type and location of the upcoming pitch through deep neural network models. His model, EP2, has a 62% accuracy and discovers that it is more predictive in high-tense situations, displaying how pitchers are more predictable under pressure. Bloom takes a more simplistic approach and opts for multinomial logistic regression models which can be used to predict the next pitch selection. The analysis done by Bloom as he mentions has been taken up by MLB and collegiate clubs to help strategize offensive schemes against a pitcher.

Sequencing is not only useful in identifying the next pitch but also in identifying when it may be useful to take a pitcher out as described by Soto-Valero, Perez-Morales, and Gonzalez Castellanos (2017). Their work, which uses time-series analysis through pitch-by-pitch sequences, uses an interactive k-nearest neighbors model that learns from past successes to determine when a starting pitcher should be removed and replaced by a reliever. In order to compare the time series of pitchers' performance, Dynamic Time Warping is used as the dissimilarity measure in conjunction with Keogh's lower bound technique. They validate the proposed model using real data from 20 Major League Baseball starting pitchers during the 2009 regular season and find a value of precision near 0.9.

B. Stolen Base Analysis

Pressure in baseball is not only applied to the pitcher but the rest of the players on the field as well, especially the base stealer. Stealing a base can create great rewards, however, the cost if not successful can be deadly. Sharpe (2017) constructs a metric, Swipe Rate Above Average, or SRAA, which attempts to independently measure the probability of a stolen base above the average player through a mixed model. He uses the residuals of his model to attribute the contributions of random participants in a given play. His main finding is the direct correlation between pitch speed and stolen base success with only 8% of successful stolen bases occurring on pitches above 95 MPH. The best base stealers, such as Billy Hamilton, had roughly 12% of their stolen bases occur at speeds 95 or higher, displaying their independent base stealing success. Identifying the best at stealing bases across the league independent of external factors can help better quantify the effects of a stolen base. King (2020) follows a similar approach as Sharpe and aims to isolate each component of a stolen base to better understand the positional impact of each attempt through an ELO model to calculate relative skill for each position. His research corresponds to and verifies Weinstein's (2013) assumption that a pitcher is 70% responsible for a stolen base while the catcher can control just the remaining 30%.

Rybarczyk (2013) quantified stolen base effectiveness for each position as well but instead used an aggregated value using the likelihood of a caught stealing through different variables like runner time to second, pitch delivery time, and catcher pop time to combine the positional effects on a stolen base attempt for a final run value. His research isolates run values to positional effects and thus averages run expectancy for each pitcher and runner classification (slow, fast) for run prevention and addition attributes. These articles seek to eliminate the bias that takes place during stolen base attempts with the goal of properly crediting the correct influences on a stolen base opportunity.

The concept of whether or not a stolen base should be attempted has been analyzed for years with many different modeling techniques done to perform such analysis. Lin (2018) built a logistic regression to create a stolen base predictor to assist managers in their decision-making. He derived specific run value expectancies from each stolen base situation and uses game situation variables to help drive his analysis, rather than actual baserunner ability. This analysis serves as a guideline for run expectancy in situations without controlling for runner, pitcher, and catcher effects. As a follow-up to the work done by Lin, Ashbrock (2020) uses RE24, run expectancy based on 24 outs, to help facilitate decisions on stolen base attempts. He discovers that about a 71% successful stolen base probability warrants the risk of the attempt due to the run expectancy number in an attempt, including whether it may be unsuccessful, outperforming the expectancy when not stealing at all. The difference between Lin and Ashbrock’s analysis is the run expectancy metric used, RE24, which takes into account the context of an inning more than previous RE metrics, specifically game situation. Popowitz (2020) also uses RE24 in his analysis for understanding ability on both the team and player level. He uses the run expectancy matrix to develop RE+ that uses both the player and team wOBA as a means for determining the number of runs that are expected to score in each half inning. Possible stolen base opportunities can be identified through RE+ as well as put a number on the change in expected runs as a result of a stolen base attempt if successful.

Not only do game situations play a role in the odds for a successful stolen base, but the skill and talent of the player attempting that stolen base is critical as well. Woodrum (2013) develops a metric that measures stolen base efficiency, attempting to quantify how effective the following stolen base attempt would be as it relates to scoring runs. He uses logistic regression to predict the success of a stolen base attempt and then applies that probability to determine the worth of the attempt in runs. Varying from Ashbrock's 71%, Woodrum identifies a warranted stolen base attempt needing to be 74% successful for it to be deemed "worth" the attempt.

Following the idea of advanced technology changing player evaluation, Bailey (2016) analyzes the differences between traditional stopwatch time collection and a new advanced method, infrared electronic timing. He finds the electronic time collection to be much more precise in its official times and advocates for this technology to be used in stolen base settings. This analysis, as he states, can help alleviate the differences in stolen base analysis and further minimize the "human error" of baseball research. Other stolen base analysis has been done in the economic realm as well. Turocy (2014) studied and modeled a stolen base attempt as a zero-sum two-player game and offered equilibrium predictions relating the frequency with which a stolen base play is attempted, and how often it is successful. When there is an exogenous environmental shift due to increased scoring of runs (increased average number of runs per game between 1978 and 2011), this relationship between frequency and success is consistent with the theory's predictions. He discovers that the defense typically shifts and adjusts its strategy when a player who is deemed a threat is on base. In addition, their research is qualitatively in agreement with the theory that is found by examining the increase in batter performance when a player who is a stolen base threat is on base.

C. Defensive Strategy

Defensive positioning and strategy are critical in preventing a stolen base. Ben-Porat (2017) attempted to create a defense metric that essentially divides the playing field into zones and develops an out % number that attributes the plays made by a defender in their respective zone. This analysis, as he states, is useful in understanding the defensive position at the time of a stolen base attempt and how to better align a defense to prevent a successful attempt. By utilizing defender tracking data, influences like angle and total movement to the bag can help identify defensive worth in a stolen base attempt. Chernoff (2018) uses stepwise regression and Liu estimates to formulate models on the dependent variable, runs, in order to determine which variables are most significant in run prevention and creation. When it comes to scoring runs, the variable he found to be one of the most significant was runners left on base- the more runners you leave on base the worse you typically are. This finding demonstrates the importance of stolen base attempts and how wasting a runner stranded on a base only declines offensive performance, which goes hand in hand with the run expectancy findings detailed previously in stolen base attempt situations.

D. Pressure Effects

When thinking about the impact of pitcher pitch quality and stolen base effects together, there has been little statistical research done. Loughlin & Bargen (2008) first studied the extent to which pitchers and catchers can influence stolen-base attempts and successes through mixed-effects logistic regression models. They discover that while both the catcher and pitcher show clear evidence that skill is involved in preventing a stolen base, pitchers display a greater influence than the catcher- following the idea of Weinstein's 70:30 split mentioned prior. They also found that the hand with which the pitcher throws has a clear effect on stolen base success with lefty pitchers being the harder pitcher to steal off of. Their analysis of "faster base stealers applying pressure is verified through the more recent analysis done by Bogaty, Duncan, and Benz (2017). Bogaty et. al investigated the effect baserunners have on a pitcher's pitch selection in a given situation and discovered a runner on first, one of the fastest runners in the league on first, and one of the top base stealers increase the percentage of fastballs by 2.5%, 5%, and 8% respectively.

As a follow-up to the work done by Bogaty et. al, Wallach, Esrig, and Mathieson (2016) studied how pitchers alter their strategy when there is a runner on first and ultimately find that pitchers don't display any significant changes in pitch location but do tend to also throw fastballs more often- verifying previous work. The researchers conclude that due to the added "pressure" of a potential stolen base, pitchers begin changing their typical sequencing and opt for more fastballs than typical due to them being a defensive/combative approach to a stolen base. Clemens (2021) looked into the post-successful stolen base effect on a pitcher's performance and whether pitchers tend to feel the pressure following the steal. By comparing average runs allowed following a stolen base to expected runs in these situations, Clemens attempts to compare how pitchers react. His analysis finds nothing significant and can not conclude that any pressure is evident following a successful stolen base- pitchers do not perform worse.

E. Modeling

Research pertaining to the worth of a stolen base dates back decades and decades of baseball data. Maury Wills, one of the most successful base stealers of the 1960s, served as research for stolen base analysis in the last 1970s as many baseball fans wanted to know just how impactful Wills was to his team. Smith (1980) attempts to quantify the impact Willis' stolen base numbers had on his team's total number of runs in each of those years by following Pete Palmer's linear weight model, which says that steals are worth 0.2 runs each, caught stealing (and pickoffs) are about 0.35 runs each, and the scoring of 10 additional runs over the course of a season will lead to one additional win. The impact of Wills was quite striking. The analysis shows that in a season only roughly 10 batters in the league contributed as many as three wins, Wills' running was directly responsible for 7 wins over the three seasons, 3 of them in 1962.

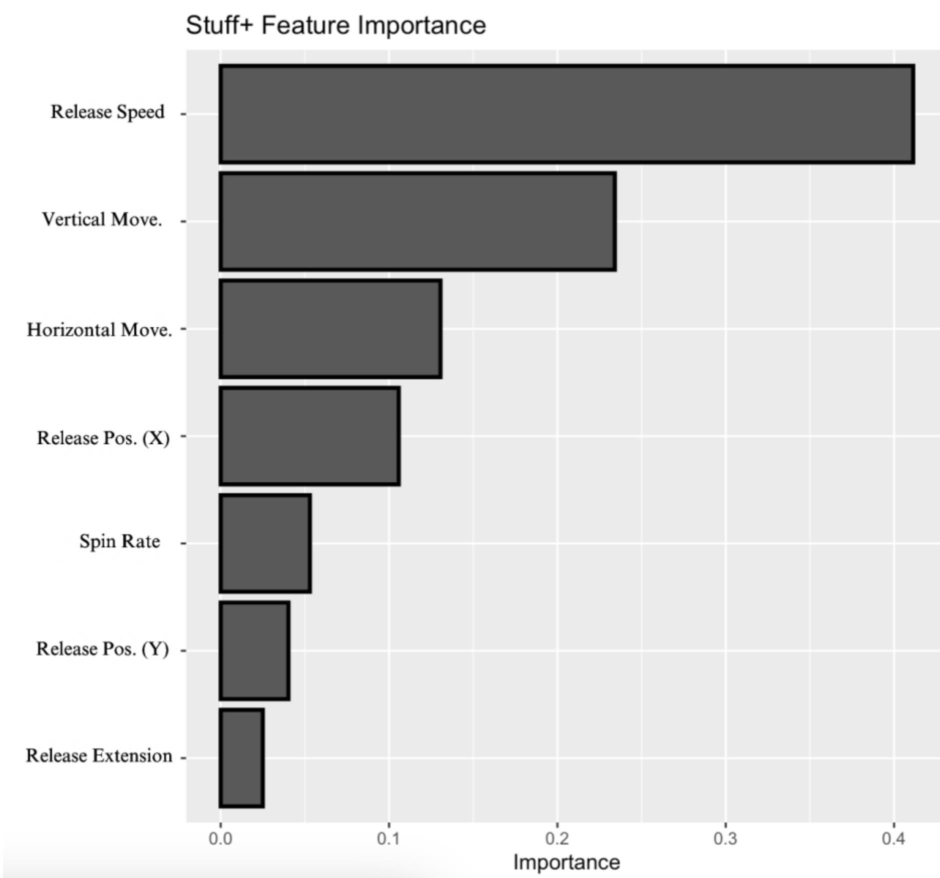
Statistical modeling has developed tremendously since Smith's research in 1980. The analysis of a run has shifted from Palmer's simple linear model to Frank McAfee's, co-founder of SEQNZR, Monte Carlo mathematical model for identifying player worth in terms of runs and wins. This analysis done by SEQNZR, a data-driven strategy company that has a deal with the Cincinnati Reds, looks at the impact of a player in comparison to a replacement-level player and the number of runs that the addition of X player would create for the team. The author also mentions its use in given situations with the output of expected runs (RE216) occurring in that event. The analysis is done using RE216, rather than the more popular RE24 that we've seen in previous papers, as it accounts for baserunner and batter ability more accurately than its counterpart.

Predictive modeling in baseball settings has experienced all forms of game prediction- including the popular MLB app game, Beat the Streak. In an effort to maximize predicting which player will get a hit on a specific day, Alceo and Henriques (2020) expand on their previous work published in 2019 to develop an 81% correct pick ratio through a Multi-layer Perceptron model. Through modeling data from between the 2015 and 2018 seasons and including specific variables that influence hit probability like ballpark dimensions, weather conditions, and pitcher/batter matchup the authors develop three strategies for betting: betting every day on the two most likely batters, according to the model; Betting only when there are batters that are over the pre-defined threshold; Betting only when a set of good batters are over the pre-defined threshold. Sports betting has influenced sports research profusely over recent years. With machine learning techniques increasing in popularity since Google's DeepMind beat the world champion of Go in 2016, machine learning betting models to predict outcomes of games have become of interest to many. Nourse (2021) uses a random forest algorithm with the help of pitch effect, team success, batter performance, and recent-performance controlled effects for both teams to develop a model with a 61.1% accuracy, beating the Vegas betting odds of 58.2% accuracy over the previous six seasons.

Methodology and Data

The data I collected in order to construct my empirical research was pitch-by-pitch data from the 2011 to 2021 MLB seasons via the statcast scraping function from the baseballR package. Using pitch-by-pitch data allows us to look at individual, isolated effects from pitch to pitch to understand how various situations impact a pitcher’s pitch quality. I also gathered baserunner data from FanGraphs, with the two main variables being used to capture a stolen base threat as the number of stolen bases and FanGraphs’ speed rating. In addition, I acquired batter and pitcher performance data such as wRC+ and xFIP to help control for performance measures in our modeling.

The first step in the analysis was to create our measure of pitch quality. As Stuff+ has become so prominent in recent years, I opted to replicate Eno Sarris of The Athletic's XGBoost model to develop a Stuff+ metric which we use as our proxy for pitch quality. This approach uses various pitch tracking variables acquired through statcast to develop an overall pitch quality metric, or Stuff+. The exact variables and the importance of those variables in the model can be seen below.



Other popular features of pitch performance have been popularized recently, including Location+ and Pitching+. Those are two factors that make up a successful pitch, however, we want to focus solely on the effectiveness and efficiency of each pitch as a result of these baserunning factors. Understanding how "nasty" a pitch may be and how less successful a pitch becomes as a result of the threat of a stolen base can tell us a lot about the impact these threats can have on a pitcher's pitch quality.

Once our Stuff+ model was created, we then predicted this number for each pitch in our overall dataset which consisted of just under 4 million observations. This dataset was then joined with our FanGraphs and baserunner speed datasets in order to begin our research. The variables of interest collected for our analysis are batter performance (WRC+), pitcher performance (xFIP), base runner speed (runner on 1st Spd, runner on 1st stolen bases), score difference, pitcher and batter handedness, number of pitches in at bat, inning, and outs. Our empirical strategy is to use a linear regression model to estimate the effects of these variables that may be associated with the decline in a pitcher's pitch quality. Testing these variables will give us insight into the impact of the potential effects and potentially help draw conclusions for how speed and the threat of the stolen base could damage a pitcher's pitch quality.

The summary statistics from our variables for both the Stuff+ model and empirical research are presented below. These statistics are split up by different stolen base situation settings, giving us some understanding as to what our results may possibly entail. We can briefly see that a pitcher's Stuff+ decreases slightly with a runner on first only compared to a runner on second and a runner on first and second. Intuitively this makes sense as we see more stolen bases in settings with just a runner on first, meaning the pressure effects would be greater in these settings. We also observe that the mean Spd rating for a runner on 1st and 2nd is lower than with just a runner on second. To follow that, the Stuff+ rating is also higher in these situations with a lower Spd rating, meaning the effects of a stolen base may be felt more with a higher speed or stolen base total. This is a possible sign of our results following what we initially hypothesized. The summary statistics also confirm that adjustments need to be made in our dataset before we begin our modeling. We see the minimum pitch speed in our dataset is 36 miles per hour, meaning that our collected data consists of position players pitching. Thus we filter them out by only including games with a run difference of less than 10.

Summary Statistics (Runner on 1st Only)

Statistic	Min	Median	Mean	Max	St. Dev.
Inning	1	5	4.9	19	2.6
Outs	0	1	1.1	2	0.8
Home Score	0	1	2.3	29	2.6
Away Score	0	2	2.4	24	2.7
Swinging Strike (Binary)	0	0	0.1	1	0.3
Pitch Speed	36.3	90.2	88.9	104.4	5.8
Pitcher Release Position (X)	-5.4	-1.5	-0.7	5.2	1.9
Pitcher Release Position (Y)	50.0	54.3	53.8	58.2	1.5
Horizontal movement in feet	-3.6	-0.3	-0.2	2.9	0.9
Vertical movement in feet	-2.1	0.9	0.7	4.0	0.7
Spin Axis	0	197	180.7	360	66.6
Release Extension (Ft.)	0.0	6.1	6.1	9.0	0.5
Raw Stuff	-0.1	0.1	0.1	0.8	0.04
Stuff+	84.7	99.5	99.9	170.3	3.6
1st Base Runner BsR	-70.5	1.3	2.8	74.4	18.2
1st Base Runner SB	0	30	51.4	336	62.0
1st Base Runner CS	0	13	18.2	111	18.4
1st Base Runner Spd	0.0	4.1	4.2	9.3	1.5

Summary Statistics (Runner on 2nd Only)

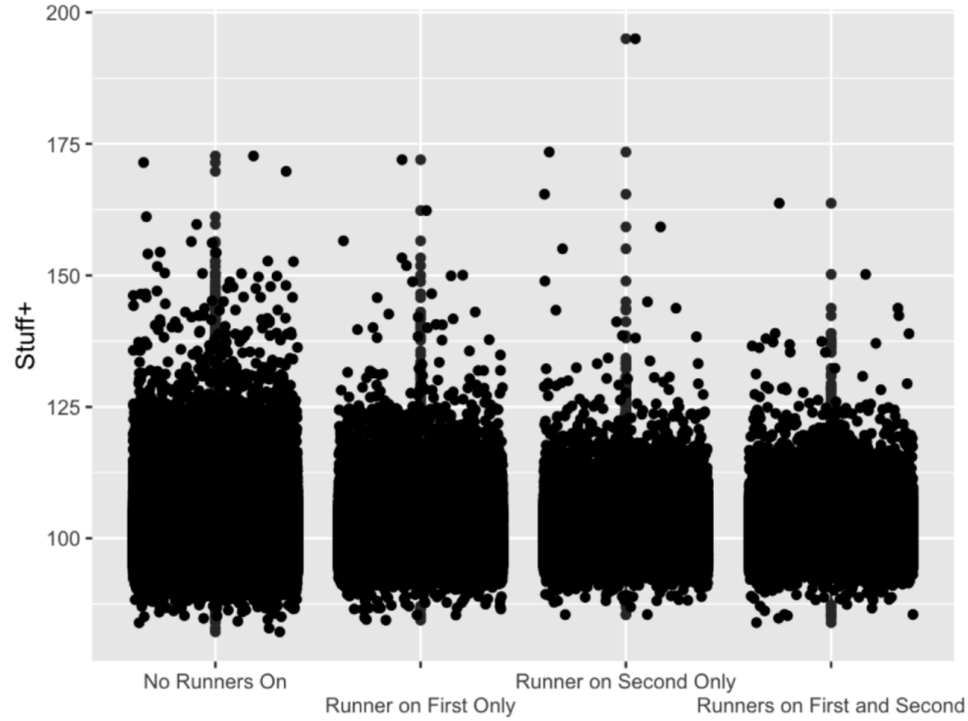
Statistic	Min	Median	Mean	Max	St. Dev.
Inning	1	5	5.0	19	2.7
Outs	0	1	1.2	2	0.8
Home Score	0	2	2.4	25	2.7
Away Score	0	2	2.5	23	2.7
Swinging Strike (Binary)	0	0	0.1	1	0.3
Pitch Speed	37.6	89.3	88.4	104.6	6.1
Pitcher Release Position (X)	-6.4	-1.5	-0.8	5.1	1.9
Pitcher Release Position (Y)	46.8	54.3	53.8	57.4	1.5
Horizontal movement in feet	-3.5	-0.2	-0.2	2.6	0.9
Vertical movement in feet	-4.5	0.8	0.7	5.0	0.8
Spin Axis	0	195	177.4	360	71.0
Release Extension (Ft.)	3.1	6.1	6.1	13.7	0.5
Raw Stuff	-0.1	0.1	0.1	0.9	0.04
Stuff+	84.3	99.9	100.2	182.6	3.6
2nd Base Runner BsR	-70.5	2.6	4.4	74.4	18.3
2nd Base Runner SB	0	34	56.3	336	66.2
2nd Base Runner CS	0	14	19.3	111	19.2
2nd Base Runner Spd	0.1	4.4	4.4	9.3	1.6

Summary Statistics (Runner on 1st and 2nd)

Statistic	Min	Median	Mean	Max	St. Dev.
Inning	1	5	5.0	19	2.7
Outs	0	1	1.2	2	0.8
Home Score	0	2	2.5	29	2.7
Away Score	0	2	2.6	23	2.8
Swinging Strike (Binary)	0	0	0.1	1	0.3
Pitch Speed	39.6	89.8	88.7	103.8	6.0
Pitcher Release Position (X)	-5.5	-1.5	-0.8	5.3	1.9
Pitcher Release Position (Y)	50.0	54.3	54.0	57.3	1.3
Horizontal movement in feet	-2.5	-0.2	-0.1	2.3	0.9
Vertical movement in feet	-9.9	0.8	0.7	3.7	0.7
Spin Axis	0	195	177.8	360	70.5
Release Extension (Ft.)	3.2	6.2	6.1	8.7	0.5
Raw Stuff	-0.04	0.1	0.1	0.8	0.04
Stuff+	85.7	99.9	100.3	170.0	3.6
1st Base Runner BsR	-70.5	1.1	2.3	74.4	18.2
1st Base Runner SB	0	29	49.9	336	60.6
1st Base Runner CS	0	13	17.6	111	18.0
1st Base Runner Spd	0.1	4.1	4.2	9.3	1.5
2nd Base Runner BsR	-70.5	1.0	2.3	74.4	17.5
2nd Base Runner SB	0	28	49.1	336	60.3
2nd Base Runner CS	0	12	17.4	111	17.9
2nd Base Runner Spd	0.0	4.1	4.2	9.3	1.5

Our initial findings based on these summary statistics can be reconfirmed through Figure 1. We notice a slight decrease in average and max Stuff+ with runners on first or second, which provides a basic understanding of potential pressure effects being exhibited in terms of pitch quality. As we place more runners on base, the quality of a pitcher's pitch slightly decreases. To be more precise, the average stuff+ with no runners on is just under 100, however, average Stuff+ decreases to 99.5 with a runner on first and 99.9 with a runner on second. Without any added speed element, we can already see a bit of influence stolen base settings may have on the success of a pitcher's pitches.

Figure 1
Comparison of Stuff+ by Situation



Model Results

The first situation we look at is the effects of a few variables, including runner speed, stolen bases, score difference and count on pitch quality with various baserunner situations. The results, using a linear regression model, are displayed below in Table 1.

Table 1

	Dependent variable:		
	Stuff+		
	Runner on 1st Only	Runner on 2nd Only	Runners on 1st and 2nd
	(1)	(2)	(3)
wRC+	0.006***	0.006***	0.006***
	(0.0002)	(0.0003)	(0.0002)
xFIP	-0.716***	-0.748***	-0.692***
	(0.008)	(0.012)	(0.012)
1 Out	0.172***	0.241***	0.147***
	(0.011)	(0.018)	(0.019)
2 Outs	0.355***	0.368***	0.359***
	(0.011)	(0.017)	(0.018)
Inning	0.108***	0.104***	0.096***
	(0.002)	(0.002)	(0.002)
Runner on 1st Spd	0.008**		
	(0.004)		
Runner on 1st Stolen Bases	-0.001***		
	(0.0001)		
Runner on 2nd Spd		0.039***	0.055***
		(0.005)	(0.006)
Runner on 2nd Stolen Bases		-0.001***	-0.002***
		(0.0001)	(0.0001)
Score Dif	0.005	0.003	-0.003
	(0.005)	(0.007)	(0.007)
Pitcher Throws (Right)	0.111***	0.245***	0.208***
	(0.009)	(0.015)	(0.015)
Batter Stance (Right)	0.275***	0.268***	0.245***
	(0.009)	(0.013)	(0.013)
Count: 0-1	0.525***	0.268***	0.233***
	(0.017)	(0.027)	(0.027)
Count: 0-2	1.215***	0.960***	0.914***
	(0.029)	(0.043)	(0.044)
Count: 1-0	0.300***	0.150***	-0.222***
	(0.018)	(0.028)	(0.028)
Count: 1-1	0.628***	0.350***	0.125***
	(0.025)	(0.037)	(0.038)
Count: 1-2	1.241***	1.012***	0.865***
	(0.037)	(0.053)	(0.056)
Count: 2-0	-0.187***	0.044	-0.773***
	(0.031)	(0.044)	(0.047)
Count: 2-1	0.482***	0.410***	-0.077
	(0.036)	(0.051)	(0.055)
Count: 2-2	1.139***	0.952***	0.690***
	(0.048)	(0.067)	(0.073)
Count: 3-0	-1.520***	-1.520***	-2.033***
	(0.051)	(0.069)	(0.077)
Count: 3-1	-0.449***	-0.027	-1.004***
	(0.050)	(0.068)	(0.075)
Count: 3-2	0.727***	0.790***	0.054
	(0.061)	(0.085)	(0.092)
Pitch Number	0.008	-0.026*	0.001
	(0.010)	(0.014)	(0.015)
Runner on 1st Stolen Bases X Score Dif	0.0001**		
	(0.00003)		
Runner on 1st Spd X Score Dif	-0.002		
	(0.001)		
Runner on 2nd Stolen Bases X Score Dif		-0.00001	0.00003
		(0.00005)	(0.00005)
Runner on 2nd Spd X Score Dif		0.0004	0.001
		(0.002)	(0.002)
Observations	776,925	337,547	321,545
R^2	0.043	0.037	0.040
Adjusted R^2	0.043	0.037	0.040
Residual Std. Error	3.677 (df = 776900)	3.716 (df = 337522)	3.696 (df = 321520)
F Statistic	1,459.108*** (df = 24; 776900)	540.883*** (df = 24; 337522)	556.594*** (df = 24; 321520)
Note:			*p<0.1; **p<0.05; ***p<0.01

When analyzing these results, the first thing we notice is that both the runner speed and runner stolen base variables are statistically significant for all three situations. However, the coefficients of two variables display opposite signs with speed being positive and stolen bases being negative. This finding displays how player speed may not be as influential in affecting a pitchers performance as the actual likelihood of a stolen base attempt may. We can interpret the stolen base coefficient for a runner on 1st only as a 1 stolen base increase leading to a 0.001 decrease in Stuff+. The greatest effect magnitude of all variables in the initial model is the 3-0 count variable which contributes greatly to a decrease in quality of pitches. In that specific setting where batters are most likely taking the pitch no matter what, pitchers typically don't produce the best pitches in terms of quality. Relating this to the base stealing "pressure" scenario, pitchers on average do worse in quality in higher pressure situations i.e. needing to throw a strike. Interestingly enough, the score difference coefficient as well as the score difference and runner speed and stolen base interaction variables are not statistically significant. We can conclude that the speed of a base runner and their likelihood of stealing does not have a great effect on the quality of a pitcher's pitch in our first model (all events).

Table 2, as depicted below, takes a look at the effects of the aforementioned variables on Stuff+ in various situations. By introducing different game situations, we can understand how these effects vary as a result. In the second model, which is constricted to just the 7th inning or later, we follow a similar pattern to the original model with the runner on first stolen base total being statistically significant and negative. In these results however we also see the runner on first speed interaction term be statistically significant and negative as well, our first indication of base runner speed rating playing a role in a decreased Stuff+ number. This finding also tells us that the closer a game gets in late innings, the greater the effect on pitcher performance. In a one run game, the magnitude of the runner on first base stolen base total is greatest with a 1 stolen base increase leading to a 0.002 decrease in Stuff+. In the 4th model, the 7th inning or later and 1 run game model, both the runner on 1st speed and runner on 1st stolen base variables are negative and statistically significant, the first model in which both have displayed similar effects. As a game gets later and the score is within a run, pitchers typically experience greater pressure of succeeding a stolen base and experience a worse Stuff+.

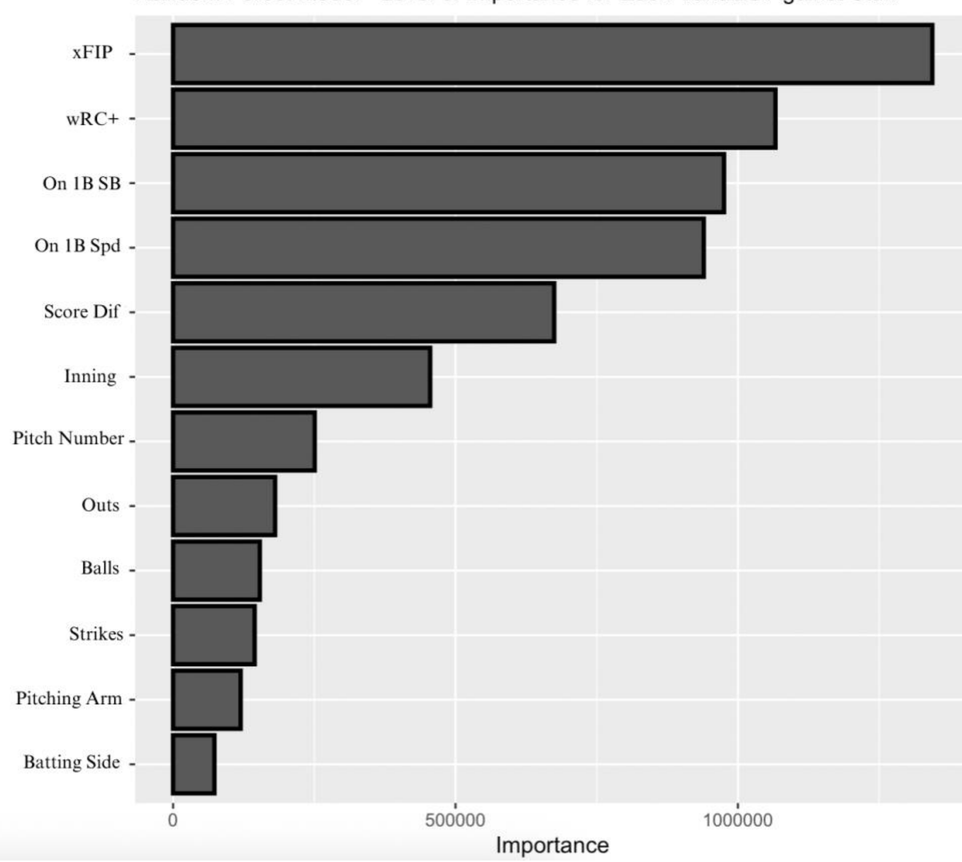
Table 2: Analysis of Runner on 1st Only

	Dependent variable:			
	Stuff+			
	All Situations	7th Inning or Later	1 Run Game	1 Run Game & 7th Inning or Later
	(1)	(2)	(3)	(4)
wRC+	0.006^{***}	0.006^{***}	0.006^{***}	0.006^{***}
	(0.0002)	(0.0004)	(0.0002)	(0.001)
xFIP	-0.766^{***}	-0.836^{***}	-0.833^{***}	-0.961^{***}
	(0.008)	(0.014)	(0.011)	(0.023)
Runner on 1st Spd	0.014^{***}	-0.004	0.011^{**}	-0.018^{*}
	(0.004)	(0.006)	(0.005)	(0.011)
Runner on 1st Stolen Bases	-0.002^{***}	-0.001^{***}	-0.002^{***}	-0.001^{***}
	(0.0001)	(0.0002)	(0.0001)	(0.0003)
Score Dif	0.002	0.021^{***}	-0.057^{**}	-0.104^{*}
	(0.005)	(0.007)	(0.027)	(0.054)
Pitcher Throws (Right)	0.143^{***}	0.091^{***}	0.089^{***}	-0.100^{***}
	(0.009)	(0.018)	(0.013)	(0.030)
Batter Stance (Right)	0.271^{***}	0.299^{***}	0.253^{***}	0.331^{***}
	(0.009)	(0.015)	(0.012)	(0.026)
Count: 0-1	0.524^{***}	0.534^{***}	0.524^{***}	0.358^{***}
	(0.017)	(0.031)	(0.024)	(0.052)
Count: 0-2	1.219^{***}	1.242^{***}	1.220^{***}	1.057^{***}
	(0.029)	(0.051)	(0.040)	(0.087)
Count: 1-0	0.298^{***}	0.069^{**}	0.351^{***}	0.002
	(0.018)	(0.033)	(0.025)	(0.055)
Count: 1-1	0.625^{***}	0.535^{***}	0.657^{***}	0.431^{***}
	(0.025)	(0.045)	(0.035)	(0.077)
Count: 1-2	1.238^{***}	1.192^{***}	1.259^{***}	1.020^{***}
	(0.037)	(0.066)	(0.052)	(0.113)
Count: 2-0	-0.191^{***}	-0.386^{***}	-0.025	-0.216^{**}
	(0.031)	(0.056)	(0.043)	(0.095)
Count: 2-1	0.479^{***}	0.236^{***}	0.563^{***}	0.164
	(0.036)	(0.065)	(0.051)	(0.110)
Count: 2-2	1.137^{***}	1.088^{***}	1.146^{***}	0.862^{***}
	(0.048)	(0.087)	(0.068)	(0.148)
Count: 3-0	-1.523^{***}	-1.326^{***}	-1.431^{***}	-1.230^{***}
	(0.051)	(0.093)	(0.071)	(0.154)
Count: 3-1	-0.454^{***}	-0.558^{***}	-0.317^{***}	-0.429^{***}
	(0.050)	(0.090)	(0.070)	(0.153)
Count: 3-2	0.722^{***}	0.604^{***}	0.797^{***}	0.553^{***}
	(0.061)	(0.110)	(0.086)	(0.187)
Pitch Number	0.008	-0.0005	0.018	0.039
	(0.010)	(0.018)	(0.014)	(0.030)
Runner on 1st Stolen Bases X Score Dif	0.0001^{**}	0.00005	0.00003	0.0001
	(0.00003)	(0.00004)	(0.0002)	(0.0003)
Runner on 1st Spd X Score Dif	-0.001	-0.005^{***}	0.011	0.011
	(0.001)	(0.002)	(0.007)	(0.014)
Observations	776,925	236,003	398,227	84,676
R^2	0.036	0.039	0.038	0.040
Adjusted R^2	0.036	0.038	0.038	0.040
Residual Std. Error	3.691 (df = 776903)	3.690 (df = 235981)	3.684 (df = 398205)	3.715 (df = 84654)
F Statistic	$1,385.245^{***}$ (df = 21; 776903)	450.965^{***} (df = 21; 235981)	753.497^{***} (df = 21; 398205)	167.666^{***} (df = 21; 84654)
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Tackling this question from a machine learning perspective can give us a greater insight to how these variables interact with each other on a greater level. This process can give us more information about what impacts a pitcher's pitch quality and which variables contribute the most to that effect. Figure 2 below shows the results of the level of importance for each variable in a Random Forest Model against Stuff+. We see that xFIP, our proxy for pitcher performance, is the most critical variable in determining Stuff+ with the batter-skill control variable, wRC+ right behind. The following two variables, in terms of importance, are our baserunner variables with the number of stolen bases being slightly more important than speed. This details how our hypothesis of the threat of a stolen base being even more apparent in damaging the success of a pitcher's pitch quality.

Figure 2

Random Forest Model - Level of Importance for Each Variable Against Stuff+



The visualization below details the impact of both the runner on first base speed and the runner on first base stolen bases on pitch quality. We see that as we increase both speed and stolen bases, the average Stuff+ for pitchers drops. This effect increases even greater for the fastest groups in both categories as pitchers lose quality the greatest in those events.

Difference in Stuff+ By Career Stolen Bases

2011 to 2021 Seasons | Runner on 1st Only

RUNNER STOLEN BASES	AVERAGE SPD	AVERAGE SB	AVERAGE STUFF+
0 to 9	2.67	3.63	100.03
10 to 50	4.05	26.67	99.99
51 to 73	4.85	63.45	99.97
74 to 392	5.61	142.66	99.83

Difference in Stuff+ By Baserunner Spd

2011 to 2021 Seasons | Runner on 1st Only

RUNNER SPD	AVERAGE SPD	AVERAGE SB	AVERAGE STUFF+
0.1 to 2.5	1.97	4.98	100.01
2.6 to 5	3.85	36.80	99.99
5.1 to 7.5	5.96	111.60	99.87
7.6 to 9.4	8.15	183.85	99.69

Discussion & Conclusion

The results across the models confirm our initial hypothesis that pitcher's ultimately do in fact experience a decrease in the quality of their pitches when placed in stolen base situations. These effects are noticeable in late game situations as well as when the game is close and are even greater when more is on the line i.e. it's the 7th inning or later as well as a one run game. We also identify the general importance of specific base runner characteristics of our model through a random forest and reconfirm that these variables are significant and indicative of having a factor on pitching quality. This verifies our psychological idea that pitchers do suffer from pressure effects given by a potential stolen base and can ultimately have their performance hindered by an increased likelihood of a stolen base attempt. We do find it surprising that the runner stolen base number was far more critical than the runner speed metric throughout the various models. Intuitively, I suspected that base runner speed would lead to similar effects as stolen bases as speed essentially captures the strength of a stolen base stealer. However, our analysis confirms that the FanGraphs speed metric does not necessarily capture base stealing likelihood as well as career stolen bases and thus pitchers are not as affected by base runner speed.

With pitcher biomechanics becoming increasingly popular over the last few years and the introduction of pitcher pitch quality through concepts like Stuff+, we are now able to analyze how various effects influence that measure. By understanding how external factors in a stolen base setting play a role on pitcher performance, we can identify possible edges or market gains in baseball. Staples in the game of baseball like the stolen base or the hit and run may reap additional benefits from this information and add more action in the game.

With the new MLB rule changes beginning in the 2023 season, future research could potentially look at how the magnitude of these effects are changed by the pitch clock and bigger bases. Stolen bases have gone up so far this season as teams have been more willing to take a risk. It will be interesting to see if pitch quality declines even further because of increased stolen base threats and how teams are able to take advantage of this opportunity.

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