The 4-Seam Fastball: Spin Effects and Effects of Spin

Introduction

Sports constantly change in how they are played. Elements of a game that may not have been valued before can suddenly have tremendous value. In recent years, technology has given access to information and analytics that the past missed out on. One technology driven aspect of baseball that surfaced in the last few years analyzes the spin rate of the baseball, with a specific focus on the spin rate of a pitch. The baseball community tends to value higher spin pitches and marvel at pitchers with incredibly high spin rates. As someone who has followed and played the game of baseball as a pitcher for a long time and at the college level, I have learned to understand how the spin of a pitch affects how the ball moves. Backspin allows the ball to not drop as much as it constantly falls due to gravity, just as top spin causes the ball to drop even more, such as on a curveball. Sidespin moves the ball to the side. The different pitches that pitchers throw, such as a fastball, slider, or changeup, come from pitchers manipulating the spin of the baseball. Due to the way a pitcher releases each of these pitches, different pitches will spin at different rotations per minute (rpm). As this information becomes more and more accessible, it has the opportunity to affect the game at many levels.

The baseball world has centered most of its focus around the spin rate of fastballs. There are multiple types of fastballs, but general knowledge says that 4-seam fastballs have the highest spin out of fastballs, so this paper will analyze four seam fastball spin as its variable of interest. Pitchers generate more spin on 4-seam fastballs due to them having a better grip on a specific seam on the baseball, allowing for them to pull across the baseball with a greater force. Since fastballs spin with backspin, higher fastball spin will prevent the ball from falling quite as much. Nowadays, pitchers pitch at such speeds that a hitter's brain needs to predict where it thinks the ball will be at a certain point[1]. With a high spin fastball, the ball might be higher than the brain projects it to be, and to the hitter it will appear as if the ball jumps upwards, which is an impossibility due to gravity. This phenomenon where the baseball "jumps up" is often called "getting good ride" on the fastball. This should make hitting very difficult as the hitter would have a harder time squaring up the baseball. Additionally, if spin does help a pitcher's performance, will they utilize their gift if they have a high spin rate and throw more fastballs? With spin being seemingly so important, this paper will aim to find factors that may or may not influence spin, as well as answer the questions does spin actually increase performance and if so, do players take advantage of this? The answers to these questions could help coaches better understand how to develop and recruit pitchers as well as how to utilize their talents.

Model

Given that higher spin should theoretically make hitting much more difficult than it already is, a pitcher with a high spin rate should have greater success. The problem that coaches face is that nobody knows much of how to increase a player's spin without using illegal substances for extra grip such as pine tar. Some pitchers have higher spin than others but increasing an individual's spin poses a challenge. People don't even have much knowledge of

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[1] Stromberg, Joseph. "How the Human Brain Tracks a 100-mph Fastball." *Smithsonian Magazine*. May 8, 2013. https://www.smithsonianmag.com/science-nature/how-the-human-brain-tracks-a-100-mph-fastball-55036022/

what leads some pitchers to have higher or lower spin than others, much less a factor on which they could improve.

There are some factors that logically seem like they should influence spin, and this paper will analyze some of them. These factors will be physical attributes such as height, weight, handedness, and how hard the pitcher throws, as well as environmental attributes such as temperature and altitude. Spin is created by the pitcher releasing the ball off of their fingers, so one would expect that a higher force on the ball upon release would induce higher spin. Taller players could possibly use their longer levers to create that force. Heavier players will have more weight behind the ball, which would increase momentum. Players that throw harder are obviously creating more force than those that throw slower. Temperature and altitude could positively affect how the ball flies, and possibly spins, through the air. For example, a study in 2008 found that the average fly ball at the Colorado Rockies stadium in Denver, almost a mile above sea level, flies 303 feet, while the average at the other 13 parks in the National League was 285 feet[2]. Handedness should not affect the spin of the baseball since neither lefties nor righties have genetic advantages over others, but it will tell us if spin is a sought-after attribute. A higher percentage of the population is right-handed. With a larger pool of players, the average talent of righties should be higher than that of lefties. If spin is a sought-after attribute, righties having more spin should reflect that. Another factor to consider would be the age of a pitcher, as their physical abilities might decline as they grow older. The final factor to take into account will be whether the pitcher is a relief pitcher or a starting pitcher. Starting pitchers pitch more innings, and therefore may need to conserve energy, possibly leading to less spin. With all of our factors listed, we can write up a model.

$$Spin = \propto_1 Age + \propto_2 Position + \propto_3 Height + \propto_4 Weight + \propto_5 Hand + \propto_6 Temperature + \propto_7 Altitude + \propto_8 Velocity$$

One issue that could arise will be multicollinearity between independent variables that have relationships of their own. When we run the data, we will find which variables this impacts, and run a new regression on spin with interaction variables that take into account the relationships that exist between certain independent variables. The values of an interaction variable are simply the product of the values of the two variables to be analyzed. The new models with interaction variables will be discussed and displayed in the results and analysis section of this paper.

We also want to analyze how spin affects success. However, spin may not be the only factor. We must also consider other pitches, such as breaking balls. Higher spin breaking balls move more and move more sharply, which should make them more difficult to hit. This will likely increase a pitcher's success. The velocity at which a pitcher throws the ball should also have a large positive effect, so this must also be considered. Finally, location of the pitch can make the difference of an easy pitch to hit and a difficult pitch to hit. For this, we must take

[2] Chambers, Frederick, Brian Page, and Clyde Zaidins. "Atmosphere, weather, and baseball: How much farther do baseballs really fly at Denver's Coors Field?." *The Professional Geographer* 55, no. 4 (2003): 491-504.

location into account when analyzing the success of a pitcher. This leaves us with the following model:

$$Success = \propto_1 Velocity + \propto_2 Four\ Seam\ Spin + \propto_3 Breaking\ Ball\ Spin + \propto_4 Location$$

The same procedure used to address multicollinearity in the spin model will be utilized in this model.

The final model that relates to this topic is how coaches utilize spin. We want to test 4-seam spin versus 4-seam usage to see how valued spin is within strategy. Other factors that can affect 4-seam usage would be 4-seam velocity and breaking ball spin. We would expect velocity to have a positive effect on usage. We also recognize that pitchers with exceptionally good breaking balls will throw less fastballs, so breaking ball spin must be accounted for. This creates the model:

$$Four\ Seam\ Usage\ Rate = \propto_1 Velocity + \propto_2 Four\ Seam\ Spin + \propto_3 Breaking\ Ball\ Spin$$

The interaction variables may also need to be used to adjust this model.

Data

There will be multiple ways to measure some of the discussed variables, so we will clarify how we intend to measure them and from where we got our data. The website Baseball Savant[3], created by Daren Willman and run together with Major League Baseball, has data on many different aspects of the game. Users can create custom data tables filled with many different statistics of all MLB players. They have the average 4-seam spin of all pitchers that throw 4-seam fastballs. We begin by finding this data from all pitchers that faced a minimum of 50 hitters in 2019. We will use 2019 data since this is the most recent full 162-game season played by the MLB. Given all of the conditions, this left us with 602 pitchers in the data set. We then collect the rest of the data only on these 602 pitchers. Baseball Savant provides users with average fastball velocity, their handedness, their height and weight, their age in 2019, their breaking ball spin, and meatball percentage. Meatball percentage is a measure of the rate a pitcher throws the ball in the middle of the strike zone, the easiest area to hit for most hitters.

In our model for spin, we can use the age data for the age variable. The position variable proves a little more complicated because some pitchers start and relieve in games, but since starters typically throw more innings per game than relief pitchers, we can use a variable of innings pitched per game to replicate this factor. This also control for the fact that some relievers throw more innings per appearance than other relievers. Baseball Savant gives users innings and appearance data as well. Height will be measured in inches and weight in pounds. Handedness can be represented with a binary variable, with a "1" representing right handers.

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[3] Willman, Daren. "Custom Leaderboard." *Baseball Savant*.
https://baseballsavant.mlb.com/leaderboard/custom?year=2019&type=pitcher&filter=&sort=4&sortDir=asc&min=q&selections=xba,xslg,xwoba,xobp,xiso,exit_velocity_avg,launch_angle_avg,barrel_batted_rate,&chart=false&x=xba&y=xba&r=no&chartType=beeswarm

Temperature and altitude will be measured in Fahrenheit and feet, respectively. Lastly, velocity is represented with miles per hour.

In our model explaining success, we first must decide how to define success. One statistic that is used is weighted on base average, or wOBA. This is similar to on base percentage, the rate at which hitters get on base, but it weights how they get on base, giving more weight to better hits such as homeruns or triples and less weight to singles or walks. The measure of success of a pitcher can be the wOBA hitters have against him. Another statistic expected wOBA, or xwOBA, factors in the trajectory and speed of each hit and finds what the expected result would be for that ball. We will use xwOBA, as it factors in how the ball was hit and leaves less up to luck, since sometimes poorly hit balls can be hits and well struck balls end up being outs. This brings us to our next measure of success: hard-hit percentage – the percentage of hits in play given up by a pitcher that are hit hard. 4-seam spin will me found as before, as will velocity. We measure breaking ball spin the same as 4-seam spin, and location will be represented with meatball percentage. One important note is that 4-seam usage, hard-hit percentage, and meatball percentage were both collected as the percentage value, rather than a decimal (43.4% is 43.4 instead 0.434). Now that we have assessed how we will model these variables, we can run a regression on them and find the effects.

Results and Analysis

First, we will run the model for spin. We perform a regression on the factors listed, and the results can be found in Table 1 in the Appendix, along with all tables used in this discussion. Only two variables showed statistically significant effects: age and velocity. Before we begin to interpret the results, we must account for multicollinearity. We do this by incorporating interaction variables. These interaction variables account for the relationships between these factors. Many of these variables could have a dependency with velocity. In order to find which variables, we can run a regression with all of the independent variables found in Table 1 versus velocity. One more variable will also be added. Since height and weight have a correlation, we must include an interaction variable for these two factors. The model for velocity is as follows.

$$\begin{aligned} Velocity = &\propto_1 Age + \propto_2 Position + \propto_3 Height + \propto_4 Weight + \propto_5 Hand \\ &+ \propto_6 Temperature + \propto_7 Altitude + \propto_8 Height * Weight \end{aligned}$$

The results from the regression on velocity are shown in Table 2. We find that every variable with the exception of altitude has a statistically significant effect on velocity. Every variable had the expected effect. We see that age has a negative correlation with velocity, which makes intuitive sense given that player's physicality declines with age. Relievers will throw harder than starters as well, at a rate of 0.3 mph per 1 less inning pitched per game. Given that many relievers throw less than 1 inning per appearance and many starters throw more than 5, relievers could be throwing over 1 mph faster than starters on average. This likely results from starters needing to conserve their energy over the course of a game. Height and weight both have positive effects on velocity, which is to be expected as longer levers and more momentum should create more force on the ball. Right handers throw harder than left handers, about 1.6 mph harder. This is likely not true for all baseball players at all levels cumulatively, but since there are more right handers than left handers in the world, the MLB can recruit from a higher talent level when it comes to right handers. This also shows that teams value velocity in recruitment, or else there would not exist a difference. Temperature has a positive effect as well, which follows from the general consensus amongst pitchers that their arms feel healthier in warm weather. The increase in velocity from temperature could be a result of this or it could possibly be the characteristics of the air. The height-weight interaction variable also had an effect, showing a negative correlation with velocity. This corrects the multicollinearity that is caused by the height and weight variables, which inflates their respective coefficients. The effect of height on velocity can be interpreted as 0.773 - 0.003*Weight. The same adjustment is made for weight with its own coefficient and the relationship with height. Finally, the R-square value for this model was low, at about 0.27. This means that other variables that we have not considered greatly affect velocity.

Since many variables had an effect on velocity, we must now include interaction variables for each of them paired with velocity in a new regression model for spin. This new model is the following:

$$\begin{aligned} Spin = {} & \propto_1 Age + \propto_2 Position + \propto_3 Height + \propto_4 Weight + \propto_5 Hand + \propto_6 Temperature \\ & + \propto_7 Altitude + \propto_8 Velocity + \propto_9 Height * Weight + \propto_{10} Age * Velocity \\ & + \propto_{11} Position * Velocity + \propto_{12} Height * Velocity + \propto_{13} Weight * Velocity \\ & + \propto_{14} Height * Weight * Velocity + \propto_{15} Hand * Velocity \\ & + \propto_{16} Temperature * Velocity \end{aligned}$$

We see the results for the new spin model's regression displayed in Table 3. The interaction variables drastically changed the resulting coefficients and significance levels. No independent variables remain statistically significant, and none of them were anywhere close to significance. Additionally, velocity has taken a negative correlation with spin, which does not make any intuitive sense. This number is not statistically significant however, and the upper bound for a 95% confidence interval ranges far above 0. Velocity could still have a positive effect, but this regression cannot confirm that for us. The R-square for this regression also came out very low, at around 0.12. There are clearly many factors outside of this model that impact spin.

What we learn from the models of the effects on velocity and effects on spin is that velocity is much more controllable than spin. The low R-square on each mean that other factors influence velocity and spin. These factors are likely to be limited to two cases: pitching mechanics (being the movement patterns a pitcher has when pitching) and how well someone moves. Better mechanics could increase velocity or spin without changing any of the current independent variables. Additionally, one person could have the same height and weight as another person but might be stronger or more explosive in their movements than the other. This could result in more velocity and spin. These two factors would prove difficult to account for in an analysis. Strength could possibly be represented with weight-lifting numbers, but mechanics are completely intangible.

Despite the difficulty in finding what might cause spin, we still want to analyze its effect on success. The general public tends to believe that more spin leads to higher success. We first run the regression of the aforementioned model for success using xwOBA as the measure of success. The results are found in Table 4. This regression showed 4-seam velocity and 4-seam spin to have statistically significant negative effects. Remembering that a lower xwOBA against for a pitcher is better, this means that better spin and velocity correlate to better success. However, multicollinearity may exist between 4-seam spin and breaking ball spin. These two variables have a very statistically significant relationship with 4-seam spin correlating to 0.72 of the breaking ball spin rates. After incorporating a 4-seam spin and breaking ball spin interaction variable into the model, we have:

$$Success = \propto_1 Velocity + \propto_2 Four\ Seam\ Spin + \propto_3 Breaking\ Ball\ Spin + \propto_4 Location \\ + \propto_5 Four\ Seam\ Spin * Breaking\ Ball\ Spin$$

We find that only 4-seam velocity remains statistically significant, with a negative effect on xwOBA. The standard error for xwOBA was 0.0415, and a decrease of this much requires an increase of 18.7 mph, a very large number, with velocity's standard error at about 2.2 mph. Thus, while velocity has a statistically significant effect, the effect is fairly small. Again, the R-square remains very low, at less than 0.05. Many variables not included in this regression have an effect on xwOBA such as the hitters against which the pitchers pitch.

Next, we want to find if a different measure of success produces different results. We will use hard-hit percentage as our second measure of success. In this model, we include the interaction variable for 4-seam spin and breaking ball spin. The results of this regression can be seen in Table 6. 4-seam velocity actually takes on a positive effect on hard-hit percentage with about 5 mph correlating to an increase of 1% hard hits. Velocity has a standard error of about 2.2 mph and hard-hit percentage's is 5.5%, so this effect is not very economically significant as it would take a very large increase in velocity in order to increase hard-hit percentage by a noteworthy amount. This positive effect could make intuitive sense. Common baseball knowledge says that a player can hit a faster ball harder with the same amount of effort, but in a game, a faster ball should be harder to make quality contact with. According to this regression, the former takes over the latter. Since higher velocity results in higher hard-hit percentage, one might think that the xwOBA should be higher as well. Hard-hit percentage only takes into account balls that were put into play, so it is likely that higher velocity results in more swings and misses. Using hard-hit percentage, meatball percentage now has a positive effect on this measure of success, meaning it has a negative effect on success itself. This makes intuitive sense since hitters can hit meatballs better and more consistently, resulting in a decrease in success of a pitcher who throws a lot of meatballs. An increase of .44% meatballs leads to an increase of about 1% hard hits. This model has a very low R-square at 0.034, meaning there are many variables that affect hard-hit percentage for which we have not accounted, such as the hitters against which the pitchers face. Overall, it appears that velocity can have mixed results in terms of success, but spin does not have an effect on the success of a pitcher.

The last aspect of spin we would like to analyze is its perceived value. That is, do coaches and players believe that higher spin helps success. We can model this by running a regression of 4-seam spin versus 4-seam usage. Breaking ball spin and 4-seam velocity must be taken into account, and we expect these to have negative and positive effects on 4-seam usage, respectively. Since 4-seam spin and breaking ball spin are both in this model, we must also include their interaction variable. This new model is as follows:

$$\begin{aligned} Four\ Seam\ Usage\ Rate \\ &= \propto_1 Velocity + \propto_2 Four\ Seam\ Spin + \propto_3 Breaking\ Ball\ Spin \\ &+ \propto_4 Four\ Seam\ Spin * Breaking\ Ball\ Spin \end{aligned}$$

The results from this model are in Table 7. 4-seam spin has a fairly statistically significant (95%) positive effect on 4-seam usage. With the standard error of 4-seam spin at 148 rpm, this level of increase in spin would constitute a 4-seam usage rate increase of 14%, a substantial effect considering the standard error of 4-seam usage of just under 19%. This would insinuate that whoever decides what pitches to throw values high spin fastballs to a large extent. Players with higher spin 4-seam fastballs use that pitch more. 4-seam velocity also had a very statistically significant positive effect on 4-seam usage. An increase in the standard error of velocity (about 2.2 mph) correlates to an increase of approximately 2.8% 4-seams thrown. This is much less economically significant than the effect of spin, but still noteworthy. However, we would have expected the effect of velocity to be higher, if not higher than spin's effect, since velocity has been valued as a talent for a long time. Finally, similar to all of the models in this analysis, the R-square remains small, at 0.12. Other effects such as what team the pitcher plays on and preferences of various strategists could be affecting the 4-seam usage.

Conclusions

No tested variables had an effect on the production of spin, and spin did not have an effect on any levels of success tested. Despite this, spin positively affected 4-seam usage, meaning that whoever decides what pitches a pitcher throws definitely places value on high spin fastballs. Since most tangible factors that could have caused spin showed to not affect spin, it would follow that it could take a considerable effort to increase a pitcher's spin, and even then, it might not jump. The only elements that could maybe help spin would be pitching mechanics and working on one's strength and explosiveness. Strength could be measured with lift numbers as well as possibly body fat percentage, to see how much of that weight is muscle. Explosiveness could be measured by testing certain movements such as vertical jumps. However, some pitchers simply have bodies that move more efficiently than others, which could induce more spin and velocity. This factor can prove very difficult to teach as a coach and is not a tangible and measurable statistic.

Given the difficulty of increasing spin and the fact that spin does not seem to affect in-game success, one wonders if coaches should focus on developing spin at all. Additionally, when recruiting players, it might not be so important to favor players based on spin. Since spin does not change according to handedness in the MLB, it would follow that recruitment based on spin has either not occurred extensively or has started recently enough that the players had not reached the big leagues by 2019. The latter is certainly possible, given that the collection spin metrics, done through technology called StatCast, began in 2015.

One more aspect of spin not discussed yet in this paper is low spin fastballs. As said before, high spin fastballs fall less due to gravity. This means that low spin fastballs drop more, often being labeled as sinkers. There is a subset of pitchers who are dubbed "sinkerballers". Since spin showed no effect on success, low spin fastball pitchers will have neither more nor less success than high spin fastball pitchers. Low spin fastball pitchers might throw less fastballs though.

Velocity showed its importance throughout this study, especially on its effect on success. Even though it had a positive correlation with hard-hit percentage, its negative effect on xwOBA, meaning greater success, should outweigh that. xwOBA carries more weight in its effect on team success, as hard-hit baseballs do not matter if a hit does not result from them. Velocity also appears to be much more controllable than spin. Thus, coaches should center their development of pitchers more around velocity rather than spin. When recruiting, teams can also project more velocity on pitchers who they think could throw harder in the future given a chance to work with the team's coaches.

No results are results in and of themselves. The importance of spin has likely been overstated and overhyped in the baseball world. It can be fun to marvel at pitchers who spin the ball at extraordinary rates, but we must recognize that this might not actually correlate to success for the pitcher or for the team.

Final Thoughts on Experimental Design and Procedures

The data collection for this project proved very arduous. I could collect most of the data fairly easily through Baseball Savant's "Custom Leaderboard". Here, I put every variable except height, weight, handedness, and the team the pitcher played for in 2019, and downloaded the table as a CSV. Additionally, I combined innings pitched with games to get innings pitched per game. With the rest of the stated variables, I had to go to each of the over 600 players' Baseball Savant pages and collect the data myself. This would likely have been possible through scraping methods. There were two methods of scraping that were considered. The first was through the use of Selenium, a program that automates web surfing. This would have been somewhat difficult to code, but since the code actually surfs through pages and collects the data, this would have taken about as long to run as it would to collect the data manually. This would be added to the time it would take to write the code and set up the Selenium program on the computer. The second method would be through traditional scraping techniques by choosing one web page and scraping the data from that. To do this, we would need to run through all of the player ID numbers in the CSV that was downloaded from Baseball Savant and use that to run through each player's Baseball Savant page's URL. I am not familiar with how this works, and I would have had to teach myself the techniques involved in running code through a CSV. It likely would not have been impossible or even too difficult, but I elected to collect the data manually, as I figured the code would take just as long to write, if not longer.

All of the interaction variables were calculated after data collection and added into the data set. These were done on an as-needed basis, with only the interaction variables that would be used in the regressions being calculated.

The limit of time and resources somewhat inhibited this project. It would be very interesting to get data on players' strength, explosiveness, and movements patterns in order to run another regression with hopefully a better R-square. Maybe then we can find true factors of spin. This data would likely be very hard to collect, especially since once the data was collected, it must be sorted through and matched to each of the around 600 players. This would all be in the scenario that this data on MLB players is even available to the public. Another piece of data that would have had a tremendous impact on the results is spin efficiency. Spin efficiency enumerates how well the spin works to push the ball in the desired direction. For example, a fastball lower efficiency would drop vertically more than a fastball of the same spin and higher efficiency. This could have a drastic effect on success of a pitcher. Unfortunately, the data set did not have information of spin efficiency. Additionally, this project could have been enhanced with a greater sample size of players, possibly across many years, however time did not permit this large of a data set. Despite the shortcomings of this paper, I believe this paper sheds some light on the importance, or lack of importance, of spin and how it could possibly be overhyped. This paper also highlighted the need for interaction variables, especially when analyzing sports related topics. Sports and sports performance can become complicated with many variables having relationships of their own. The inclusion of all variables is likely impossible, however as more variables are discovered and interaction variables accounted for, the models for spin, velocity, and other sports performance attributes can heighten in accuracy.

Appendix

Table 1: vs 4-Seam Spin

Variable	Coefficient	Standard Error	P-Value	Lower 95%	Upper 95%
Age**	4.26937603	1.809186532	0.0186062	0.71618347	7.82256859
IP/G	-0.2474824	3.364423855	0.9413864	-6.8551183	6.36015345
Height (in.)	-3.5029557	3.271423927	0.2847067	-9.9279422	2.92203089
Weight (lbs.)	-0.1329651	0.341788382	0.6973954	-0.8042281	0.53829787
Hand	12.2906624	14.50012807	0.3969892	-16.18719	40.7685148
Temperature	0.07695561	0.97751783	0.9372775	-1.8428625	1.99677373
Altitude	-0.0038784	0.006149223	0.5284727	-0.0159553	0.00819852
4-Seam Velo***	21.6523142	2.788651782	3.616E-14	16.1754789	27.1291496

Note: ***, **, and * mean statistically significant at the 99%, 95%, and 90% level, respectively. These are determined by the p-values given in the regression analysis.

Table 2: vs 4-Seam Velocity

Variable	Coefficient	Standard Error	P-Value	Lower 95%	Upper 95%
Age***	-0.2125235	0.02514506	2.2247E-16	-0.2619077	-0.1631393
IP/G***	-0.3117419	0.04782142	1.5163E-10	-0.4056619	-0.217822
Height (in.)*	0.77315189	0.43937686	0.07898184	-0.0897722	1.63607596
Weight (lbs.)*	0.27786324	0.15130274	0.06678827	-0.0192912	0.57501765
Hand***	1.57185919	0.20324466	4.5008E-14	1.17269227	1.9710261
Temperature*	0.02491043	0.01433208	0.0827141	-0.0032374	0.05305824
Altitude	-3.09E-06	9.0351E-05	0.97273132	-0.0001805	0.00017436
Height-Weight Interaction*	-0.0034112	0.00202476	0.09256672	-0.0073878	0.0005654

Note: ***, **, and * mean statistically significant at the 99%, 95%, and 90% level, respectively. These are determined by the p-values given in the regression analysis.

Table 3: vs 4-Seam Spin

Variable	Coefficient	Standard Error	P-Value	Lower 95%	Upper 95%
Age	20.6809721	65.70633452	0.7530648	-108.36807	149.730014
IP/G	-11.41314	126.8385042	0.9283326	-260.52744	237.701159
Height (in.)	-813.76363	1024.211259	0.4272108	-2825.3426	1197.81536
Weight (lbs.)	-247.23176	350.758053	0.4811842	-936.13019	441.666671
Hand	-50.940272	534.6757866	0.9241305	-1101.0582	999.177628
Temperature	0.552843	36.63140171	0.9879639	-71.392234	72.49792
Altitude	-0.0032312	0.006210859	0.6030878	-0.0154295	0.00896711
Height-Weight Interaction	3.52649184	4.701624596	0.4535212	-5.7076277	12.7606114
Age-Velo Interaction	-0.1795293	0.708536147	0.8000632	-1.5711137	1.21205516
IP/G-Velo Interaction	0.11141896	1.363460282	0.9348991	-2.5664544	2.78929233
Height-Velo Interaction	8.78820349	11.01763301	0.4253979	-12.85073	30.4271367
Weight-Velo Interaction	2.68329203	3.76719905	0.4765768	-4.7155902	10.0821742
Height-Weight-Velo Interaction	-0.0382667	0.050504652	0.4489442	-0.1374592	0.06092586
Hand-Velo Interaction	0.70005056	5.783318619	0.9036958	-10.658546	12.0586468
Weather-Velo Interaction	-0.0055178	0.393541626	0.9888181	-0.7784444	0.76740872
4-Seam Velo	-592.36789	829.3331353	0.4753451	-2221.2009	1036.46512

Note: ***, **, and * mean statistically significant at the 99%, 95%, and 90% level, respectively. These are determined by the p-values given in the regression analysis.

Table 4: vs xwOBA

Variable	Coefficient	Standard Error	P-Value	Lower 95%	Upper 95%
4-Seam Velo***	-0.0022545	0.000714785	0.001691	-0.0036583	-0.0008507
4-Seam Spin**	-3.115E-05	1.27787E-05	0.0150625	-5.625E-05	-6.057E-06
Breaking Ball Spin	-2.63E-06	7.45528E-06	0.7243429	-1.727E-05	1.2011E-05
Meatball %	-0.0006579	0.001274309	0.6058768	-0.0031605	0.00184482

Note: ***, **, and * mean statistically significant at the 99%, 95%, and 90% level, respectively. These are determined by the p-values given in the regression analysis.

Table 5: vs xwOBA

Variable	Coefficient	Standard Error	P-Value	Lower 95%	Upper 95%
4-Seam Velo***	-0.0022132	0.000718303	0.0021571	-0.0036239	-0.0008025
4-Seam Spin	-9.519E-05	0.000104928	0.3646647	-0.0003013	0.00011088
Breaking Ball Spin	-6.125E-05	9.56289E-05	0.5220828	-0.0002491	0.00012656
4Spin-BreakSpin Interaction	2.5725E-08	4.18375E-08	0.5388662	-5.644E-08	1.0789E-07
Meatball %	-0.000772	0.001288408	0.5492968	-0.0033023	0.00175841

Note: ***, **, and * mean statistically significant at the 99%, 95%, and 90% level, respectively. These are determined by the p-values given in the regression analysis.

Table 6: vs Hard-Hit %

Variable	Coefficient	Standard Error	P-Value	Lower 95%	Upper 95%
4-Seam Velo**	0.19008891	0.095240664	0.0464016	0.0030408	0.37713703
4-Seam Spin	-0.0027665	0.013912555	0.8424461	-0.0300901	0.02455705
Breaking Ball Spin	0.00194462	0.012679544	0.8781607	-0.0229574	0.02684664
4Spin_Bspin Interaction	-1.052E-06	5.54728E-06	0.8497142	-1.195E-05	9.843E-06
Meatball %**	0.43509905	0.170831471	0.0111171	0.0995942	0.77060391

Note: ***, **, and * mean statistically significant at the 99%, 95%, and 90% level, respectively. These are determined by the p-values given in the regression analysis.

Table 7: vs 4-Seam %

Variable	Coefficient	Standard Error	P-Value	Lower 95%	Upper 95%
4-Seam Velo***	1.29670235	0.324918882	7.403E-05	0.65857936	1.93482535
4-Seam Spin**	0.09480363	0.047279764	0.0453965	0.00194874	0.18765851
Breaking Ball Spin	0.04316726	0.043018801	0.3160498	-0.0413193	0.12765384
4Spin_Bspin Interaction	-2.397E-05	1.88264E-05	0.2034021	-6.095E-05	1.3002E-05

Note: ***, **, and * mean statistically significant at the 99%, 95%, and 90% level, respectively. These are determined by the p-values given in the regression analysis.

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