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An Analysis of Salary Difference for Left-Handed Pitchers

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Abstract

This thesis examines whether there is a difference in salary for left-handed pitchers in Major League Baseball. I review prior research regarding the valuation of MLB pitchers, salary discrimination in baseball, and left-handed pitchers to shape my methodology. Using Sean Lahman's Baseball Database, I utilize various regression models to analyze effects on salary. Variables are transformed into cumulative, per 9-inning values and left-handed interaction variables are created to observe any difference in salary experienced only by left-handers. The models show that for variables with a statistically significant effect on salary, left-handers experience a statistically significant effect on salary above and beyond the effect on all pitchers, providing evidence that there is a difference in salary for left-handed pitchers in the MLB.

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I. Introduction

When watching a baseball game, you may hear a play-by-play commentator refer to a pitcher as a “crafty lefty” or “lefty specialist”. However, you never hear about a “crafty righty” or “righty specialist”. The term crafty lefty is generally in reference to a left-handed pitcher who does not throw with overpowering velocity, but still is able to produce quality results, while a lefty specialist is typically a left-handed pitcher with a unique delivery who is brought into high leverage situations for a short stint to face left-handed hitters.

In youth baseball, parents will often joke, “I should have taught him to throw left-handed!” When lefties step on to the mound, there is a sense of enamor among spectators that lasts from Little League all the way to the big leagues. Left-handed fastballs that tail are called “wicked”, yet right-handers who have run on their fastball are dubbed as generic “sinkerball pitchers”.

As a pitcher myself, I have observed these differences throughout my life. This thesis aims to explore whether there is any substance to the apparent differing view of left and right-handed pitchers. I will examine pitchers at the highest level, in Major League Baseball, to investigate whether there is a difference in salary between pitchers based on their throwing hand.

To begin, I will review previous research on player valuation, left-handed pitchers, and salary discrimination in baseball to help guide the analysis in this thesis. Next, I describe the dataset, which contains information on the source of data, selected time period, statistical and player identification variables used, and variables created from the given data. The methodology section will present the structure of the regression models relied upon in my analysis, as well as reasoning for why statistics were included or excluded in various models. Discussion of the results will follow, where the effects of various included statistics will be interpreted along with what they might reveal about salaries for left-handed pitchers. The conclusion will consist of applying the results to this thesis' initial question of a difference in pitchers' salary based on their throwing hand, as well as hypothesizing about potential factors that could have measurable impacts on salary for pitchers that have not been controlled for in this analysis.

II. Literature Review

In the article "What Really Gives Left-Handed Pitchers Their Advantage?" on the popular sports analytics and election research site FiveThirtyEight.com, Guy Molyneux and Phil Birnbaum attempted to discern the reasoning behind why left-handed pitchers are such a valued commodity in baseball.[1]

Spanning across the 2010 to 2019 MLB seasons, left-handed pitchers logged 27.45%[2] of all innings pitched league wide. However, left-hand dominant people only make up approximately 10.6% of the total population, according to a 2020 study.[3] Given that about 10.6% of the population is left-handed, conventional wisdom would expect the proportion of left-handed pitchers in the MLB to be somewhere close to 10.6%. This would translate to just under 39% of the current left-handed pitchers in the Major Leagues still pitching for an MLB club. Molyneux and Birnbaum explain that this translates to only 39% of current left-handed pitchers having good enough pitch quality to be in the Major Leagues when compared to all pitchers and ignoring handedness. The

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[1] https://fivethirtyeight.com/features/what-really-gives-left-handed-pitchers-their-edge/

[2] https://www.fangraphs.com/leaders/splits-leaderboards?splitArr=&splitArrPitch=&position=P&autoPt=false&splitTeams=false&statType=mlb&statgroup=2&startDate=2010-03-01&endDate=2019-11-01&players=&filter=&groupBy=career&wxTemperature=&wxPressure=&wxAirDensity=&wxElevation=&wxWindSpeed=&sort=23,1

[3] Papadatou-Pastou, M., Ntolka, E., Schmitz, J., Martin, M., Munafò, M. R., Ocklenburg, S., & Paracchini, S. (2020). Human handedness: A meta-analysis. *Psychological Bulletin, 146*(6), 481–524. https://doi.org/10.1037/bul0000229

other 61% of lefties would be demoted and replaced by lesser right-handed pitchers whose pitch quality, or what is commonly referred to as “stuff” in baseball circles, is better than that of the bottom tier left-handers, but not quite on par with the top tier right-handers.

As analytics have become more prominent in sports, and baseball in particular, pitchers have begun to be evaluated more so by their pitch metrics than the traditional “eye test” employed by scouts. Here, Molyneux and Birnbaum quantify pitch quality using two observable metrics: velocity and movement. They examine pitchers who threw a minimum of 100 innings between the years of 2007 and 2019 and were left with a dataset of 300 left-handed pitchers and 839 right-handed pitchers. Over the 13-year span, the two groups had nearly identical pitching metrics in traditional categories including earned run average (ERA), strikeouts per 9 innings (K/9), walks per 9 innings (BB/9), home runs allowed per 9 innings (HR/9), batting average on balls in play (BABIP), and fielding independent pitching (FIP). Once the interaction between the pitcher and hitter was removed, the underlying pitch quality metrics did not tell the same story. Across the board, right-handers consistently had a higher average velocity (miles per hour) on their pitches than did left-handers. The gap between righties and lefties was 1.5 mph on four-seam fastballs, 1.3 mph on sinkers, 2.1 mph on cutters, 1.9 mph on sliders, 1.7 mph on changeups, and 1.9 mph on curveballs. After determining the difference in average velocity, Molyneux and Birnbaum considered the possibility that left-handers are able to generate more movement on their pitches to produce traditional pitching metrics equal to that of right-handers. During the 2017, 2018, and 2019 seasons for pitchers who recorded at least 50 innings in each season, right-handers averaged higher spin rates (revolutions per minute) on all pitches except the changeup. Right-handers averaged 40 rpm more on four-seam fastballs, 33 rpm more on sinkers, 164 rpm more on cutters, 78 rpm more on sliders, and 117 rpm more on curveballs, while left-handers averaged 78 rpm more on changeups.

The combination of lesser velocity and spin rate for left-handers led Molyneux and Birnbaum to the conclusion that left-handers have inferior pitch quality to right-handers. They add that it makes logical sense, referring to the disparity in left-handed general population share and representation within MLB pitchers. Given the share of left-handed pitchers is so much greater than the share of left-handers in society, teams are forced to reach deeper into the talent pool of left-handed pitchers, resulting in pitchers with lesser talent and pitch quality still being desired by teams.

Despite the inferiority of left-handed pitchers to right-handed pitchers in terms of pitch quality, they still were able to produce essentially identical statistics in ERA, K/9, BB/9, HR/9, BABIP, and FIP as right handers. The authors hypothesized that left-handers have what they referred to as a "southpaw advantage". This is simply a "hidden advantage that has nothing to do with their ability to throw a baseball, based solely on the fact that they throw with their left hand."[4] They estimate the "southpaw advantage" to be worth about 0.60 runs allowed per 9 innings. This was arrived at by comparing the top 30% of left handers to all right handers, creating two groups who had similar average velocities on each of their pitch types. Even though velocity was nearly the same for the two groups, left handers now allowed 0.62 less RA/9, contributing to the authors' hypothesis of the "southpaw advantage".

[4] https://fivethirtyeight.com/features/what-really-gives-left-handed-pitchers-their-edge/

Baseball often emphasizes platoon advantages, or having hitters face pitchers of the opposite hand, something that is meant to give hitters a better chance at success. Because most hitters are right-handed, left-handers suffer a "platoon penalty", which is estimated by Molyneux and Birnbaum to be about 0.20 RA/9. This results in the final estimate of left-handers' unfamiliarity advantage being worth 0.80 RA/9 in the estimation of the authors.

This article has had a measurable impact on the direction of this thesis. The evidence provided by Molyneux and Birnbaum proves that the talent standards for left and right handed pitchers in Major League Baseball are different, as left handers have a natural advantage simply from being a minority group. While there is no discussion of how a pitcher's salary may be impacted by handedness, it certainly opens the door to further investigation of whether there is a difference in salary solely based on a pitcher's throwing hand.

In his article "Calculating the Expected Earnings of a Major League Pitcher, Roger Ian Abrams examines the case of Steve Bechler, a former minor league baseball player who died during spring training.[5] Bechler had used a supplement containing the substance ephedra to help control his weight, and his wife and daughter sued the maker of ephedra seeking compensatory damages for the earnings as a Major League pitcher that were lost. Abrams attempts to create his own valuation for what Bechler's expected career earnings should have been estimated at.

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[5] Abrams, Roger Ian, Calculating the Expected Earnings of a Major League Pitcher (2009). Virginia Sports & Entertainment Law Journal, Vol. 8, No. 2, pp. 193-222, Spring 2009, Northeastern University School of Law Research Paper , Available at SSRN: https://ssrn.com/abstract=2061005

He cites prior cases that were similar, such as *Felder v. Physiotherapy Associates*, a case where a Milwaukee Brewers minor leaguer, Kenneth Felder, was awarded $7 million in damages based primarily on the opinions of scouts and agents who believed that Felder would become a major leaguer.

Abrams then lays out the salary structure in Major League Baseball at the time of publishing (2009), which is unique to that of all other major sports. In a player's first six years in the major leagues, his salary was determined by the reserve system, which allowed clubs to offer to a player any salary that the club determined was appropriate for their value, with the only requirement being that it is at least the minimum salary.

Generally, after three years of service time (at least 172 days on a Major League roster),[6] a player will be eligible for salary arbitration. This is a process where the club presents the player with a salary offer, and the player can accept it or present their own offer before a three-person arbitration panel jointly selected by the Commissioner's Office and Players Association. The player's agent and a club representative will make their cases as to why their offer is more reflective of the player's true value, and the panel will decide which of the two is more accurate based on the evidence presented.

During the salary arbitration process, arbitrators are required to use six criteria in their decision: "The criteria will be the quality of the Player's contribution to his Club during the past season (including but not limited to his overall performance, special qualities of leadership and public appeal), the length and consistency of his career contribution, the record of the Player's past compensation, comparative baseball salaries … the existence of any physical or mental defects on the part of the Player, and the recent

[6] https://www.mlb.com/glossary/transactions/service-time

performance record of the Club including but not limited to its League standing and attendance as an indication of public acceptance…”[7] Abrams notes that despite these six criteria being listed, the arbitrators' decision almost always comes down to comparable salaries. He also points out that in addition to the criteria that are to be relied upon, there are five that are not to be considered, including the club and player's financial position, any public comments by the player or club, any offers made by the player or club prior to the start of the arbitration process, the cost to the player and club of their representatives and attorneys, and salaries in any other sports.

After six years of service time, a player becomes a free agent and can negotiate a contract with any club.

The biggest takeaway from Abrams's article and methodology is his decision to use comparable players' salary for his valuation of Bechler's estimated career earnings, consistent with the criteria that MLB's arbitration process generally is based upon. This was chosen ahead of the other five criteria used in the salary arbitration process as well as opinions of scouts and agents, as was used in the *Felder v. Physiotherapy Associates* case that Abrams referenced. Even though Abrams ultimately chose to base his analysis on comparable salaries rather than other arbitration criteria, selecting comparable players still involves some level of consideration for a player's contributions during the previous season and career, as well as accounting for any injuries the player may have. By using comparable salary analysis, Abrams effectively captures variation stemming from all the arbitration criteria in one composite approximation. In an analysis such as this thesis where there is a much larger dataset, utilizing past performance data still controls for

[7] Basic Agreement, Art. VI(E)(10) or pg. 207 of article note 69

much of what Abrams tries to capture, while doing so in a more time-efficient manner than selecting comparable players for thousands of data points.

In his 2009 article, "Frontiers in Major League Baseball: Nonparametric Analysis of Performance Using Data Envelopment Analysis," John Ruggiero evaluates hitter and pitcher performance and measures the efficiency of club payrolls as well as managerial decisions.[8] Ruggiero ultimately combines various measures of performance together to find out how to maximize wins and attendance for MLB clubs, two of the primary measures for success of a club. When looking at pitchers, Ruggiero defined pitcher performance using three metrics: total innings pitched, innings pitched per earned run allowed, and innings pitched per hit allowed. He also limited his sample to just pitchers with that recorded at least 40 outs, or 13 ⅓ innings, in the 2009 season.

One important omission Ruggiero made was that of pitching wins in his metrics of pitcher performance. He explains that while pitching wins do depend on the quality of a pitcher's performance in each appearance, it also is largely influenced by the performance of the team's hitters and fielders in a game, and thus should not outweigh any of the chosen criteria. In the context of this thesis, data is not available to control for a team's hitting and fielding performance behind a pitcher in each game, so pitching wins are included in my analysis to capture any value placed on them by clubs. Although pitching wins might not be the most indicative statistic for pitching performance, Ruggeiro's attempt to disprove their value indicates that they might currently influence perception of pitching performance and should be included in this model.

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[8] Ruggiero, John. *Frontiers in Major League Baseball : Nonparametric Analysis of Performance Using Data Envelopment Analysis*, Springer New York, 2010. *ProQuest Ebook Central*, https://ebookcentral.proquest.com/lib/claremont/detail.action?docID=646411.

Wilbert M. Leonard's article "Salaries and Race/Ethnicity in Major League Baseball: The Pitching Component" examined a very similar issue to this thesis, looking at possible differences in salary between pitchers based on race.[9] While this study was conducted in 1989, the methodology rather than results is what will be considered for the purposes of this thesis.

Included in Leonard's dataset were variables for experience (number of seasons played), walks allowed per 9 innings (BB/9), strikeouts per 9 innings (K/9), hits allowed per 9 innings (H/9), wins per 9 innings (W/9), losses per 9 innings (L/9), a ratio of strikeouts to walks (SO/BB), a ratio of wins to losses (W/L), race/ethnicity (categorized into white, hispanic, and black), media money received by the pitcher's team, a dummy variable with value of 1 if the pitcher made the playoffs (playoff), and innings pitched (IP). Many of these variables are in terms of rates per 9 innings pitched, as Leonard noted how dependent the raw values were on total innings pitched. The variables IP, W, L, H, ER, SO, and BB were highly intercorrelated, with correlations of 0.80 or higher. To avoid problems in his analysis arising from multicollinearity, Leonard dismissed the raw values in favor of rates per 9 innings.

Leonard was not able to find any evidence of salary discrimination on a racial/ethnic basis among MLB pitchers. The paper does note that this conclusion could also be a result of analytical issues stemming from the small sample size of just 257.

Leonard included multiple observations in his conclusion regarding his model in relation to previous and future models. He explains that measures of pitching

[9] Leonard, Wilbert M. "Salaries and Race/Ethnicity in Major League Baseball: The Pitching Component." Sociology of Sport Journal, vol. 6, no. 2, 1989, pp. 152–162., https://doi.org/10.1123/ssj.6.2.152.

performance are not independent of measures of team performance, which can work to cloud some of the analysis and interpretation in a model. Additionally, the model presented by Leonard is not applicable to long-term contracts, as a player's current salary who signed a multi-year deal is derived from his past performance, in some cases multiple years prior.

The use of rates per 9 innings rather than raw values to avoid multicollinearity issues applies to this thesis, as when looking at either season-long statistics or career statistics, all raw values will increase with more innings pitched. Starting pitchers will have higher raw values across the board than relief pitchers due to pitching more innings. By scaling to per 9 innings as Leonard does, comparison between pitchers is more meaningful as values are reported in rates rather than totals.

To measure the marginal revenue product (MRP) of pitchers, J.C. Bradbury examines whether ERA is the best metric for evaluating a pitcher's ability to prevent runs.[10] Bradbury acknowledges that ERA has traditionally been used by analysts as one of the primary statistics for judging pitchers' success and concedes that it is possible that it is the best measure. However, he argues that further investigation is needed to justify the use of ERA rather than other statistics.

The paper claims that ERA is a joint output statistic, and the delineation of responsibility between pitchers and fielders is unclear. Pitchers have nearly zero control over balls after they have been put in play, leaving a large amount of responsibility on fielders.

[10] Bradbury, J. C. (2007). Does the Baseball Labor Market Properly Value Pitchers? Journal of Sports Economics, 8(6), 616–632. https://doi.org/10.1177/1527002506296366

Bradbury finds that there are better statistics for measuring pitcher skill and ability to prevent runs than ERA, specifically those which measure pitchers' run prevention ability without the assistance of fielders. He calls these metrics "DIPS', or defense-independent metrics. Among these are strikeouts, walks, and home runs, all of which are events that involve either the ball not being put in play or being hit out of the park, excluding any influence that defenders may have on the play, which have come to be known as the "three true outcomes".[11]

Some of these papers attempt to create their own valuation for pitchers and use statistics that are more representative of true pitching performance, while dismissing traditional statistics that might be influenced by outside factors. These "better" factors can be used in this thesis' analysis to control for pitching performance more accurately, but I am just attempting to account for what is valued by teams, so the traditional statistics will still be included. Even if there are statistics that can more accurately reflect pitching performance, they might not explain variation in salaries, as teams may reward traditional statistics like wins and ERA.

[11] https://www.mlb.com/glossary/idioms/three-true-outcomes

III. Methodology

The null hypothesis that will be tested in this study is that there is no difference in the salary of Major League pitchers based on their throwing hand, with all else held equal. The alternate hypothesis is that there is a difference in the salary of Major League pitchers based on their throwing hand, with all else held equal.

H_0: No difference in pitchers' salary based on their throwing hand

H_A: There is a difference in pitchers' salary based on their throwing hand

As Guy Molyneux and Phil Birnbaum explain in their article on FiveThirtyEight.com, left-handed pitchers are heavily over-represented in Major League Baseball in comparison to their share of the population. Left-handers consistently have lower average velocities on all their pitches in comparison to right-handers and have lower average spin rates on every pitch. Basic economic intuition would lead one to believe that righties and lefties would be consumed (or more appropriately rostered) by MLB clubs to the point at which an additional right-handed pitcher would have less ability than the last left-handed pitcher, and vice versa, with ability being quantified by a pitcher's throwing velocity and spin rate. However, due to left-handers' lower measures in both velocity and spin rate, this intuition is obviously not employed.

Despite the disparity in ability, or "stuff", between left-handed pitchers and right-handed pitchers, Molyneux and Birnbaum found that the statistics produced by righty and lefty pitchers in baseball from 2007-2019 were nearly identical. This suggests that clubs do in fact act as rational economic consumers, rostering pitchers at a level such that the next available right-handed pitcher would perform worse than the last rostered left-handed pitcher, and vice versa.

Now considering the fact left handers have lesser stuff but still perform the same as right handers, Molyneux and Birnbaum's analysis led them to the conclusion that left-handers have an intrinsic advantage just from being left-handed that they called an "unfamiliarity advantage", which they estimated to be worth 0.80 runs allowed per 9 innings. Coupling this with the fact that left-handed pitchers threw only 28 percent of all MLB innings during the 2007-2019 time period of their analysis, left handers are essentially a minority of pitchers who do not need to have the same level of talent or ability as right handers due to their intrinsic advantage of being unfamiliar to hitters.

Due to the minority fraction of left-handed pitchers in the MLB and their advantage simply from hitters not seeing left-handed pitching as much, this paper's hypothesis is that there is a difference in salary for pitchers based on their throwing hand. This is driven by the notion that Major League clubs covet the left-handed pitchers who can perform statistically at a comparable level to right handers. This value placed on capable left-handed pitchers is hypothesized to ultimately be reflected in their salary.

The hypothesis will be tested using regression analysis, with one baseline model and several variations of the baseline. All variables included in the regression models represent values for player *i* in time *t*. Each model utilizes heteroskedasticity-robust standard errors. This baseline model is specified in Equation 1:

$$\ln(salary)_{i,t} = \beta_0 + \beta_1\, twa\_era_{i,t} + \beta_2\, l\_twa\_era_{i,t} \ldots + \beta_6\, tenure\_2_{i,t} + \varepsilon_{i,t} \qquad (1)$$

The left hand side variable used in the regression models is the natural log of salary. As illustrated in Figure 1, the distribution of *salary* is exponential and makes interpretation difficult in regression analysis. To linearize the data, the natural log of salary was generated (*lnsalary*) for use in place of *salary* for this paper's analysis.

In his analysis, Ruggiero (2010) limited his analysis to pitchers that recorded at least 40 outs (13.33 innings) in 2009. To avoid including extreme values in my analysis, the dataset is trimmed based on a player's experience. Observations in their first year of experience (*tenure* = 1) were excluded from the dataset used in regression models. Despite Ruggiero's use of a minimum inning limit, *tenure* is chosen as the trim variable due to a notable advantage of left-handed pitchers being that they can be brought into the game for specific situations where they only face a few batters. If a pitcher proved enough to survive in the Major Leagues for another year, he will be kept in the dataset, serving as a version of self-selection. Additionally, in a player's first season, there is no past performance to base his salary from, so his salary is determined by rules in place for the reserve system, as discussed in Abrams (2009). After eliminating all players who only had one year of tenure from the dataset, there are 4.070 observations remaining, which will be the data utilized in my analysis.

Figure 1

Shows the distribution of salary. Due to the heavy skew, the natural log of salary is used as the independent variable in regression models.

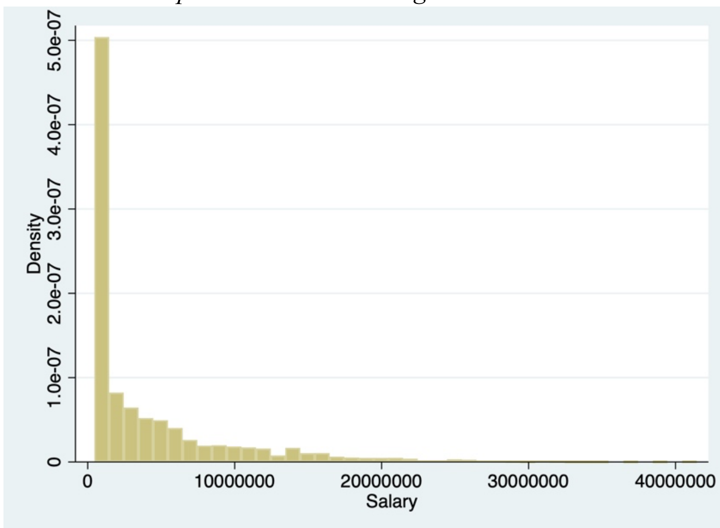

Table 1

Summary of statistical variables in the form of cumulative per 9 inning values.

	Mean	S.D.	First Quartile	Median	Third Quartile	N
left	0.28	0.45	0.00	0.00	1.00	4070
c_ip	369.53	376.23	117.00	239.33	477.33	4070
twa_era	4.17	2.39	3.38	3.95	4.56	4070
c_w_9	0.49	0.28	0.39	0.51	0.60	4070
c_h_9	8.86	2.59	7.89	8.74	9.55	4070
c_hr_9	1.00	0.73	0.74	0.93	1.15	4070
c_so_9	7.32	2.09	6.01	7.32	8.55	4070
c_realbb_9	3.09	1.57	2.32	2.90	3.60	4070
tenure	6.44	3.91	3.00	6.00	9.00	4070
tenure_2	56.78	70.49	9.00	36.00	81.00	4070

Table 2

Correlations of statistical variables in the form of cumulative per 9 inning values.

	c_ip	twa_era	c_w_9	c_h_9	c_hr_9	c_so_9	BB/9	tenure	tenure_2
c_ip	1								
twa_era	-0.11	1							
c_w_9	0.17	-0.18	1						
c_h_9	-0.05	0.85	-0.16	1					
c_hr_9	-0.06	0.49	-0.15	0.43	1				
c_so_9	0.12	-0.19	0.05	-0.31	-0.13	1			
c_realbb_9	-0.19	0.32	-0.08	0.09	0.04	0.05	1		
tenure	0.35	-0.04	0.03	-0.01	-0.01	-0.10	-0.09	1	
tenure_2	0.28	-0.03	0.03	0.01	-0.01	-0.11	-0.09	0.96	1

Experience is controlled for in the baseline model by using *tenure* and *tenure_2*. As previously discussed, *tenure* is preferred over *age_630* when measuring experience by better capturing the timeline of a player's career. It is also preferred over *c_ip*, as innings pitched over a player's career also serves as a measure of experience for a pitcher. Innings pitched is already used to normalize the statistical measures to per-9-innings rates and has an induced negative correlation with other right hand side variables due to it being used to calculate them. Both *tenure* and *tenure_2* are included to capture whether experience has a non-linear trend. A positive coefficient on *tenure* indicates that more years of experience leads to a higher salary, which is true up to a point. By also including *tenure_2*, we can determine if an increase in *tenure* begins to decrease salary at a certain point.

Due to the *left* dummy having a very high Variance Inflation Factor (VIF) when included in regressions with left interaction effects and correlations approaching 1 with left interaction effects, the dummy is left out of some models in favor of the left interactions. The high VIF on *left* when included with the interaction effects reduces the significance of the interactions, and thus is left out.

Bradbury (2007) found that ERA was not the most accurate statistic for judging pitcher performance. Rather, statistics that gauge pitchers' run prevention ability without the influence of fielders, or what Bradbury calls defense independent metrics (DIPS), more accurately reflect the pitcher's performance. These "three true outcomes" are walks, strikeouts, and home runs, all of which are included as cumulative per 9 innings values to include some results that rely primarily on performance measures that are within the pitcher's control. Even though ERA might not be a great indicator of pitcher ability and performance, the purpose of this paper is not to create a valuation for pitchers, but rather to observe what their valuation is. Given the popularity of ERA as a shorthand method of judging pitcher performance, regression models include *twa_era* as a dependent variable to capture the effect it has on pitchers' salary.

Pitching wins are discussed by Ruggiero (2009) as heavily influenced by the performance of hitters and fielders in a given game, setting a moving standard for the quality of performance needed to earn a win. The reason Ruggiero had to disprove their value and explain why they were omitted in his analysis is because of the common use of wins to evaluate a pitcher. Due to their historical prevalence in perception of pitching performance, they are included as a dependent variable to control for this, even though they may not be the best metric for evaluating a pitcher's ability.

In both Ruggiero (2009) and Leonard (1989), variables for hits were included in their analysis. Ruggiero uses an innings pitched per hit allowed ratio, while Leonard uses a ratio of hits allowed per 9 innings. However, *twa_era* and *c_h_9* have a correlation of 0.74, shown in Table 5 resulting in *c_h_9* being excluded from the specified models.

IV. Data

The data used in this thesis is from Sean Lahman's Baseball Database,[12] a compilation of pitching and batting statistics dating back to 1871. Sean Lahman is an investigative reporter with the *Rochester Democrat and Chronicle*, a newspaper which is a part of the *USA Today Network*. He has been a part of the publication of over a dozen sports reference books and has served as data projects manager for SABR (Society of American Baseball Research). The database also includes yearly standings, team stats, post-season data, managerial data, and player information. Each category of data covers a different period, as some variables have only been tracked for a certain period of time, such as intentional walks which were first tracked in 1955.[13] While variables such as wins, hits allowed, and strikeouts are available dating back to 1871, data for player salaries are only available dating back to 1985.

The period of the data used in this paper's analysis ranges from 2005-2016. The lower limit of 2005 was selected with respect to the beginning of Major League Baseball's performance-enhancing drug testing program. Throughout the 1990s and early 2000s, steroid use was rampant throughout baseball. In a 2002 interview with Sports Illustrated, Ken Caminiti, who won the National League MVP award in 1996, admitted to using steroids during that season and claimed that "At least half the guys are using

[12] https://www.seanlahman.com/baseball-archive/statistics/
[13] https://www.baseball-almanac.com/recbooks/rb_wk3.shtml

steroids."[14] In 1991, the MLB added steroids to its list of banned substances, but did nothing about it. It wasn't until the 2004 season that major leaguers were tested for performance-enhancing drugs, but even then, a positive test only resulted in the player going to counseling, and the names of those who tested positive were not publicly revealed unless they had two positive tests. Prior to the 2005 season, a new agreement was reached where players would be suspended for any failed drug test. Also prior to the 2005 season, the *San Francisco Chronicle* reported that multiple high-profile stars such as Barry Bonds and Jason Giambi were found to have either knowingly or unknowingly taken steroids while testifying in front of a grand jury.[15] Just under 2 months before the 2005 season, Jose Canseco released his book that detailed his own steroid use as well as that of countless other players. Because of the obvious likelihood that steroid use greatly influenced offensive production in baseball, I excluded seasons where steroid use by both pitchers and hitters were more likely to influence outcomes. Given the occurrences in the 2004-05 offseason, 2005 appeared to be an inflection point with respect to steroid use and possible pitcher performance in baseball.

Ideally, 2019 would have been included as the final year included in the dataset, as an MLB rule change instituted prior to the 2020 season required any pitcher that enters the game to face at least 3 batters unless he completes a half-inning.[16] This has changed the way managers handle their decisions with bullpen pitchers, as they can no longer bring in a pitcher to specifically face one hitter that they think may be an advantageous

[14] https://www.si.com/mlb/2014/09/09/totally-juiced-tom-verducci-ken-caminiti-si-60
[15] Bonds – https://www.sfgate.com/sports/article/What-Bonds-told-BALCO-grand-jury-2667365.php
Giambi - https://www.sfgate.com/sports/article/Giambi-admitted-taking-steroids-2631890.php
[16] https://www.mlb.com/glossary/rules/three-batter-minimum

matchup. However, this rule has only been in place for three seasons, so it may still be difficult to tell what effect, if any, it has on the way various pitchers are valued.

When looking at the dataset that was available, data for player salary was only available up to the 2016 season, so that is the most recent year of data that will be included in this paper's analysis. This leaves 4,750 observations of pitchers that recorded an out in a major league game from 2005-2016, which is then narrowed down to 4,070 after excluding pitchers with only one year of experience.

The dataset uses identification variables based on a player's name, team, season, and league. Together, they individualize each data point down to a player in a given season, specifying which league the player is playing in and for which MLB team. Additionally, I created a dummy variable for left handers that equals 1 if the pitcher is left-handed. These variables are defined in Table 3.

The statistical variables in the dataset reflect measures of player performance for the player specified by the identification variables at time *t*. These variables are defined in Table 4.

A few additional variables were created from the given measures in the original dataset, and the formulas used to calculate those are given in Table 5.

Each of the variables included are intended to reveal something about a specific aspect of each pitcher's performance. While pitchers' wins and losses have traditionally been relied upon as an important metric of pitcher performance, baseball has begun to place less emphasis on them when evaluating pitchers due to the numerous external factors that can affect whether a pitcher is credited with a win or loss. Low run support can lead to starting pitchers being charged with a loss in a 1-0 or 2-1 game, when they

Table 3
Description of the identification variables used in the dataset.

Variable Name	Description
playerID	A unique identification code for each player using the first two letters of their first name and the first five letters of their last name, with a two digit number at the end to further differentiate between any players who may have identical seven letter codes based on their name
teamID	Three letter code to identify which MLB club's roster a player was on for the given year
yearID	The year for which the row of data refers to
lgID	Specifies whether the team is in the American League or National League, helpful for distinguishing between teams that share a city, such as the New York Yankees and New York Mets, Chicago Cubs and Chicago White Sox, and Los Angeles Dodgers and Los Angeles Angels. American League teams are able to have a designated hitter in the batting lineup in place of their pitcher, while National League teams must have the pitcher hitting in the batting lineup.
left	Binary variable with the value of 1 if the player throws left-handed

Note: Starting in 2022, the designated hitter is allowed in both the American and National Leagues.[17] This was also the case in the COVID-shortened 2020 season. The dataset used in this thesis does not include any of those years, covering 2005-2016, so the designated hitter was still not permitted in the National League for the period examined.

may have only allowed one or two runs, which would be a great start by all accounts. If a pitcher's defense makes an error that leads to unearned runs scoring, the pitcher will still be on the hook for the loss even if he allowed zero earned runs, as pitching wins and losses do not account for earned or unearned runs. For relief pitchers, their individual win-loss record can be largely dependent on the point in the game in which they enter. If they enter a tie game, throw one shutout inning, and then their team takes the lead, they will be the pitcher in line for the win despite throwing just 1 inning. A relief pitcher can

[17] https://www.mlb.com/glossary/rules/designated-hitter-rule

Table 4
Description of the quantitative variables utilized for analysis.

Variable Name	Description
w	The number of wins accredited to the individual pitcher's win-loss record
ip	The total number of innings a pitcher recorded. Values ending in .333 refer to ⅓ of an inning, or 1 additional out, and values ending in .667 refer to ⅔ of an inning, or 2 additional outs
h	The total number of hits allowed by the pitcher
er	The total number of earned runs allowed by the pitcher. This excludes runs that are scored due to fielding errors.
hr	The total number of home runs allowed by the pitcher
realbb	The total number of walks (bb) less the number of intentional walks (ibb) charged to the pitcher. This gives a more accurate representation of the number of batters walked by the pitcher due to his inability to throw strikes.
so	The total number of strikeouts recorded by the pitcher
twa_era	A time-weighted average of *era* for the pitcher's career thus far
salary	The pitcher's salary in 2022 US dollars
tenure	The number of years the pitcher had recorded an out in the major leagues prior to the given season, within the dataset of 2005-2016
tenure_2	The square of *tenure*
age_630	The player's age as of June 30 in the given year
age_630_2	The square of *age_630*

even be credited with a win after a poor performance. If a pitcher enters the game and surrenders the lead, he then becomes the pitcher of record if his team retakes the lead while he is still in the game, essentially earning a win for surrendering the lead. Because of these complex rules, the emphasis placed on pitchers' wins and losses has decreased.

Table 5

Formulas used to create new variables from existing ones in the dataset.

Variable	Formula
ip	ipouts / 3
realbb	bb - ibb
twa_era	(c_er / c_ip) * 9
tenure	yearid - debut year
tenure_2	$tenure^2$
age_630	6/30/yearid – date of birth
age_630_2	age_630^2

However, given their previous importance as a measure of gauging pitching success, they are included to capture any effect they may have on the salary of a pitcher.

The variables *g* and *gs* for games appeared in and games started are included as a measure for a pitcher's consistency and availability. Obviously, if a pitcher appears in more games for his team, he is likely a better pitcher, so this helps to account for how sheer volume of appearances might be reflected in a pitcher's salary. Additionally, if a pitcher starts or appears in many games, that means he is healthy and able to pitch, which is valuable itself.

Along similar lines, the variables *ipouts* and *ip* can serve to measure consistency and availability for pitchers. *Ipouts* is a measure of the total number of outs recorded by the pitcher (3 in an inning), while *ip* is simply the total number of innings pitched. In theory, each MLB team must get 4,374 outs (27 outs * 162 games) every season, although that number can be higher or lower based on if games go to extra innings or if teams lose on the road, meaning the home team does not hit in the bottom of the 9th and only 24 outs are recorded by the visiting pitchers. Thus, each team needs pitchers who can consistently get hitters out throughout an entire season, and the value that teams place on pitchers who can "eat innings" can help to be explained with these variables.

The variable *h* reflects the number of times a pitcher is essentially "beat" in an at bat by the hitter, allowing the hitter to reach base via a hit. Teams would therefore want pitchers who give up less hits, so that less runners reach base, and it is more difficult for the opponent to score runs.

In its simplest form, a baseball game is won by scoring more runs than the other team. There are other things that might predict what might make a team more likely to end a game with more runs than the opponent, but only one measure for runs. Pitchers' primary goal is to minimize the number of runs given up so that their team will have the best chance of winning the game. The variables *er* and *era* measure the total number of earned runs given up by a pitcher and the average number of earned runs given up by a pitcher over a 9-inning span (the length of a Major League Baseball game). Due to the total number of earned runs allowed being largely dependent on the total number of innings a pitcher throws (a starter that throws 150 innings will almost assuredly allow more runs than a reliever who throws 40 innings), *era* is more commonly used instead of *er* when looking at how prone a pitcher is to give up earned runs. Both *er* and *era* also exclude any runs that score because of fielding errors (unearned runs), giving a more accurate representation of the runs surrendered by the pitcher himself.

One of the most important metrics in baseball today is exit velocity, the speed at which the ball leaves a hitter's bat. The harder a batter hits the ball, the more likely it is to result in a hit or even home run. Other metrics derived from exit velocity such as hard-hit rate[18] (the % of at bats in which a ball is hit in play at 95 mph or harder) are indicators of pitcher performance and can reveal if the pitcher has possibly had good or bad luck with balls put in play. If a pitcher has a high hard-hit rate but low *era*, that may be a sign that he has been lucky, with pitches being hit hard, but maybe at defenders for outs. The opposite could be true if a pitcher has a high *era* but low hard-hit rate, indicating that he has not been allowing a lot of hard contact, and a lot of weakly hit balls may have been resulting in hits, something that is unlikely to continue. Due to the limited availability of data involving exit velocity, as the Statcast era began in 2015,[19] *hr* is used as a proxy to measure hard contact allowed by a pitcher. The shortest distance that a home run can be hit in the MLB today is 302 feet,[20] the distance to the right field foul pole known as Pesky's Pole at Boston's Fenway Park. Thus, a ball today must be hit at least 302 feet to be a home run. In the Statcast era, the slowest home run hit has been 85.4 mph[21] by Tampa Bay's Harold Ramirez, so a ball must be hit hard to travel the 300+ feet for a home run. A home run is one of the three true outcomes, as mentioned by Bradbury (2007). These three outcomes only involve the pitcher and hitter, eliminating all other influence from defenders on the play and providing a more accurate representation of pitcher performance.

Walks allowed by pitchers can be just as important, if not more, than the hits that they allow. Hits are bound to happen eventually, so minimizing the number of runners on base when those hits occur is crucial for teams. A walk is when a pitcher throws 4 balls

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18 https://www.mlb.com/glossary/statcast/hard-hit-rate
19 https://www.mlb.com/glossary/statcast
20 https://www.baseball-reference.com/bullpen/Pesky%27s_Pole
21 https://www.mlb.com/news/harold-ramirez-hits-85-4-mph-home-run

out of the strike zone before the hitter either puts the ball in play or strikes out, with a few rare exceptions. This essentially gives the opposing team a "free base" by allowing the batter to reach base without him having to get a hit. A high number of walks indicates that a pitcher struggles to command his pitches well and makes it more likely that runs will score when hits do occur because there are already runners on base. This is another of the three true outcomes, as a walk almost entirely indicates the pitcher's inability to throw the ball consistently in the strike zone, with minor consideration given to different umpires' strike zones and hitters having a tough at bat where they force the pitcher to throw sometimes 10+ pitches. The total number of walks allowed by a pitcher is represented by *bb*, but this includes all intentional walks (*ibb*) that occur while the pitcher is in the game. An intentional walk is when the team decides to give the batter first base rather than pitch to him, usually to produce a better situation in a close game or tense inning, either by creating a force out on the bases or avoiding one of the opponent's best hitters. These are counted equally to walks when the pitcher fails to throw strikes. Given we are trying to simply measure the pitcher's command and strike-throwing ability here, a new variable was created, *realbb*, that subtracts out *ibb* from *bb* to reflect only the number of times that the pitcher walked a batter due to his failure to throw strikes.

In recent years with the rise of analytics, a greater emphasis has been placed on strikeouts, the third true outcome, because it eliminates any possibility (ignoring a dropped 3rd strike) for the batter to reach base. It eliminates softly hit balls finding their way into a hole for a hit or a fielder making an error that allows the batter to reach base, essentially the only way a pitcher can guarantee to get the batter out. The variable *so* shows the frequency with which pitchers strikeout batters, on an absolute scale. We can observe any effect that larger total strikeout numbers may have on pitcher salary, as the yearly strikeout leaders are generally regarded among the best pitchers in the game.

Because of the value of strikeouts and the detriment of walks to teams, the best pitchers in theory would provide a balance of both. Thus, a ratio of strikeouts recorded to walks allowed, *so_bb*, gives a metric for the ability of a pitcher to strikeout batters relative to their propensity to walk batters. Out of qualified players (those that threw at least 162 innings - all starting pitchers) in 2022, the highest strikeout to walk ratio was Aaron Nola's 8.10, and the lowest was Marco Gonzales's 2.06.[22]

The values for *age_630* and *tenure* both serve as measures of experience for pitchers. A pitcher's age can not only provide insights on how much pitching experience the individual has, but also can explain where in an athlete's "lifetime" they stand. Many athletes generally begin to decline in performance throughout their 30s, with their prime being regarded as their mid-to-late 20s. While *tenure* is similar to *age_630*, its "count" does not start until the player's debut in the Major Leagues. Thus, this captures the career timeline of a player in a way that *age_630* does not. A player who debuts at 29 years of age will still have a learning period as a new player in the league just as a 22-year-old would have, which is accounted for by *tenure*. This can also serve as a gauge for the individual's pitching ability, since teams would not continue to sign pitchers who struggle to perform at the Major League level.

The independent variable for this paper is *salary*. This will be reported in US dollars and will serve as a method of identifying how MLB clubs value pitchers, as

[22] https://www.mlb.com/stats/pitching/strikeout-to-walk-ratio/regular-season?expanded=true&page=2&playerPool=QUALIFIED

logically the more a team values a pitcher, the more money they will be willing to pay him.

In baseball, salary is often a backwards-looking measure. At times, a player's salary can be based on the potential that an organization sees in a player, paying them for the level of production that they expect in the future from the player rather than how the player has produced thus far in his career. Generally, this only applies to young, developing players who have only had a few seasons in the Major Leagues or have not yet had the chance to be an everyday starter for a team. However, most salaries in the MLB are based on how the player has previously performed in his career. Players that produce at a higher level statistically will be valued higher by teams and that value will be reflected in the form of a larger salary.

Due to the backwards-looking nature of salaries in Major League Baseball, the variables included in this thesis' analysis have been transformed into cumulative measures over the period covered by the dataset, 2005-2016. A variable for player *i* in time *t* will represent the player's cumulative performance over the covered period up to time *t*. For example, player *i*'s cumulative hits allowed (c_h) for the observation in 2011 will represent the number of hits allowed by the player from 2005-2011. The prefix "*c_*" on a variable indicates that it represents a cumulative value for the given statistic, accumulated starting in 2005 and going up to *yearid*.

All statistical variables utilized in the regression models will be in the form of cumulative rates, with the prefix "*c_*". By using the per-9-innings rate for the player's career, values will be more representative of their overall performance and ability that they have proven over the course of their career.

The cumulative measure for ERA is *twa_era*, a time-weighted average measure. This does not carry the same "*c_*" prefix as other cumulative measures but represents the pitcher's cumulative ERA throughout the time period of the dataset.

Over the course of a single MLB season, starting pitchers will easily pitch 2 times, 3 times or even 4 times as much as relievers, and that disparity only increases when accumulated over multiple seasons. Thus, the variables used to measure pitcher performance and ability must be standardized to make comparison between pitchers possible. Statistical variables measuring pitcher performance shown in Table 2 have been transformed into values per 9 innings pitched. The suffix "*9*" on a variable indicates that it represents a value standardized to per 9 innings.

All statistical variables utilized will also be in the form of per-9-innings rates, with the suffix "*9*". This will better allow for interpretation of the results and application to the average pitcher. With raw values, starting pitchers would have larger values in nearly every statistic, as values would increase together. The correlation between the raw variables is at least 0.74 for *ip*, *w*, *h*, *hr*, *so*, and *bb* as shown in Table A1.

As a supplement to the *left* dummy variable, left-handed interactions with main effects were generated. This will take on a value equal to the main effect for left handers but will be 0 for right handers. The prefix "*l_*" on a variable indicates that it is a left interaction with the main effect. In a regression model, this provides insights on the effect of a given variable for left handers above and beyond what is already explained by the main effect itself. For example, *l_twa_era* shows the effect on salary of *twa_era* for left handers in addition to the effect of *twa_era* for pitchers in general. The left interaction effects show the marginal impact for left-handers for each variable.

In the United States between 2005 and 2016, inflation was between -0.36% and 3.84%, ending at 1.26% or higher in 10 of 12 years.[23] To control for any effect that inflation may have had on player salary, all salaries were transformed into 2022 dollars using the United States CPI.

[23] https://www.macrotrends.net/countries/USA/united-states/inflation-rate-cpi

V. Results

Three regression models are specified, with each being a variation of the baseline model shown in Formula 1. Table 6 displays the results of these three regression models. The explanatory power of the various models is relatively similar, as the R^2 values range from 0.4433 to 0.4549.

In each model, *tenure* and *tenure_2* are highly significant, both up to the 1% level. They are true to the expected experience curve, as *tenure* has a positive coefficient in each while *tenure_2* has a negative coefficient in each. This indicates that there is a value for experience that is reflected in pitchers' salaries up to a point, and then a pitcher's salary begins to decline with many years of experience. This may be due to chronic and nagging injuries affecting pitchers after several seasons, or more generally, their body beginning to decline with so much wear and tear. There may only be so many innings the average pitcher can throw before his arm cannot perform at the same level, with obvious outliers.

In the baseline model, *twa_era* is significant to the 1% level, with the expected negative sign on the coefficient of -0.038, indicating a 1 run increase in *twa_era* leads to a 3.8% decrease in salary for a pitcher. The left interaction, *l_twa_era*, is also significant to the 1% level with the expected negative sign. Its coefficient of -0.048 suggests that left-handed pitchers see a 4.8% decrease in salary for each 1 run increase in *twa_era* in addition to the 3.8% decrease in salary already captured by *twa_era*. Both *c_w_9* and *l_c_w_9* have the expected positive signs on their coefficients, and both are statistically significant. The left interaction, *l_c_w_9*, has a coefficient of 0.449, indicating that left handers see a 44.9% increase in salary for each additional win per 9 innings (W/9) over their career on top of the 32.8% salary increase for each W/9 that applies to all pitchers.

The second model includes the dummy variable *left* along with the interactions and main effects present in the baseline model. The main effects of *twa_era* and *c_w_9* retain the expected coefficients but decrease in significance to the 5% level for *twa_era* and insignificant completely for *c_w_9*. The effect of *tenure* and *tenure_2* did stay nearly identical, with both remaining highly significant. The dummy *left* is statistically significant, with a t-stat of -1.93. However, the inclusion of *left* reduces the significance of the interaction with ERA, causing the t-stat for *l_twa_era* to go from -2.73 to -0.41, while the t-stat of *l_c_w_9* slightly increasing from 2.83 to 3.08, though the main effect lost significance. This is likely attributable to the high VIF of *left* when included in the model. The *left* dummy is very highly correlated with the interactions, such as *l_twa_era* (0.89) and *l_c_w_9* (0.90), which can be found in Table A2. To avoid the issue of *left* knocking out the effects of left interaction variables, many of the models include just left interactions.

When including *c_realbb_9* and its interaction in the baseline model, the main effect for walks has a t-stat of -3.58, making it highly significant, while its interaction is significant to the 10% level. Both the main and interaction effects for walks carry the expected negative sign on their coefficient, meaning that more walks per 9 innings over a

Table 6

*Main regression results. Model (1) is the baseline model as specified in Equation 1. Model (2) adds the left dummy, and Model (3) adds walks. Robust standard errors appear in parentheses. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.*

	(1) lnsalary	(2) lnsalary	(3) lnsalary
left		-0.359*	
		-1.93	
twa_era	-0.038***	-0.044**	-0.026*
	-2.74	-2.55	-1.87
l_twa_era	-0.048***	-0.010	-0.022
	-2.73	-0.41	-1.14
c_w_9	0.328*	0.280	0.292*
	1.86	1.62	1.80
l_c_w_9	0.449***	0.811***	0.621***
	2.83	3.08	3.57
c_realbb_9			-0.071***
			-3.58
l_c_realbb_9			-0.057*
			-1.85
tenure	0.502***	0.503***	0.505***
	34.92	35.10	35.35
tenure_2	-0.019***	-0.019***	-0.020***
	-21.78	-21.94	-22.32
Constant	12.508***	12.559***	12.696***
	109.22	97.58	112.23
R^2	0.4433	0.4447	0.4549
Observations	4070	4070	4070

t-statistics are listed below the coefficient

$*p < 0.10$, $**p < 0.05$, $***p < 0.01$

pitcher's career will result in lower salaries. When accounting for walks, however, *twa_era* and its interaction decrease in significance, with their t-stats dropping to -1.87 for *twa_era* and -1.14 for *l_twa_era*, respectively. The correlation between *twa_era* and *c_realbb_9* is 0.32, possibly explaining the decrease in statistical significance. Wins remain a significant effect, and the significance of the left interaction with wins increases in comparison to the first two models, significant to the 1% level with a t-stat of 3.57.

Table 7

*Additional regression results. All are variations of the baseline in which unexpected results were obtained. Robust standard errors appear in parentheses. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.*

	(1) lnsalary	(2) lnsalary	(3) lnsalary	(4) lnsalary	(5) lnsalary
left					
twa_era	-0.035***	-0.036**	-0.033**	-0.020	-0.017*
	-3.03	-2.1	-2.48	-1.38	-1.65
l_twa_era	-0.014	-0.079***	-0.049**	0.050*	-0.005
	-0.85	-2.96	-2.09	-1.95	-0.31
c_w_9	0.274*	0.333*	0.277*	0.293*	0.262*
	1.87	1.87	1.87	1.79	1.93
l_c_w_9	0.804***	0.409***	0.780***	0.579***	0.783***
	3.76	2.64	3.70	3.35	3.90
c_hr_9		-0.009	-0.011	-0.035	
		-0.28	-0.39	-1.25	
l_c_hr_9		0.157**	0.191***	0.139**	
		2.00	2.81	1.98	
c_so_9	0.066***		0.067***		0.070***
	7.85		8.03		7.68
l_c_so_9	-0.047***		-0.050***		-0.031*
	-3.25		-3.58		-1.80
c_realbb_9				-0.072***	-0.083***
				-3.63	-3.24
l_c_realbb_9				-0.055*	-0.039
				-1.80	-0.95
tenure	0.506	0.502***	0.507***	0.505***	0.508***
	35.48	34.99	35.62	35.38	35.75
tenure_2	-0.019***	-0.019***	-0.019***	-0.020***	-0.020***
	-22.02	-21.86	-22.16	-22.36	-22.39
Constant	12.027***	12.506***	12.019***	12.707***	12.181***
	115.54	113.56	123.60	115.89	125.98
R^2	0.4544	0.4442	0.4556	0.4556	0.4668
Observations	4070	4070	4070	4070	4070

t-statistics are listed below the coefficient
$*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Five additional regression models were specified, the results of which can be seen in Table 7. The first included *c_so_9* and its interaction, *l_c_so_9*, in the baseline model. The main effect for strikeouts is highly significant with a t-stat of 7.85, and has the expected positive coefficient, while the left interaction is also highly significant with a t-stat of -3.25 but has a negative coefficient. This indicates that left-handed pitchers who have more strikeouts per 9 innings over their career are paid less, contrary to basic intuition. In this model, *twa_era* remains significant along with *c_w_9* and its interaction, while the left interaction with *twa_era* is no longer significant, as its t-stat drops to -0.85.

When including a control for the effect of home runs with the baseline model, only the left interaction is significant as *c_hr_9* has a t-stat of -0.28, while the interaction has a t-stat of 2.00. Like strikeouts, the main and interaction effects of home runs have opposite signs on their coefficients, with the main effect having a negative, though insignificant, coefficient, and he interaction having an unexpected positive coefficient while being significant with a t-stat of 2.00. This would imply that a left-handed pitcher who allows more home runs per 9 innings will see their salary increase, which is clearly counterintuitive. The main and interaction effects for *twa_era* remain significant with the expected signs on their coefficients, and *c_w_9* along with its interaction remain significant still retaining the expected positive coefficient.

Three of the additional models combine the effects of the three true outcomes, home runs, strikeouts, and walks, with the baseline model. When including *c_hr_9* and *c_so_9* along with their left interactions, home runs and strikeouts both still have opposite signs on the main and interaction effects. The main and interaction effects for home runs and strikeouts are highly significant except for the min effect of home runs, which is insignificant entirely. The main effects for ERA and wins remain significant, while the interaction effects are more significant, to the 5% level for *l_twa_era* and 1% level for *l_c_w_9*.

The combination of home runs and walks results in the main effect of walks being highly significant, with a t-stat of -3.63, while the main effect for home runs is again insignificant. Despite the insignificant negative coefficient on *c_hr_9*, the left interaction for home runs is significant to the 5% level, but again has an unexpected positive coefficient. The main and interaction effects for walks have the expected negative coefficients, though the interaction *l_c_realbb_9* is only statistically significant to the 10% level with a t-stat of -1.80. The main and interaction effects of wins remain significant with the expected coefficients, while *twa_era* and its interaction decrease in significance, with t-stats of -1.38 for *twa_era* and -1.95 for *l_twa_era*.

The final model adds controls for strikeouts and walks into the baseline model with their interaction effects. Both the main and interaction effects for strikeouts are significant, though the main and interaction effect again have opposite signs. The interaction effect for strikeouts, *l_c_so_9*, still has a slightly negative coefficient of -0.031, although it is the smallest coefficient in absolute value on *l_c_so_9* in the models presented. The main effect on walks is again highly significant with the expected negative coefficient. Its interaction also has the expected negative coefficient, though it is not significant with a t-stat of -0.95. The effect of wins remains significant, and the interaction effect is highly significant to the 1% level, both with a positive coefficient. Just as in the other 2 models that included walks, *twa_era* and *l_twa_era* decease in significance, the main effect is barely significant to the 10% level with a t-stat of -1.65 and the interaction effect has its lowest t-stat in absolute value throughout the models at -0.31.

Across nearly all the models, *twa_era* is significant and carries the expected coefficient. The experience variable of *tenure* along with *tenure_2* are highly significant in every model, and have the expected positive coefficient on *tenure* and negative coefficient on *tenure_2*, indicating that the value for experience is nonlinear, increasing to a point and then decreasing after so many seasons. When including walks, the main effect, *c_realbb_9*, is highly significant and has the expected coefficient, but it reduces the significance of *twa_era* every time it is included, from highly significant to only significant at the 10% level or insignificant entirely. The two other "true outcome" measures of *c_so_9* and *c_hr_9* did not carry the expected coefficients when they were significant in the specified models, as the main and interaction effect had opposite signs while the interaction for home runs had a positive coefficient.

The variable *c_w_9* is significant, exhibiting significance up to the 10% level in every one of the specified regressions. Its' coefficient ranged between 0.262 and 0.333, indicating that every additional win per 9 innings translated to approximately a 30% increase of a pitcher's salary. This could, however, be more reflective of organizations' value of starting pitchers over relief pitchers. A starting pitcher is much more likely to be credited with a win if his team wins the game than a relief pitcher is, since the relief pitcher would need to be in the game when a lead change occurs in his favor.

The left interactions for the two most consistently significant variables, *l_twa_era* and *l_c_w_9*, were both highly significant in the baseline model. In additional models, the significance of *l_twa*_era roughly changed in unison with its main effect, while *l_c_w_9* was highly significant in every model despite its main effect never being significant past the 10% level.

In the baseline regression model, the two explanatory variables *twa_era* and *c_w_9* were both significant and their left interactions were significant as well. This trend persisted in further models, with interactions tending to rise and fall in significance with their main effect when *left* was not also included. This means that when a variable had a statistically significant impact on the salary of a pitcher, there was an additional statistically significant marginal impact on salary of left-handed pitchers. Thus, the models provide sufficient evidence that there is a difference in pitchers' salary based on their throwing hand.

VI. Conclusion

This thesis finds evidence there is a difference in salary for left-handed pitchers in comparison to right-handed pitchers. In the eight regression models analyzed, when a measure of performance has a statistically significant effect on salary, there is an additional statistically significant impact on salary that left-handers encounter, above and beyond the effect of that variable for pitchers generally. The traditional statistics of ERA and wins were relied upon most heavily, while the three true outcomes of home runs, strikeouts, and walks were included as supplements.

One effect not accounted for in this thesis that certainly influences players' salaries is the salary structure in the MLB. Abrams (2009) lays out the path between the reserve system, salary arbitration, and free agency for a player. A player's salary in his first six years is determined by the reserve system and arbitration, then entering free agency where he can negotiate a contract with any team. During the first six years however, salary is either decided on by the organization or negotiated by the player and club with the option of going to an independent arbitrator. However, player salaries in arbitration are often much lower than they would receive as a free agent since they remain under club control and are unable to sign with other teams. Thus, players who are eligible for free agency would be expected to have much larger salaries than players in the reserve system or arbitration. Once a player is eligible for arbitration, there is also an expected salary increase as the player gains some leverage with the ability to negotiate and take their case to an arbitration trial if they choose. A logical extension of this thesis' analysis would be to control for these expected differences by separating data based on whether a player's contract is decided by the reserve system, arbitration, or free agency. Another important control variable might be race categorized into white, Hispanic, and black used by Leonard (1989).

While cumulative statistics give a better representation of a player's true ability and performance, a player who has just had a productive season or string of productive seasons would be expected to earn a higher salary. With so much available data now for players and organizations, it is not uncommon for pitchers to make adjustments well into their career and perform at a much higher level than they previously had. The experience variable included, *tenure*, might not be the best measure to account for pitchers who don't find sustained success until their late 20s or 30s such as Kevin Gausman, Robbie Ray, and Charlie Morton, who all had not consistently performed well until their tenth, ninth, and tenth seasons, respectively. Another extension of my model is to place a greater weight on recent performance over the last season or two, while still accounting for career performance. This will better account for pitchers who might have made an adjustment mechanically, to their pitch usage, or pitch arsenal that led to more success, while still considering performance over the entirety of their career.

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VIII. Appendix

Table A1

Correlation matrix of raw variables

	ip	w	h	hr	so	bb
ip	1					
w	0.91	1				
h	0.97	0.86	1			
hr	0.86	0.75	0.89	1		
so	0.93	0.87	0.85	0.76	1	
bb	0.86	0.76	0.84	0.76	0.81	1

Table A2

Correlation matrix of left interactions

	left	l_c_ip	t_twa_era	l_c_w_9	l_c_h_9	l_c_hr_9	l_c_so_9	l_c_realbb_9
left	1							
l_c_ip	0.64	1						
l_twa_era	0.89	0.53	1					
l_c_w_9	0.90	0.68	0.76	1				
l_c_h_9	0.96	0.60	0.96	0.84	1			
l_c_hr_9	0.84	0.53	0.88	0.72	0.89	1		
l_c_so_9	0.96	0.61	0.81	0.87	0.88	0.76	1	
l_c_realbb_9	0.90	0.50	0.85	0.80	0.86	0.75	0.88	1