Capturing Risk-Premiums in Major League Baseball Contracts

An analysis of player variance in performance and the subsequent effect on player compensation

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Abstract

Risk premiums are witnessed in many aspects of economics. A risk premium is generally thought of as the minimum amount of expected return on a risky asset above a risk free asset in order to justify holding the risky asset. Major League Baseball is a unique setting in which to study risk premiums. Individual output is well documented and therefore variance in production for an individual employee is easy to capture. This paper attempts to examine the effect that a player's variance in performance has on the compensation he receives. Empirical results from Major League Baseball using simple OLS Regressions illustrate that only good teams take into account variance in performance when offering player compensation. Not only do good teams consider variance in performance when offering compensation, but they actually value risk as a means to slide up the convex portion of the Major League payoff structure where risk-loving behavior is promoted.

Introduction

Major League Baseball (MLB) has always been a valuable setting in which to observe labor economics. Lawrence Kahn eloquently stated that "there is no research setting other than sports where we know the name, face, and life history of every production worker and supervisor in the industry[1]." Baseball is a game which is forever intertwined with its almost neurotic obsession with statistics. These statistics were created as a means to capture an individual's contribution to the overall team success. Because of the abundance of relevant statistics and information on player (employee) performance, it can be expected that owners (employers) will offer contracts which take into account these performance statistics when compensating players.

Numerous studies have been conducted to identify which offensive statistics most significantly capture a player's contribution to a team's success. David Berri and John Bradbury constructed an equation aimed at objectively quantifying the amount of runs that a player helps his team score; the ultimate objective of an offensive player. They used the following equation to illustrate this idea[2]:

Equation 1: Runs scored per game = $\boldsymbol{\alpha_0 + a_1 * performance\ measure + e_{1t}}$

Berri and Bradbury continued to use performance measures to see which best explained the variation of runs scored per game. They used batting average, slugging percentage, and on-base plus slugging percentage (OPS) and found that they explained 65%, 78%, and 89% of the variation of runs scored per game respectively[3]. The powerful explanatory value of OPS is the reason why I have chosen OPS as my relevant performance statistic when evaluating variation in player performance and its subsequent effect on player compensation.

Introduction to OPS

Because the metric OPS will be heavily referred to in this text, it is important to have a general understanding how it is measured. OPS is on-base plus slugging percentage. As stated above, it is a metric derived to accurately capture a player's offensive contributions to the team. The relevant equations are given below:

OBP= On-base percentage
SLG= Slugging percentage
H = Hits
BB= Walks
HBP= Times hit by pitch
AB= At bats
SF= Sacrifice Flies
TB= Total Bases

Equation 2: $$\text{OPS} = \text{OBP} + \text{SLG}$$

Equation 3: $$\text{SLG} = \frac{TB}{AB}$$

Equation 4: $$\text{OBP} = \frac{H+BB+HBP}{AB+BB+SF+HBP}$$

Now that OPS has been defined and proven as a reliable measure of player performance, we can begin to discuss the data for this research more in depth.

Data

Data Collection

I compiled a dataset taking the skeletal framework of a previous study performed by Professor Joel Maxcy on the determination of long term labor contracts in Major League Baseball. I elected to add on to this particular dataset because it had contract information that I was having trouble locating for more recent years. The dataset included all players' contract information who signed a contract between the years 1986 and 1993.

I then added my performance statistics of interest to his dataset. I collected month to month statistics on all sixteen hundred plus players by hand. I used baseball-reference.com as my main source for collecting data. The process, while tedious, was not very difficult. The following steps were used repeatedly throughout the data collection process.

1. Input the players name into baseball-reference.com
2. Open that players monthly splits for the *year prior* to that player signing a contract (if the player signed a contract in 1992, the relevant statistical period would be 1991)
3. Input the players monthly performance in OPS, GS, and ABs
4. Repeat this process 1728 times

While I collected a large majority of the data, I did have some degree of help. The UCSD soccer team (all 25 of them) collected data for about two hours one day. This could lead to problems with the accuracy and integrity of part of the dataset. To control for this problem, I personally went back and checked every piece of data that they collected. While this by no stretch of the imagination insinuates that this is a perfect dataset – with such a tedious process there are bound to be mistakes – it does limit the amount of mistakes and thus increases the accuracy of the dataset and my subsequent findings.

Data Description

The data utilized for this analysis is primarily longitudinal panel data recording contract information and performance statistics on 1626 Major League Baseball players from 1986-1993. Each observation contains the players' statistics from the year prior to signing a contract as well as other information that was necessary to conducting this research.

The data for each observation can be broken into three specific categories. The first category is information that can affect the player's compensation on an individual level outside of his performance such as arbitration eligibility, free agent eligibility, age, experience, defensive position, and year signed.

The second category is the player's performance statistics which were gathered to calculate offensive contributions to the team. These statistics include OPS, OPS by month, at bats, games started by month, games started for the season, and our "risk" measurement of OPS variance. OPS variance is calculated in the traditional manner of variance by simply taking deviations from the mean squared and dividing by the number of observations as shown by Equation 5.

Equation 5: $$\sigma^2 = \frac{\sum(X-\mu)^2}{N}$$

The third and final category of data that was collected was team level data. This included the team that signed the player, the opening day payroll of that team, that teams previous year win total, and the amount of wins that team was away from 95 wins.

Of these 1626 observations, there were 1341 one year contracts and 285 long term contracts. A more detailed account of the contract type with relevant information is shown in table 1 below.

Table 1: Summary of Statistics by Contract Length

	1 Year Contract	2 Year Contract	3 Year Contract	4 Year Contract	5 Year Contract	6 Year Contract	Total
Number of Observations	1341	150	103	20	11	1	1626
Mean OPS	.695	.735	.770	.784	.861	1.08	.706
St. Dev. OPS	.112	.104	.098	.0995	.0994	Na	.1136
Mean OPSVAR	.0305	.0276	.0165	.0171	.0219	.0282	.0291
St. Dev. OPSVAR	.053	.0440	.0141	.0087	.0156	Na	.0502
Mean EXP	4.94	8.15	7.27	7.4	7.54	7	5.43
Mean Age	28.2	31.03	29.7	29.5	29	28	28.58
Mean GS	84.8	103.35	131.33	138.65	133.27	138	90.52

Data Breakdown for Analysis

Along with simply running a regression over the entire dataset, I have also decided to decompose the data and run similar regressions over these sub-datasets. The first way in which the data was broken down was by the amount of wins the team recorded during the previous year. I decided to do this because it is entirely possible that good teams view variance in a significantly different manner than bad teams. It is my hypothesis that "good teams" are likely to value low variance type players while "bad teams" are more likely to value high variance type players.

I believe that good teams will value low variance type players because they already have a high previous year win total. If a team is already successful, it is unlikely that they would value a player that will provide uneven contribution to the club. They would prefer to sign a player who has a low variance in performance and can help the good team continue their winning ways. Risk is not something that a good team needs to add because they have proven that they can win as the team is currently built. Adding unnecessary risk is not a proposition that a good team should favor.

Bad teams might take a different approach to evaluating variance in performance. In baseball, there is little difference between losing 100 games and 110 games. Either way, your team is probably in last place in your division. This general rule is why I hypothesize that bad teams will greatly value variance in performance when signing players.

Bad teams employ a strategy which I will call the "Hail Mary" approach (different sport same idea). Bad teams will want to sign as many high variance players as they can. They should do this for two reasons. First, high variance players should be cheaper if my initial hypothesis for how good teams should act in player bargaining holds. Because good teams do not target these kinds of players, their market value should be lowered. Bad teams could sign these players at a discount because there is less competition in the market for high variance type players.

Second, if a few of these high variance type players happen to perform at their highest percentile for an extended period of time, the bad team might have a chance of winning their division, making the playoffs, and even winning the world series. Using this logic, bad teams look to sign as many high variance type contracts as possible because they know that is their only way of competing. And what if these players all perform at their lowest percentile and end up making the team worse? Well, the bad team loses a few more games than they did before and miss the playoffs by 25 games instead of 20. With these high variance type players, bad teams at least have a shot at winning. This low-risk medium-reward strategy is what I believe will incentivize bad teams to value high variance type players.

One interesting case might be if a good team loses many of its good players from the previous year. A good team that has multiple star players eligible for arbitration or free agency might not be able to retain them given certain payroll constraints. If a good club loses many of its key impact players, they might act as a bad team in their valuation of variance even if they had a high win total from the previous year. A good team, as defined from previous year wins, valuating risk as a bad team might be occasionally observed for this reason. However, I believe that my original hypothesis, that good teams will dislike variation in performance while bad teams will prefer it, can be proven correct despite admitted exceptions.

Good teams and bad teams were separated by how many wins away they were from the average amount of wins needed to make the playoffs during this time period. The average number of wins needed to make the playoffs was calculated to be right around 95 games. Thus, if a team was within 15 games of making the playoffs the previous season, they were considered a good team. If they were not within 15 games of making the playoffs, they were classified as a bad team.

This classification of good and bad teams is problematic in that you lose explanatory value when binary classifications are made. There are obvious differences between the 1988

Braves who won 54 games and were -41 games away from 95 wins and the 1986 Cardinals who won 79 games and were -16 games away from 95 wins. However, this way is sufficient in differentiating good and bad teams so that their differing views on variance in performance can be analyzed. The breakdown between good and bad teams is summarized in Table 2 below.

Table 2: Good Teams vs. Bad Teams

	Good Team (within 15 wins of 95)	Bad Team (not within 15 wins of 95)
# of Observations	889	848
Mean OPS	.714	.714
SD OPS	.1176	.1184
Mean OPSVAR	.0289	.029
SD OPSVAR	.0508	.0516
Mean EXP	5.57	5.55
Mean AGE	28.7	28.6
Mean GS	91.32	91.12
Mean COMP	766,231.60	710,686.90

The second way in which I broke down the data was between starters and nonstarters. It is again possible that variance in performance is viewed differently when teams are evaluating starters than when evaluating nonstarters. When a team looks to sign a player to a contract, they know whether they are looking for a starter or not. Although nonstarters can become starters by performing at a high level, and vice versa for starters performing at a low level, the players are still paid on the expectation of being a starter or nonstarter for the team offering the contract. It is then logical that a team might view variance in a player they expect to play 162 games during the season much differently than a player they expect to play only 35 games.

In regards to valuing variance in starters and nonstarters, it is my hypothesis that teams will value variance in nonstarters and dislike variance in starters. If a team is signing a player they expect to be a substantial contributor on an every game basis, they might pay for a little more certainty about their offensive output. For nonstarters, a team might prefer a player with high variance because they are not expected to be everyday contributors. The coach can put in these types of players when they need an extraordinary performance that he believes a high variance type player might be able to deliver.

Table 3: Starters vs. Nonstarters

	Starters (started at least 130 games)	Nonstarters (started fewer than 130 games)
# of Observations	432	1194
Mean OPS	.766	.684
SD OPS	.0948	.112
Mean OPSVAR	.0149	.0342
SD OPSVAR	.0104	.0574
Mean EXP	5.85	5.28
Mean AGE	28.18	28.73
Mean COMP	1,1410,831	498,724

Bias in the Data

For the subsequent discussion of bias captured by the dataset, it is important to understand that much of the analysis will be taken from Joel Maxcy's original research. Because the contract data which I am utilizing is the same data collected by Maxcy years before, the same bias which his collection introduced into the system will still exist. A brief summary of his analysis of these biases is the basis of the following two paragraphs.

The amount of times that a player is represented in this dataset varies based on the number of contracts a player signed during this particular time period. Many players signed multiple contracts of varying lengths during our years of interest while some only signed one contract. This can be because of many reasons, but for our purposes, understanding that some players are represented in this dataset more than once is sufficient[4].

The contract data also contains some selection bias because it is possible that some contract terms went unreported. Thus, those that were not reported would not be included in the dataset. This problem obviously makes the dataset neither comprehensive nor random. Most common in these omissions are players which did not hold a major league contract but played with the club for all or part of the season. Also missing from the data might be veteran players who elected to sign unreported extensions rather than new contracts. Signing an unreported multi-year extension, akin to signing a multi-year contract, could lead to observations being omitted[5].

Other biases pertaining to my added performance statistics outside of the contract data collected by Maxcy also exist. It is outside of the realm of this dataset to account for a player whose statistics were hampered due to an injury. Teams at the time of signing would have a better understanding of whether or not a player's injuries were the cause of his low output. If teams believe that a player's low output could have been caused by a minor injury that should heal, the team might sign the player to a larger contract than his injury impaired statistics justify.

Another situation which cannot be accounted for within my dataset is minor league players who are mid-season call ups. This would result in fewer observations of monthly splits for younger players and thus increase their variance in OPS simply by decreasing the number of monthly observations.

Also relevant to this study is the convicted collusion of the MLB owners from 1986-1988. Owners colluded against free agents during this time period to keep the price of star players down[6]. This resulted in a negative shock on compensation that was unrelated to a decline in performance. To control for this, a dummy variable YR1989 was created for all contracts that were signed between 1986 and 1989.

Some players were dropped from the study for a variety of reasons. The main reasons for dropping players were the absence of performance statistics for the relevant time period and if the player was a pitcher.

This dataset contains only offensive players. Pitchers were not included in this study because their contribution to the team is measured much differently than position players. Pitchers are not compensated based on their offensive production but rather their ability to get opposing players out.

The final bias that exists in the data is probably the most important as it relates to this study specifically. I evaluate variance in performance over a six month sample with one observation each month. However, to obtain a high variance in performance, a player must be *capable* of performing extremely well for some period of time. For example, a player that has a low variance in performance might have monthly splits in OPS of .500, .550, .525, .530, .550, and .525 over the six month season. This is a below average player. He is very consistent, but he is consistently below average.

Contrast this with a player who might have high variance in performance. This player might have monthly splits in OPS that are .900, 1.240, .560, .675, .800, and .950. He has a higher OPS in every month than our theoretically consistent player. Thus, he should be expected to be paid substantially more despite his perceived inconsistency. Because I am unable to distinguish between these two situations, it could cause the regressions to overvalue variance in performance in player compensation because it is capturing the player’s ability to obtain a high OPS rather than how teams view his variance in performance.

I believe that the above scenario should not arise very often and should be mitigated by another scenario that will lead to an undervaluation of OPS variance. A player could have the same OPS statistics as our second hypothetical high variance type player but with a very low number of at-bats. The low number of at-bats might be the reason for a poor player posting a very high OPS during a certain month. The poor player might only get 4 at-bats one month, hit a home run and post an OPS of 1.250. This is obviously different from a very good player attaining such an OPS over 120 at-bats during a given month. Because a team can observe that the player getting fewer at-bats could have been lucky, he would not be compensated as a player capable of posting such a high OPS. This scenario, which could cause OPS variance to be undervalued, should work to offset the original circumstance which overvalued variance in OPS. Finally, the inclusion of OPS in the regression itself should help control for these types of situations.

The Model Specification

The model used to test the significance of the data will be a simple Ordinary Least Squares regression (OLS). One of the major biases I expect within the framework of an OLS regression for this study is the fact that not all teams have perfect information about a player outside of his statistics. For example, a player might have subpar performance statistics but be paid a higher compensation by his current team because of his intangible value to the club. These types of positive externalities that a single player might have on his team are something which is unobservable in the data and to other clubs who are bidding on that player.

While it might be fair to assume that during the time of bidding, other clubs had a general understanding of what "intangibles" a player might bring to their team, it is obvious that this is a market in which perfect information is not available to all parties. In hopes of partially correcting for this problem, I will use a variable found in Maxcy's original dataset known as SWITCH. This is a dummy variable coded 1 if the player switched teams when he signed his contract and 0 otherwise. This should control for some of the compensation given to a player because of information that is unavailable to all bidders.

The opposite case can also be true. A team might have information about a player on their current roster that is a negative externality to the team for a variety of reasons. The SWITCH dummy is used to control for this problem as well. The regression utilized during this study is given in Equation 6 on the next page.

Equation 6: **OLS Regression**

$$COMP = \beta_0 + \beta_1 OPS\_VAR + \beta_2 VarWin95 + \beta_3 VarGS + \beta_4 YR1989 + \beta_5 SWITCH + \beta_6 EXP + \beta_7 AGE + \beta_8 OPEN\_PYRL + \beta_9 WINS\_FROM\_95 + \beta_{10} OPS + \beta_{11} GS\_SEASON + \beta_{12} AE1 + \beta_{13} AE2 + \beta_{14} AE3 + \beta_{15} FA + \beta_{16} C + \beta_{17} SS$$

Table 4: Variable Definitions

Variable	Definition
OPS_VAR	Variance in monthly OPS over the season prior to signing the new contract
VARGS	Interaction term between OPS_VAR and GS_SEASON
VARWIN95	Interaction term between OPS_VAR and Wins_From_95
WINS_FROM_95	Amount of wins the team was from 95 the year prior to signing the player
EXP	Years of experience the player has in the league when contract was signed
AGE	Players age as of June 1st of the year he signed his contract
SWITCH	Dummy variable if the player switched teams is 1, 0 if otherwise
OPEN_PYRL	Opening day payroll of the team for the year that they signed the player
OPS	Season on-base plus slugging percentage
GS_SEASON	Games started for the season the year prior to signing the contract
AE1	Dummy variable coded 1 for the 1st year of arbitration eligibility, 0 otherwise
AE2	Dummy variable coded 1 for 2nd year of arbitration eligibility, 0 otherwise
AE3	Dummy variable coded 1 for 3rd year of arbitration eligibility, 0 otherwise
FA	Dummy variable coded 1 if free agent eligible, 0 otherwise
YR1989	Dummy variable coded 1 if the contract signed between 1986-1989, 0 otherwise
C	Dummy variable coded 1 if the players primary position is catcher, 0 otherwise
SS	Dummy variable coded 1 if the players primary position is shortstop, 0 otherwise
COMP	Compensation in terms of dollars per year as stated in his contract

Results

Entire Dataset

The initial regression involving the entire dataset shows that variance in performance is not significant in determining compensation if the data for the league is taken as a whole. The results table of Regression 1 can be found at the end of this section.

Owner collusion, represented by the variable YR1989, showed that players who signed contracts between the years 1986 and 1989 could expect to earn substantially less than if they had not signed during this time period. Switching teams also had a negative relationship towards player compensation. This is probably because of the incomplete information that the bidding teams have about a player not currently on their roster. Teams do not want to offer as much money for a player who they have questions or concerns about.

Age is also negative which speaks to the expected career arc of a Major League player. Players are expected to hit their primes somewhere between the ages of 26 and 32. A players performance plotted against age would look like an inverse parabola. A player's peak earning years should be during his prime and then taper off from there.

Opening day payroll has a positive effect on player compensation. This is to be expected that higher revenue grossing teams can afford to spend more on targeted players. Our performance statistic OPS is the most impactful coefficient on player compensation. Players are paid for their offensive contribution to the team. Because OPS is an accurate measure capturing this contribution, the coefficient should be significant and positive.

Games started the previous season have a positive effect and a high level of significance. Again, this is an expected finding. Players that started games the previous season should command a higher salary than those who did not.

All three of our arbitration eligibility measures are significant. This is because the player is gaining more bargaining power and essentially eroding the restrictive monopsony power held by clubs[7]. By the time a player hits free agent eligibility, the monopsony power of clubs has been wiped away completely.

While it might seem shocking that experience is insignificant in this regression, the above paragraph reveals why. The main reason why experience should be positively correlated with a higher salary is because of the increased negotiating power that the player obtains by accruing years of service in the league. Obtaining arbitration eligibility and free agency both increase the player's ability to openly negotiate with other teams and increases his market value. The positive effect that experience would have on compensation is absorbed by the inclusion of the different arbitration levels and free agency.

Regression Results 1: Entire Dataset

Variable Name	Reg 1.1	Reg 1.2	Reg 1.3
ops_var	168578.92	145195.76	583679.74
	(342727.91)	(562954.13)	(628188.98)
YR1989	-158245.61***	-158387.48***	-155057.47***
	(44031.801)	(44128.692)	(44159.561)
switch	-88690.911	-88827.795	-83988.377
	(45828.114)	(45916.785)	(45999.26)
exp	6107.9036	6128.4644	6720.5517
	(10905.213)	(10915.657)	(10917.202)
age	-21332.61*	-21336.774*	-21905.25*
	(8699.0153)	(8702.0756)	(8705.6459)
open_pyrl	0.0271339***	0.0271326***	0.02717428***
	(0.00198067)	(0.00198144)	(0.00198072)
wins_from_95	-2554.7482	-2509.7287	-2427.0596
	(1662.9159)	(1872.4497)	(1872.3376)
ops	1695374.3***	1695545.7***	1723413.1***
	(173441.15)	(173525.82)	(174352.56)
gs_season	6567.8374***	6567.1249***	6810.6177***
	(462.76903)	(463.11243)	(488.18852)
ae1	199025.99***	199012.36***	200925.61***
	(54805.423)	(54823.034)	(54811.62)
ae2	585701.43***	585609.51***	586819.91***
	(59686.22)	(59730.526)	(59708.308)
ae3	767580.67***	767438.21***	769178.65***
	(69380.236)	(69455.038)	(69432.265)
Fa	881971.59***	881795.21***	879377.32***
	(83788.287)	(83881.915)	(83857.865)
C	14906.535	14945.645	17047.224
	(46846.67)	(46867.146)	(46864.926)
ss	-849.85551	-996.41494	-3043.4694
	(60427.695)	(60511.185)	(60497.685)
nl	21747.184	21739.878	23527.075
	(33176.541)	(33187.121)	(33191.535)
VarWin95		-1565.488	-7439.8608
		(29894.382)	(30114.093)
VarGS			-16637.466
			(10596.441)
_cons	-1401875.3***	-1401075.5***	-1413666.5***
	(253771.22)	(254308.91)	(254319.59)

=.05 significance level** *=.01 significance level** *****=.001 significance level**

Good Team Results

Breaking down the data into two sub-datasets containing good teams and bad teams has yielded very interesting results that contradict my initial hypotheses. Regression 2.1 (which can be found at the end of the chapter) shows that when a regression was run on the dataset containing only good teams, the variance in performance measure (OPS_VAR) was large and significant at the 5% level. Not only is OPS_VAR large, it is large and positive. This evidence starkly contradicts my original hypothesis that good teams will devalue a player if they have a high variance in performance. Because these results were in direct contradiction with my original hypothesis, I will attempt to offer an explanation as to why we are witnessing good teams paying for OPS_VAR.

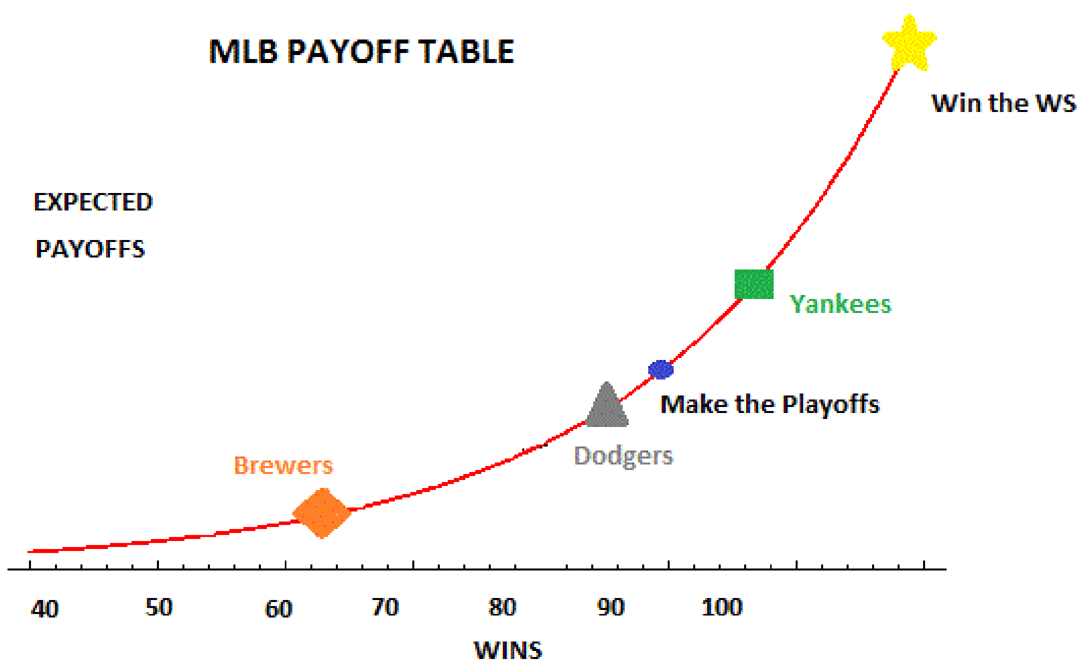
I believe that we are witnessing this risk-loving behavior because the payoff table for a MLB club is convex. Payoff is generally defined here as an all-encompassing capture of any benefit to the club (who is offering the contract) for winning. This includes increased attendance at the ballpark, explicit financial rewards for making the playoffs and winning the World Series, and job security for the front office that puts together a winning team. When analyzed in this manner, it is not a significant assumption to view the MLB payoff structure as an exponentially increasing payoff table that culminates in a World Series victory.

Because of the convex nature of the MLB payoff table, teams should employ a risk-loving strategy. The return on the investment for a player with a high variance can possibly be enormous because of the shape of the MLB payoff table.

A graphical representation of this theoretical analysis can be found in Graph 1 below. Looking at the graph, a 5 win increase for the Yankees or Dodgers will provide a large increase in their payoffs because of the exponentially increasing nature of the payoff table. Compare the potential gains of a 5 win increase with the potential losses of a 5 win decrease (if the high variance player does not perform). Gains obtained by sliding up the payoff curve will always outweigh the losses realized from sliding down the payoff curve by the same amount. Because of the convexity of the payoff table, the rewards outweigh the risk.

This can be mathematically understood using simple derivatives. If you are at a certain point on an increasing function, $\frac{dy}{dx}$ towards the increasing region of the function (to the right in Graph 1) is always greater than $\frac{dy}{dx}$ towards the decreasing region (to the left in Graph 1). This is why good teams are not only willing to bring on a player who displays a higher variance in performance, but they actually target these types of players.

Graph 1: MLB Payoff Table



The interaction term VarGS representing the interaction between OPS_VAR and GS_SEASON represents the idea that good teams view variance in performance differently depending on how many games the player started the previous year. The effect is small and negative implying that the more games a player started the less variance a good team would like out of that player. Although the effect is rather small, this illustrates that good teams would like their starters to be more consistent than their bench players.

There were no meaningful changes in the level of significance reached or the coefficient magnitude for the variables that were also included in Regression 1. I expect many core variables – YR1989, age, open_pyrl, wins_from_95, ops, gs_season, ae1, ae2, ae3, and fa – to more or less remain significant throughout all regressions.

In regression 2.2 I decided to add the term wins_from_95. As might be expected, the introduction of this term did not change the size or significance of any other variables. The dataset is already broken down into good and bad teams so adding a variable controlling for wins should have little effect.

Regression Results 2: Good teams

Variables	Reg 2.1	Reg 2.2
ops_var	1143581.4*	1143677.7*
	(575312.4)	(575838.39)
VarGS	-37426.287*	-37430.317*
	(15206.633)	(15228.314)
YR1989	-138088.57*	-138032.28*
	(59062.933)	(59744.005)
switch	-47157.809	-47182.246
	(61134.185)	(61287.658)
exp	5369.096	5370.6768
	(14328.341)	(14338.679)
age	-30234.144*	-30236.046*
	(12138.271)	(12148.854)
open_pyrl	0.02828477***	0.02828838***
	(0.00265966)	(0.0027199)
ops	1446504***	1446560.2***
	(224368.79)	(224668.27)
gs_season	7534.9509***	7534.9128***
	(637.89914)	(638.29287)
ae1	239170.51***	239183.04***
	(71387.433)	(71455.049)
ae2	722092.14***	722100.41***
	(78557.329)	(78612.97)
ae3	862932.21***	862944.68***
	(91343.428)	(91416.509)
fa	923692.86***	923722.85***
	(109739.1)	(109901.49)
c	10763.405	10762.451
	(60526.228)	(60561.144)
ss	-125905.65	-125897.24
	(81457.424)	(81514.691)
nl	74954.686	74962.404
	(43433.842)	(43475.4)
Wins_from_95		-24.257964
		(3779.6304)
_cons	-1096128.4**	-1096377.4**
	(349879.75)	(352223.01)

=.05 significance level** *=.01 significance level** *****=.001 significance level**

Bad Team Results

The same regressions that were run utilizing the good team dataset were subsequently run on the bad team dataset and the results are shown in the Regression 3 results table at the end of the chapter. Many variables which were significant in the determination of compensation for good teams are insignificant for bad teams.

Our main variable of interest, OPS_VAR, is now insignificant. The fact that OPS_VAR is insignificant for bad teams neither rejects nor confirms my initial hypothesis that bad teams should value risk in some type of "Hail Mary" strategy. However, it is problematic for my above analysis about the convexity of the MLB payoff table. If the MLB payoff structure is indeed convex, then all teams, regardless of initial placement, should employ risk-loving behavior.

For example, let us refer back to Graph 1 and see what happens if the Brewers see a 5 win increase (the same size increase as for the Yankees and Dodgers in the good team analysis). This increase will not realize an impressive increase in pay off because of their position on the payoff curve. However, a 5 win decrease does not lose the Brewers very much payoff either. The rewards of taking on a high variance type player seem to outweigh the risk even for teams on the lower end of the payoff table. So why don't the regressions show that the bad teams value variation in performance? If the payoff structure of Major League Baseball is in fact convex, then shouldn't all clubs take on a risk-loving strategy?

I believe that the answer to the above question is not necessarily. Decisions between how good and bad teams value variance are not made in a vacuum. The good teams will target high variance type players, as shown in regression 2**.** By targeting these players, good teams drive up the price of the high variance type player. Not only do they drive up that player's price, but because of their current location on the MLB payoff table, their expected reward of signing that player is strictly greater than the expected payoff of a bad team signing the same player. Because their expected reward is greater, good teams should theoretically pay strictly more for a high variance type player than a bad team. Many of the high variance type players are absorbed by the good teams for larger contracts. This is illustrated mathematically below.

Equations: 7-10

$$(7) \qquad E(\phi)_{Good} - \gamma_{Good} = 0 \;\; ; E(\phi)_{Bad} - \gamma_{Bad} = 0$$

$$(8) \qquad E(\phi)_{Good} \geq E(\phi)_{Bad}$$

$$(9) \qquad \gamma_{Good} \geq \gamma_{Bad}$$

$$(10) \quad \gamma_{Good} > E(\phi)_{Bad}$$

- $E(\phi)_{Good}$= Good teams expected payoff of signing player X
- $E(\phi)_{Bad}$= Bad teams expected payoff of signing player X
- γ_{Good}= Good teams compensation offer to player X
- γ_{Bad}= Bad teams compensation offer to Player X

The above equations are an attempt to explain why a risk-loving strategy might not be observed by bad teams despite the convex nature of the MLB payoff curve. In order to complete the analysis, it should be assumed that both the good team and the bad team want player X equally. Also, they will both offer the max contract which they are capable of offering to player X.

Equation 7 shows the fair equilibrium of a contract in this case. The compensation offered to the player by a club should be equal to the expected value that player will bring to the club. Equation 8 shows that because of the difference in position on the convex MLB payoff curve, good teams have an expected payoff from signing player X that is greater than or equal to the bad team's expected payoff. If this statement is true, then equation 9 is also true. The compensation offered by a good team to Player X should be greater than or equal to the compensation offered by a bad team. Because a good team can justify offering more money to Player X than a bad team, we can end up at a situation like Equation 10. Equation 10 shows that, assuming our previous equations and assumptions hold, the highest compensation offered to Player X by a good team *will always be* greater than the expected return that a bad team can expect for signing that player (assuming both teams offer the max amount they are capable of offering). In this circumstance, a bad team will obviously choose not to pursue the high variance type player. They have essentially been priced out by the better teams.

Following the same iterative logic as provided above, the opposite case can never be true. Bad teams highest contract offer can *never be* higher than a good teams highest contract offer. This is why we can see risk-loving behavior from the top portion of our convex curve and not from the bottom portion.

It should be understood that the above analysis offers a general theory as to why we might witness good teams targeting variance while bad teams do not despite the convexity of the MLB payoff curve. I am not attempting to prove any type of general equilibrium for contract negotiations. There are many other factors that go into offering a player a contract as shown by the multiple regressions I have run. I am offering a theory as to why bad teams might not employ a high-risk strategy despite the fact that the convexity of the MLB payoff table promotes risk-loving behavior regardless of current position.

The interaction term between variance and games started (VarGS) has also lost its significance. If our variance term has lost significance, it makes sense that its interaction terms involving variance will also lose significance.

The dummy variable SWITCH has now become significant at the 5% level in a large and negative way. This large negative effect probably captures efforts by bad teams to build from within their farm system. Teams that are out of contention often look to rebuild within their organization by using cheap players that were recently drafted and are still on their rookie contracts. They purge their current roster in order to make room for these cheaper and usually younger players. Signing or retaining major league tested players is too expensive for a team that has little hope of competing. Instead, they usually choose to build for the future through players who are both cheap and young.

Two of our previously coined “core variables” have lost their significance. Age and AE1 are now insignificant in Regression 3.1. Age and AE1’s decline can possibly be explained by bad team’s propensity to purge their roster and build from within the organization. They do not want to retain bad players at a higher cost so they would rather use young talent on minor league rosters to fill out their team.

Regression 3.2 shows that the introduction of the variable wins_from_95 has no effect on the original results obtained from Regression 3.1. Only the variable SWITCH, which barely made the cut off for significance at the 5% level (t-test was -1.96), lost its significance.

Regression Results 3: Bad Teams

Variable	Reg 3.1	Reg 3.2
ops_var	88243.391 (838693.25)	101481.26 (839962.75)
VarGS	2352.846 (15638.434)	2115.9988 (15660.974)
YR1989	-190206.57** (65642.698)	-195610.06** (67293.669)
switch	-136898.47* (69746.348)	-135822.31 (69849.095)
exp	13041.358 (16786.834)	12624.493 (16834.836)
age	-18953.131 (12598.289)	-18983.821 (12606.127)
open_pyrl	0.02524362*** (0.00289054)	0.02497204*** (0.00298439)
ops	2059911.1*** (276837.58)	2057606.5*** (277074.14)
gs_season	5771.6106*** (758.76227)	5781.9053*** (759.7299)
ae1	149980.12 (85000.456)	150186.26 (85053.321)
ae2	435529.04*** (91681.382)	438794.45*** (92161.991)
ae3	666635.96*** (106402.12)	665130.71*** (106544.07)
Fa	859806.15*** (129363.34)	863598.97*** (129848.21)
C	27649.92 (73486.549)	28736.428 (73589.561)
Ss	100596.01 (90755.388)	101472.62 (90840.924)
Nl	-35777.608 (51604.404)	-34807.433 (51702.237)
wins_from_95		1653.5683 (4479.7866)
_cons	-1504357.6*** (363363.58)	-1457326.6*** (385261.15)

=.05 significance level** *=.01 significance level** *****=.001 significance level**

Starter Results

The results on the sub-dataset containing only starters are provided on the next page. The results for starters are fairly ambiguous and do little to help confirm or deny my hypothesis that teams will dislike variance in starters and value variance in non-starters.

One interesting finding with regards to the starters dataset is the wins_from_95 variable. Wins_from_95 has a significant negative effect on the compensation of a starter. This was a variable which has been insignificant in all of the previous regressions. The further a team is away from 95 wins, the further that team is away from the playoffs. Because this type of team probably expects to be more than a few starters away from making a major jump in win total, they would rather not pay for a starter to come make their team marginally better. Instead, they would like to rebuild their team from within their own farm system (as previously discussed) and sign the final pieces when they have a better team. This process possibly accounts for the significant negative relationship between wins_from_95 and compensation of starters.

Regression Results 4: Starters

Variable	reg4_1
ops_var	-4057245.9
	(6059790.6)
VarWin95	139984.56
	(382765.86)
YR1989	-297281.83**
	(108776.13)
switch	-25019.992
	(132856.52)
exp	-4458.8753
	(29533.01)
age	-38618.393
	(26940.397)
open_pyrl	0.0558645***
	(0.00485201)
wins_from_95	-15527.552*
	(6794.4923)
ops	4372161.9***
	(501243.96)
gs_season	15690.717**
	(4801.0644)
ae1	559917.7***
	(125789.98)
ae2	1105824.3***
	(137047.15)
ae3	1494553.2***
	(152971.73)
Fa	1694621.7***
	(214390.9)
C	-65003.93
	(210841.84)
Ss	74907.178
	(127036.19)
nl	17243.273
	(79784.051)
_cons	-5169102.6***
	(1035462.5)

=.05 significance level** *=.01 significance level** *****=.001 significance level**

Non-Starters Results

The regression run over the non-starter dataset also neither confirms nor denies my original hypothesis with regards to starters and non-starters. The variables which held significance in the starters' regression also held significance in the non-starters' regression with one exception: wins_from_95.

Not only did wins_from_95 become insignificant, the standard error is ten times larger than the actual coefficient. A team's win total from the previous year does not seem to influence the compensation of a non-starter. A possible reason could be because the market for non-starters is not as competitive. Bad teams are able to sign non-starters at market value even though they are rebuilding because their market value is relatively cheap.

Regression Results 5: Non-Starters

Variable	reg5_1
ops_var	69272.319
	(378553.18)
VarWin95	-526.4978
	(20162.683)
YR1989	-123714.93***
	(33868.312)
switch	-57012.165
	(33849.944)
exp	7338.7923
	(8183.6263)
age	-10165.369
	(6302.089)
open_pyrl	0.01319816***
	(0.00153273)
wins_from_95	-146.51705
	(1444.4985)
ops	863409.67***
	(128592.9)
gs_season	4707.8194***
	(423.1313)
ae1	157174.91***
	(43236.229)
ae2	354127.5***
	(47448.591)
ae3	499465.46***
	(55968.258)
Fa	577305.42***
	(63641.117)
C	37959.97
	(32563.637)
Ss	95292.612
	(51089.142)
nl	9370.3969
	(25608.168)
_cons	-659397.29***
	(184010.22)

=.05 significance level** *=.01 significance level** *****=.001 significance level**

Summary

Although almost all of my original hypotheses were either inconclusive or completely wrong, this paper still has provided many interesting results. In this paper, I attempted to capture how variance in performance is evaluated by Major League Baseball teams. Through the regressions, it can be seen that risk is evaluated differently depending on certain factors such as team and individual success. Because of the increasing nature of the MLB payoff structure, good teams take on a risk-loving strategy that essentially prices out the bad teams. However, there is little evidence to suggest that variance is a significant factor in determining compensation between starters and non-starters.

Further research would be interesting and necessary to truly capture variance in performance and its subsequent effect on player compensation. A similar study using more recent data would be interesting for multiple reasons. First, the payoff structure of Major League Baseball has undoubtedly changed over the years. Eight teams make the playoffs under the current format as opposed to four during the time period of this study. Also, baseball has grown into a multi-billion dollar globalized industry. The expected increase in payoffs from making the playoffs and winning the World Series are possibly greater in today's game than they used to be.

Secondly, revenue sharing might have skewed the payoff structure of Major League Baseball so that it is in a low-revenue team's best interest to continue with a low payroll even if signing a high profile player can increase their win total. It is possible that this would create some type of parabolic payoff structure that causes teams to try to get to either end of the payoff structure because the value in this type of situation should be at the margins. It would be perverse if revenue sharing, a policy implemented to subsidize the payroll of small market teams, actually incentivizes teams to take on *even less* payroll. A study examining the effect of revenue sharing on the MLB payoff structure and its subsequent effect on player compensation would be very interesting.

The third thing that has changed in baseball today is the typical contract structure. More and more long-term guaranteed contracts are now being given to players. Players routinely sign for six years and one hundred million dollars in 2010. These types of numbers were unheard of between 1986 and 1993.

The fourth thing that has evolved during twenty-first century baseball is the use of advanced metrics to evaluate player performance. While OPS is still a highly valuable statistic, new stats such as wins above replacement (wins added by an individual player to a team), ultimate zone rating (a defensive metric), and batting average on balls in play (a metric used to assess the luck of a player) might be valuable metrics to consider when conducting a future study on variance in performance.

A final problem which I believe a future study could improve upon is my inability to distinguish “good variance” from “bad variance”. As discussed in the bias section, in order to have a high variance in performance, the player must be good enough to achieve a high OPS over some period of time. In contrast, some players are lucky to achieve such an OPS over a small sample. Extracting the difference in these types of variances could be very interesting to work with in the future. However, I was unable to identify this type of variance and thus eliminate the bias that coincides with this problem.

I believe that this paper is a first step into capturing how teams evaluate variance in performance when signing players to Major League contracts. It is hard to believe that few people have ever tried to capture a risk-premium in this way before. It is a difficult undertaking and a flawless method might be years away, but the research must start somewhere and I believe that this research is a significant step in the right direction.

Appendix

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