

Claremont Colleges Scholarship @ Claremont

CMC Senior Theses

CMC Student Scholarship

2016

Paying for Performance at the Plate: An Investigation of Variable Pay Systems in Major League Baseball

Mitchell S. Bremermann
Claremont McKenna College

Recommended Citation

Bremermann, Mitchell S., "Paying for Performance at the Plate: An Investigation of Variable Pay Systems in Major League Baseball" (2016). *CMC Senior Theses*. Paper 1244.
http://scholarship.claremont.edu/cmc_theses/1244

This Open Access Senior Thesis is brought to you by Scholarship@Claremont. It has been accepted for inclusion in this collection by an authorized administrator. For more information, please contact scholarship@cuc.claremont.edu.

Claremont McKenna College

Paying for Performance at the Plate:
An investigation of variable pay systems in Major League Baseball

Submitted to

Professor Janet Kiholm Smith
and
And Dean Peter Uvin

By
Mitchell Bremermann

For
Senior Thesis
Fall 2015
11/30/2105

Table of Contents:

4 - Abstract

4 – Introduction

6 – Background and Hypothesis Formation

14 – Coding and Rationale

20 – Data Sources

21 – Initial Conclusions from Descriptive Statistics

25 – Results and Analysis

35 – Conclusions and Extensions

40 – Tables and Figures

49 – References

Abstract:

Previous empirical research on variable pay systems have suggested that possible gains can come from paying for performance, but highlight the difficulty firms face in measuring performance. Using contracts signed in Major League Baseball's free agent market, I find that over the 2010-2014 period, teams utilized variable pay schemes with players that were more productive or signaled greater risk, either in their contract terms or via overspecialization. However, not all forms of risk signaling were correlated with greater use of performance incentives, including age and proxies for injury history. These findings have significant implications for labor practices more broadly, as the high-information environment of Major League Baseball can shed light on how principals behave when performance measurement costs are effectively eliminated.

Introduction:

In January of 2011 Johnny Damon, an outfielder for the Detroit Tigers, signed a free agent contract with the Tampa Bay Rays. There are roughly one hundred free agent contracts signed every season, and his one year, \$5.25 million deal didn't seem to stick out at first glance, but the details of Johnny Damon's contract have a lot to teach us about baseball, and perhaps even more about labor economics more broadly. While most contracts observed in this period had performance incentives for plate appearance, innings pitched, winning awards, etc., Damon's contract contained a unique performance incentive that stipulated his eligibility to gain \$750,000 in bonuses based on the amount of fan attendance at Rays' home games. The goal of this study is to utilize a case study, data-oriented approach in order to understand how, in situations where principals have access to highly detailed performance measures, MLB teams utilize contract incentives to make the most out of their investment in player salaries. While Johnny Damon is certainly an anomaly, his case speaks to the variety of incentives that can and do exist in this environment. The Major League Baseball (MLB) collective bargaining agreement

effectively does not limit performance incentive negotiations at all when free agents contract with teams, and accordingly teams have the freedom to offer contracts with incentives that include body weight targets, specific provisions against injuries, and as Johnny Damon showed, even stadium attendance.

The objective of this research is not simply to understand how teams reward players who hit home runs versus those that steal bases, but to use (MLB) as a sort of naturally occurring experiment from which we can glean economically relevant insights about wider labor market topics. MLB offers us an example of a labor market where all firms and all labor units are aware of the performance of every other actor in the market, down to specific levels. Because of the level of information availability regarding performance, MLB is a laboratory that enables outside researchers like myself to analyze how principals and agents behave when measuring performance is not a restraint on decision making. Unlike analyzing salesmen at a range of insurance firms, for example, I can tell you exactly how many hits Johnny Damon had in 2011, how many home runs he hit in 2009, how many steals he had in 2012, etc. Understanding the relationship between hitting home runs and incentives that encourage excellent performance may be central to baseball teams, but knowing how employers with high levels of information contract their employees has implications for nearly every industry.

The MLB free agency market offers a labor market where performance incentives are utilized with enough frequency for us to be able to make some connections to performance pay more broadly. Over the five year signing period analyzed here (2010-2014), 38.97% of free agent contracts contained some sort of performance-dependent bonus. With a total sample size of 661 contracts, and a total of 258 of those containing

the incentives, significant results were found in a number of areas regarding performance incentives. Labor economics literature certainly has much to say on performance-pay schemes, but this is the first investigation of MLB in this regard. There is a certain degree of uncertainty that comes with uncharted territory, which I learned as some of my initial hypotheses failed to align with conclusions from data, but I believe this case study opens more avenues of research for the intersection of sports and labor economics, which I hope other scholars are willing to chase down.

Background and Hypothesis Formation:

The motivation for this research is to shed some light on possible alternatives to one of the central challenges to and questions facing modern organizations. Though the “principal-agent” problem was originally labeled by Jensen and Meckling in 1976, the tenuous relationship between ownership and employee self-interest is a seemingly unavoidable facet of the firm. In nearly any firm in any industry you can imagine, the interest of ownership and the interest of the employees do not always perfectly align, and this imbalance can lead to significant agency costs for the firm. (Jensen and Meckling, 1976) While it may seem strange that the search for answers to such a pressing economic question takes us to the world of professional sports, the abundance of contractual data and unique opportunities for performance measurement makes this research a highly logical case study.

Performance measurement has long been highlighted as arguably the primary challenge facing firms that choose to institute incentive pay systems (Roberts, 2010), and MLB offers principals (owners/front offices) a nearly unmatched level of performance

measurement. A Study of the MLB labor market may be able to provide insights into how principals make decisions on variable pay contracting when information is highly accessible. As Lazear suggests, if measurement costs are sufficiently low, like we assume them to be in the MLB market, variable pay schemes are better at maximizing output (Lazear, 1995), so we should see a relatively high level of performance pay usage in MLB. While the initial impact of the study applies most directly to the sports world, a better understanding of how to design contracts to address the principal-agent problem has managerial implications across a wide variety of industries.

To begin this analysis, we must establish a background of contract theory, specifically as it pertains to incentive pay contracts and principal-agent issues. The core of contract theory addresses the basic problem defined in principal-agent theory, which seeks to remedy the misaligned self-interests of the principal (owners, shareholders, etc.) and employees, defined as agents. Consider an example from our industry: a player (agent) may not be exerting as much effort as he could at the end of a season in which his team has been eliminated from making the postseason. Nevertheless, it is still in the interest of the principal (the owner) for that player to perform at maximum effort to maximize their value via ticket sales, merchandising, etc. This problem is especially salient in MLB where contracts are typically made for multiple years, so providing less than optimal effort in the second year of a five year contract might not negatively impact the player, this behavior certainly does not align with the interest of the ownership. This problem leads us directly to consider incentives, which “can limit divergences from [the principle’s] interest.” (Jensen and Meckling, 1976) These divergences from the

principle's interest can take the form of reduced effort, as described above, or by factors outside the player's control like injury risk.

The contract as a whole is the most basic type of incentive, but a standard salary may not always be enough of a finely tuned incentive to induce complete cooperation with, and commitment to, the firm. The idea that "incentives matter" and that they are the primary means to motivate economic actors to exert effort and subsequently improve performance is nothing new in the field of economics. (Gneezy, 2011) Beyond the structure of the basic salary, which is the first form of incentivizing labor, encouraging sustained high levels of effort has been a focus of literature regarding pay-for-performance contracts. The possible benefits of performance pay systems could be immense, considering that agency costs are becoming more and more recognized as a major challenge facing firms, especially large ones. (Posner, 2010) Certain studies have indeed found that productivity gains can be fairly substantial for firms that institute these kinds of systems, though the gains are not as simple to generate as it may seem. (Gielen, 2008; Lazear, 2000) Incentives within organizations are built with the intention that they will encourage employees to work smarter and harder if there is the possibility for further financial reward that corresponds with higher productivity. (Roberts, 2010) This is not to say that incentives are some simple factor that firms can turn on and off in order to easily address agency costs, in fact, the specifics design of incentives has been shown to be a key determinant of their effectiveness. (Roberts, 2010; Kauhanen and Napari, 2012; Holmstrom and Milgrom, 1994)

As mentioned above, the reason that this paper focuses on MLB is that performance measures are much more accessible, both to management and to outside

researchers such as myself, than they would be in most firms. The implication for performance pay is influential, as much of the literature regarding the design of incentives suggests a central role of performance measurement in decision making. (Holmstrom and Milgrom, 1994; Roberts, 2010) As Gibbs suggests, “Performance measurement is perhaps the most difficult challenge in the design and implementation of incentive systems.” (Gibbs, 2009) Most economists would agree that incentives are powerful determinants of behavior, so designing well measured and accurately targeted incentives can be an invaluable tool for firms. On the other hand, strong (in terms of incentive value relative to salary) incentives that are misguided in their measurement can have powerful negative implications. (Roberts, 2010) Firms must also consider monitoring costs when deciding on how to monitor employee performance. (Barth et al, 2008) Why is it that many firms have such a hard time determining the productivity of their employees? The simple answer is that, in many cases, there are a wide variety of actions that employees can take that contribute to productivity, and it is difficult for the firm to properly weight incentives on which contribute most to overall value of the firm. (Kerr, 1975)

This idea is perhaps best described by Gibbons, who suggests an example where an agent is rewarded for task “p” and observes the wage function $w = s + bp$; where w is earned wage, s is base salary, and b is the bonus rate. The goal of the principal is to maximize “y,” which is overall output, but the goal of the agent is to maximize “p” because it that measure that contributes to the agent’s wage and not overall productivity. (Gibbons, 1998) The goal now for the principal is to decide on a measurement, “p,” that is as closely related as possible to the increase in overall output. Luckily for us, there are

a variety of measures that baseball analysts believe are closely tied to the overall output of the firm, namely; Wins Against Replacement, Total Wins Added, etc. Baseball offers us a unique opportunity to see how principals design incentives when the issue of performance measurement is less of a concern. Granted, there is still some debate as to how accurate these measures are with respect to measuring total contribution to wins, and if in fact teams are win maximizers as opposed to profit maximizers, but overall the performance measurement hurdle is considerably lower for baseball teams than it is for an average business.

If we assume that baseball teams are interested in maximizing wins, and/or the profits that are typically associated with winning, and we have measurements that can tell us directly how players contribute to that end (where “p” is directly correlated with output), we must ask why baseball teams do not exclusively use high degrees of pay for performance incentives in their contracts. This idea leads us directly into the counterweight to incentives in classical agency theory: risk. Pioneered by Prendergast, the agency theory literature suggests that agents are risk averse, and in order to take on more risk via variable pay systems, the overall wage rate must be higher to account for the risk (Prendergast, 2002). If we again consider the $w=s+bp$ basic model, our risk-averse agent demands a higher “b” value to take on the risk of lowering the value of a constant “s.” Prendergast also suggests, and the theory is then followed in subsequent literature, that risk increases with the uncertainty of the environment as it pertains to “p,” meaning that the agent will demand higher returns in cases where the agent has less control over the variance in “p.” Given the wide variety of factors that are outside of a player’s control, and that incentives are shown to be more effective when agents feel they have a real

ability to affect the outcome, we would expect risk-averse players to charge a hefty premium for taking on the immense risk of heavily performance-dependent contracts. (Kauhanen and Piekkola, 2006)

Despite the risks that agents face by taking on performance-based contracts, the advantages could be powerful if the incentives are smartly designed. Lazear's study, though a limited case study, showed an increase of 44% in output per worker. (Lazear, 2000) When positive productivity effects for performance pay were reported, existing studies have often suggested that both the expected increase in motivation due to increased incentives played a role, as well as a self-sorting process where highly productive workers were drawn to the firms with greater opportunities for total compensation. (Gielen, 2010; Dohmen, 2011) Self-sorting certainly plays a role in determining the effectiveness of performance pay programs, especially when competition in the labor and product markets, such as in MLB, dominates. Studies have shown that market competition is positively associated with the use of performance pay schemes, and the constant competition of MLB certainly represents a highly competitive market. (Barth, 2008) Barth's research also shows that performance pay schemes are positively associated with the educational level of workers, because "the quality and effort of high-skilled workers have larger impacts of productivity than the quality and effort of other groups of workers," and that "paying for performance has a greater effect on output for high than low-skilled workers." (Barth, 2008) Given the incredibly high level of performance of MLB players and the razor-thin margins that separate wins and losses, Barth's thesis suggests that teams could benefit greatly from paying for performance.

Hypotheses:

Throughout this paper the distinction developed by Lazear (1998) will be used to differentiate between two types of incentives: those dependent on employee input actions, and those dependent on the output of those employees. These two variations can be simply referred to as input and output incentives. The preceding research forms the basis for my following hypotheses regarding the use of performance incentives in MLB contracts:

1. As a form of allocating risk to the agent and away from the principal, or encouraging high effort levels, performance-dependent bonuses will occur in situations of higher risk, including:
 - a. Players with an injury history that has forced them to miss a significant number of games in past seasons
 - b. Older players
 - c. Players that are given relatively long or high value contracts
 - d. Players whose value is highly dependent on performance in a specific skill area, controlling for overall productivity.
2. Highly productive players will be contracted under incentives more often than less productive players

Hypothesis (1) is a basic extension of the central risk tradeoff that is discussed in agency theory. It is not difficult to understand the sub-sections of this hypothesis as situations of heightened risk. Parts (a), (b), and (d) all leverage the concern of teams that past productivity of players may soon decline via natural aging or sudden incapacitation

of ability, via injury or some such event. A history of significant injury was not easily accessible data, and would make an interesting extension of this research with more time, so proxies were developed to indicate a non-durable history. These include measures of variance in at-bats for hitters and the number of innings pitched compared to the positional average for pitchers. Part (d) deserves a bit more explanation, however. The basic rationale for this hypothesis is tied to the literature that suggests the possibility of pay-for-performance to promote perverse incentives, which is built with an assumption that there are many tasks that can provide value to the firm. (Gibbons, 1998; Kerr, 1975) Baseball players can take a wide variety of actions to be productive, and players that are specifically focused, and subsequently derive much of their value from a single skill, are less capable of undertaking all actions that can contribute to value. Subsequently, these players are less capable of remaining productive if their performance in their specialized area dips for one reason or another (injury, age, anomalously bad performance) and therefore it would make sense for teams to contract these kinds of players under incentives more often in order to protect themselves from this kind of risk. Part (c) is also fairly simple, as teams that make fixed investments in players are committing to a certain degree of risk by projecting a player's value for such a long period or monetary investment (most often both).

The second hypothesis follows from Barth's research, which suggests that the rewards that firms can earn by encouraging higher effort levels for their most productive employees are greater than the rewards that can be gained from average employees. (Barth, 2008) Accordingly, we would expect these kinds of players to be contract

specifically under incentives that encourage excellent performance, as opposed to more input style incentives.

Coding and Rationale:

In this section I will describe how I chose the variable that I used, where that data came from, and how I combined the data into useful aggregates for use in this research.

The core of this project is understanding performance pay and variable pay incentives, and the first step in the process was coding in the different kinds of incentives that teams can attach to free agent contracts. Teams can employ a wide range of incentives in their contract negotiations with players, and the restrictions on these bonuses are surprisingly limited. The league collective bargaining agreement, which is decided upon by the MLB Players Association (MLBPA) and the owners and applies in five year periods, does not have any significant restrictions on the kind of measures that can be used to determine bonuses. (MLB General Agreement, 2007, 2012) The only real restrictions arise from the nearly century-old MLB constitution and the normal restriction on general contract negotiations, which stipulate that incentives cannot be based upon the standing of the team and can only be based on the performance of the player. (MLB constitution, 1921) Beyond those restrictions, there are provisions that define how the bonuses are to be paid (at the end of the season, over a set number of years, etc.), but teams can effectively assign performance targets to any metric they want if both sides mutually agree on it and the base salary is above the league minimum. (MLB General Agreement, 2007, 2012) Given the wide range of performance incentives that teams can offer, this research will seek to categorize them into manageable types.

Coding the performance targets falls into three categories: Output, Input, and some combination of the two, simply labeled Both. Output and Input categories can be defined as follows: Input incentives are those based on plate appearances, games played, innings pitched, starts made, injury occurrence, and weight targets. Output incentives are those based on All-Star appearances, gold gloves, MVP voting, batting titles, silver slugger awards, and Cy Young award voting. The only significant exception to these award winning conditions is the 2010 Johnny Damon stadium-attendance incentive mentioned in the introduction, which was coded into the excellence category. The Both category consists of player who had incentives from both the Input and Output groups, and those that had incentives based on games finished (more on this shortly). The coding of these incentives matches up well with the input/output designation used in Edward Lazear's 1998 work to define the different types of pay mechanisms. We can think of input incentives like plate appearances similar to the way Lazear considers a typical laborer's hours worked; in that, barring some outside force (like injury, for example), the agent has a high degree of control over the achievement of this incentive. Gold gloves and MVP awards, on the other hand, are much more closely tied to the outcome of an agent's effort in the same way that we may analogize to a salesperson's commissions. By simply showing up to the office every day the worker can control the input incentive, similar to a salesperson's commissions, players need to achieve some output mark in order to earn output bonuses.

The rationale behind the coding lies in a personal knowledge of baseball and a rational approach utilizing the input/output framework. For example, appearance-based incentives like games played, innings pitched, etc. are certainly very different from

winning awards, by the distinction described in the previous paragraph, and have therefore been coded into the input category. I define these as input incentives because they are not necessarily designed to award a player for achieving an excellent level of performance, but instead to insulate the team from the risk of a player experiencing a significant injury or unexpected massive decline in ability for some other reason tied to their ability to input effort. With that said, it is worth noting that contract negotiations are a bilateral process where players may retain a good deal of bargaining power, both individually and as a collective represented by the MLBPA. There may be some characteristics of players, such as a higher level of confidence in their own ability, which may make them more likely to accept the risk. Interesting further research could certainly be done on the ways that players/agents decide to accept risk, though the focus of this paper is on team/principal decision making. On the other side, the output coded incentives are all tied to awards that are only given to players performing at an incredibly high level in comparison to the rest of the league (MVP, batting titles) or their positional peers (Cy Young, Gold Glove, Silver Slugger). The one outlier was for relief pitchers and the “games finished designation,” which is unique because, depending on the standing of a player, it can be either an incentive that is awarded for a significant increase in performance or one that functions in a similar way to appearance incentives. Specifically, if a player is a non-closer (the closer being the most high-leverage, most valuable relief pitcher on a team) who through excellent performance wins the job as the closer, and subsequently will finish more games than if he was still pitching in the seventh or eighth inning, then rewarding that player with a games finished bonus is a form of rewarding output excellence. On the other hand, if the player is already the closer, finishing games

is part of his basic job description, so hitting this target is very similar to a starting pitcher reaching a conservative innings target designed to protect the team from risk of injury.

The determination for a player's position was standardized across my data sources in the following way: if a player recorded more than half of their appearances at a given position, they are coded into that position; if a player did not appear at one position for more than 50% of their games, they are coded into the position in which they made the most appearances; if a player only registered as a pinch hitter, they are coded as a designated hitter (<10 occurrences).

The determination for specialists was made to approximate roughly the top 10% of players specializing in a given skill at each position. Without utilizing a plate appearance minimum (so as not to exclude observed players) this top 10% came out to roughly ten players per position. There may have been slightly more players who registered a start in left field in a given season than registered a start at shortstop, but in order to standardize, I took the top ten players in each category per position. The shortstop that hits the tenth most home runs in a given season may not seem like a power-hitting specialized labor unit, but a shortstop that ranks in the top ten at his position every year for five years certainly has proven to be a valuable contributor in an offensive category that is relatively underrepresented for comparable labor units. Without breaking down the leaders by position, the fifteenth or twentieth best power-hitting first baseman (a traditionally power-rich position) may have registered as being a more specialized player than a center fielder (a traditionally power-starved position) ranked much higher at his position, but that assumes a degree of interchangeability between these two labor units, which is highly unlikely.

With that said, the process for determining specialists was different with respect to the steals category. Instead of using a positional division, I chose to use the top 3% of all hitters in a given year to determine a specialist cutoff point. The critical factor that forced me to change the approach here was the fact that certain positions just don't steal bases nearly at all. For example, if I were to use the same top-10 approach for catchers in 2014, the maximum would have been four steals, with nine catchers recording more than one. With the home run hitters, ties for tenth place resulted in me including both players (if the 10th most home runs for left fielders was 18 and two players hit 18, both were given a specialist point), but if this approach had held for the 2014 catchers fifteen players would have earned a specialist point for stealing bases despite *stealing just one base all season!* These catchers certainly didn't fit the mold for speed specialists, so I had to change the approach. The top-10 strategy effectively provided the top 10% at each position, but when I eliminated the positional designation, the 10% steals mark for all players who registered an at bat was less than ten steals. We typically don't think of a player with eight steals as being a speedster, so I had to change the cutoff to get to players who registered, depending on the season, between seventeen and twenty steals. This definition fits much more closely with players that we would consider to be speed specialists. Only one catcher made the grade here, with Russel Martin's 2008 season coming in at eighteen steals. No other catcher recorded more than twelve steals in any season from 2008-2014.

The skills chosen; home runs and steals, are meant to isolate players who possess a uniquely excellent skill at one facet of the game (power, speed), and to imply that specializing in one of these skills has a different effect on contracting than a player that

may excel at a more common skill (hits, runs, etc.). For each category, a player who made the specialist cutoff is given a point for each season they make this group. For example, if a player is in the specialist group in home runs three times over the observation period and in the steals specialization once, that player receives a three specialization score in home runs, a one in steals, and a four as the total. This is meant to imply that a player who consistently hits home runs at a high rate is viewed differently than one who has an anomalous year and sneaks into the top ten once over a five year period. This may bias the scales against younger players, but what we want to understand is what kinds of past performance influence decisions, and having more past performance to draw on is certainly a fair way for teams to evaluate players.

The process for finding these specialists amongst the pitchers took a slightly different shape. The data available for pitchers does not provide quite as many opportunities for the same sort of breakdowns that I used for the hitters, so I decided to focus on one particular kind of specialist: the “power pitcher.” Power pitchers, in baseball terms, are players that typically earn a higher portion of their outs via striking out hitters, as opposed to pitchers that excel by pitching to soft contact and induce a lot of ground balls, for example. Typically, this sort of pitching is associated with high velocity, and it would be an interesting extension of this research to investigate the connection between velocity and incentives, but for this analysis strikeouts were used as a measure of this kind of specialist. Unlike the hitters, positional adjustments were much easier to make, as pitchers fall into only two primary categories: starting and relief pitchers.

Because of the simpler positional differences, I decided against using the same specialist score framework that I utilized for the hitters, instead opting for a more

continuous measure of specialization. The degree of specialization in a given skill, strikeouts are compared to innings pitched and earned run average (ERA) here, is shown continuously by the amount of that statistic above the positional average that a player produces in a given year. Suppose in one season relief pitchers average forty-five strikeouts and a given pitcher records sixty strikeouts. That pitcher will have a fifteen in the data column for strikeouts above average for that season. In this way, pitchers that continuously exceed the average for their position are continuously scaled as specialists.

Data Sources:

The data used in the project was based on the Lahman Database, courtesy of Sean Lahman, but used many sources to generate my full dataset. Lahman's work gave me data for all of my seasons of interest (2014-2008) on individual player statistics, player salaries, positional appearances, and many others. As a disclaimer applying to potential bias issues, it is worth noting that the salary data in the Lahman database is reported via the MLBPA. While the salary data is not critical to my results (I relied more on contract value data than yearly salary), it is worth noting here for disclosure's sake. I utilized a matching process using player id codes and player names to combine the raw data from the Lahman database with data from Baseball Reference, Fangraphs.com, and ESPN to address my variable of interest. Specifically, Baseball Reference helped me fill in some of the holes in the Lahman database, as well as providing the leaders for yearly statistics like home runs, steals, strikeouts, etc. Fangraphs was used for their WAR calculations and projections. ESPN gave me yearly lists of all free agents with major league service

time, the number of seasons and value of the contracts they signed, and the age at the date of signing said deals.

Initial conclusions from descriptive statistics:

In this section I will run through some of the descriptive statistics of the data and offer some initial results that can be seen through simple descriptive measures. The dataset presented here describes MLB players who negotiated contracts as free agents from those following the 2010 season to those following the 2014 season. These contracts, because of their nature as in the free agent market, were negotiated on an open labor market where players were able to contract with any team, meaning these data do not include arbitration signings, rookie signings, or extensions (which can only be negotiated with the current team). The only contract signings reported here are for players who had previously registered an at bat or inning pitched in the major leagues, so though some former major league players do appear in this dataset when they sign minor-league contracts, minor league free agents do not. (Also, this dataset does not include foreign players who sign with MLB teams).

The total number of observations, 661, represents contracts negotiated between hundreds of players and negotiated with every one of the league's thirty teams. This is not to say that all teams are equal, as some teams were considerably more active in the free agent market than other teams. For example, the New York Yankees signed thirty-five free agents over this period, while other teams like the Oakland A's signed only thirteen free agents over this period. There is a wide breadth of literature in the economics of sports on competitive balance, market size, free agency, and a wide variety

of topics in that vein, but that is not the focus of this paper. It is worth noting, however, that teams can take very different approaches to build their rosters with respect to the free agent market, so all of the models developed in this research control for differences in each of the thirty teams.

The focus of this research is not the number or distributing of free agent contracts, but the incentives that may come attached to those contracts. The basic descriptive statistics with respect to incentives are as appear in Table 1. As previously mentioned, the kinds of incentives have been coded into categories by the nature of the incentivized task. (See: Data Description; Coding and Rationale) Over the whole period, the percentage of contracts negotiated that contained some sort of performance incentive was 38.97%. Broken down with more detail, 7.70% of the total number of contracts contained what I've categorized as "Output" incentives, 18.88% fell into the "Input" category, and 12.39% contained both types or utilized a game's finished measurement for bonuses.

One key element of the free agent market that must be mentioned here is that the behavior of teams does not have any mandatory effect on the behavior they may undertake in the following signing period, especially with respect to incentives. Because the market is essentially reset, and the labor units change almost completely from year to year, we must understand that each negotiating period is unique, as evidenced by the massive differences in the use of incentives from year to year. The use of incentives by signing period varied from 27.90% following the 2011 season to more than twice that percentage a year later. Following the 2012 season, an astonishing 56.99% of contracts negotiated over the signing period contained some kind of incentive. I must admit that I do not have a compelling theory as to why the swings in contract incentives are so wide,

and it may well be a good avenue for future research to examine free agency periods as unique laboratories of labor negotiation, but for now, that question will have to wait.

Table 2 shows the use of incentives broken down by team, which highlights the varied nature of the teams that come to the negotiating table on the employer side. The measurements presented show the percentage of all free agent contracts awarded by a given team during the five year period that contained some type of performance based incentive. The percentage of contracts that contain performance incentives varied from under 10% (White Sox, Blue Jays) and pushed upwards of 70% at the other extreme (Twins). Teams are often controlled by a small group of individuals that make up what is typically called the front office, consisting of the team owner(s), president, business executives, and most importantly, the general manager (GM). Given the massive amount of decision making power that a few individuals may have in MLB organizations, it may be that certain GM's have their own rationales for offering or not offering performance incentives, which certainly is part of the variability in usage shown here.

Some of the most interesting observations that I was able to make from the descriptive statistics came from comparing how performance incentives were used in different positional groups. For the purposes of the research here I broke down the positions as seen in table 3: one for each defensive position, one for starting pitchers, one for relief pitchers, and one for the designated hitter. It is worth noting that designated hitters are only available positions for players in the American League, meaning that half of the teams in MLB do not employ a full-time designated hitter. It is worth noting that certain positions were severely lacking in the free agent market over the past few seasons, namely center fielders (10) and shortstops (28). It appears that teams are more inclined to

acquire shortstops and center fielders via the amateur draft, and those that they do draft (or trade for) are often given contract extensions before they reach the free agent market. This is perhaps tied to a perception of heightened value at the position, as both are labeled as “premium defensive positions” in baseball circles, meaning that the benefit of a good defensive center fielder outweighs the benefit of a good defensive right fielder, for example.

Despite a low volume of observations with respect to certain positions, we can draw some interesting observations from the use of performance incentives based on position. One interesting difference is between starting and relief pitchers, who are contracted with input performance provisions 30.1% and 12.9% of the time, respectively. The difference between the two ($p=0.0004$) suggests that teams are less willing to take on extra risk when it comes to starting pitchers than they are for relief pitchers, subsequently allocating a greater degree of risk to the starting pitchers. One possible reason for this is there may be a greater variance in the performance of the starting pitchers compared to the relief pitchers, which holds true when looking at WAR (Wins Against Replacement, calculated by fangraphs). The variance in WAR of relief pitchers who signed free agent contracts over the given period is the lowest of any position, at 0.286, while the performance of starting pitchers was considerably more variable, as evidenced by their 2.643 variance over the same period. (WAR measurement taken in year prior to signing) It is also worth noting that while the variance in WAR was fairly high for starting pitchers, only shortstop was higher when excluding the DH, the average WAR for players over this period was the highest for starting pitchers, suggesting that the risk may also come with significant rewards for teams. This corresponds to the large difference

between the two groups specifically with respect to the input performance incentives, where 30.70% of starting pitchers signed this type of contract, compared to only 12.87% for relief pitchers ($p=0.0004$).

While starting pitchers offered the highest reward, at least according to WAR, the right field positional group claimed the highest usage of performance incentives at 58.82%. Why specifically right fielders were contracted under variable terms so often is an interesting question, and certainly one that could lead to interesting future research, especially since the closest positional comparison (left field) was nearly twenty percentage points away in terms of incentive usage (39.47%, $t=0.0639$). Right fielders did not hold the top spot in WAR averages across position players, and their distributing between the types of incentives was relatively similar to the other positions, though elevated.

Results and Analysis:

Result 1: Incentives and Contract Value

Figure 1 shows the results of the first regression of the choice to adopt performance incentives, controlling for position, season, and age. The use of performance incentives is positively correlated with the total value of the contract. (See Table 4, Model 1) The positive correlation between these two variables suggests that when teams agree to pay a larger sum of money over the course of a contract, they are more inclined to pass along some of the risk to the other party. This follows logically from an understanding of risk, as agreeing to a high-value contract is certainly a risk for a team to take on because there is effectively no insurance that a player will remain as productive

as they imagine him to be at the time of signing. It thus follows that teams would want to allocate some risk to the other party instead of bearing all of the risk of that labor unit losing significant value over the fixed length of the contract.

The coefficient on value, converted into millions for simpler understanding, is 0.002, significant at 0.1%. (Table 4) This statistic may seem small, but when you consider the massive values that teams can offer in the modern free agent market, it becomes quite significant. Consider for example the largest value contract awarded during this period: the \$250,000,000, eleven year deal that Albert Pujols signed with the Anaheim Angels following the 2011 season. While I understand that he represents the extreme, purely based on the small coefficient tied to value, he is 49.8 percentage points more likely to have incentives in his contract than is a player who signs a one million dollar contract. Not all players are receiving deals of this magnitude, and most of those in this sample are not, but it certainly appears that when players do get these kind of contracts, teams are very adamant about allocating even a small amount of risk to these type of players.

Interestingly, it appears that the vast majority of the correlation between incentives and value is tied up in the use of output incentives, as opposed to input incentives. The coefficient on value (again in millions) on the use of output based incentives is .003, Significant at 0.1%, slightly higher than it was for incentives as a whole. On the other side, there is a statistically (at 5%) significant negative relationship between the use of input incentives and the total value of a contract. What this seems to suggest is that teams are not as concerned with the possibility that a player receiving a high value deal will become completely worthless (via significant injury, for example),

but that they are paying for an all-star caliber player and the player should be paid less if they lose this premier differentiation. Essentially, teams are taking on so much risk that they want to protect against small drops in value. The negative correlation with input incentives is likely linked to the power of these incredibly valuable labor units, who are likely to feel insulted by a contract that protects a team from the possibility that the player is demoted to the minor leagues, which would negate a bonus for plate appearances, innings pitched, etc.

The same holds true for the correlation between incentive use and the number of years agreed upon in a contract. (See Table 4, Model 2) The coefficient attached to the number of years contracted and the use of incentives is 0.034, significant at 5%. This value implies that for each additional year in a contract, a player becomes 3.4 percentage points more likely to have performance incentives included in his contract. For example, we can return to Albert Pujols and his massive deal. On the basis of length, his eleven year contract is thirty-four percentage points more likely to include incentives than a player who signs a one year deal. This again follows very logically in the same way that the correlation with value did, suggesting that lengthy contracts place high amounts of risk on teams, who subsequently look to divert some of that risk to the employee. What's more, the same pattern holds that excellence based incentives are even more strongly correlated with contract length (0.052, significant at .1%) and that input incentives are negatively correlated with the overall length of a contract (-.026, significant at 10%). The negative correlation with respect to input incentives is a puzzling finding, and though we may be able to conjecture at an explanation tied to employee bargaining power, more research into this connection would certainly prove interesting. Despite the lack of a truly

satisfying explanation to this result, the different directions of correlation implied by the coefficients help us paint a picture of what type of players receive what type of incentives: players that are valued more highly are more likely to receive output-based incentives than lower value players, who are more likely to receive input incentives in their contracts.

These results offer some evidence in support of, and in contradiction to, hypothesis (1). Though it is used only as a control in these models, age does not appear to have a significant impact on the use of performance incentives. This result, which contradicts hypothesis (1b), is persistent across nearly all of the models developed in this research, the variety of variables included in the models providing a relatively robust check to this lack of correlation. On the other hand, part (c) of hypothesis (1) seems to be supported by the data. The positive correlations between output incentives and contract value/commitment described above lend support to part (c).

Result 2: Incentives and Specialization

Regression analysis also revealed a correlation between players with specialized skills and the use of contract incentives. There appears to be a positive relationship between a player having a special skill and the use of contract performance incentives, according to Table 5. This relationship held for both pitchers and hitters, and the results for both positional groups were obtained entirely separately in order to avoid any contamination (Table 6, Table 7). As previously mentioned, the specialization process is meant to identify players who are uniquely skilled at one facet of their duties. For hitters, steals and home runs were chosen as these specialized skills. For pitchers, the approach

was slightly different, as just strikeouts were chosen as the primary specialization with the goal of highlighting what the baseball community would tab “power pitchers.” In both of the models presented these specialization statistics appear alongside less specialized measures (innings pitched for pitchers and at-bats for hitters), as well as measures of variance for all the statistics, in order to control for anomalous seasons and opportunity volume. All models presented include controls for the signing team, player age, and season.

The results with respect to specialization appear to support Hypothesis (1d), which suggests that highly specialized players will be contracted under performance incentives more often. There are many nuances to this claim, which will be discussed in detail below, but the overall trend appears to support this hypothesis. Also worth noting, Hypothesis (1a) was not supported in these results, as the proxies developed for injury history (high variability in appearance statistics, appearances below average) did not show any significant correlation with incentive usage.

Result 2.1: Incentives and Specialization; Hitters

The central result of the tests for specialization with respect to hitters is that the use of incentives is positively associated with labor units that specialize in home runs, but not with those who specialize in stealing bases. These specializations are defined in detail in the Coding and Rationale section. For the first kind of specialists, we can generally refer to them as power hitters, while the second group can be defined as base stealers. As evidenced by Table 5, it appears that teams in general contract specialist players with performance incentives more often than non-specialists, as evidenced by the positive

correlation between incentive use and the total specialist score. (.03, significant at 10%) This positive correlation suggests that for every time a player rates in the specialist category for a season, they are three percentage points more likely to sign a contract with performance incentives. For a player who has placed in the top ten power hitters at his respective position for five years, he could expect a fifteen percentage point increase in the likelihood of receiving an incentivized contract. Keep in mind that these results control for the standard fixed effects of position, age, and signing team, as well as controlling for the value of the contract. This means that these results are not picking up a positive correlation with respect to specialization just because these specialist players are valued more highly, but that there is something unique about these specialist players, beyond their total productivity, that alters the way teams contract them. To understand this rationale, we have to dig past the total specialist rating and into the individual measures of steals and home runs.

There is evidence for a positive correlation between the use of incentives and players that specialize in hitting home runs, but not for base stealers. According to Table 6, a higher specialist score in the home run category is positively correlated with the use of incentives, while a higher specialist score in the steals category is not. The coefficient of .0395 on the home run specialist score, significant at 10%, indicates that for each previous season in which the player was in the power hitters category, they are roughly four percentage points more likely to have performance incentives in their contract. Steals, on the other hand, are not close to showing any sort of statistical significance, as it appears base stealing does not have an incredibly significant effect on team decision making in this regard. To develop a hypothesis as to why this difference exists between

how teams contract these two kinds of specialists, we must turn to one of the statistics initially included for control purposes in this test: the variance of these two measures.

The difference in variance between home runs and steals for this sample leads to the following hypothesis: teams are more likely to include performance incentives when contracting with power hitting specialists because there is more variability in home runs than there is in steals. Because these kinds of specialist players derive so much of their value from excelling at a particular skill, any sort of reduction in their performance at that skill would significantly reduce their overall value. Therefore, it is not surprising to find that the higher use of performance incentives for power hitters matches up with a higher variance in home run hitting, compared to the variance in base stealing. ($\text{Var}(\text{home runs})=35.97$, $\text{Var}(\text{steals})=21.56$) This result implies that teams are cognizant of the variability in these specialized tasks, and correspondingly try to protect themselves from the risk associated with players dependent on these more variable tasks.

Result 2.2: Incentives and Specialization; pitchers

The results found among the hitters sample with respect to specialization and incentives were similar to those found in the pitching sample. As mentioned in the coding and rationale section, the degree of specialization for pitchers was computed on a continuous grade by comparing yearly results to positional averages. With respect to specialization, the power pitchers group, defined by high strikeout totals, did show a positive correlation with incentive use, according to Table 7. For every ten strikeouts above the positional average that a pitcher recorded he was five percentage points more likely to be under a contract that included performance incentives. The result was

significant at the five percent level. Interestingly, there was no statistically significant correlation between the use of incentives and pitchers that register an above average amount of innings pitched. This seems to follow the results from the hitters, suggesting that there is something special about the strikeout skill that makes teams concerned about performance changes. Perhaps there is a connection with the perceived connection between strikeouts and velocity mentioned above, but further research would be needed to make a definitive claim on this connection.

It is also worth noting that there exists a negative correlation between relative ERA and the use of incentives, with pitchers that allow fewer runs being contracted under incentives more often. The coefficient on ERA was shown to be -0.0696 , significant at 5%, suggesting that for every run a pitcher shaved off his ERA he would be about seven percentage points more likely to be contracted with performance incentives. Preventing runs is the most central job of a pitcher, so it is unreasonable to call this a specialized skill, but in this case we must consider the magnitude. The significance of taking a full run off a pitcher's ERA is incredibly large, as a pitcher with a 3.50 ERA is a solid contributor that might be the third best starting pitcher on his team, while a pitcher with a 2.50 ERA is likely one of the best in the league and has a legitimate chance at competing for a Cy Young award in many years. While ERA might have statistical significance, it is likely tied to the fact that players who have exceedingly high ERA numbers will likely be excluded from any sort of excellence incentive, as shaving off so many runs is so unlikely, subsequently weighing down the high-ERA pitchers with artificially low levels of incentive use.

The results regarding innings pitched surprised me, especially with respect to the input subcategory of incentives. I expected to find a correlation between a pitcher that threw a below average amount of innings and/or had a higher variance in innings and the use of incentives, but the data does not bear that out. This result appears to contradict the claim made in hypothesis (1a), as we would expect injury prone players to pitch a below-average number of innings and to have a higher variance in innings pitched. This result appears to be consistent with the hitters positional group as well, as the variance in at-bats was not correlated with any sort of incentive usage.

When controlling for the standard set of fixed effects, as well as value, I did not find any significant positive correlation between innings pitched and the use of incentives; output, input, or otherwise. The one statistically significant connection that did come out of the innings pitched variables was not in the input category, but rather a negative correlation with excellence incentives. Though puzzling, the data showed that players who pitched a higher amount of innings were in fact *less likely* to be contracted under excellence incentives than those with fewer innings. This result pushes counter to our understanding of the positive correlation between contract value and these kind of incentives. Previous tests (See Table 4, Model 1) showed that value was positively correlated with the use of output based incentives, and we would expect pitchers that pitched more innings to be valued more highly, so it would follow that pitching an above average number of innings would be positively correlated with excellence incentives. Oddly, that second assumption is not supported by the data, as Table 8 shows a negative correlation between innings pitched above average and contract value. Why are pitchers that pitch more innings being valued lower than their lesser used counterparts? It is

certainly an interesting question for further research, but one possibility lies with the relief pitchers, who make up 63% of the pitchers contracted over this period. For relief pitchers, the most valuable are those that pitch the innings with the highest importance, not those that pitch the highest number of innings. A relief pitcher that throws an above average number of innings is likely what would be called a long-relief pitcher, who is typically a starting pitcher that didn't make the top five spots for starters and was relegated to be a relief pitcher that soaks up inning when the game isn't especially close. These low-leverage pitchers are certainly not valued at the same level as closers, those that pitch the highest leverage inning at the end of a close game. Therefore, one possible explanation for this quandary is that, for relief pitchers, the most valuable pitchers in fact throw fewer innings and the low-value pitchers throw more.

Result 3: Player Productivity and Incentive Use:

Hypothesis 2 suggests that, following previous literature by Barth (2008), players who are more productive will be contracted under incentives more often than less productive players. Table 9 show some support for this hypothesis, where the WAR of a player's previous season is positively correlated with incentive use. Before diving into the regression analysis, a quick note on WAR. An acronym for Wins Against Replacement, WAR is designed to represent the overall production of a player as it pertains to creating wins for his team. The WAR data presented here is courtesy of fangraphs.com, one of the leading sabermetrics sources. Though WAR is calculated slightly differently depending on the source, the differences are typically small, and as a measure for total productivity I believe it to be the best statistic for this purpose.

The coefficient on WAR with respect to incentive use is 0.0349 (significant at 5%), which indicates that an increase of one win makes a player about 3.5% more likely to be contracted under performance incentives. The models in Table 5 also show that WAR is not correlated with the use of input incentives, which is consistent with previous results regarding the differences between the types of incentives and contract values (See Table 4 Model 1). For the output-type incentives, the correlation was highly significant (at 0.01%) though the coefficient was slightly less, coming in at 3.08% for each extra win created. Despite the slightly lower coefficient, the significance of this positive coefficient furthers the notion that teams understand the higher returns that can be garnered by extra incentives for highly productive players.

Conclusions and Extensions:

The research presented here is by no means definitive, but rather the first step into what I believe to be an under-analyzed intersection of labor and sports economics. My investigation into pay-for performance in MLB produced some interesting, statistically significant, results in a number of areas, but also highlighted previously unseen connections that were not researched as part of the central thread of this paper. It is my wish that more scholars will see the value of the world as sports as a possible laboratory for economic research, perhaps investigating why contracting behavior (in this case as it pertained to performance incentives) varied so significantly from year to year. Despite the many questions that my research has raised, I still was able to draw some noteworthy conclusions that have significant implications for performance pay research in a broad sense.

One of the most interesting results that I discovered in this research was how many of my initial hypotheses did not come out through the data. Hypothesis (1), which suggested that teams that take on riskier players will tend to allocate some of that heightened risk to players via performance incentives, was supported in the data on some counts, but not all. . Parts (a) and (b) were both shown to have no significant correlation with the use of incentives; suggesting that teams do not take into account the age and injury history of a player when crafting performance incentives. This is not to say that teams did not take these factors into account at all when contracting these players, because as Table 8 shows, age did have a significant negative effect on the value of the contract, at least for pitchers.

Two elements of risk-allocation highlighted in this hypothesis did come through in the data, however, suggesting that performance incentives may be used for this function in some cases, but not all. Both models in Table 4 show a positive correlation between risk-allocation to players and the value teams stand to lose on poorly performing or injured players. The positive correlations between incentive use and contract value, and between incentive use and the length of contracts, lend support to the risk tradeoff described in classical agency theory. (Prendergast, 2002) Logically, firms that take on risk by offering fixed term contracts would jump at the opportunity to put some of that risk on the agent via performance based pay. It appears that the market is willing to build in the risk of age and injury history into a player's base salary, but teams are willing to offer higher value contracts individually if they can trade off some of that risk back to the agent.

The second significant finding with respect to risk and incentive use came via the investigation of specialization. The results in Table 6 indicate that players who specialize in a highly variable skill (hitting home runs, for example) are more likely to be contracted under performance incentives. The heightened risk level that comes from players that are less well-rounded certainly seems to be a factor in team decision making, even when controlling for the total value of those players. Interestingly, this trend appears to be consistent across both hitters and pitchers, as pitchers were contracted under incentives more often when they were more specialized in the strikeout skill and hitters received performance dependent deals when they specialized in the home run skill.

The second hypothesis, which suggested that highly skilled players were going to be contracted under incentives more often than lower quality players, seemed to be supported in the data. The first way that this result appeared was through the positive correlation with contract value, as the skill of the player is obviously connected to the value of the contract in a competitive labor market. As Table 9 shows, incentive use was also positively correlated with the WAR of the player in the previous season. There are certainly valid criticisms one can make of WAR, but few would disagree that WAR at least approximates the skill of a player. This follows from Barth's research, which suggests that principals have more to gain by encouraging performance at higher skill levels. (Barth, 2008)

The question that plagues many studies of sport economics is: "so what?" Why should anyone outside of the small group of people that actually make decisions for baseball teams care that player who hit more home runs are contract under performance incentives more often? That small group should certainly care, though I suspect they

already know, but I believe the extensions of this research could hold significant implications for labor economics across industries. Each one of the proposed hypotheses tells us something about how firms behave in a competitive labor market where information about employee performance is near-perfect for all actors in the market. Stated that way, it is easy to see how this research can have wider implications, and if the gains from this type of contracting can be as productive as authors like Lazear suggest, the gains for industry could be immense. (Lazear, 2000)

In the MLB laboratory, we were able to see that firms use a combination of basic salary and performance based pay to control for employee productivity risk. Some factors, like age and injury history, contributed to a reduction in base salary. This seems to indicate that certain characteristics of employees are taken by all actors in the market to be significant indications of risk, prompting a lower base salary. However, other indicators of risk like excessive specialization and the length of the commitment were taken into account via variable pay schemes. This may indicate that firms would be more likely to contract a sales staff under performance incentives than their accounting department because the productivity of the salespeople would likely be more variable than the accountants. These results can tell us a great deal about how well-informed firms behave, utilizing a combination of market-accepted salary reductions and performance based pay to protect themselves from risk.

We can also see, following from the second hypothesis, that firms are likely aware of the greater gains that can be made from contracting highly productive workers under performance incentives. Very few firms have employees as productive as Mike Trout (the centerfielder for the Anaheim Angels, one of the most productive players in

baseball), but Mike Trout and his contract seem to indicate that encouraging the top salesperson to be a little more productive can pay greater dividends, something that many firms can certainly make use of.

The conclusions that I have made here are a first step into this field, opening the door for further research in this area. The results that I have discovered can have an impact in a wide range of industries, and should be strongly considered in MLB contracting. Now I just have to hope that other scholars continue down the path I have set out, and that maybe someone drops this on the desk of A.J. Preller, the general manager of my hometown San Diego Padres.

Tables and Figures:**Table 1: Incentive use by year and type**

This table shows basic summary statistics for the percentage of contracts in each year that contained the different types of performance incentives.

	Output	Input	Both	Total
2010	4%	17%	10%	31%
2011	5%	10%	12%	28%
2012	12%	22%	24%	57%
2013	8%	22%	8%	38%
2014	12%	27%	11%	51%

Table 2: Average use of incentives by team

This table shows the percentage of free agent contracts over the given five year period (2010-2014) that contained some type of performance based incentive, broken down by team.

Team	Incentive Use
Angels	60%
Astros	27.3%
A's	38.5%
Blue Jays	5%
Braves	46.7%
Brewers	42.9%
Cardinals	31.6%
Cubs	48.3%
Diamondbacks	17.4%
Dodgers	44.1%
Giants	43.5%
Indians	40.9%
Mariners	50%
Marlins	37.5%
Mets	41.7%
Nationals	34.6%
Orioles	47.8%
Padres	22.2%
Phillies	54.5%
Pirates	27.3%
Rangers	36.4%
Rays	25%
Red Sox	51.5%
Reds	23.8%
Rockies	33.3%
Royals	47.1%
Tigers	36.8%
Twins	72.2%
White Sox	47.6%
Yankees	57.1%

Table 3: Incentive use by type and position

This table shows the percentage of contracts containing the various incentive types, broken down by position.

	Number	Input Mean	Output Mean	Both Mean	Total Mean
Relief P	202	0.044554	0.128713	0.207921	0.381188
Starting P	114	0.086957	0.307018	0.090476	0.508772
Catcher	60	0.05	0.2	0.083333	0.333333
First Base	36	0.111111	0.138889	0.027778	0.277778
Second Base	40	0.075	0.25	0.025	0.35
Third Base	41	0.04878	0.170732	0.073171	0.292683
Shortstop	28	0.107143	0.214286	0.107143	0.428571
Left Field	76	0.118421	0.184211	0.092105	0.394737
Center Field	10	0	0.2	0	0.2
Right Field	34	0.235294	0.176471	0.176471	0.588235
Designated Hitter	20	0	0.1	0.05	0.15
All pitchers	316	0.060127	0.193038	0.174051	0.427215
All hitters	345	0.092754	0.185507	0.078261	0.356522
TOTAL	661	0.077039	0.188822	0.123867	0.389728

Table 4: Incentive use and contract terms

This table presents the results of regressions on incentive usage, focused on the effects of total contract value and contract length. Controls are added for each of the thirty MLB teams, the five signing periods used in this dataset, player age at the time of signing, and positional controls for each of the positions (relief pitcher is the omitted position). The variable for contract value is reported in millions of dollars and the variable for contract length is reported in years.

	<i>Incentive Use by Type:</i>					
	<u>Model 1: Value</u>			<u>Model 2: Length</u>		
	All	Output	Input	All	Output	Input
	(1)	(2)	(3)	(4)	(5)	(6)
Controls						
Team Controls	YES	YES	YES	YES	YES	YES
Year Controls	YES	YES	YES	YES	YES	YES
Positional Controls	YES	YES	YES	YES	YES	YES
Age	-0.005 (0.006)	0.001 (0.003)	-0.006 (0.005)	-0.006 (0.006)	0.0003 (0.003)	-0.006 (0.005)
Value (Millions)	0.002 ^{***} (0.001)	0.003 ^{***} (0.0004)	-0.001 ^{**} (0.001)			
Contract Length (years)				0.034 ^{**} (0.016)	0.052 ^{***} (0.009)	-0.026 [*] (0.013)
Constant	0.677 ^{***} (0.236)	0.042 (0.130)	0.393 ^{**} (0.195)	0.666 ^{***} (0.242)	0.020 (0.135)	0.413 ^{**} (0.200)
Observations	661	661	661	661	661	661
R ²	0.167	0.160	0.115	0.162	0.130	0.113
Adjusted R ²	0.106	0.099	0.050	0.101	0.066	0.048
Residual Std. Error (df = 615)	0.462	0.254	0.382	0.463	0.258	0.382
F Statistic (df = 45; 615)	2.735 ^{***}	2.604 ^{***}	1.780 ^{***}	2.647 ^{***}	2.036 ^{***}	1.745 ^{***}

Table 5: Incentive use and specialization (1)

This table shows the effects of specialization on the use of incentives for hitters in the sample. Controls are added for each of the thirty MLB teams, the five signing periods used in this dataset, player age at the time of signing, and positional controls for each of the positions (catcher is the omitted position). A control is also added in this regression for total contract value, in order to separate out the effect of specialization from a player's total productivity, which we assume is correlated with contract value. For the tracked performance statistics, measures of variances are also included in order to test for a correlation between the variability of a player's performance and the use of incentives. The specialist score variable is computed by awarding a player a point for each season in which they rate in the top ten players at their position in home runs or finish in the top three percent of all players in stolen bases. Each time a player finishes in one of these categories they are awarded a point towards their specialist score, the total of which is reported as "TOT specialist score."

	<i>Incentive Use by Type:</i>		
	All (1)	Output (2)	Input (3)
Controls			
Team Controls	YES	YES	YES
Year Controls	YES	YES	YES
Position Controls	YES	YES	YES
Value	0.000 (0.000)	0.000*** (0.000)	-0.000 (0.000)
Age	-0.002 (0.008)	0.002 (0.005)	-0.004 (0.007)
Tracked Statistic Variance			
AB variance	0.00000 (0.00000)	0.00000 (0.00000)	-0.00000 (0.00000)
HR variance	-0.001 (0.001)	-0.001 (0.0004)	-0.0001 (0.001)
SB variance	-0.001* (0.001)	0.0002 (0.0003)	-0.001 (0.0004)
TOT specialist score	0.032* (0.018)	0.013 (0.011)	0.014 (0.016)
Constant	0.412 (0.340)	0.111 (0.204)	0.341 (0.295)
Observations	345	345	345
R ²	0.255	0.265	0.145
Adjusted R ²	0.137	0.149	0.010
Residual Std. Error (df = 297)	0.446	0.268	0.387
F Statistic (df = 47; 297)	2.161***	2.284***	1.074

Table 6: Incentive use and specialization (2)

This table shows the effects of specialization on the use of incentives for hitters in the sample. Controls are added for each of the thirty MLB teams, the five signing periods used in this dataset, player age at the time of signing, and positional controls for each of the positions (catcher is the omitted position). A control is also added in this regression for total contract value, in order to separate out the effect of specialization from a player's total productivity, which we assume is correlated with contract value. For the tracked performance statistics, measures of variances are also included in order to test for a correlation between the variability of a player's performance and the use of incentives. Specialist score variables are computed by awarding a player a point for each season in which they rate in the top ten players at their position in home runs or finish in the top three percent of all players in stolen bases. The "HR specialist score" represents the total score for the home run leaders, while "SB specialist score" represents the total score for the stolen base leaders. "TOT specialist score" is the sum of the two categories.

	<i>Incentive Use by Type:</i>		
	All	Output	Input
Controls			
Team Controls	YES	YES	YES
Year Controls	YES	YES	YES
Positional Controls	YES	YES	YES
Value	0.000 (0.000)	0.000*** (0.000)	-0.000 (0.000)
Age	-0.001 (0.008)	0.003 (0.005)	-0.004 (0.007)
Tracked Statistic Variance			
AB variance	0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)
HR variance	-0.001 (0.001)	-0.001 (0.0004)	-0.0001 (0.001)
SB variance	-0.001 (0.001)	0.001* (0.0004)	-0.0005 (0.001)
Specializations			
HR specialist score	0.039* (0.021)	0.025** (0.013)	0.018 (0.018)
SB specialist score	0.011 (0.037)	-0.023 (0.022)	0.003 (0.032)
Constant	0.382 (0.343)	0.060 (0.205)	0.325 (0.298)
Observations	345	345	345
R ²	0.256	0.274	0.146
Adjusted R ²	0.135	0.156	0.007
Residual Std. Error (df = 296)	0.446	0.267	0.388
F Statistic (df = 48; 296)	2.121***	2.325***	1.052

Table 7: Incentive use and specialization (3)

This table shows the effects of specialization on the use of incentives for pitchers. Controls are added for each of the thirty MLB teams, the five signing periods used in this dataset, player age at the time of signing, and positional controls for each of the positions (relief pitcher is the omitted position). A control is also added in this regression for total contract value, in order to separate out the effect of specialization from a player's total productivity, which we assume is correlated with contract value. For the tracked performance statistics, measures of variances are also included in order to test for a correlation between the variability of a player's performance and the use of incentives. The relative statistics report Innings Pitched (IP) above average, Strike Outs (SO) above average, and ERA above average relative to a player's positional peers. These variables are computed by taking the average of each statistic for both positions for a given season, subtracting this average from an individual player's production of that statistic for that season, and then finally taking the mean of those differences over the three year period prior to signing the contract.

	<i>Incentive Use by Type:</i>		
	All	Output	Input
Controls			
Team Controls	YES	YES	YES
Year Controls	YES	YES	YES
Position Controls	YES	YES	YES
Age	-0.017*	-0.003	-0.008
	(0.009)	(0.005)	(0.007)
Value	-0.000	0.000**	-0.000***
	(0.000)	(0.000)	(0.000)
Tracked Statistics Variance			
IP variance	0.00004	0.00002	0.00001
	(0.00003)	(0.00001)	(0.00002)
SO variance	-0.00003	-0.00003	0.00004
	(0.0001)	(0.00003)	(0.00004)
ERA variance	0.0004	0.0003	-0.001
	(0.002)	(0.001)	(0.002)
Relative Statistics			
IP above average	-0.002	-0.002*	-0.0001
	(0.002)	(0.001)	(0.002)
SO above average	0.005**	0.002*	0.003
	(0.002)	(0.001)	(0.002)
ERA above average	-0.070**	-0.017	-0.003
	(0.032)	(0.016)	(0.025)
Constant	1.220***	0.048	0.520*
	(0.356)	(0.178)	(0.279)
Observations	316	316	316
R ²	0.222	0.162	0.251
Adjusted R ²	0.102	0.033	0.136
Residual Std. Error (df = 273)	0.469	0.234	0.367
F Statistic (df = 42; 273)	1.853***	1.253	2.184***

Table 8: Pitcher Characteristics and Contract Value

This table shows the output of a regression on total contract value. Controls are added for each of the thirty MLB teams, the five signing periods used in this dataset, player age at the time of signing, and positional controls for each of the positions (relief pitcher is the omitted position).

	<i>Total Contract Value:</i>
	Value
Controls	
Team Controls	YES
Year Controls	YES
Position Controls	YES
Age	-910,869.300 ^{***} (293,996.200)
Tracked Statistics Variance	
IP variance	2,232.508 ^{**} (893.631)
SO variance	-5,626.473 ^{***} (1,623.889)
ERA variance	359,800.100 ^{***} (78,358.900)
Relative Statistics	
IP above average	-226,156.200 ^{***} (61,959.730)
SO above average	621,790.700 ^{***} (71,637.250)
ERA above average	-4,444,009.000 ^{***} (1,007,930.000)
Constant	40,961,364.000 ^{***} (11,444,617.000)
Observations	316
R ²	0.529
Adjusted R ²	0.459
Residual Std. Error	15,430,959.000 (df = 274)
F Statistic	7.511 ^{***} (df = 41; 274)

Table 9: Incentive use and player productivity

This table shows the relationship between the productivity of a player, denoted by the player's WAR in the previous season, and the existence of incentives in their free agent contract. Controls are added for each of the thirty MLB teams, the five signing periods used in this dataset, player age at the time of signing, and positional controls for each of the positions (relief pitcher is the omitted position).

	<i>Incentive Use by Type:</i>		
	All (1)	Excellence (2)	Risk (3)
Controls			
Team Controls	YES	YES	YES
Year Controls	YES	YES	YES
Position Controls	YES	YES	YES
Age	-0.006 (0.006)	-0.002 (0.003)	-0.005 (0.005)
Previous Season WAR	0.035** (0.014)	0.031*** (0.008)	-0.005 (0.012)
Constant	0.754*** (0.232)	0.194 (0.132)	0.308 (0.193)
Observations	661	661	661
R ²	0.164	0.104	0.108
Adjusted R ²	0.103	0.038	0.043
Residual Std. Error (df = 615)	0.462	0.262	0.383
F Statistic (df = 45; 615)	2.685***	1.579**	1.655***

References:

- Baker, G. (1992). Incentive Contracts and Performance Measurement. *Journal of Political Economy*, 100(3), 598–614. <http://doi.org/10.1086/261831>
- Barth, E., Bratsberg, B., Hægeland, T., & Raaum, O. (2008). Who pays for performance? *International Journal of Manpower*, 29(1), 8–29. <http://doi.org/10.1108/01437720810861985>
- Baseball Reference (2015). Baseball Reference Play Index. Retrieved October 2015, from http://www.baseball-reference.com/play-index/season_finder.cgi?type=b
- Baseball Prospectus (2015). Cot's Baseball Contracts. Retrieved October 2015, from <http://www.baseballprospectus.com/compensation/cots/>
- Dohmen, T., & Falk, A. (2011). Performance Pay and Multidimensional Sorting: Productivity, Preferences, and Gender. *American Economic Review*, 101(April), 556–590.
- ESPN (2015). 2015 MLB Free Agents. Retrieved October 2015, from <http://espn.go.com/mlb/freeagents>
- Fangraphs (2015). Fangraphs WAR leaders. Retrieved November 2015, from <http://www.fangraphs.com/leaders.aspx?pos=all&stats=bat&lg=all&qual=y&type=6&season=2015&month=0>
- Gibbons, R. (1998). Incentives in Organizations. *Journal of Economic Perspectives*, 12(4), 115–132. <http://doi.org/10.1257/jep.12.4.115>
- Gibbs, M. J., Merchant, K. a., Van Der Stede, W. a., & Vargus, M. E. (2009). Performance measure properties and incentive system design. *Industrial Relations*, 48(2), 237–264. <http://doi.org/10.1111/j.1468-232X.2009.00556.x>
- Gielen, A. C., Kerkhofs, M. J. M., & van Ours, J. C. (2010). How performance related pay affects productivity and employment. *Journal of Population Economics*, 23(1), 291–301. <http://doi.org/10.1007/s00148-009-0252-9>
- Gneezy, U., Meier, S., & Rey-Biel, P. (2011). When and Why Incentives (Don't) Work to Modify Behavior. *Journal of Economic Perspectives*, 25(4), 191–210. <http://doi.org/10.1257/jep.25.4.191>
- Holmstrom, B., Holmstrom, B., Milgrom, P., & Milgrom, P. (1994). The Firm as an Incentive System. *The American Economic Review*, 84(4), 972–991. <http://doi.org/10.1126/science.151.3712.867-a>

- Jensen, C., & Meckling, H. (1976). THEORY OF THE FIRM : MANAGERIAL BEHAVIOR , AGENCY COSTS AND OWNERSHIP STRUCTURE I . *Journal of Financial Economics*, 3(4), 305–360.
- Kauhanen, A., & Napari, S. (2012). Performance Measurement and Incentive Plans. *Industrial Relations*, 51(3), 645–669. <http://doi.org/10.1111/j.1468-232X.2012.00694.x>
- Kauhanen, A., & Piekkola, H. (2006). What makes performance-related pay schemes work? Finnish evidence. *Journal of Management and Governance*, 10(2), 149–177. <http://doi.org/10.1007/s10997-006-0005-z>
- Kerr, S. (1975). On the Folly of Rewarding A, While Hoping for B. *The Academy of Management Journal*, 18(4), 769–783. <http://doi.org/10.2307/255378>
- Lahman, S. (2015). Lahman’s Baseball Database 2014. Retrieved October 2015, from <http://seanlahman.com/baseball-archive/statistics>
- Lazear, E. P. (1995). Personnel economics. Wicksell Lectures.
- Lazear, E. P. (1998). Personnel economics for managers. New York; Chichester and Toronto.
- Lazear, E. P. (2000a). Performance pay and productivity. *American Economic Review*, 90(5), 1346–1361. <http://doi.org/10.1257/aer.90.5.1346>
- Lazear, E. P. (2000b). The Power of Incentives. *American Economic Review*, 90(2), 410–414. <http://doi.org/10.1257/aer.90.2.410>
- Major League Baseball Club Owners, Major League Baseball Players Association. (2007). "2007-2011 Basic Agreement."
- Major League Baseball Club Owners, Major League Baseball Players Association. (2012) "2012-2016 Basic Agreement."
- Major League Baseball Club Owners. (1921). "Major League Constitution."
- Posner, R. a. (2010). *From the new institutional economics to organization economics: with applications to corporate governance, government agencies, and legal institutions*. *Journal of Institutional Economics* (Vol. 6). <http://doi.org/10.1017/S1744137409990270>
- Prendergast, C. (2002). The tenuous trade-off between risk and incentives. *Journal of Political Economy*, 110(5), 1071–1102. <http://doi.org/10.1257/aer.90.2.421>

Roberts, J. (2010). Designing incentives in organizations. *Journal of Institutional Economics*, 6(01), 125. <http://doi.org/10.1017/S1744137409990221>