Compensating Against Turnover: Managers' Talent Retention Decisions in Major League Baseball Under a Budget Constraint

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COMPENSATING AGAINST TURNOVER: MANAGERS’ TALENT RETENTION DECISIONS IN MAJOR LEAGUE BASEBALL UNDER A BUDGET CONSTRAINT

by

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SUBMITTED TO SCRIPPS COLLEGE IN PARTIAL FULFILLMENT OF THE DEGREE OF BACHELOR OF ARTS

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Abstract

From 1997 to 1999 and 2003 to the present, Major League Baseball has had a luxury tax on high payroll teams. This paper analyzes the impact of the tax as a budget constraint on teams’ ability to reward and retain high performing players. In contrast to other papers, we use wins above replacement (WAR), a popular sabermetrics statistic, to measure performance. Using this metric, we quantify the number of top performers, how this performance is rewarded with salary, and how salary impacts players’ mobility decisions. We conclude that when using WAR, the distribution of performance is not heavy tailed and rather follows an exponential distribution. Our results suggest that there are fewer top performers in periods with a luxury tax/budget constraint. We use efficiency wage theory to understand this decrease in top performers as the result of a decrease in motivators. We understand two different mechanisms of motivating performance: (1) under a stochastic budget constraint, managers did not choose to extend the contracts of top players; and (2) under a fixed budget constraint, managers decreased the monetary reward for an increase in performance. Both these mechanisms decrease the motivation for top talent to perform highly.
Acknowledgements

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I. Introduction

Human capital is one of the most important resources that a firm possesses. In 2016, 44% of U.S. Gross Domestic Product (GDP) consisted of salaries and wages. However, even this number fails to capture the entrepreneurial capital that business owners invest in a firm that also drives profit. In a global survey of CEOs by PricewaterhouseCoopers, 72% of CEOs claimed that they were concerned about the availability of necessary talent (PwC, 2016). Harvard Business Review interviewed CEOs in 2013 and talent management was their top concern (Groysberg, et al., 2015). In addition to this scarcity, a main challenge of human capital management is that individuals can leave a firm at any time and take their human capital with them. This loss of capital is one reason turnover can be very costly to firms—especially in the cost of training new hires. These trends make talent retention highly important to firm success. Salary is the main reason that employees consider leaving a firm (Ramlall, 2003), but firms have budget constraints which dictate how much they can allocate to talent retention and salary. We analyze the challenge of firms to reward top performers in a manner that fits their budget constraints and retains top talent.

Access to data makes studying the retention of top performers difficult, if not entirely impossible: private companies protect their own performance data as highly confidential. One exception is professional sports where performance data is readily available. We choose to focus on professional baseball, Major League Baseball (MLB), for two main reasons. First, performance in MLB is relatively independent of other players’ performance with mainly the pitcher and batter interacting with each other. In more interdependent sports, the performance statistics of any one player incorporates how well the entire team works together as well as the

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1 FRED, Compensation of Employees/GDP: [https://fred.stlouisfed.org/graph/?g=2Xa](https://fred.stlouisfed.org/graph/?g=2Xa). Accessed April, 2017.
talent of that individual—this interdependency makes it challenging to track individual performance. Second, the league has had an additional budget constraint placed on teams in the last two decades in the form of a luxury tax. We exploit this change in regulation to see how talent retention strategy depends on budget.

MLB enacts a tax on each dollar spent on payroll over a certain threshold, called a luxury tax. MLB has had two different tax regimes in place, one from 1997 to 1999 (referred to as the 1996 luxury tax, named for the year it was approved) and another from 2003 to the present (referred to as the 2002 luxury tax, similarly named). Under the 1996 luxury tax, MLB taxed the 5 teams with the highest payrolls for each dollar spent over the midpoint of the 5th and 6th highest payroll. Under the 2002 luxury tax, MLB taxes teams above a certain predetermined cap. The most salient difference between the two tax regimes is the absolute payroll level after which a team faces the tax under the 2002 luxury tax (instead of one which depends on the payroll level of other teams as with the 1996 luxury tax). For the 2014 to 2016 seasons, the threshold was $189 million.\(^2\) Further, the 2002 measure increases the tax percentage for repeat offenders. In 2016, the luxury tax was amended to include surcharges for the magnitude by which a team violates the cap.\(^3\) In the 2015 season, four teams were in violation: the Los Angeles Dodgers, the New York Yankees, the Boston Red Sox, and the San Francisco Giants. In the 2016 season, the four teams were joined by the Detroit Tigers and the Chicago Cubs. In 2015, the highest spending team in MLB, the Los Angeles Dodgers, spent over $305 million on their roster.


contrast, the lowest spending team, the Miami Marlins, spent only $67.5 million—22% of the highest payroll.4

We use this luxury tax to study the following question: how do firm level decisions around using compensation as a tool to retain top talent change under this additional budget constraint? In this paper, we analyze the impact of the two different luxury taxes on the distribution of performance, compensation, and the ability of teams to retain top talent. Key to the decisions around compensation strategy are assumptions about the distribution of performance—specifically, what percent of a firm’s labor force is top talent? This question addresses the overarching question of what is the distribution of performance and how heavily populated is the upper tail of the distribution. Previous literature has demonstrated the connection between pay and performance (Bloom, 1999; Debrock et al., 2004; Bruenig et al., 2014; Tao et al., 2016) and specifically, the ability of salary to motivate workers under efficiency wage theory (Yellen, 1995; Akerlof, 1984; Stiglitz, 1976). When considering MLB’s luxury tax, the taxes’ impact on how teams use salary to motivate players may also impact performance. In this paper, we use wins above replacements (WAR)—a measure of the marginal impact of each player explained extensively in our methodology section—to measure performance instead of the more traditionally used vector of different performance metrics. As we will explain further, we believe WAR provides a measure of performance that more accurately measures the marginal contribution of a player as well as facilitates comparison across seasons and teams.

While baseball has the advantage of having easily accessible performance data as mentioned earlier, not all data is easily accessible. One of our largest limitations is the lack of data on salary, particularly for players with low WARs. We also were not able to get a cohesive

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dataset on which players were under contracts, for what length and what the terms of those contracts were. Despite the data limitations, we still believe our work meaningfully contributes to the literature about luxury taxes in professional sports and more generally, budget constraints in talent management. There has been no empirical research on the impact of MLB’s luxury tax on performance and pay. The theoretical work (Marburger, 1997; Dietl et al., 2009) has used tax regimes that are dissimilar from the one in place in MLB, as discussed in our literature review.

We use the following models to understand how teams use salary to reward top performers and how the ability of teams to retain top talent has changed. We look at the empirical survival function of performance as well as log and semi-log plots in four distinct phases: (1) 1985 to 1996, before any luxury tax was imposed; (2) 1997 to 1999, when the 1996 luxury tax was in place; (3) 2000 to 2002, when the league again did not have a luxury tax; (4) 2003 to 2015, when the 2002 luxury tax was in place. We also run a regression of salary against performance as well as a probit model of player retention explained by compensation.

The rest of the paper will be structured as follows: first, we provide background information on MLB’s rationale for the luxury tax and the probability theory that we will use in this paper. Second, we overview the current literature to explain the context of our work in both personnel and sports economics. Third, we give an overview of our model and methodology. Fourth, we present the data and the results as well as discuss the economic significance of our findings. We conclude by discussing our contribution to the literature as well as areas of further research.
II. Background Information

i. History of the Luxury Tax

Sport leagues such as MLB have a unique challenge in maintaining what is referred to as “competitive balance”— firms want their teams to be strong because of the increased revenue from a strong fan base and apparel and ticket sales but firms also want other teams to be strong so that games do not get boring and tickets sales will continue. Forrest and Simmons (2002) demonstrated this phenomena in English soccer—as the uncertainty of who will win a game increased, ticket sales increased as well. Schreyer et al. (2016) confirmed this finding in German soccer—an increase in uncertainty led to more ticket sales and people staying at stadiums longer (and perhaps purchasing more commodities). MLB has tried to establish competitive balance in multiple ways, most recently with the luxury tax that is the focus of this paper and previously, with the reserve clause.

Professional baseball in the U.S. started in 1869 and by the late 1870’s, team owners were already discussing the problem of roster jumping. Players would get stolen away from teams and switch teams between seasons. Team owners decided to circulate a list of five players that they “reserved” from such jumping—by 1883, that list included the entire team and by 1887, teams were including a reserve clause in contracts (Haupert, 2016). The reserve clause prevented a free labor market from existing in MLB by preventing players’ from choosing their teams. As Rottenberg (1956) concluded in his seminal paper, the reserve clause transferred wealth from players to team owners. Not surprisingly, players were dissatisfied with the reserve clause and made multiple retaliation attempts (Haupert, 2016). Success came in 1976 when MLB and the Major League Baseball Players Association (MLBPA) agreed that players who had more than 6
years of major league experience had the right to solicit contracts at the end of a season—this right became known as free agency (Villanova, 2016).

From 1976 on, owners attempted to limit free agency and salary growth—after all, it just increased the cost of owning a team. The tension between owners and the MLBPA ultimately culminated in the 1994 strike which lasted for 232 days, canceling 900 games and the 1994 World Series.\(^5\) Largely in response to the strike, MLB passed the 1996 Competitive Balance Agreement (CBA). Part of this agreement was the luxury tax—in the 1997, 1998, and 1999 seasons, the five teams with the highest payrolls were taxed 35% (in 1997 and 1998) or 34% (in 1999) for every dollar above the average of the fifth and sixth highest payrolls. Calculating the total payroll for a given season is complicated and includes the team’s contribution to the league-wide player benefits (which is split evenly between the teams), the annual salary of players on the roster for the entire season, and the portion of long term contracts attributed to that year (Dosh, 2007).

Despite the 1996 CBA, the Yankees made it to the World Series four consecutive times from 1998 to 2001, winning 3 of the 4 titles (Barbosa, 2015). While this is not necessarily evidence that the 1996 luxury tax was ineffective at maintaining competitive balance, it was largely interpreted as such. As the opportunity to renew the 1996 CBA came and passed without action, the 2000 to 2002 seasons passed with no luxury tax in effect. In 2002, MLB reintroduced a luxury tax in the 2002 CBA, now dubbed the competitive balance tax. The 2002 luxury tax’s largest difference from that of the 1996 CBA was establishing a fixed salary cap rather than one dependent on team payrolls. The cap in 2003 was $117 million and in 2020 will reach $206

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The 2002 CBA also set up a progressive tax scheme under which repeat offenders faced an increased tax rate. Though the exact rates have changed with the renewals of the 2002 CBA, first time offenders face a rate between 17.5 to 22.5%, second time offenders 30%, third time offenders 40% and since 2012, fourth time offenders face 50%. As of the 2017 season, teams will face an additional penalty for the magnitude by which they violate the cap—for being $20 million to $40 million over the threshold, 12%; $40 million over, 40%; and the second time being $40 million over, 45%. These tax rates are additional to the tax rates for just being in violation of the luxury tax payroll cap. Some have accused the 2002 CBA of allocating an increasing share of revenue away from players and to owners (Grow, 2015) similar to the accusations of the reserve clause by Rottenberg (1956).

In the 2015 season, the Los Angeles Dodgers paid $43.7 million under the luxury tax, the highest penalty ever paid in the tax’s history (Nightengale, 2015). The New York Yankees have paid the tax for every year the tax has been in place and account for over $297 million of the $403 million of tax revenue from 2003 to 2015. None of the teams that paid the tax in the 2015 season (Los Angeles Dodgers, New York Yankees, Boston Red Sox, and San Francisco Giants) made it to the World Series. However, the World Series winners in 2016, the Chicago Cubs, did pay the tax in the same season and were the fifth highest payroll in the league. Contrary to the 1996 CBA, it seems that high payroll teams are not necessarily also top performing teams under the 2002 CBA.

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8 Even though the owner of the Yankees, Steinbrenner, was one of the largest opponents of the 2002 CBA and the only owner to vote against it (Dosh, 2007), he has since announced that the Yankees aim to get its payroll below the luxury tax threshold (Hawkins, 2015).
Teams can and do exploit the requirement for 6 years of experience in the major leagues before being granted free agent status. One recent example is Kris Bryant who was sent down to the minor leagues at the beginning of the 2015 season by the Chicago Cubs. This move allowed the Cubs to retain Bryant for an additional season without having to enter salary negotiations because he would be just shy of 6 years of major league experience at the end of the 2020 season. Bryant went on to be recognized as National League Rookie of the Year in same season (2015) and MVP in the National League in the following season (2016), the same year the Cubs won the World Series. This practice in MLB demonstrates that teams are concerned at retaining top talent at a minimal cost to the team. Recently, the MLBPA has threatened litigation, presumably finding these moves to not be in the best interest of the player’s earning potential whereas MLB claims that these moves are in the discretion of a team’s ability to decide their roster. The MLBPA and the owners are clearly still in conflict over what is permissible to curb salary growth.

ii. Probability Theory

In our paper, we will use distribution theory to analyze the likelihood of high performers in different periods of the luxury tax. Here, we review some of the foundations of distribution theory and the relevant distributions that we will discuss and compare. The cornerstone of distribution theory is a random variable, a function from a sample space to the real numbers. For example, for a coin toss, the event of getting heads can be represented as 1 and the event of getting tails as 0. For a random variable $X$, we define the cumulative distribution function (cdf) as $F(x) = P(X \leq x)$ where $P$ is a probability measure with range $[0,1]$. In layman’s term, the cdf looks at the probability that a random variable is less than or equal to a particular value.

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(represented by $x$ in the definition). Since we are interested in high performers, we find it more useful to define a survival function, the probability that a random variable is greater than a particular value. Formally, we define the survival function as $y(x) = P(X > x) = 1 - F(x)$. Looking at the survival function allows us to focus on the right tail of the distribution which contains the highest performers without our analysis being impacted by random variation and/or outliers in the rest of our dataset.

Specifically, we will look at whether our dataset has a heavy tail. A random variable $X$ is said to be heavy tailed if it has an absolute moment that is infinite ($\exists n > 0: E|X|^n = \infty$). The heavier a tail, the more likely it is to find observations in the tail and hence, in our situation, the higher abundance of top performers. One of the most common examples of a heavy tailed distribution is the Pareto distribution, $P(X > x) = Cx^{-\alpha}$ for $x > 0$, a constant $C$, and parameter $\alpha$. Some common uses of Pareto distributions are to model city sizes, incomes, and the magnitude of earthquakes (Krishnan, 2006). Figure 1 shows a Pareto distribution for $\alpha \in \{1,2,10\}$.

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11 The Pareto distribution is also commonly referred to as the Power Law distribution because of its functional form. The discrete version of the Pareto distribution is called the Zipf distribution.
In comparison to the Pareto distribution, the exponential and normal distributions are both light tailed ($\forall n > 0: E|X|^n < \infty$). The survival function of an exponential distribution is $P(X > x) = e^{-\lambda x}$ for $x > 0$ and parameter $\lambda$. An intuitive manner to think about the exponential distribution is that if one is at a particular value, say $m$, the probability of decreasing from $m$ is larger than the probability of increasing from $m$. Figure 2 shows an exponential distribution for $\lambda \in \{1,2,10\}$.
Perhaps the distribution that economists use mostly widely is the normal (or Gaussian) distribution. By the Central Limit Theorem, under some general conditions, the sum of random variables with a general distribution converges to a normal. Figure 3 shows the right tail of the Pareto distribution (for $\alpha = 1$), exponential (for $\lambda = 1$), and normal (for $\mu = 0, \sigma = 1$). As one can see, the Pareto distribution has a heavy tail while both the exponential and normal distributions have light tails—though, the tail of the normal distribution is significantly lighter than that of the exponential. We will consider each of these distributions as potential underlying distributions for performance later in this paper.
III. Literature Review

In looking at how the change in the luxury tax has impacted player performance and ultimately, player mobility in MLB, our literature review focuses on a few central areas: the relationship and dispersion of pay and performance, how pay impacts turnover decisions, and the impact of luxury taxes and salary caps on pay and performance. We consider both personnel economics and sports economics as well as relevant research from the fields of mathematics and organizational psychology.

The literature provides multiple rationales for the existence of heavy tails in performance including both market and job characteristics. Ultimately, heavy tails mean that there are more “super stars”—individual workers or firms whose performance far exceeds their peers—than under light tailed distributions such as the normal. In a theoretical framework, Rosen (1981) explained the existence of “super stars” at a firm level as a result of market conditions that allow firms to capitalize on decreasing costs per unit of output. Mizuno et al. (2012) applied a more
mathematical approach showing that firm productivity in 30 countries followed a Pareto distribution with a heavy tail instead of a normal—additionally, the heaviness of the tail varied by industry. O’Boyle and Aguinis (2012) studied five different industries including professional sports and demonstrated that a Pareto distribution was a more likely distribution than a normal for individual performance. Aguinis and O’Boyle (2014) confirmed these findings. Aguinis et al. (2016) narrowed down characteristics such as job autonomy and job complexity that are correlated with a heavier tail in the power law distributions of individual performance. Crawford (2012) urged that common conceptions of personnel psychology and economics be revisited in the light of the “myth of normality”. This pervasiveness in research of Pareto distributions causes a challenge for organizational researchers and economists since most statistical training has focused on normally distributed statistics (Andriani and McKelvey, 2009).

In a review of the current literature on performance and productivity, Syverson (2011) called for further research into the impacts of the heavy tail distribution of performance. Specifically, Syverson calls for research into how heavy tails impact firms’ decisions to invest in projects. In the context of baseball, signing a contract with a player can be viewed as an investment. While teams can trade players during the season, signing a player who ends up being a low performer means less leverage in a trade than a player who was signed cheap and now performs highly. When teams sign new players, they have imperfect knowledge of a player’s performance. If the player has played in the league, the firm knows previous performance but not how that performance will change. In the case of a rookie player, the team must rely on performance in a similar, though different situation such as college or the minor leagues. Longley and Wong (2011) find that prior performance metrics in the minor leagues are poor performance indicators of pitchers once they reach the major league indicating that experience in
MLB may be most pertinent in predicting future performance. Again, the firm faces uncertainty as to whether that performance will continue from the minor to major league. This process is similar to most industries where firms rely on observable employee characteristics until they can observe actual on-the-job performance and are able to make more educated pay changes (Lazear and Oyer, 2009). However, MLB managers are able to observe new players actually playing baseball (though perhaps in a different league/environment), and therefore have an advantage in determining compensation as compared to most other industries where managers must use proxies such as education.

But, does pay dispersion also impacts performance? This question is another one which the literature has addressed. Outside the field of sport economics, research has demonstrated that pay dispersion can cause an increase in effort and in turn, performance (Lazear, 2000; Shaw et al., 2002; Shaw, 2014). Lazear (2000) further added on his previous research by showing that changing to a pay-for-performance structure increased overall firm productivity. While Lazear addressed some questions about the relationship between performance and pay structure, Abowd et al. (1999) confirmed that higher wages did indeed lead to higher productivity.

Some of the literature supports an argument against pay dispersion and for pay compression. Lazear (1989, 1991) demonstrated that evenly distributed pay increases cooperation and ultimately, productive efficiency. Perhaps because cooperation is so important in sports, sports economics has largely found a negative correlation between pay dispersion and performance. Harder (1992) found that the pay-for-performance strategy in basketball and baseball significantly decreased cooperation, specifically of those individuals who were not high performers. Frick, et al. (2003) compared the impact of intra-team wage disparity on

12 Though perhaps not relevant to my discussion in this paper, Abowd et al. (1999) did find that this increase in productivity did not always translate to higher profits because of the increased payroll cost.
performance and concluded that disparity decreased the overall team performance in baseball (though they found the opposite in basketball and hockey, where the rosters are much smaller). Borghesi (2008) found that under the National Football League’s (NFL) salary cap, teams that paid a few players highly (and thus, had a wide pay dispersion) performed worse overall. In both the National Basketball Association (NBA) and German soccer league, Frey et al. (2013) found a negative correlation between the relative income position of players and performance. Multiple studies also corroborate this effect in MLB (Bloom, 1999; Debrock et al., 2004; Breunig et al., 2014; Tao et al., 2016).

Wang et al. (2014) conducted panel granger tests to investigate the causality between pay and performance in the Korean Professional Baseball League. They found that causality runs from the dispersion of pay to team performance but not vice versa. Further, pay dispersion has a stronger overall causality on team performance than total team payroll implying that paying a few star players highly was not a successful talent strategy. Tao et al. (2016) used a data set of MLB from 1985 to 2013. In the dataset, wage disparity negatively correlated with team performance but the relationship was insignificant when controlling for the overall level of team payroll. When considering MLB’s luxury tax in light of this research, the taxes’ impact on the dispersion of pay may be a means by which the tax has impacted performance or even turnover.

When considering leaving a team, a player may be unhappy with his current compensation and/or be offered a higher compensation from another team. Additional literature suggests that pay dispersion as well as an individual’s position in the pay structure also impacts turnover (Pfeffer and Blake-Davis, 1992). Pfeffer and Blake-Davis (1992) find that salary dispersion negatively impacts turnover. Further, Abbasi and Hollman (2000) theorize that lack of competitive compensation is a leading cause for turnover along with a lack of recognition for
worker achievement. Samuel and Chipunza (2009) analyzed several intrinsic and extrinsic motivators for turnover and found that salary package is statistically significant in preventing turnover; however, the duo does not report a magnitude of this correlation leaving the economic significance in question. Ramlall (2003) found that salary was the second most common reason for staying with a company (the first was company location) and the most common reason to contemplating leaving a firm. In Meudell and Rodham’s (1998) research, workers named benefits, salary, and bonuses as their top three motivators to work and to work harder.

However, high mobility may also impact the salary that players are offered. Vincent and Eastman (2012) studied the National Hockey League (NHL) and found that frequent team changes were negatively correlated with salary. They attributed this largely to team specific knowledge that became essentially worthless when a player switched teams. Glenn, et al. (2001) studied the impact of team specific knowledge on turnover in MLB from 1990 to 1992. Their study indicated that certain positions switched teams more frequently and that these positions tended to be in the outfield where there was less team specific knowledge (compared to the infield). While there is team specific human capital, Singell (1991) found that the player’s tenure in the major league was a stronger measure of human capital attained than performance when looking at which players were offered coaching positions.

Though we will predominately focus on pay in this paper, pay is only one means of motivating employees—as Lazear and Oyer (2009) commented on in an overview of the personnel economics literature, there is also significant research around other forms of motivation and non-monetary compensation. In baseball, specifically, Pedace and Hall (2012) looked at the wage differentials of risk reducing contract measures. They found evidence of a monetary tradeoff for the inclusion of a no-trade clause (which limit trades only to when they are
mutually agreed upon by the team and player), especially when part of long-term contracts. While logic might also lead one to believe that long term contracts would also lead to a compensating wage differential, Maxcy (2004) makes the argument that long-term contracts reduce risk for both the player and the team and because of the shared benefit, there is not a compensating wage differential for long term contracts.

Measures such as a salary cap or luxury tax may impact the pay decisions of firms and thus, may also impact performance. Marburger (1997) established a theoretical framework under which he found that under a uniform luxury tax, overall player salaries would decrease. However, the luxury tax in MLB is not uniform and further, the rate differs depending on how many consecutive years a team is in violation since the 2003 season. Dietl et al. (2009) also studied the luxury tax through a theoretical model. The group found that a luxury tax increases the total payroll of the league as well as competitive balance. More specifically, their model resulted in lower payroll teams increasing their payrolls as they hire “star” players that had previously played for larger payroll teams as these players became too expensive for larger teams to hold in the presence of the tax. However, the tax in this model also looked very different from that in place in MLB—all teams that were above the league average faced the tax and the revenue was redistributed to those teams below the average payroll. In empirical work, Kowalewski and Leeds (1999, 2001) found that the NFL’s salary cap increased the reward for performance especially for players that were on the lower end of the pay distribution. Ajilore and Hendrickson (2007) found that MLB’s luxury tax had the effect of making teams more competitive but ultimately, teams with higher payrolls still had the most wins.

There has not been empirical research on the impact of MLB’s luxury tax on performance and pay. The luxury tax in MLB significantly differs from that of Marburger (1997) and Dietl et
al. (2009). Further, while there has been work around the impact of the tax on the league (Ajilore and Hendrickson, 2007), the literature has not addressed how the tax impacts the individual personnel decisions of how much a team pays a player and whether a player chooses to stay at a specific team or leave. Studying the impact of MLB’s luxury tax on the league mandates a consideration of how the tax has impacted the ability of teams to retain talent. While ultimately pay is only one of the means of retaining talent, the literature has shown it to increase performance specifically in baseball (Debrock et al., 2004). This study contributes to the literature by tying together considerations about the relationship between the spread of pay and performance with MLB’s luxury tax and how that has influenced player mobility.

IV. Methods and Model

All firms need to make pay decisions regarding how much to pay each of their workers for the value they provide to the firm. These decisions must be made under budget constraints. The luxury tax imposed on MLB is one such budget constraint. As managers decide on their rosters for a season and the corresponding payroll of that roster, they must consider how close they are to the luxury tax cap, after which they must pay the tax. In MLB, there are two types of managers: General Managers (analogous to the CEO) and Team Managers (who are responsible for on the field strategy and oversight). We do not make a distinction between the two and consider both as managers for the purpose of this paper. The luxury tax may be of larger concern to the managers of certain teams than for others. The amount of concern can be seen as being caused by two effects: the proximity of the tax and the magnitude of the tax. By the proximity of the tax, we mean that for a team whose overall budget is far below the luxury tax cap, the luxury tax will not factor into their decision making as much as teams who have a budget close to the cap. The magnitude of the tax refers to the tax rate—in the fourth period that we consider in our
analysis (refer to Table 1), the tax rate increases with the number of years a team has been in violation.

Our analysis will compare four time periods which each have different luxury tax regulations. These time periods are described in Table 1. These periods were chosen because they capture the two different luxury tax regimes that MLB has enacted as well as two control periods where there was no luxury tax. They also look at a continuous period of time. Arguably the most significant change in MLB was the advent of free agency in 1976 (Villanova, 2016). With free agency, players have more control over what teams they play for—after 6 years of play in the major leagues, players can solicit, negotiate, and sign contracts with any team. This change increases competition for players and in turn, increases the bargaining power of the players. Thus, our earliest period starts well after 1976.

<table>
<thead>
<tr>
<th>Time Period</th>
<th>Description</th>
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<tbody>
<tr>
<td>(1) No Regulation I (1985 to 1996)</td>
<td>MLB had no luxury tax in place.</td>
</tr>
<tr>
<td>(2) 1996 Luxury Tax (1997 to 1999)</td>
<td>The 5 teams with the highest payroll had to pay a 34% tax on every dollar spend above the midpoint of the 5th and 6th highest teams’ payrolls.</td>
</tr>
<tr>
<td>(3) No Regulation II (2000 to 2002)</td>
<td>MLB has no luxury tax in place again.</td>
</tr>
<tr>
<td>(4) 2002 Luxury Tax (2003 to 2015)</td>
<td>A team is taxed on every dollar spent over a certain payroll cap. The rate of the tax depends on the number of times the team has consecutively violated the cap. The tax rate since 2012 has been 17.5% for first time offenders, 30% for second time offenders, 40% for third time offenders, and 50% for fourth time offenders.</td>
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</tbody>
</table>

In this section, we will review the general framework for our model as decomposed in three sections: (i) the number of high performers: an input into salary decisions; (ii) a regression of salary on performance: the link between performance and salary; and, (iii) a regression of retention on salary: salary as a tool to retain top talent. The first section addresses how many top
performers exist in each period. The second, how performance is rewarded through salary. And the third, how salary impacts talent retention. We compare the 4 periods of analysis (Table 1) to understand if the answers depend on the luxury tax regime (or lack thereof). Our model assumes the luxury tax impacts a team’s budget and thus, influences how a team pays players. If a player faces a lower pay than he might otherwise receive without the luxury tax, he may be more likely to try to switch teams under free agency.

i. The Number of High Performers: An Input into Salary Decisions

Given her budget, a manager would optimally pay top performers the highest since these top performers contribute the most to overall team performance. However, a player’s performance only has significance relative to the performance of other players. A player’s negotiating power increases with the scarcity of his skill set or ability. Thus, the fewer players that perform as well or better than a player, the more attractive that player becomes. This analysis raises the question for managers of what the overall talent landscape looks like and specifically, just how many top performers there are in a labor market.

We begin our analysis by considering the distribution of performance for each of the four time periods in Table 1, using random variable \( W_p \), where \( p \in \{1, 2, 3, 4\} \) indicates the time period. \( W_p \) is measured using wins above replacement (WAR), our performance metric. Our WAR data is from the sabermetrics site, Baseball Reference.\(^\text{13}\) WAR measures the marginal contribution of a player and is calculated in two steps: (1) comparing the specific player to the average player; (2) comparing the average to the replacement.\(^\text{14}\) The statistic overall compares a specific player to a replacement player instead of the average player because if a star player


\(^{14}\) For a more detailed description of Baseball Reference’s methodology than provided here, please visit its own methodology description: http://www.baseball-reference.com/about/war_explained.shtml.
leaves a team or gets injured mid-season, a team will not be able to replace said player with one who is average since those players will already be under a contract. Rather, a team will normally need to use what is referred to as a replacement player whose performance is below average and who is normally from the minor leagues. Thus, a more accurate measure of the marginal impact of a player is comparing him to this replacement player.

The most recent version of Baseball Reference’s methodology sets the replacement level at a .294 winning percentage which is a record of 48 wins and 118 losses. The sum of the WAR of all players on a team and the replacement level should be very close to the winning percentage of the team for that season. While a scalar metric may seem simple compared to a vector, WAR is an advanced statistic that considers multiple measures of performance. At a basic level, the statistic is computed based on runs contributed and avoided by each player. The manner that Baseball Reference calculates WAR is tailored towards position players and pitchers.

There are 6 components of WAR for position players: (1) Batting Runs, (2) Baserunning Runs, (3) Runs added or lost due to Grounding in Double Plays, (4) Fielding Runs, (5) Positional Adjustment Runs, and (6) Replacement Level Runs. For the first 5 components, Baseball Reference calculates the number of runs attributed to each of these components that a player has acquired over the course of the season. Afterwards, the runs data is put through a win-loss estimator software, called PythagenPat, which changes runs to wins in a probabilistic manner that relies on interactions between a player and the entire league. Ten runs roughly lead to one win (though not always). The simulator translates runs to wins given the environment of the league for that season. After calculating wins above average (WAA), the statistic is compared to the replacement level. The replacement level, as previously stated, is a winning percentage of .294. This leads to 1,000 wins above replacement for the entire league (the product of 30 teams, 162
games, and the difference between .294 and .500). These wins are divided amongst position players (59%) and pitchers (41%) based on the salary decomposition of the two groups.

The WAR calculation for pitchers fundamentally has two components: runs allowed and innings pitched. The complexity in WAR for pitchers is in calculating what an average pitcher would have done when faced with the same scenario as the specific pitcher for which Baseball Reference is calculating the WAR. Using game logs, the site considers the opposition that the pitchers faces in terms of batter, the quality of defense, and park specific factors among others. The results of this analysis are once again run through the win-loss simulator before being compared to the replacement level as described for position players.

WAR as a statistic for research has a few advantages: primarily, it consolidates a wide range of league and player characteristics into one value. As with any aggregation, some of the detail is lost in the calculation; however, the concision also enables the comparison of players across different positions, strengths, teams, time periods, and situations. Since our paper analyzes the overall distribution of performers to understand the number of top performers in a league, the ability to compare players facilitates this analysis.

We use WAR as a measure of $W_p$ to build the empirical survival function of performance. A survival function measures the probability that a random variable is larger than a given value (refer to Background Information section for more detail). We define our empirical survival function $\hat{y}$ evaluated at dummy variable $x$ for performance (random variable $W_p$) with $n$ observations as follows:

$$\hat{y}(x) = \bar{P}(W_p > x) = \frac{\#\{i: W_{p,i} > x\}}{n}$$


Using \( \hat{y} \), we will analyze the right tail of the distribution. The heavier a tail, the more likely we are to find observations (in this case, players) who are high performers.

The heavy tail distribution we consider is the Pareto distribution, where for a random variable \( X, P(X > x) = Cx^{-a} \) for \( x > 0 \), a constant \( C \), and parameter \( a \). The log of the survival function is \( \log(C) - a \log(x) \).\(^{15}\) By taking the log, the empirical survival function is equal to the log of \( x \) multiplied by a constant\(^{16}\) with a shift factor. Thus, the log-log plot of the empirical survival function and \( x \) would be linear. Further, the slope of this line would approximate \( a \). Such a method was pioneered by Mandelbrot (1963).

In our analysis of the tail of the distribution of \( W \), looking at the Hill estimator and plot can also be helpful to determine whether the data fits a Pareto distribution. For \( X_{(1)} \leq X_{(2)} \leq X_{(3)} \leq \cdots \leq X_{(n)} \) order statistics,\(^{17}\) \( a \) can be approximated using linear regression. Specifically, the slope of the line between the points \( \left( \log \left( \frac{i}{n} \right), \log(X_{(n-i+1)}) \right) \) for \( 1 \leq i \leq r \) approximates \(-1/a\). Kratz and Resnick (1996) and Schultze and Steinebach (1996) both developed this strategy independently. The Hill estimator is a popular estimator for the tail of a distribution, below it is defined with our random variable for performance, \( W_p \):

\[ H(r) = \frac{1}{r} \sum_{i=1}^{r} \left( \ln(W_{p,(n-i+1)}) - \ln(W_{p,(n-r+1)}) \right) \]

The Hill estimator was derived by Hill (1975) as the conditional maximum likelihood estimator of \( a \) based on the \( r \) largest order statistics. A Hill plot shows this estimator as a function of the order statistic and should stabilize for data with an underlying Pareto distribution.

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\(^{15}\) Unless otherwise noted, “log” refers to the natural log.

\(^{16}\) This constant will be \( \alpha \).

\(^{17}\) How ties are broken is arbitrary.
Whether a dataset fits a light tailed distribution can also be analyzed using log-log and semi-log plots. If random variable \( X \) is normally distributed with mean \( \mu \) and standard deviation \( \sigma \), the density of \( X \) is \( \exp\left(-\frac{(x - \mu)^2}{2\sigma^2}\right) / \sqrt{2\sigma^2 \pi} \). Without loss of generality, we can assume the mean is 0 and variance is 1. The survival function evaluated at \( x \) will be the integral of this density from \( x \) to infinity: \( \int_x^\infty \exp\left(-\frac{s^2}{2}\right) / \sqrt{2\pi} \, ds \). We multiply the integrand by \( s/x \) (which is greater than or equal to 1 for \( s \geq x \)), to result in \( \int_x^\infty \exp\left(-\frac{s^2}{2}\right) / \sqrt{2\pi} \, ds \leq \int_x^\infty s \times \frac{\exp\left(-\frac{s^2}{2}\right)}{x \sqrt{2\pi}} \, ds = C \exp\left(-\frac{(x)^2}{2}\right) \) where \( C \) is a constant. From taking the log of both sides, the plot of the log of the survival function against \( x^2 \) should be linear if \( X \) is normally distributed. This type of analysis can be applied to \( W \): the log of the empirical survival function for \( W \) evaluated at dummy variable \( x \) against \( x^2 \) should be linear if \( W \) is normally distributed.

If instead a random variable \( X \) is exponentially distributed with parameter \( \lambda \), the survival function of \( X \) is \( \exp(-\lambda x) \). The log of the survival function is equal to \( x \) times a constant equal to the parameter \( \lambda \). The semi-log plot of the survival function and \( x \) will be linear.

From this analysis, we produce a measure of how many top performers there are in the league in each of the four time periods we study—for the purpose of our work, we define a top performer as anyone’s who WAR is two standard deviations above the mean of the overall dataset. This measure will be integrated in our following two models.

**ii. A Regression of Salary on Performance: The Link between Performance and Salary**

Determining the exact relationship between performance and compensation can be challenging. Pay can be both a tool to retain top performers and can cause employees to improve performance (Lazear, 1991). Thus, rather than trying to untangle the interdependencies of this relationship, our paper focuses on the correlation of performance and compensation. Under
elementary supply-demand theory, the scarcity or abundance of top performers impacts the salary of those top performers. Thus, the relative scarcity of a player’s ability is an input into a manager’s decision on salary. Equation 3 displays our model to examine the relationship between performance distribution and salary.

Equation 3

\[
\log(S_{i,t}) = \beta_0 + W_{i,t-1}^2 \beta_1 + W_{i,t-1} \beta_2 + Star_{i,t-1} \beta_3 + Team_{i,t} \beta_4 + Exper_{i,t} \beta_5 + Y_{i,t-1} \beta_6 + (T_t - Y_{i,t-1}) \times \tilde{R}_t \beta_7 + \tilde{R}_t \beta_8 + Team_{i,t} \tilde{\beta}_9 + Birth_{i} \tilde{\beta}_{10}
\]

The subscripts \(i\) and \(t\) denote player and year respectively. Thus, \(\log(S_{i,t})\) is the natural log of the pay for a specific player \(i\) in year \(t\). Salary data comes predominately from the Lahman database, supplemented by Baseball Reference.\(^{18}\) As mentioned earlier, \(W\) is our metric of performance, as measured by WAR. Salary decisions are made before observing a worker’s real performance (Lazear and Oyer, 2009). Decision makers must rely on observable features when deciding a player’s salary—the most salient feature being previous performance and thus, we include the WAR of the previous season. We also include the square of the WAR from the previous season to allow the relationship between salary and WAR to depend on the level of WAR. Salary decisions also rely on the scarcity of top performers, for this reason we also include a binary variable which has the value 1 if we characterize the players as a top performer (\(Star_{i,t-1}\)).

Any one salary decision is made in the broader context of the entire payroll of a division, department, or work group. To incorporate a measure of team budget, we include the opening day payroll of the player’s team (\(Y_{i,t-1}\)) in the previous year—however, opening team payroll is just a proxy for the team’s payroll budget.\(^{19}\) Another team level impact is the luxury tax (if it is


\(^{19}\) For the 1984 to 1997 seasons, we use Baseball Chronology ([http://www.baseballchronology.com/Baseball/](http://www.baseballchronology.com/Baseball/)) and for the 1998 to 2015 seasons, we use Steve the Ump’s dataset ([http://www.stevetheump.com/Payrolls.htm](http://www.stevetheump.com/Payrolls.htm)).
in effect in the given time period)—\( \vec{R}_t \) is a vector that indicates in which time period the season is (refer to Table 1). The luxury tax is of larger concern to teams whose budgets approach the cap. Thus, in the periods with a luxury tax, we include the difference between the team’s previous payroll and the salary cap \( (T_t) \) to understand the sensitivity to the cap. For the 1997 to 1999 seasons, we take the 5\(^{th} \) highest payroll from the previous season as a proxy for the cap since this cap depends on being one of the five teams with the highest payroll.

As we indicated in our literature review, Glenn, et al. (2001) found that team specific knowledge impacted the value of a player to a specific team. To control for this effect, we include the variable \( Teamexp_{i,t} \) which is the number of years that a player has played with their current team (whether or not they were consecutive seasons) before season \( t \). In baseball, like many other industries, players sign multi-year contracts. A manager may already have a good amount of her team’s payroll set long before that season. Contracts limit player mobility in two main ways: (1) MLB only allows players to become free agents after 6 years of major league service and (2) players can negotiate no-trade clauses into their contract which prevents them from being traded to another team without their consent. Pedace and Hall (2012) showed that there is a salary tradeoff for players seeking the risk neutralizing no-trade clause, particularly in the case of long term contracts. However, because of the challenge in collecting data for which players are under contracts and which contracts contain no-trade clauses for all years in our dataset, we cannot include this factor in our analysis. Long term contracts are the exception rather than the rule—in Pedace and Hall’s (2012) research, the average contract length was 1.8 years in their dataset of 382 free agents. However, this is still a limitation to our work. Blass (1992) found that salary in baseball increases with number of years, independent of an increase in performance. To control for this type of effect, we also include a player’s number of years
since a player’s debut year, \((E_{x\text{peri},t})\)—important to note, how we calculate this variable does not take into account if a player takes a season off (for example, to serve in the military).

We also realize that certain teams have specific team characteristics that might impact how they compensate their players. Since we cannot capture every characteristic of every team in a finite number of variables, we include a binary variable for each team to control for team fixed effects \((\text{Team}_{i,t})\).\(^{20}\) We also include fixed effects for country of birth \((\text{Birth}_i)\). One reason to include these fixed effects is that only U.S. and Canadian residents can enter the MLB draft—thus, the scouting procedure and the resulting contracts can be different for other countries.\(^{21}\)

While birth country is only a rough proxy for residency when drafted, country of birth also accounts for any type of institutional or cultural discrimination that players from a specific country might experience.

\[\text{iii. A Regression of Retention on Salary: Salary as a Tool to Retain Top Talent}\]

Salary is also a means by which firms retain workers. A worker who feels undercompensated and undervalued by his or her firm has higher incentive to look for work elsewhere. As previously mentioned, this effect is impacted by MLB’s regulation on free agency by requiring that a player has at least six years of experience in the major leagues before being able to negotiate his own contract and controls for which team he plays. While six years are required before being declared a free agent, teams may extend a contract beyond those six years at any point if the player agrees. Thus, not every player becomes a free agent after the same amount of

\[\]

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\(^{20}\) We use our judgement to discern what type of team changes constitute a new team fixed effect. The Tampa Blue Rays changed their name from the Tampa Blue Devil Rays to Tampa Blue Rays—we consider this as still one team. Similarly, when the Florida Marlins changed their name to the Miami Marlins they moved from one part of Miami to another, however we still include them as one team in the team fixed effects. In contrast, the Montreal Expos where moved and changed to the Washington Nationals in 2004. Since this change was a major relocation, we include two team fixed effects—one for the Montreal Expos and another for the Washington Nationals.

time. Whether a free agent remains on a team from one year to the next can be broken into two decisions: (1) the player’s decision to stay on a specific team and (2) the team’s decision to retain that player. We are predominately interested in this first decision. In order to analyze this decision, we look at the decisions of all free agents between seasons from 1985 to 2015 (including between the 2015 and 2016 seasons). We get the data on free agents as well as which teams they leave and join from Baseball Reference.\(^{22}\) Free agency is not a perfect assessment of turnover decisions since, as previously mentioned, a player’s contract can be extended before it expires. If a player is intending to stay at their current team, they may choose to exercise the ability to extend their contract rather than go up for free agency. In our dataset, 77% of free agents decide to change teams—this is most likely over representing turnover. Below is our model of retention decisions under which the dependent variable takes on the value 1 if a player moves from one team to another between seasons:

\[
P(\text{Team}_{i,t} \neq \text{Team}_{i,t-1}) = \Phi(\beta_0 + S_{i,t-1}\beta_1 + \frac{S_{i,t-1} - \mu_{St-1}}{\sigma_{S,\text{Team}_{t-1}}} \beta_2 + \ln(\sigma_{S,\text{Team}_{t-1}})\beta_3 + W_{i,t-1}\beta_4 \\
+ \bar{W}_{\text{ins}_{\text{Team}_{t-1}}}\beta_5 + \bar{M}_{\text{gmt}_{\text{Team}_{t-1}}}\beta_6 + W_{i,t-1}\times \bar{M}_{\text{gmt}_{\text{Team}_{t-1}}}\beta_7 + \bar{R}_t\beta_8 \\
+ \bar{\text{Team}_{i,t-1}}\beta_9 + \bar{\text{Team}_{i,t}}\beta_10)
\]

This model develops the model introduced in Pedace and Smith (2013) to include WAR as a measure of performance (instead of a vector of performance characteristics). In contrast to Pedace and Smith’s (2013) model, we use a probit model instead of a linear probability model because the range of a probit model better fits the 0 to 1 range of a probability. \(\Phi\) is the inverse

normal cumulative distribution function. To reflect the literature which claims that pay dispersion decreases player morale (Bloom, 1999; Debrock et al., 2004; Bruenig et al., 2014; Tao et al., 2016), our model includes the natural log of the standard deviation of the teams’ payroll ($\sigma_P$). Since a player who is at the bottom of the pay dispersion on their team will be more disgruntled than a player who is one of the highest paid players, our model also includes the z-score of a player’s position in the team’s salary dispersion: $\frac{S_{i,t-1} - \bar{S}_{t-1}}{\sigma_{S,Team,t-1}}$. Since we use the z-score as a measure of how many standard deviations a player’s salary is from the team’s mean salary, we make no assumption of the distribution of salary beyond a finite standard deviation. Our model also includes the salary of the player in the previous season as well as the player’s WAR.

If a team has had a strong season, a player is more likely to remain with that team to continue playing on a strong team. The model includes a vector ($\overline{Wins}_{Team,t-1}$) that contains the team’s record from the previous season in three values: the team’s win percentage, a binary variable that is 1 if the team made the playoffs, and another binary variable that is 1 if the team won the World Series. The data for this vector was contained within the Lahman database.

$Mgmt_{Team,t-1}$ is a vector that contains two binary variables—one which takes the value of 1 if there was a mid-season change in management in the previous season and another which takes the value of 1 if there was a management change between seasons. We include both midseason and between season management changes separately since a midseason management change might indicate poor management previously while a between season change might be more routine. These binaries depict changes in both General Managers and Team Managers. $Mgmt_{Team,t-1}$ is interacted with a player’s WAR since new management will be more inclined to remove lower performers from the roster. All data on management changes comes from
As in our previous model, we include two vectors to control for team fixed effects from the team which a player leaves and joins as well as a vector ($\tilde{R}_t$) to control for the impact of the different luxury tax regulations and time fixed effects (refer to Table 1).

V. Results

In this section, we first discuss the data used in our research and then the results of each of the three statistical models that we are testing: (i) the number of high performers: an input into salary decisions; (ii) a regression of salary on performance: the link between performance and salary; and, (iii) a regression of retention on salary: salary as a tool to retain top talent.

i. Data

Our analysis primarily uses wins above replacement (WAR) as a measurement of performance and salary data for MLB players from 1985 to 2015. WAR data comes from Baseball Reference, a sabermetrics site. Additional information on the calculation of WAR is provided in our Methods and Model section. The use of statistics in sports, and specifically baseball has proliferated in the last two decades (Barnwell 2014; London 2014). In sabermetrics, WAR has become one of the most widely used metrics—DuPaul (2012) found that the WAR computed by Baseball Reference very closely predicted winning percentage (with an $R^2$ of .83 and coefficients very close to the theoretical values). However, as DuPaul (2012) notes, there are skeptics of WAR because of how much the defensive metrics tend to vary from year to year for most players. While using single-season WAR has its limitations, we believe it is superior to using a vector of values because of its power in being able to compare players’ marginal contributions across seasons, eras, and teams. There has been attempts to make WAR metrics for

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other sports such as football; however, they face the difficulty of finding the independent
performance of a player in sports that are much more interdependent than baseball (Hughes et al
2015). Both Newman et al. (2015) and Barnes and Bjarandóttir (2016) use WAR as a proxy for
performance.

Salary data primarily comes from the Lahman database, supplemented by the salary data
on Baseball Reference when the Lahman database did not have salary data for a specific player.\textsuperscript{18}
All salaries are measured in 2015 dollars using the annual average of the CPI-U from the Bureau
of Labor Statistics.\textsuperscript{24} Salary data was available for fewer players than WAR. For this reason, the
dataset was restricted to include only those players for whom both WAR and salary data was
available. Table 2 displays summary statistics for WAR under the unrestricted data set, which
includes all WAR data available on Baseball Reference, and the restricted data set, which is
limited to those observations with salary data.

\textsuperscript{24} The use of the CPI-U instead of the CPI was chosen because baseball teams are exclusively in urban cities and
thus, CPI-U represents the price changes most relevant to baseball players. CPI FRED Dataset:
Table 2. Summary Statistics for WAR under the Restricted and Unrestricted Data Sets and the 4 Time Periods

<table>
<thead>
<tr>
<th></th>
<th>Restricted Data Set</th>
<th>Unrestricted Data Set</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1985 to 2015</strong></td>
<td>µ = 0.9819</td>
<td>µ = 0.7256</td>
</tr>
<tr>
<td></td>
<td>σ = 1.7396</td>
<td>σ = 1.5640</td>
</tr>
<tr>
<td></td>
<td>n = 22,731</td>
<td>n = 31,876</td>
</tr>
<tr>
<td></td>
<td>min = -3.27 max = 13.25</td>
<td>min = -3.27 max = 13.25</td>
</tr>
<tr>
<td><strong>No Regulation I (1985 to 1996)</strong></td>
<td>µ = 1.0245</td>
<td>µ = 0.7792</td>
</tr>
<tr>
<td></td>
<td>σ = 1.7496</td>
<td>σ = 1.6179</td>
</tr>
<tr>
<td></td>
<td>n = 7,979</td>
<td>n = 10,440</td>
</tr>
<tr>
<td></td>
<td>min = -3.07 max = 13.25</td>
<td>min = -3.07 max = 13.25</td>
</tr>
<tr>
<td><strong>1996 Luxury Tax (1997 to 1999)</strong></td>
<td>µ = 0.9154</td>
<td>µ = 0.7349</td>
</tr>
<tr>
<td></td>
<td>σ = 1.7419</td>
<td>σ = 1.6247</td>
</tr>
<tr>
<td></td>
<td>n = 2,605</td>
<td>n = 3,195</td>
</tr>
<tr>
<td></td>
<td>min = -3.27 max = 12.15</td>
<td>min = -3.27 max = 12.15</td>
</tr>
<tr>
<td><strong>No Regulation II (2000 to 2002)</strong></td>
<td>µ = 0.9963</td>
<td>µ = .7196</td>
</tr>
<tr>
<td></td>
<td>σ = 1.7903</td>
<td>σ = 1.5833</td>
</tr>
<tr>
<td></td>
<td>n = 2,302</td>
<td>n = 3,353</td>
</tr>
<tr>
<td></td>
<td>min = -2.75 max = 11.85</td>
<td>min = -2.75 max = 11.85</td>
</tr>
<tr>
<td><strong>2002 Luxury Tax (2003 to 2015)</strong></td>
<td>µ = 0.9615</td>
<td>µ = .6873</td>
</tr>
<tr>
<td></td>
<td>σ = 1.7180</td>
<td>σ = 1.5059</td>
</tr>
<tr>
<td></td>
<td>n = 9,845</td>
<td>n = 14,888</td>
</tr>
<tr>
<td></td>
<td>min = -2.93 max = 10.62</td>
<td>min = -2.93 max = 10.62</td>
</tr>
</tbody>
</table>

Note: Restricted refers players for which both WAR and salary data was available. Unrestricted is all players for which WAR was available.

Table 3. Magnitude of the Difference in Means and Variance for Between the Restricted and Unrestricted Dataset of WAR

<table>
<thead>
<tr>
<th></th>
<th>Difference in Means</th>
<th>Difference in Variances</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1985 to 2015</strong></td>
<td>.2563</td>
<td>.1756</td>
</tr>
<tr>
<td>(1) No Regulation I (1985 to 1996)</td>
<td>.2453</td>
<td>.1317</td>
</tr>
<tr>
<td>(2) 1996 Luxury Tax (1997 to 1999)</td>
<td>.1805</td>
<td>.1172</td>
</tr>
<tr>
<td>(3) No Regulation II (2000 to 2002)</td>
<td>.2767</td>
<td>.2070</td>
</tr>
<tr>
<td>(4) 2002 Luxury Tax (2003 to 2015)</td>
<td>.2742</td>
<td>.2121</td>
</tr>
</tbody>
</table>

Note: Difference is calculated as the value of the unrestricted dataset requested from the restricted dataset.

As evident in Table 2 and 3, excluding the players that do not have salary data skews the summary statistics of our sample to the right. Players with lower WARs are systematically more likely to not have salaries reported in our dataset. To understand this impact more, we ran statistical inference tests that tested for the difference of means and the difference of variances.
To test for the difference of means, we used the nonparametric Wilcoxon Rank Sum Test under the null that the mean of the WAR for players with salary data was the same as those without (Wilcoxon, 1945). To test for the difference of variances, we used the nonparametric Levene’s Test defined with the median\(^{25}\) under the null that the variance of WAR for players with salary data was the same as those without (Levene, 1960). Each test was conducted for each of the four periods. The results of these tests are in Table 4—all the tests showed a significant difference between the means and variances of the two samples at the 1% significance level. Thus, salary information is not randomly missing. There is a bias in which players have missing salary data towards those with low WARs. While we cannot control for which salary data is reported or not, this effect may impact our results.

<table>
<thead>
<tr>
<th>Time Period</th>
<th>Wilcoxon Rank Sum Test for Difference of Means (W)</th>
<th>p-value</th>
<th>Levene’s Test Statistic for Difference of Variance (L)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) No Regulation I (1985 to 1996)</td>
<td>30.472</td>
<td>0.0000</td>
<td>1,579.65</td>
<td>0.0000</td>
</tr>
<tr>
<td>(2) 1996 Luxury Tax (1997 to 1999)</td>
<td>14.568</td>
<td>0.0000</td>
<td>458.64</td>
<td>0.0000</td>
</tr>
<tr>
<td>(3) No Regulation II (2000 to 2002)</td>
<td>14.473</td>
<td>0.0000</td>
<td>512.53</td>
<td>0.0000</td>
</tr>
<tr>
<td>(4) 2002 Luxury Tax (2003 to 2015)</td>
<td>28.095</td>
<td>0.0000</td>
<td>2,459.89</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

Figure 4 depicts the summary statistics of our two main variables of interest: salary and WAR for the four time periods in question. While the summary statistics of WAR do not change much over the four time periods, there is a clear trend in salary in which average salary, as well as the overall dispersion of salary, increases.

\(^{25}\) Our conclusions do not change if we had used the Levene’s test defined by the mean or trimmed mean.
In our third model, we look specifically at players who go up for free agency after the seasons of 1985 to 2015. We get the data for players who are up for free agency from Baseball Reference. We link this dataset to our data on WAR and salary in order to analyze how salary decisions on the part of the previous team influences a player’s turnover decision which results in 3,830 observations. As mentioned previously, our dataset most likely over represents turnover decisions because of players’ and teams’ ability to extend contracts.

ii. The Results of the Number of High Performers: An Input into Salary Decisions

We defined the empirical survival function of $W$ (our random variable for performance as measured by WAR) in our model section. On their own, the empirical survival functions are not very enlightening in regards to the underlying distribution. To understand the underlying distribution for performance, we consider the log-log and semi-log plots of the survival function.

Figure 5 shows the log-log plots for our dataset. These would be linear if the underlying distribution was Pareto distributed but these plots are not linear. Figure 6 shows the Hill plot for each of the four periods. A Hill plot shows the Hill estimator (Hill, 1975) for the inverse of the
parameter of a power law distribution which is a function of the order statistic. For data with an underlying power law distribution, the Hill plot should stabilize around the value of the estimate. As evident in Figure 6, the Hill plot does not stabilize and instead produces Hill “Horror” plots of an estimator gone awry (Resnick, 2007). These plots provide further evidence that \( W \) does not have a power law distribution. This finding is contrary to previous literature of a broad variety of industries (Rosen, 1981; Mizuno et al., 2012; O’Boyle and Aguinis, 2012; Aguinis and O’Boyle, 2014; Aguinis et al, 2016).

Figure 5. Log-log plots of the empirical survival function of \( W \) evaluated at dummy variable \( x \) against \( x \) to test for the power law distribution.
Figure 6. Hill plots to estimate the parameter of a power law distribution

Period 1

Period 2

Period 3

Period 4
After having evidence that $W$ is not heavy tailed, we turn to non-heavy tailed distributions. Figure 7 shows the semi-log plots of the log of the empirical survival function for $W$ evaluated at dummy variable $x$ against $x^2$—this plot should be linear if $W$ is normally distributed. Figure 8 shows the empirical survival function of $W$ evaluated at $x$ plotted against $x$. These plots should be linear if the underlying distribution is exponential. The strong linearity of Figure 8 shows strong evidence that $W$ is exponentially distributed despite the slight linearity in part of Figure 7.

Figure 7. Semi-log plots of the log of the empirical survival function for $W$ evaluated at dummy variable $x$ against $x^2$ to test for normality
Some might ask about the noise in the right tails of Figure 8. Because of a low probability of drawing from the right tail of an exponential distribution, a small number of observations can cause a deviation from linearity. For example, Figure 9 shows a semi-log plot for a random sample from an exponential distribution with parameter 1. In contrast, Figure 10 shows a semi-log plot for a random sample from a normal distribution with mean 0 and standard deviation 1. Even when the sample is from a true exponential distribution, there can be random variation.
Once we have narrowed down the underlying distribution of our data, we can compute the maximum likelihood estimator (MLE) for the parameter of an exponential distribution for each of the four periods. For a random variable $X$ distributed exponentially with parameter $\lambda$ and
a random sample, the MLE is \( \hat{\lambda} = 1/\bar{x} \) where \( \bar{x} \) is the sample average of the random sample.\(^{26}\)

Table 5 shows the MLE estimator of \( \lambda \). Objectively, the periods with a luxury tax have a larger parameter than those without.

<table>
<thead>
<tr>
<th>Period</th>
<th>Parameter Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Periods (1985 to 2015)</td>
<td>( \hat{\lambda} = 1.0184 )</td>
</tr>
<tr>
<td>(1) No Regulation I (1985 to 1996)</td>
<td>( \hat{\lambda} = 0.9760 )</td>
</tr>
<tr>
<td>(2) 1996 Luxury Tax (1997 to 1999)</td>
<td>( \hat{\lambda} = 1.0923 )</td>
</tr>
<tr>
<td>(3) No Regulation II (2000 to 2002)</td>
<td>( \hat{\lambda} = 1.0036 )</td>
</tr>
<tr>
<td>(4) 2002 Luxury Tax (2003 to 2015)</td>
<td>( \hat{\lambda} = 1.03625 )</td>
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</tbody>
</table>

To understand the impact of the luxury tax on the distribution of performance, we can consider the individual distributions for each of the four periods. We use the Wilcoxon Rank Sum statistic (Wilcoxon, 1945) to test for whether the periods with the two different luxury taxes are significantly different from those without any luxury tax or if the difference in the parameter estimate occurred by chance. Table 6 shows the Wilcoxon Rank Sum statistic for the two periods without a luxury tax and for each of the periods with a luxury tax compared to the periods without. The null hypothesis is that the distribution of the two groups is the same.

<table>
<thead>
<tr>
<th>Periods for Comparison</th>
<th>Wilcoxon Rank Sum Statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) No Regulation I (1985 to 1996) against (3) No Regulation II (2000 to 2002)</td>
<td>1.353</td>
<td>.1761</td>
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<tr>
<td>( n_1 = 7,979; n_2 = 2,302 )</td>
<td></td>
<td></td>
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<tr>
<td>(1) No Regulation I (1985 to 1996) and (3) No Regulation II (2000 to 2002) against (2) 1996 Luxury Tax (1997 to 1999)</td>
<td>3.096</td>
<td>.0020</td>
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<td>( n_1 = 10,605; n_2 = 2,698 )</td>
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<tr>
<td>(1) No Regulation I (1985 to 1996) and (3) No Regulation II (2000 to 2002) against (4) 2002 Luxury Tax (2003 to 2015)</td>
<td>2.441</td>
<td>.0146</td>
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<td>( n_1 = 10,605; n_2 = 10,162 )</td>
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</tbody>
</table>

\(^{26}\) The sample average is the sum of the data points divided by the number of data points.
We cannot reject the null that the data for the two periods without a luxury tax come from the same distribution. Assuming that they both come from the same distribution, we continue to compare both period 2 and period 4 to this combined data of the two periods without a luxury tax. The test statistic rejects the null that they come from the same distribution for both period 2 (at the 1% level) and period 4 (at the 5% level). These results suggest that the distribution of performance under either of the luxury tax regimes is different at a statistically significant level from that under no luxury tax.

We define top performers to be those who have WAR more than two standard deviations from the mean of the overall dataset. The mean of our overall dataset is .9819 and using the overall MLE estimator, the standard deviation is also .9819 which means that any player with a WAR strictly above 2.94 is designated as a top performer. We use the MLE estimator to get the standard deviation because the estimator is based on the sample mean which is a more stable estimate than the standard deviation. To get a general idea of magnitude and possible economic significance, the probability of being a top performer in period 1 is 5.67% (assuming the MLE parameter estimated in Table 6). Comparably, the chance of a random player being above that same WAR in period 2 is 4.02% and in period 4, 4.75% (also assuming the MLE parameter). Assuming a binomial distribution and 30 MLB teams each with a roster of 25 players, these findings result in an average of 43 top performers per season in period 1, 30 top performers in period 2, and 36 top performers in period 4. The periods with a luxury tax had on average 7 to 13 fewer high performers (assuming equivalent number of teams).\textsuperscript{27}

In comparison to a Pareto distribution, the light tail of an exponential means that the farther one gets from the mean and into the tail, the less likely to find observations. So, a top

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\textsuperscript{27} Teams were added in the period we are analyzing; however, for comparison purposes, we assume the number of teams in MLB at the end of our period—thirty teams.
performer is on average less common when the underlying distribution is exponential than when the distribution is Pareto. Using basic supply and demand theory, the decreased supply of top performers should make them more scarce and thus, able to demand a wage premium in the labor market. The larger the parameter for an exponential (as we found for the two periods with a luxury tax), the less likely it is to find observations in the tail and the scarcer these top performers become.

Another question raised by these results is why top performers are less common in years with the luxury tax. Traditional wage theory suggests that pay is set at the marginal value of a worker to the company or at a market rate below that marginal value and does not consider the impact of wage on worker performance. Another theory is that of efficiency wages which indicates that under certain conditions, an increase in wages increases productivity because the increase in wages increases motivation (Yellen, 1995; Akerlof, 1984; Stiglitz, 1976). In this situation, we might be seeing the effect of the opposite—the luxury tax may be decreasing the salaries of high performers and thus, these players similarly decrease their effort. This type of mechanism may be triggered because the luxury tax impacts the entire labor market—in the traditional model, if a worker is dissatisfied with wages, she would switch to another firm. However, in the situation of the luxury tax, all the teams may be impacted (or all the teams that can pay large salaries). To explore this relationship more, in our next section of results, we will look at how performance is translated into salary in each of the four periods we are considering.

**ii. The Results of a Regression of Salary on Performance: The Link between Performance and Salary**

Using the definition of a top performer from the previous section, we ran the regression in Equation 3. The results are displayed in Table 7. Model 5 and Model 6, which include fixed
effects for year, period, team, and country of birth, both explain 58% of variation in the natural log of salary—the difference between these two models are their functional form. Model 6 includes a squared term for the lag of WAR. We do not interpret the impact of a change in WAR under Model 6 because of the lack of significance of the WAR squared coefficient. While the addition of the square term changes the coefficient value of the Star binary, the values for the other control variables do not significantly change.

In our linear model (model 5), a 1 unit increase in WAR in one season leads to a 21.4% increase in salary in the next. While this increase in WAR is by no means small, it is an attainable increase in performance for a player from one season to the next. This shorthand calculation assumes that the change in WAR does not place the player over the 2.94 cut off by which we define a superstar—for a player whose WAR is above 2.94, his salary is boosted by 15.0% to 16.0% (depending on whether using model 5 or model 6, respectively). The high statistical significance as well as economic significance of this coefficient indicates that a player does get an additional benefit from being a rare, high performing player.

In Model 7, we added an interaction term between the lag of WAR and period of regulation. The interactions terms for both period 2 and period 3 are statistically insignificant while the interaction term for period 4 is statistically significant and negative. Thus, per our model the change in salary is 2.1% lower in period 4 than in period 1 for a one unit increase in WAR. These results indicate that when controlling for all the other factors in our model, high performance was less rewarded since the 2002 luxury tax. This finding supports our rationale in the preceding sub-section that efficiency wages could be a mechanism by which the luxury tax is impacting performance. Since 2002, players are less financially rewarded for an increase in
performance and thus, they are less motivated to perform highly. This decrease in motivation is reflected in the lower percentage of top performers in period 4.

Our results also indicate a relationship between tax regime and overall team payroll. Team payroll is only significant in our models until we add in team fixed effects indicating that the same teams consistently have higher payroll budgets. Our model also indicates that under period 2 (the 1996 luxury tax), teams were more responsive to their total payroll proximity to the tax taking effect than in period 4. For example, using Model 5,\textsuperscript{28} being $10 million closer to when the tax might take effect in period 2 led to a 2.7\% decrease in salary while in period 4, that same increase in payroll lead to a .75\% decrease in salary.\textsuperscript{29} This result may reflect the structure of the two different tax regimes—because of the uncertainty in when the tax goes into effect under the 1996 luxury tax, teams may be a little more conservative with their payroll. The 1996 luxury tax also did not have a progressive tax scheme depending on the numbers of years in violation. Thus, the tax penalty faced was higher in the first year of violation under the 1996 luxury tax than under the 2002 luxury tax.

While not the focus of this paper, our results also confirm the importance of team specific knowledge and major league playing experience. Like Glenn, et al.’s (2001) conclusions which reinforce the importance of team specific knowledge, our models find a 6.3\% to 7.1\% increase in salary for each additional year with the same team. Our model predicts a 14.7\% to 14.9\% increase in salary per year of major league playing experience which is similar to the findings of Blass (1992) which found that salary and years of experience are positively correlated.

\textsuperscript{28} The general magnitude of these results does not change in Model 5-7. \textsuperscript{29} One of the main attributes of the 1996 luxury tax is that teams face uncertainty of when the tax will take effect because only the five teams with the highest payroll face the tax.
Table 7. Regression Results for Model 2: Natural Log of Salary against lag of WAR

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<td>0.217***</td>
<td>0.217***</td>
<td>0.216***</td>
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<td>0.148***</td>
<td>0.147***</td>
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<td>Team Payroll (in millions)</td>
<td>0.00386***</td>
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<td>(Per. 2)</td>
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<td>R-squared</td>
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</table>

Robust standard errors in parentheses. All variables are lag variables (besides salary, the dependent variable).

*** p<0.01, ** p<0.05, * p<0.1
iv. The Results of a Regression of Retention on Salary: Salary as a Tool to Retain Top Talent

In our third model, we want to understand how the luxury tax might be impacting turnover decisions of players and thus, talent retention. The results of our regression from Equation 4 are displayed in Table 8. The probit estimates for the coefficients for salary are not consistent across our different models nor are they statistically significant in Model 4 and 5, the two models which we include both time and team fixed effects. Our results similarly do not support the statistical significance of the natural log of the standard deviation of team salary. The z-score did prove to be statistically significant in our model. The coefficient’s positive sign indicates that individuals who were higher in the salary dispersion of a team were more likely to change teams when they went up for free agency. This result most likely reflects the tendency of teams to extend top performers’ contracts if they want to retain them (and if the top performer similarly wants to remain with his team)—if a top performer becomes a free agent, other teams might try to negotiate an attractive enough salary to have him leave his previous team.
<table>
<thead>
<tr>
<th>VARIABLES</th>
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<th>(2)</th>
<th>(3)</th>
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<tbody>
<tr>
<td>Salary (in millions)</td>
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Robust standard errors in parentheses. All variables are of season leading up to free agency.

*** p<0.01, ** p<0.05, * p<0.1
Model 5 included interaction variables of the z-score of a player with the period of luxury tax regulation. While for period 3 and 4 the coefficients on these interactions were not statistically significant, the coefficient for period 2 was statistically significant and indicates that players in period 2 were more likely to leave their previous team if they went up for free agency than in the other periods. When analyzing this finding in the context of our previous results, it seems challenging to understand how the higher turnover in period 2 might combine with our findings in subsection ii that periods with the luxury tax had less top performers. One potential explanation is that in period 2 teams may have reacted to the luxury tax by not extending the contract of high earning players. Therefore, these players went on to obtain free agency and switch teams. These high earning players, who presumably also had a high amount of talent, were less motivated to perform highly in order to ensure team retention. This mechanism is unlike the one by which teams rewarded high performers less as we found in period 4 in our previous subsection.

While this result does not address a team’s ability to retain top talent, it does address if a team would want to retain top talent. The immediate answer to this question might seem obviously positive but our results indicate that teams in period 2 may have seen the marginal value of retaining top talent as less than the salaries these teams could negotiate with that talent. However, why might this behavior have been different in period 2 (1996 luxury tax) than in period 4 (2002 luxury tax)? As we have mentioned previously, the largest difference between the two luxury taxes is the fixed cap under the 2002 regime. After this fixed cap, teams pay the penalty compared to the stochastic cap under the 1996 regime under which only the 5 teams with the highest payroll had to pay the penalty. Our previous subsection suggested that teams are more responsive to being close to where the tax might take effect in period 2. These results
suggest that under the 1996 luxury tax, teams navigated the uncertainty of the cap by shying away from high earning players and allowing those players to enter free agency and leave their team. In contrast, teams may have been able to more intentionally plan their payrolls since 2003 to make sure they did not incur the penalty or only incurred the penalty to the level with which they were comfortable. In this period, teams would have controlled their total payroll and the level of the tax that they pay by adjusting salary level (as indicated in our previous subsection).

VI. Discussion & Conclusion

In this paper, we analyzed the impact of luxury tax on talent retention of top performers. To answer our question of how talent retention has varied from periods with and without a luxury tax in place, we quantified the probability of being a top performer in each period using distribution analysis and we analyzed two regression models of how players were rewarded using salary and of players’ turnover and retention decisions. In our analysis, data was our largest limitation. Our information on salary restricted our dataset and skewed our WAR data. Because the omission tended to be at lower WAR values, we might have overestimated the probability of high performers and the omission also may have impacted our regressions; however, because the bias was the same in each period, it should not have impacted the statistical tests of the difference between periods. The difficulty in collecting data on contract specifics such as extensions, no-trade clauses, and contract length also limited the impact of our results. The turnover data for our third model was also a limitation—because of the nature of baseball contracts, our analysis of free agents did not capture many of the retention decisions as teams and players extended contracts instead of becoming free agents. Future research could try to collect data on when players extend contracts and for how long as a component of analyzing talent retention.
The literature widely concludes that the distribution of performance is heavy-tailed (Rosen, 1981; Mizuno et al., 2012; O’Boyle and Aguinis, 2012; Aguinis and O’Boyle, 2014; Aguinis et al, 2016). Our findings contradict this literature and find a light tailed distribution for individual performance in MLB. O’Boyle and Aguinis (2012) also considered professional athletes and MLB in their analysis. For MLB, they considered career strike outs and career home runs as performance metrics and O’Boyle and Aguinis demonstrated that a Pareto distribution better fits the data than a normal. O’Boyle and Aguinis did not consider an exponential distribution and thus, leaving out this comparison may have impacted their results. There also may be a difference between performance as measured by individual metrics and the more-encompassing WAR. For example, if Buster Posey of the San Francisco Giants hits another home run when a game is at the bottom of the eighth inning and the Giants are already up 6-2, his home run does not substantially contribute to the Giants win. Further, one could argue that hitting a home run when your team is already in the lead is easier since there is less pressure. One of the benefits of WAR is that it roughly attributes the winning percentage of a specific team to the players on that team. This may demonstrate both one of the weaknesses and strengths of WAR—ultimately, a higher performing player gets wins for his team; however, a team may be willing to pay more for a higher certainty of a specific number of wins. For example, two players may cause the same number of wins but one by a larger margin than the other. Logically, the certainty of the higher margin of safety may lead to a wage premium for that player.

Future research could study whether performance in other professional sports and industries is also similarly light tailed when using a metric of marginal impact. In baseball, it is relatively easy to use a statistic such as WAR that measures the marginal impact of players’

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30 Aguinis and O’Boyle (2012) also considered manager career wins in MLB, though the analysis was more to look at the performance of coaches than individual players.
performance because of the relative independence of individual performance while developing a similar statistic may be more complicated for other industries. Specifically, other scenarios in which group performance more directly impacts the bottom line than individual performance, metrics such as WAR may be a more accurate measure of the value-add to a firm of a worker’s performance. Trying to find similar statistics for other situations may enlighten why we found a light tailed distribution in professional baseball using WAR.

With regards to the luxury tax, we found that there were fewer top performers in the periods with a luxury tax in place. Since it is unlikely that the underlying talent landscape has changed, we assume that players are less motivated to perform highly. An alternate assumption that we do not pursue is that all players improve in the periods with luxury tax and thus, it is more challenging to become a top performer in these periods—more research would have to be done in order to support or debunk either assumption. We answered the question of why players may have had a decrease in motivation in our two regression models. Under the 1996 luxury tax, we found that players were more likely to leave their team when they went up for free agency when they were at the higher end of the salary distribution of their team. We concluded that teams may be less likely to extend the contract of these players as a mitigation technique for the luxury tax because of the uncertainty around the tax penalty. This theory was supported by the greater responsiveness in period 2 to the luxury tax that was demonstrated in our second model. In comparison, under the 2002 luxury tax, we found that increases in performance were less highly rewarded when compared to previous seasons. We understand our findings using efficiency wage theory—because the reward, either as retention in subsequent seasons or as salary, of high performance was lower in periods with a luxury tax in place, players were less motivated to perform highly.
Our research substantially contributes to sports economics literature by being the first empirical study into how the luxury tax has impacted talent retention decisions. Even though MLB is unique in that the budget constraint impacted the entire industry (at least in the U.S.), we believe our results also have interesting insights into the talent retention strategies of firms. Our findings suggest that when a budget constraint is fixed, managers respond by rewarding performance less with salary. When a budget constraint is stochastic, managers respond by not rehiring high earners (who may also be high performers) and letting them go. Though not every industry has a contract system like baseball, one could compare the decision to offer another contract (normally at a higher salary) as similar to the decision to accept when an individual comes up for a promotion. Firms need to be cognizant of the impact of the budget constraints that managers face and how they might impact talent performance as well as talent drain through turnover.
VII. References


Barbosa, V., 2015. MLB: What Made the Yankees So Great in the Late 90s. The Cheat Sheet.


Nightengale, B., 2015. Dodgers’ tax bill comes due at record $43.7 million. USA TODAY.


