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Three Essays on Sports Economics

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本論文係張毓天君（學號 F95323027）在國立臺灣大學經濟學系完成之博士學位論文，於民國一零三年十二月十七日承下列考試委員審查通過及口試及格，特此證明

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中文摘要

本論文集結三篇有關美國職棒大聯盟之運動經濟學研究。首篇探討工作過度是否會影響職業棒球選手的生涯與壽命。本文美國職棒大聯盟的球員資料，建構了決定球員工作時間的模型，並藉此計算出球員受到隊友表現影響而產生的工作時間差異，作為計劃外工作時間的估計值。接著，再觀察前一期的計劃外工作時間的多寡是否影響到球員當期的工作時間和個人表現，以及球員的生涯計劃外工作時間是否會對球員的壽命造成傷害。結果顯示，計劃外工作時間較高的大聯盟打者，下一個球季的出場機會將會減少，但投手的出場機會不會受到計劃外工作時間影響。此外，球員也會因為計劃外工作時間的增加而表現下滑、提早退休。然而，工作過度對球員壽命的影響並不明顯。

次篇則探討打者面對使用與自身相異的慣用手投球的投手所佔的優勢(異手優勢)。雖然異手優勢相當顯而易見，但球員表現的數據是同時受到球員天生能力、異手優勢、以及球隊管理策略影響的結果。本研究以西元 2000 年至 2012 年間大聯盟球員一百三十萬次的投打對決，提出異手優勢的量化分析及其造成的影響。結果顯示，異手優勢大約佔打者攻擊指數的 7%至 15%。其次，敵對左投手的比例對實力較差的打者的上場時間所造成的影響，會較其對一般打者造成的影響來得大。最後，若純綷以打擊策略而言，大聯盟應該再增加 7.5%的左打者。

最後一篇文章則是檢視球員的季後賽經驗是否會反映在球員的身價上，以線性迴歸來判定曾經參與過季後賽或世界大賽的自由球員是否有較高的薪水。結果顯示，球隊對於在前一個球季贏得世界大賽的投手有較高的需求，但對於打者來說，上一個球季的季後賽經驗不會讓他們獲得更高的薪水。不過打者生涯累積的季後賽經驗比投手的經驗來得更有價值。此外，於季後賽中較常晉級成功的打者，退休的機率也較高，而最常得到世界大賽冠軍的打者的退休機率也是最高的。

關鍵詞：運動經濟、美國職棒大聯盟、工作過度、異手優勢、季後賽經驗。

Abstract

This dissertation consists of three essays revolving around Major League Baseball in relation to sports economics. The first essay discusses the effects of overwork on the career and lifespan of professional baseball players. By using the data of players from Major League Baseball (MLB), a working time determination model is used to derive the unplanned working time influenced by a player's teammate performance. Previous unplanned working time is then added to the working time model to see if it influences the future working time and performance of the players. A career average unplanned working time is also calculated to check if it is related to a player's lifespan. The results show that, for MLB batters, high unplanned working time leads to working less in the following season, but the working time of the pitchers seems to be unaffected. Moreover, high unplanned working time makes players perform poorly and more likely to retire. However, the effect of overworked on a player's mortality rate is not obvious.

The second essay examines the seemingly self-explanatory concept that batters have an advantage when facing opposite-hand (OH) pitchers. While this opposite-hand (OH) advantage is known to be ex ante, the performance of players is ex post, which contains information about their intrinsic skill, hand (dis)advantage, and teams' recruiting strategies. Based on more than 1.3 million MLB play-by-play data from 2000 to 2012, we provided a quantitative estimate of the OH advantage and made analyses. The results showed OH advantage accounts for about 7-15% of the ex post on-base plus slugging. Second, marginal batters, both right-handed and left-handed, are more subjective to the proportion of left-handed pitchers than the average batters. Third, there should be 7.5% more left-handed batters in MLB.

The third essay investigate the common belief that postseason experience is quite valuable and players with postseason experience are highly esteemed. Regressions are made to determine if the free agent players who had participated in postseason games or won the World Series are more valuable. The results show that teams have higher demand on pitchers who won in the previous World Series, but batters with previous postseason experience do not earn higher salary. However, the batters' career postseason experience is more valuable than the pitchers'. Also, batters who had more experiences in higher stages of postseason will less likely to keep playing in the future, and those who won the Championships more often are most inclined to retire.

Key Words: sports economics; MLB; overwork; opposite-hand advantage; postseason experience

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The Impact of Overwork on the Career and Lifespan of Professional Baseball Players

1. Introduction

On January 17, 1915, the *New York Times* published an article by the famous American League umpire Billy Evans, titled “Overwork Reduces Career of Pitchers.” This short article began with questions: “Does it pay to be known as the ‘Iron Man’ in the world of baseball? Is it a fact that every pitcher and catcher has just so many games in his system? Is it possible for a pitcher or a catcher to greatly shorten his career by overworking himself?” Evans did not provide answers, but briefly reviewed the career of three players and concluded with a sigh for the catcher Charley Street, who left the big league due to the injured arm: “That right arm, once the fear of every base runner, had gone lame; they were running wild. It marked his exit from the big show.”

Has the overwork phenomenon changed over the past 100 years? Have pitching injuries been reduced since 1915? On the one hand, we have the “baseball numbers” by Keith Woolner (2006) telling us pitchers have been going fewer and fewer pitches, given the fact that the percentage of complete games for the starters declines from 55.0% in 1914 to 3.1% in 2004, and the fact that the average relievers used per game rises from around 1.5 in 1910 to 3.75 in 2004 (p. 74-76). On the other hand, according to *MLB Reports*, the number of players (including pitchers and non-pitchers) who have undergone Tommy John surgery has been growing in the past decade, from 11 in 2004, to 46 in 2012, and already to 29 in August 2014. The rise is considered as “epidemic” and drove the founder surgeon of the American Sports Medicine Institute to issue a

"Position Statement" in May 2014, warning against overusing pitchers.

For the players, the managers and the owners of professional baseball teams, the core of the issue is how to measure the workload of the players. There have been relatively few studies examining the working time for such a group of people who are engaged in works as professional baseball players. This essay tries to address the working time of baseball players by employing regression analysis on the seasonal data from Major League Baseball (MLB). It is hoped that a working time model will help to assess if the players are overworked and in what ways a player's career and lifespan are influenced by the time he plays on the field.

A professional baseball player's job is to play baseball for his team. His "working time" is thus defined as the time a player spends on the field in the games. Specifically, it is the plate appearances (PA) of the batters and the numbers of batters faced by the pitchers (BFP). In principal, the maximum working time a club can assign to its players is written in the basic agreement between the clubs and the players. According to the current MLB Player Association (MLBPA) Basic Agreement, "each Club shall be scheduled to play 162 games during each championship season. A championship season will not be scheduled over a period of less than 178 days or more than 183 days." (MLBPA 2012-2016 *Basic Agreement*, 2011, p3-4). Thus, a regular player will be working for his team for 162 games in a season at max, plus up to 20 games[1] of post-season. However, these are not the real working hours for the players, but just their "possible" working hours.

The true working time of the professional players during the season is the plate appearances of the batters and the numbers of batters faced by the pitchers, and is usually controlled by their managers. The managers decide which pitcher and which

[1] 1 game for the Wild Card round, 5 games for the Division Series, 7 games for the Championship Series, and another 7 games for the World Series.

batter will start the games, how long the players will play in each game, and when to substitute the players. Thus, the playing time between the players often varies a lot. A regular starting batter has at least 500 plate appearances in a season, while a replacement one may just have at most 200 plate appearances. A starting pitcher may face 700 batters in a season, while a standard reliever normally will not face more than 300 batters. Even if the season length is the same for all the players, their actual working time may differ a lot, and some players may have to work twice as long as other players. This would never happen to a normal occupation, where co-workers are supposed to have more or less equal working hours. Whenever it is observed that an individual is working twice as long as his colleague, people would usually think that either one of them is overworking, or the other one is not working hard enough.

Of course, overworking is a phenomenon of long existence, though everyone knows that to overwork is detrimental to health. As early as 1767, Adam Smith already pointed out, “the desire of greater gain” usually drove people “to overwork themselves, and to hurt their health by excessive labour’ (Smith, 1981, p. 100). In dealing with the long term psychological and physical impact of overwork, Burke and Cooper (2008) remarked that "[a]dditional hours spent at work eventually creates[*sic*] fatigue or stress so that the worker's physical or mental health, well-being health, or quality of life is not sustainable in the longer run" (p. 65). They emphasized the adverse effects: "[i]n the extreme case, the worker quits or suffers burnout that results in labor force withdrawn" (p. 67). Excessive working not only affects one’s health and career, it may also affect one’s lifespan.

In studying the relationship between long working hours and the lifespan, Ausubel and Grübler (1995) examined the people in the United Kingdom from 1856 to 1981 and found people during that period worked less and lived longer. The lifetime working hours dropped from 150,000 to 88,000 hours for men and from 63,000 to 40,000 for women. The reduction of working time was not unique in the United Kingdom; the authors emphasized the situation was the same in other developed countries. It is also concluded that in the countries where people had more free time, the GDP per capita was higher. People spent more time in education and enjoyed their retirement, which helped them live longer.

Can this conclusion of "working less and living longer" be applied to the baseball field? Being a professional baseball player is quite different from getting a job in other occupations. First, it is not easy to determine if a player is overworked or not. For example, starting pitchers are normally required to pitch longer in a game. Relief pitchers, however, are required not to allow any runs within one or two innings, and will usually not pitch more than that. Therefore, a starting pitcher facing 700 batters a season could be under-worked, while a relief pitcher facing 300 batters might be overworked. Second, the job of playing on the baseball field requires someone to be strong and healthy. A baseball player's job is, of course, to play baseball. He needs to outmatch hundreds or even thousands of competitors to earn a job, and he needs to stay fit to keep his job. Therefore, the seemingly "overwork" players on the baseball field may also be the toughest and the healthiest men. In the professional sports league, only the strongest players who play better than the others have the capacity to "overwork."

In order to examine the effects of overwork on young pitchers, Adams (1982) and O'Brien (1982) compared the playing time of the pitchers on a year-by-year basis. It was early 80s and these two reports were simple and primitive to a certain degree. But to compare the players' working time across different periods may be a good starting point to investigate if the players are overworked. Tables 1 is the summaries of the working time of MLB players in the previous and the current seasons, from 1871 to 2012. It shows that for those who work more in the previous season, their workloads are inclined to increase in a smaller but noticeable amount. For MLB batters, those who receive about 200 to 300 PAs in the previous season tend to have at least about the same amount of working time for the next season, while those earning 300 or more PAs in the previous season usually get fewer PAs in the next season. As for the pitchers, MLB pitchers facing fewer than 500 batters maintain their working hours in the next season, while those facing more batters are prone to get fewer batters in the next season. This is not enough to say that overwork exists in the professional baseball and affects the players' future working hours, but it is clear that those who worked a lot in the past season tend to work less in the next season. In order to find the true effects of working time on a player's career and lifespan, it is necessary to control two factors first: the manager judgment and the player's innate physical strength.

Table 1 The PAs and BFP of professional baseball players between two seasons.

Batter's PA(t-1)	PA(t)	Pitcher's BFP(t-1)	BFP(t)
0≦PA(t-1)<100	155.9308	0≦BFP(t-1)<100	231.0891
100≦PA(t-1)<200	202.4411	100≦BFP(t-1)<200	279.2313
200≦PA(t-1)<300	259.0707	200≦BFP(t-1)<300	279.6814
300≦PA(t-1)<400	327.6099	300≦BFP(t-1)<400	347.78
400≦PA(t-1)<500	404.8717	400≦BFP(t-1)<500	430.3268
500≦PA(t-1)<600	478.602	500≦BFP(t-1)<600	504.869
600≦PA(t-1)<700	564.3106	600≦BFP(t-1)<700	571.7915
700≦PA(t-1)<800	631.3423	700≦BFP(t-1)<800	641.2651
		800≦BFP(t-1)<900	715.5081

	900≦BFP(t-1)<1000	805.7864
	1000≦BFP(t-1)<1100	871.3858
	1100≦BFP(t-1)<1200	975.3859
	1200≦BFP(t-1)	1209.794

In addition to the different definition of "working time," the profession of a baseball player is unique in its career span. The average career length of professional baseball players is unusually limited in comparison with that of people in other professions, such as businessmen or teachers. Most people generally start their working career around the age of 20 or when they graduate from the school. For a businessman or a teacher, if everything goes well, he will keep on working until he's about 65 years old and then retire. For a baseball player, however, that would not be true. Professional baseball players have a much shorter career length. Only the most prominent players can last in the professional league for more than 20 years. Most players retire in their early 40s, or even earlier, when they are too old to compete in the professional baseball league. For a profession characterized by "indefinite" working time and uncommonly brief career span, what kind of repercussion will this "exceptional" employment bring to the employers? In what ways and to what extent does the working time affect the employers' work? Furthermore, will such a special pattern of work eventually influence the employers' lifespan?

This study tries to control the managerial decisions and the player's innate strength to estimate the magnitude of overwork in MLB. If overwork does exist, I would like to see how it affects the performance, career and lifespan of the baseball players. After a review of related literature in Section 2, the model and data used in this research are introduced in Section 3, with the regression results presented in Section 4. Section 5 elaborates on the real life effects of overwork, followed by a conclusion in Section 6.

2. Literature Review

The mortality risk for professional baseball players has long been one of the major concerns to researchers, just as Robert Reynolds remarked in 2012, "By far the most commonly studied health outcome involving data from the MLB is mortality." Among these studies, a large number focus on MLB players' health problems or diseases, but those revolving around overwork are comparatively limited.

The first analysis on MLB players' longevity and mortality was published in 1975 in the Statistical Bulletin of the Metropolitan Life Insurance Company. A more recent analysis by Abel and Kruger (2006) focused on the healthy worker effect. They examined players who joined MLB between 1900 and 1939 and concluded MLB players had an average of living 4.8 years longer than the general public of the same age. The latest research in this regard was conducted by Reynolds and Day (2012), who provided a more comprehensive investigation on mortality and life expectancy of all the players who joined MLB from 1990 to 1999 and found not only do the players have a lower mortality rate than the general population, but the mortality rate was also declining as the years went by.

In dealing with mortality or longevity, some researchers tend to compare MLB players with the general population, whereas others prefer to go for elite players. Abel and Kruger (2005) focused on the inducted MLB Hall of Famers. They found these top players suffered higher risk of cardiovascular or stroke, and more importantly, those hall-of-famers lived 5 years shorter than those who were not inducted. This result, however, was refuted by Smith (2011), who pointed out that the data used was incomplete and misinterpreted because the players with no death dates listed were assumed by the two authors as still alive and the lifespan of those who were not in the Hall of Fame were thus skewed upward. What's more, the two authors also ignored the effect of the birth year, which is vital to the overall result when considering the medical advancement in those years. Smith found that the hall of famers actually lived about 1 year longer than the non-hall-of-famers, though it was not statistically significant.

In another article by Abel and Kruger (2007), the focus was switched to young achievers in MLB. The authors tested McCann (2001)'s precocity-longevity hypothesis, which suggested early achievers in career tended to live shorter lives, by applying it to MLB players. They confirmed McCann's hypothesis with the conclusion that players debuting earlier than the average had a shorter lifespan. On the other hand, Teramoto and Bungum (2010) investigated the effects of competitive sports on health by examining 14 journal articles dealing either with the life expectancy, standardized mortality ratio, standardized proportionate mortality ratio, mortality rate, or with morality odds rate, on the part of the elite athlete. They concluded that aerobic athletes and mixed-sports athletes, such as runners and soccer players, tended to survive longer than the general population, but the results from the power-sports athletes, such as baseball and football players, were somewhat inconsistent.

Saint Onge, Rogers, and Krueger (2008) investigated the lifespan of MLB players with discrete time hazard models to estimate the risk of death for players of different ages and eras, while controlling their anthropometric, performance, and cohort effects. The results deriving from more than 240,000 data showed that, first, as the players grew older, their rate of death increased; and second, the later a player debuted, the longer he lived, possibly due to the improvement of training methods and sports medicine. Third, a player's BMI, handedness, and career rating seemed to have no influence on his risk of death, but the career length seemed to be positively affecting longevity, because long career meant the players maintained their peak fitness for longer years. Besides, the authors also compared the life expectancy of MLB players with the US male population, and concluded that while players lived several years longer than the general US male population, the gap between the two groups grew smaller in the modern age.

In Japan, 浜口陽吉 (1971) addressed the lifespan of the athletes and sports instructors in general, but his finding was contrary to the conclusions made by others: the athletes and sports instructors actually lived shorter than the general population, with *sumo* warriors and boxers lived an especially shorter life. The reason behind this, the author explained, was that the *sumo* warriors and boxers tended to get retired in their middle ages, and their body could not get used to the sudden stoppage of exercising. Also, athletes tended to eat, drink, and smoke a lot, which was harmful to their health.

With respect to the career span of baseball players, Witnauer, Rogers, and Onge (2007) examined the career length of MLB players over the twentieth century and pointed out that the factors affecting career length included age, performance, league size, career cumulative salary, and other infrastructural factors. Many players had a really short career, some of which even shorter than a season. Past research found that the exit rate for the rookies could be as high as 26.7%. Witnauer et al. studied MLB position players to observe their career length under different infrastructure and off-field influences. The players active from 1902 to 1993 were divided into 4 groups based on the years they played in. The results indicated that, on average, a player was expected to have a career of 5.6 years. However, more than 30% of players left the league within 2 seasons, and for those who survived, they would have an expected remaining career for 6 years, or a total career of 8 years. Starting age is also important. Only 10% of 20-year-old rookies would leave the league, while more than 30% of the rookies who started their career at the age of 26 would leave the league in their first year. Finally, players from the earliest year-period had the shortest expected remaining career length and the highest exit rate, regardless of any level of experience, while players in the modern year-period had the longest career length and the lowest exit rate.

By examining the career longevity and the prowess of MLB players from 1920 to 2005, Peterson, Jung, and Stanley (2008) observed that the career stats of the players followed the scale-free power law. The players with only one appearance had the highest probability density. When the appearance increased, the density dropped in a linear way, that is, the drop of density was the same no matter the appearance is increased from 1 to 2 or from 1000 to 1001. Moreover, the base hits, RBIs, and home runs of the batters and the strikeouts, and wins of the pitchers followed the same trend, too. Also, the probability density of home runs after 1980 was higher than that before 1980, which coincided with the exposure of steroid usage in the Mitchell Report.

Spurr and Barber (1994) addressed the performance of the workers and their promotion, demotion, and turnover in the job market by focusing on Minor League pitchers. The 608 pitchers debuting during 1975-1977 were investigated on the relationship between their in-field performance and promotion/demotion. The result showed that a deviation from the mean performance increased the player's chance of turnover, whether it was a promotion or a demotion. Specifically, the higher the pitcher's strikeout rate was, and the lower his ERA and walk rate were, the more likely he would be promoted from the A league or Rookie league in less time than the average players; on the other hand, the lower the strikeout rate and the higher the ERA and walk rate were, the more likely he would be demoted or forced to leave the league sooner than the others. As for average players, the managers would need more time to determine their promotion or demotion. However, when the hazard model was applied to the promotion and demotion of the pitchers, the effect of walk rate became less obvious. Moreover, the result showed that previous experience in baseball did help the pitchers to be promoted earlier; the older the pitcher was, the more likely he was to be promoted.

3. Model and Data

In order to investigate the overwork phenomenon and its influences on the players, several steps must be taken. First, regressions will be made to determine the optimal working time of each player for each season. As explained in section 1, when a player signs a contract with a team, his maximum possible working time will be determined. However, the player does not have much power in choosing their actual optimum working time. Such decision is made by the team owner or manager. In this sense, the contract of a player sounds more like that of "slavery," since “[i]n a slave economy... the amount of labor to be extracted from a slave... are determined by the slave owner." (Barzel, 1977, p. 87) Having a job in the professional baseball league is not like working as a free laborer who is entitled to choose his optimal working time. It is the work of "voluntary slavery,” in Barzel’s (1977) terms, which means higher pay for a few years are given as stated in the slavelike contract. In dealing with the effects of overwork in such a voluntary-slave-like labor on the baseball field, it's important to first estimate the optimum working time decided by the team for each player.

As defined above, the working time refers to the total plate appearances of the batters and the number of the batters faced by the pitchers in a season. Normally, the chance to play on the field is determined by two factors: a player's performance (Staw & Hoang, 1995) and his physical capacity. Managers almost always start the good batters and put those with a high batting average or slugging percentage in the front part of the batting order. The performance of the pitchers will also affect their chance to pitch. Good pitchers stay in the game longer and face more batters. Managers will also put their best starting pitchers in the front part of their rotation, and send their best relief pitcher more times during the season to create more outs.

Physical capacity, which may be affected by age, intensity of position or injury, is also an important factor. Veteran players are inclined to be granted more time to rest. It is a common strategy that veteran batters take a rest day after every several games. Veteran pitchers also face fewer batters because their strength have declined and may not be able to face too many batters. Catchers usually get a day off once in a while because the position is more strength consuming than other positions. Players with a history of injury may be more prone to get injured again, so they are well protected and may have more chance to rest during the season.

The structural form of the determination of players' seasonal working time is:

$$Working\ Time_{i,t} = f\left(Performance_{i,t}, Capacity_{i,t}, Performance_{-i,t}, Year_{i,t}\right) + \epsilon_{i,t} \quad (1)$$

where $\epsilon_{i,t}$ is the part of a player's working time unable to be explained by either performance or capacity. This is probably due to the manager's misjudgment of a player's performance and capacity, or a reflection on the sunk cost of signing a player (Staw & Hoang, 1995; Harkins, 2011).

Working time:

$PA_{i,t}$	Batter *i*'s total PA in season *t*.
$BFP_{i,t}$	Pitcher *i*'s total batters faced in season *t*.
Batters' performance:	
$\frac{1B}{PA_{i,t}}$	Batter *i*'s singles per PA in season *t*.

$\frac{2B}{PA}_{i,t}$	Batter *i*'s doubles per PA in season *t*.
$\frac{3B}{PA}_{i,t}$	Batter *i*'s triples per PA in season *t*.
$\frac{HR}{PA}_{i,t}$	Batter *i*'s home runs per PA in season *t*.
$\frac{K}{PA}_{i,t}$	Batter *i*'s strikeouts per PA in season *t*.
$\frac{BB+HBP}{PA}_{i,t}$	Batter *i*'s walks plus hits by pitchers per PA in season *t*.
Pitchers' performance	
$\frac{H-HR}{BFP}_{i,t}$	Pitcher *i*'s non-home run base hits allowed to per batter faced in season *t*.
$\frac{HR}{BFP}_{i,t}$	Pitcher *i*'s home runs allowed to per batter faced in season *t*.
$\frac{K}{BFP}_{i,t}$	Pitcher *i*'s strikeouts per batter faced in season *t*.
$\frac{BB+HBP}{BFP}_{i,t}$	Pitcher *i*'s walks plus hits by pitches allowed to per batter faced in season *t*.
Teammate performance:	
$\frac{1B}{PA}_{-i,t}$	Batter *i*'s teammates' singles per PA in season *t*.
$\frac{2B}{PA}_{-i,t}$	Batter *i*'s teammates' doubles per PA in season *t*.
$\frac{3B}{PA}_{-i,t}$	Batter *i*'s teammates' triples per PA in season *t*.
$\frac{HR}{PA}_{-i,t}$	Batter *i*'s teammates' home runs per PA in season *t*.
$\frac{K}{PA}_{-i,t}$	Batter *i*'s teammates' strikeouts per PA in season *t*.
$\frac{BB+HBP}{PA}_{-i,t}$	Batter *i*'s teammates' walks plus hits by pitches per PA in season *t*.
$Team\ RA/G_{i,t}$	Team runs allowed per game for batter *i*'s team.

$\frac{H-HR}{BFP}_{-i,t}$	Pitcher *i*'s teammates' non-home run base hits allowed to per batter faced in season *t*.
$\frac{HR}{BFP}_{-i,t}$	Pitcher *i*'s teammates' home runs allowed to per batter faced in season *t*.
$\frac{K}{BFP}_{-i,t}$	Pitcher *i*'s teammates' strikeout per batter faced in season *t*.
$\frac{BB+HBP}{BFP}_{-i,t}$	Pitcher *i*'s teammates' walks plus hits by pitches allowed to per batter faced in season *t*.
$Team\ R/G$	Team runs scored per game for pitcher *i*'s team.
Physical capacity and structural variables:	
$Age_{i,t}$	Player *i*'s age in season *t*.
$Position_{p,t}$	Batter *i*'s defensive position dummy variable *p* in season *t*
Career Average All-stars$_{i,t-1}$	Player *i*'s career numbers of being the All-star game starter per season in season *t-1*.
$Year_t$	Year dummy variable for season *t*.
$Player_i$	Player *i*'s dummy variable for season *t*.

In this model, the defensive performance is omitted, since the current defensive stats, such as fielding percentage and zone rating, are used to compare the players with the same defensive position, not cross-positional comparisons. Moreover, players with good defense skill often come into play only in the final innings of the game to replace starting batters who may not have another turn to bat. This clearly indicates that batting skill is more important than the fielding skill, so only the defensive dummies are included in the model.

In equation (1), $Performance_{-i,t}$ is the performance of a player's teammate, which is used to estimate the magnitude of overwork. In addition to a player's performance and capacity, his relative performance in the team will influence his playing time. For example, a good player in a weak team will have a lot of playing time, but in a team filled with All-stars, he needs to compete with other great players and have less playing time. Aside from the competition within the team, it also captures the influence from the team ranking of the league. If the team is in a tight playoff race, the managers may require main roosters to play for more time. If the team is quite far from the playoff, the managers may give the inexperienced players chance to accumulate some experience. Both competition and ranking effects are controlled by the managers and are exogenous to a player. The variance from teammate performance is thus an exogenous indicator to capture the unplanned working time of the players and to be used as an estimation of overwork.

After finding out how a player's working time is determined, the working time influenced by teammate performance can be obtained. The player's working time influenced by his teammates' performance equals to the total effect of $Performance_{-i,t}$ in equation (1). It can be used as an indicator for a player's unplanned working time. The lags of the working time influenced by teammates' performance can then be added to the original model and a relationship will be derived between player's working time and his previous unplanned working time. Next, the working time influenced by teammate performance in the previous season is put into equation (1) and the model will be estimated again:

$$\begin{aligned} &Working\ Time_{i,t} \\ &= f(Teammate\ Influence_{i,t-1}, Performance_{i,t}, Capacity_{i,t}, Performance_{-i,t}, \\ &\qquad Year_{i,t}) + \mu_{i,t} \quad (2) \end{aligned}$$

If performance and capacity are able to sufficiently explain a player's working time, then the coefficient of $Teammate\ Influence_{i,t-1}$ should be zero. If, however, the coefficient of $Teammate\ Influence_{i,t-1}$ is not zero, then the unplanned or unexpected working time of the players will have some impact on the player's future working time. This means if the players are sent to the field on an unplanned basis, it will influence their future working time.

In addition to the impact on working time, overwork could also result in a decline in performance. In general, the productivity of a laborer may drop as a result of overwork, which makes him feel tired or even causes some injury. The same reasoning could be tested on the performance of baseball players:

$$Performance_{i,t} \\ = f\left(Teammate\ Influence_{i,t-1}, Performance_{i,t-1}, Capacity_{i,t}, Year_{i,t}\right) + \tau_{i,t} \quad (3)$$

Of course, current overwork should be more influential to current performance than overwork in the previous stage to current performance. However, in the baseball field, since the best players are most likely to be overworked, the effect of current overwork on current performance would be highly positively related and will cause multi-collinearity. Therefore, in order to estimate the effect of overwork on performance, it would be better to use previous overwork instead of current overwork.

Moreover, health problem may directly affect the continuation of employment, given that "...poor health is strongly correlated with the decision to remain employed" (McGarry, 2002, p644). Thus, the relationship between a player's working time of the current season and the possibility of his continuing to play in the league for the next season should be considered. The model employed here is Cox's (1972) proportional hazard model, which is also used by Ohkusa (2001) in analyzing the baseball players' quit decision in Japan, and by Frick, Pietzner and Prinz (2007) in examining the impact of institutional changes on the career duration of the soccer players in Germany. The proportional hazard model is suitable for estimating the survival data because it does not have any requirements on the surviving distribution. Moreover, independent factors that would affect the survival rate can be included. The basic form of the Cox model is:

$$h(t) = h_0(t)e^{\beta X_i}$$

where $h(t)$ is the survival rate of the samples. In this case, $h(t)$ is whether the player retired t years after he entered professional baseball. $h_0(t)$ is the probability of retiring after t years when all the independent variables are 0. X_i is a list of independent variables that may influence the probability of the players' retirement. The variables in X_i are the same as those in the performance indicator prediction models above.

Besides the working time influenced by a player's teammate, performance and capacity are the two main factors of X_i. As for the performance factor, the case of minor league may shed some light on its relation with promotion or demotion. According to the results derived from the study by Spurr and Barber (1994), minor league baseball pitchers who have outstanding performance are more prone to be promoted to the leagues of higher level, while those who perform poorly will be more likely to be demoted or even forced to leave the league. In the same way, better-performed soccer and NBA are less likely to exit the leagues, as concluded in the two studies by Hoang and Rascher (1999) and Frick, Pieztner and Prinz (2007). Once the performance factor is controlled, clubs prefer to keep the players with higher capacity. It is certainly better to have a pitcher who is able to face 200 batters in a season than have a pitcher who faces 100 batters if their pitching performances do not differ a lot.

Aside from the career, a player's lifespan can also be estimated. The discrete hazard model used by Saint Onge, Rogers, and Krueger (2008) in analyzing mortality risk for baseball players will be employed to estimate a player's lifespan. The relationship between the players' lifespan and their working time would be:

$$Player\ Passing\ Away_{i,a} = f(Career\ Average\ Working\ Time\ Influenced\ by\ Teammates_i, Structural\ Variables_{i,t}, Performance_i, Capacity_i) + v_{i,a}$$

$Player\ Passing\ Away_{i,a}$	The indicator variable for player *i* passing away at age a.
Career Average Working Time Influenced by Teammates$_i$	The player *i*'s career average working time influenced by teammates derived from (1).
Structural variables:	
$Age\ Group_g$	Players are divided into 8 age groups: 50-54, 55-59, 60-64, 65-69, 70-74, 75-79, 80-84, and 85 and more.
$Debut\ Age_i$	The debut age of player *i*.
Left-handed$_i$	If player *i* is left-handed or not.
Performance variables	
$\frac{Career\ 1B}{Career\ PA}_i$	Batter *i*'s career singles per PA.
$\frac{Career\ 2B}{Career\ PA}_i$	Batter *i*'s career doubles per PA.
$\frac{Career\ 3B}{Career\ PA}_i$	Batter *i*'s career triples per PA.
$\frac{Career\ HR}{Career\ PA}_i$	Batter *i*'s career home runs per PA.
$\frac{Career\ K}{Career\ BFP}_i$	Batter *i*'s career strikeouts per PA.
$\frac{Career\ BB + HBP}{Career\ BFP}_i$	Batter *i*'s career walks plus hit by pitches per PA.

$\left(\frac{Career\ H - HR}{Career\ BFP}\right)_i$	Pitcher *i*'s career non-home run base hits allowed per batter faced.
$\frac{Career\ HR}{Career\ BFP_i}$	Pitcher *i*'s career home runs allowed per batter faced.
$\frac{Career\ K}{Career\ BFP_i}$	Pitcher *i*'s career strikeouts per batter faced.
$\left(\frac{Career\ BB + HBP}{Career\ BFP}\right)_i$	Pitcher *i*'s career walks plus hit by pitches allowed per batter faced.
Physical capacity:	
$Mortality\ Rate_{t,a}$	The percentage of death for people who aged *a* passed away in year *t*.
$Years\ Played_i$	Total years of experience of player *i*.
$Birth\ Year_i$	The birth year dummy variable of player *i*.
$Career\ PA/Season_i$	Batter *i*'s career PA per season played.
$Career\ BFP/Season_i$	Pitcher *i*'s career batter faced per season played.

$Mortality\ Rate_{t,a}$ is retrieved from the Center for Disease Control and Prevention. It contains the yearly mortality rate for all the US population by age, and can be used to control the health status of the players in different ages. The birth year dummy is to control the medical progress across different generations. The history of MLB is longer than 100 years, and the medical care and services in the early years were not so advanced as in the later years.

The performance data of MLB players used in this model are retrieved from the Lahman Database. The data span from 1871 to 2012, and also includes records from its rival leagues such as National Association, Federal League, etc., which are also examined, though it only accounts for around 3% of the total data. However, years in which no World Series were held are removed from the data. Since part of the source of overwork is to win a spot in the postseason, the team managers may choose not to overwork the players if there is no postseason. The years without postseasons were mostly before 1900. Besides, all pitchers' battings are removed, and those who transferred teams within a season are also removed. Since the source of overwork in this study is teammate performance, it is very difficult to see how a player is affected by different teams in the same season unless teammate performance from different teams can also be divided according to the player's stint. Furthermore, only players who played long enough in a season are included in the data to avoid the extreme values of the performance indicators. The data only include batters who played at least 30 games, starting pitchers who started at least 5 games, and bullpen pitchers who never started but who relieved at least 15 games in a season. The data are highly detailed and complete, including the seasonal batting, pitching, and defensive records of every player who played in the major league. These databases also provide accurate biographical and personal information of the players, such as their height, weight, date and place of birth, year of death, college graduated, and so on. Models for the working time determination and for the influence of overwork on performance indicators will be estimated by using ordinary least squares method, while the discrete hazard model for the players' lifespan will be estimated with logit regression.

MLB data are roughly stratified into five periods based on the changes of the league structure: Pre-1900, 1901-1930, 1931-1946, 1947-1972, and 1973- present. The first period, pre-1900, is the time before American League and MLB were founded and there was only the National League, along with several other rival leagues. The second period starts from 1901, when the American League was introduced and then MLB was formed soon after that. However, before 1930, the rules of baseball had been changing constantly, such as the distance of the pitcher's mound or the pitch counts for a walk. It is after 1931 that the rules remained unchanged for a long time, so 1931 is regarded as the start of the third period. The fourth period comes in 1947, when Jackie Robinson became the first African-American player to play in the MLB in the modern era and broke the Major League color barrier. African-American players thus started to play in MLB again, which contributed to the dramatic expansion of potential players. The last period starts from 1973, when the designated hitter (DH) rule was introduced into the American League, and the baseball rules has gone little change since then.

Table 2(a) and 2(b) are the summary statistics for MLB players.

Table 2(a): Summary statistics of the batters.

Variable	Obs	Mean	Std. Dev.	Min	Max
PA (i)	27217	402.054	197.171	3	784
1B/PA (i)	27217	0.166	0.033	0	0.333
2B/PA (i)	27217	0.040	0.015	0	0.333
3B/PA (i)	27217	0.007	0.007	0	0.143
HR/PA (i)	27217	0.018	0.016	0	0.118
K/PA (i)	27217	0.121	0.067	0	0.5
(BB+HBP)/PA (i)	27217	0.092	0.036	0	0.5
1B/PA (-i)	27217	0.165	0.013	0.123	0.2145
2B/PA (-i)	27217	0.040	0.007	0.019	0.061
3B/PA (-i)	27217	0.007	0.004	0.0014	0.026
HR/PA (-i)	27217	0.019	0.009	0.0003	0.044
K/PA (-i)	27217	0.134	0.049	0	0.275
(BB+HBP)/PA (-i)	27217	0.090	0.013	0.034	0.141
Team RA/G	27217	4.426	0.682	2.458	8.949
PA(t-1)	27217	378.911	216.794	1	784
Age	27217	29.124	4.054	18	48
Age^2	27217	864.653	244.827	324	2304

Career Average All-stars (i, t-1)	27217	0.031	0.105	0	1
1st Baseman	27217	0.096	0.295	0	1
2nd Baseman	27217	0.091	0.287	0	1
3rb Baseman	27217	0.091	0.287	0	1
Catcher	27217	0.155	0.362	0	1
DH	27217	0.015	0.121	0	1
Outfielder	27217	0.338	0.473	0	1
Shortstop	27217	0.092	0.289	0	1
Utility Man	27217	0.122	0.327	0	1

Table 2(b): Summary statistics of the pitchers.

	Starter					Bullpen				
Variable	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
BFP (i)	12170	710.821	299.062	84	2736	4904	257.035	104.418	31	857
(H-HR)/BFP (i)	12170	0.216	0.027	0.113	0.348	4904	0.198	0.034	0.086	0.382
HR/BFP (i)	12170	0.020	0.011	0.000	0.085	4904	0.022	0.012	0.000	0.095
K/BFP (i)	12170	0.127	0.048	0.003	0.375	4904	0.177	0.061	0.028	0.502
(BB+HBP)/BFP (i)	12170	0.089	0.027	0.014	0.295	4904	0.104	0.033	0.014	0.354
Starter (H-HR)/BFP (-i)	12170	0.215	0.016	0.155	0.289	4904	0.210	0.011	0.160	0.261
Starter HR/BFP (-i)	12170	0.020	0.008	0.000	0.041	4904	0.025	0.006	0.006	0.039
Starter K/BFP (-i)	12170	0.128	0.036	0.044	0.243	4904	0.152	0.026	0.060	0.225
Starter (BB+HBP)/BFP (-i)	12170	0.089	0.013	0.041	0.155	4904	0.089	0.012	0.048	0.141
Bullpen (H-HR)/BFP (-i)	12170	0.216	0.050	0	1	4904	0.201	0.021	0.065	0.400
Bullpen HR/BFP (-i)	12170	0.018	0.012	0	0.2	4904	0.022	0.008	0	0.136
Bullpen K/BFP (-i)	12170	0.136	0.057	0	0.333	4904	0.173	0.039	0	0.292
Bullpen (BB+HBP)/BFP (-i)	12170	0.112	0.045	0	1	4904	0.107	0.021	0	0.545
Team R/G (i, t)	12170	4.440	0.661	2.409	8.196	4904	4.505	0.562	2.859	6.423
BFP(t-1)	12170	654.958	353.448	2	2741	4904	260.37	145.20	1	956
Age	12170	28.644	4.327	18	48	4904	30.22	4.17	17	50
Age^2	12170	839.213	262.664	324	2304	4904	930.73	264.32	289	2500
Career Average All-stars (i, t-1)	12170	0.009	0.043	0	1	4904	0.0002	0.0037	0	0.083

4. Regression Results

Table 3 is the regression results derived from the seasonal batter PA determination model based on the batters' attributes. Pitcher's batting is excluded from the PA determination, because their batting chance depends on how long they pitched, not by their batting performance. The results tell us that, first, the base hit matters. From column 4, the results indicate that more base hits give a player more chances to play on the field, which means more working time for the player. The probabilities of hitting base hits and earning walks follows the law of diminishing return, that is, even though having a higher probability to hit base is rewarded with more chance to play, the increased range will reduce as the probability gets higher. Strikeout rate, on the other hand, goes the other way around. Higher strikeout rate results in less working time. Second, the performance of teammates is also important, but it is less important than the player's own performance. Teammate performance effects in column 4 are all significant except for walks and hit by pitches per PA and runs allowed per game, while all of the player's own performance influences are significant. Third, the number of the player's PAs in the previous season also matters, but its significance dropped when the player dummies are added. The PAs in the previous season capture the working capacity of each player, which may also be captured by the player dummies.

Table 3: MLB batters' PA determination

	PA	PA	PA	PA
1B/PA (i, t)	4,357***	3,240***	2,965***	3,093***
	(225.8)	(179.3)	(177.8)	(217.2)
$(1B/PA)^2$ (i, t)	-8,817***	-6,347***	-5,473***	-6,065***
	(681.5)	(542.0)	(538.3)	(651.5)
2B/PA (i, t)	4,392***	3,104***	3,155***	2,966***
	(1,347)	(981.1)	(925.0)	(838.6)

(2B/PA)^2 (i, t)	-28,758*	-19,598	-19,157*	-17,614*
	(16,687)	(12,119)	(11,435)	(10,269)
3B/PA (i, t)	8,202***	5,631***	5,069***	3,899***
	(2,032)	(1,458)	(1,287)	(1,059)
(3B/PA)^2 (i, t)	-140,802	-102,290	-91,589*	-64,358
	(89,698)	(63,573)	(55,517)	(46,158)
HR/PA (i, t)	6,240***	4,067***	4,571***	4,520***
	(208.4)	(159.8)	(158.6)	(211.0)
(HR/PA)^2 (i, t)	-27,175***	-18,059***	-22,993***	-29,318***
	(3,529)	(2,613)	(2,574)	(3,277)
K/PA (i, t)	-1,865***	-1,061***	-987.0***	-1,295***
	(74.34)	(58.18)	(56.61)	(95.46)
(K/PA)^2 (i, t)	2,384***	1,355***	1,298***	1,654***
	(205.6)	(160.1)	(157.0)	(271.8)
BB+HBP/PA (i, t)	1,470***	928.2***	947.5***	1,002***
	(123.8)	(97.99)	(94.26)	(136.2)
(BB+HBP/PA)^2 (i, t)	-3,275***	-2,184***	-2,246***	-2,863***
	(594.9)	(471.3)	(453.2)	(648.2)
1B/PA (-i, t)	14,515***	9,885***	10,748***	6,428***
	(1,501)	(1,221)	(1,328)	(1,497)
(1B/PA)^2 (-i, t)	-39,011***	-26,695***	-28,506***	-16,298***
	(4,434)	(3,611)	(3,960)	(4,490)
2B/PA (-i, t)	-3,823***	-2,957**	-3,347***	-3,632**
	(1,421)	(1,217)	(1,255)	(1,472)
(2B/PA)^2 (-i, t)	36,228**	27,282*	47,375***	50,713***
	(17,946)	(15,301)	(15,617)	(18,287)
3B/PA (-i, t)	-1,325	-1,133	-6,297***	-4,990***
	(1,380)	(1,086)	(1,025)	(1,181)
(3B/PA)^2 (-i, t)	23,756	-7,064	205,243***	127,382**
	(68,811)	(53,781)	(49,328)	(55,899)
HR/PA (-i, t)	-7,534***	-5,483***	-6,064***	-6,318***
	(522.9)	(451.9)	(579.7)	(715.1)
(HR/PA)^2 (-i, t)	117,570***	86,415***	104,133***	96,749***
	(12,363)	(10,493)	(12,789)	(15,408)
K/PA (-i, t)	656.8***	220.9***	324.3***	807.1***
	(97.67)	(81.05)	(107.7)	(157.7)
(K/PA)^2 (-i, t)	5,111***	4,249***	6,310***	5,139***
	(354.7)	(299.9)	(410.9)	(562.2)

BB+HBP/PA (-i, t)	-1,453**	-831.6	-309.1	-305.9
	(613.6)	(512.9)	(608.6)	(740.5)
$(\text{BB+HBP/PA})^2$ (-i, t)	9,267***	5,981**	3,125	2,327
	(3,416)	(2,839)	(3,319)	(4,002)
Team RA/G	-10.34***	-0.613	-0.584	2.696
	(1.431)	(1.218)	(1.470)	(1.878)
PA (i, t-1)		0.436***	0.395***	0.194***
		(0.00556)	(0.00534)	(0.00634)
Age		-17.43***	-10.81***	27.12***
		(2.224)	(2.169)	(3.278)
Age^2		0.160***	0.0685*	-0.606***
		(0.0364)	(0.0357)	(0.0541)
Career Average		65.02***	57.02***	38.15**
All-star Starting (i, t-1)		(7.570)	(7.331)	(14.94)
Year Dummy	N	N	Y	Y
Defensive Position	N	N	Y	Y
Player Dummy[2]	N	N	N	Y
Constant	-1,484***	-735.4***	-917.2***	-1,112***
	(133.3)	(113.9)	(121.2)	(142.7)
Observations	27,217	27,217	27,217	27,217
R-squared	0.406	0.590	0.624	0.418
Number of players				5,114

Robust std. errors in (); *** p<0.01, ** $p < 0.05$, * $p < 0.1$.

Table 4 divides the MLB data into different periods and reports the results of the PA determination model of each period. It can be noted that, first, the values of singles, doubles, and triples vary a lot across the years, but the values of home runs, strikeouts, and walks are relatively stable across the periods. Second, the influence of teammate performance also varies a lot. Only the influence of teammate home run percentage is consistently stable across the periods. The influence of teammate walk percentage is not even significant during any period.

[2] After examining with Hausman tests, fixed effect models for the players are used in all the following tables, instead of using random effect models.

Table 4: MLB batters' PA determination by different periods

	-1900	1901-1930	1931-1946	1947-1972	1973-
1B/PA (i, t)	1,758	6,023***	5,113***	2,479***	2,722***
	(1,092)	(676.9)	(864.3)	(467.5)	(301.4)
$(1B/PA)^2$ (i, t)	-3,588	-13,486***	-11,769***	-4,371***	-5,105***
	(2,958)	(1,788)	(2,397)	(1,468)	(938.2)
2B/PA (i, t)	4,571***	5,226***	7,250***	6,964***	2,332***
	(1,033)	(596.6)	(846.9)	(554.7)	(561.9)
(2B/PA)^2 (i, t)	-46,948***	-47,892***	-62,511***	-76,572***	-10,515
	(12,345)	(6,954)	(8,760)	(7,427)	(6,417)
3B/PA (i, t)	4,061***	9,828***	9,334***	2,051***	7,834***
	(1,525)	(970.5)	(1,406)	(532.8)	(862.7)
$(3B/PA)^2$ (i, t)	-84,097**	-237,890***	-274,161***	-5,060	-315,808***
	(35,087)	(31,180)	(49,763)	(16,967)	(49,765)
HR/PA (i, t)	3,465***	3,600***	4,419***	5,172***	4,198***
	(1,244)	(585.6)	(781.1)	(472.2)	(260.5)
$(HR/PA)^2$ (i, t)	-45,540*	-12,838	-51,918***	-39,981***	-24,527***
	(25,851)	(10,328)	(13,593)	(7,469)	(3,819)
K/PA (i, t)	-873.8**	-1,466***	-1,446***	-1,150***	-715.7***
	(388.5)	(297.8)	(395.9)	(197.8)	(124.1)
$(K/PA)^2$ (i, t)	3,160**	2,302*	1,273	1,048*	299.9
	(1,542)	(1,274)	(1,618)	(594.4)	(332.3)
BB+HBP/PA (i, t)	620.8	876.3***	1,017**	1,327***	996.7***
	(413.6)	(311.6)	(398.4)	(256.0)	(174.5)
$(BB+HBP/PA)^2$ (i, t)	-978.6	-3,019**	-4,007**	-4,333***	-2,496***
	(1,997)	(1,425)	(1,673)	(1,120)	(838.5)
1B/PA (-i, t)	5,944	-8,974*	-332.9	2,346	889.2
	(7,010)	(5,193)	(8,187)	(4,508)	(2,818)
$(1B/PA)^2$ (-i, t)	-16,268	24,356*	8,704	-4,455	2,252
	(19,381)	(14,372)	(23,407)	(13,838)	(8,821)
2B/PA (-i, t)	-15,235**	3,075	-13,607**	-11,477*	-2,752
	(6,651)	(2,706)	(5,588)	(6,427)	(2,800)
$(2B/PA)^2$ (-i, t)	217,290**	-23,894	171,310***	167,585*	46,650
	(98,626)	(35,961)	(66,120)	(91,232)	(32,355)
3B/PA (-i, t)	-6,063	-13,693***	-4,341	-8,491	346.0

	(5,706)	(5,226)	(6,949)	(5,659)	(3,425)
$(3B/PA)^2$ (-i, t)	120,339	436,209**	96,475	306,179	-226,118
	(184,083)	(193,958)	(353,277)	(389,353)	(283,162)
HR/PA (-i, t)	-653.1	-5,700**	-11,485***	-12,620***	-5,748***
	(2,937)	(2,219)	(3,354)	(1,792)	(1,236)
$(HR/PA)^2$ (-i, t)	5,890	86,883	219,279*	229,757***	86,624***
	(83,047)	(82,928)	(113,028)	(40,420)	(24,376)
K/PA (-i, t)	-31.19	-706.5	4,246*	3,466***	2,495***
	(419.3)	(503.6)	(2,358)	(909.4)	(557.6)
$(K/PA)^2$ (-i, t)	2,717	16,661***	993.7	-2,960	-188.5
	(2,290)	(3,515)	(12,033)	(2,934)	(1,609)
BB+HBP/PA (-i, t)	-332.4	-1,865	-1,253	841.6	-1,543
	(1,795)	(1,771)	(2,772)	(1,671)	(1,385)
$(BB+HBP/PA)^2$ (-i, t)	4,819	9,850	8,449	-4,553	10,196
	(12,054)	(10,240)	(14,797)	(8,632)	(7,361)
Team RA/G	-6.270	0.910	-0.238	7.673	1.992
	(4.897)	(4.483)	(5.647)	(4.792)	(2.841)
PA (t-1)	0.0405	0.109***	0.0761***	0.166***	0.216***
	(0.0362)	(0.0169)	(0.0189)	(0.0128)	(0.00874)
Age^2	71.07***	33.44***	47.43***	57.24***	15.74***
	(18.63)	(8.399)	(10.62)	(8.013)	(4.536)
Age	-1.174***	-0.679***	-0.963***	-1.240***	-0.453***
	(0.312)	(0.141)	(0.175)	(0.135)	(0.0748)
Career Average			-33.32	23.10	33.74
All-star Starting (t-1)[a]			(34.49)	(27.23)	(20.53)
Year Dummy	Y	Y	Y	Y	Y
Defensive Position	Y	Y	Y	Y	Y
Player Dummy	Y	Y	Y	Y	Y
Constant	-1,198*	58.73	-1,197*	-1,064**	-610.2**
	(640.2)	(514.4)	(694.8)	(425.5)	(238.6)
Observations	890	4,307	2,538	5,556	13,926
R-squared	0.303	0.358	0.461	0.494	0.424
Number of players	289	1,014	675	1,197	2,551

Robust std. errors in (); *** p<0.01, ** p < 0.05, * p < 0.1.

[a]: the 1st All-stars game took place in the 3rd period (1933).

Table 5 reports the results from the perspective of pitchers. Pitchers are divided into starters and bullpen pitchers. Those who never started a game in a season are counted as bullpen pitchers, while those who started at least five games in a season are starters. First, as concluded from table 3, performance matters when determining a player's working time. More base hits, home runs, and walks allowed per batter faced will reduce the pitcher's chance of pitching, while more strikeouts give him more working time. Second, the effect of teammate performance is not very significant. Unlike the batters, the starting pitchers do not compete with each other directly. Starting pitchers always pitch in a fixed rotation, so a fabulous starter in a season does not exert much influence on the working time when his fellow starting pitchers are playing and he is resting on the bench waiting for his next start. For the bullpen pitchers, although they are directly competing with each other, their working time may depend more on their characters in the bullpen. For example, closers are usually used when the game is on the line; long-relievers are used to pitch longer innings, while other kinds of bullpen pitchers come out under different situations. Things are more complicated for the bullpen pitchers.

Table 5: MLB starting and bullpen pitchers' BFP determination

	Starter	Starter	Starter,	Starter	Bullpen	Bullpen,	Bullpen,	Bullpen,
H-HR/BFP (i, t)	8,363***	7,138***	7,413***	8,291***	2,561***	2,300***	2,133***	2,198***
	(1,039)	(919.7)	(949.7)	(1,100)	(311.3)	(290.2)	(287.0)	(314.6)
$(\text{H-HR/BFP})^2$ (i, t)	-26,854***	-23,697***	-24,408***	-25,848***	-7,648***	-7,067***	-6,590***	-6,569***
	(2,313)	(2,045)	(2,123)	(2,481)	(738.0)	(690.4)	(683.9)	(752.7)
HR/BFP (i, t)	-47.67	-1,708**	-1,018	1,984**	545.0	154.9	137.2	685.8*
	(947.2)	(836.1)	(831.7)	(992.4)	(350.7)	(319.0)	(317.5)	(359.6)
$(\text{HR/BFP})^2$ (i, t)	-138,869***	-101,827***	-110,165***	-150,129***	-45,055***	-36,945***	-35,697***	-39,770***
	(15,442)	(13,735)	(13,712)	(17,168)	(5,775)	(5,178)	(5,208)	(5,874)
K/BFP (i, t)	3,091***	2,564***	2,593***	2,434***	524.5***	571.2***	579.5***	616.7***
	(255.6)	(230.2)	(229.1)	(315.9)	(104.7)	(97.73)	(96.65)	(138.5)
$(\text{K/BFP})^2$ (i, t)	-7,570***	-7,095***	-6,929***	-6,657***	-1,123***	-1,301***	-1,188***	-1,265***
	(822.0)	(737.8)	(737.3)	(993.9)	(246.1)	(230.5)	(226.6)	(308.3)
BB+HBP/BFP (i, t)	-3,453***	-1,851***	-1,704***	-1,978***	206.2	163.1	180.1	531.0**
	(412.6)	(346.4)	(352.2)	(507.8)	(253.6)	(229.2)	(215.5)	(247.6)
$(\text{BB+HBP/BFP})^2$ (i, t)	-5,233***	-8,666***	-9,337***	-9,822***	-4,674***	-4,104***	-4,017***	-4,872***
	(1,950)	(1,623)	(1,672)	(2,390)	(1,123)	(1,007)	(946.2)	(1,048)
Starter H-HR/BFP (-i, t)	-20,683***	-11,443***	-119.2	1,541	-2,736	-692.6	2,139	5,907*
	(3,435)	(2,873)	(3,163)	(3,901)	(2,956)	(2,920)	(2,952)	(3,281)
Starter $(\text{H-HR/BFP})^2$ (-i, t)	51,048***	31,662***	5,050	1,416	5,747	1,519	-4,166	-13,096*
	(7,988)	(6,690)	(7,387)	(9,147)	(7,018)	(6,954)	(7,001)	(7,812)

Starter HR/BFP (-i, t)	-9,594***	-3,374**	3,242	3,126	2,872	3,056*	2,374	1,375
	(1,645)	(1,456)	(2,338)	(2,642)	(1,764)	(1,650)	(1,977)	(2,329)
Starter $(HR/BFP)^2$ (-i)	216,882***	136,302***	39,323	38,785	-69,773**	-57,118*	-15,512	3,857
	(34,524)	(30,765)	(47,985)	(54,025)	(33,873)	(31,669)	(37,037)	(44,045)
Starter K/BFP (-i, t)	-2,415***	-2,594***	-3,019***	-3,665***	-22.34	-40.27	-599.6	-1,301*
	(578.9)	(507.0)	(599.6)	(733.8)	(494.8)	(481.8)	(546.6)	(722.7)
Starter $(K/BFP)^2$ (-i, t)	6,258***	8,413***	11,015***	12,719***	-1,857	-1,222	1,829	3,985*
	(1,966)	(1,718)	(1,979)	(2,448)	(1,539)	(1,494)	(1,670)	(2,201)
Starter BB+HBP/BFP (-i, t)	-8,358***	-6,798***	-3,066**	-2,374	-1,852	-1,390	-736.8	472.3
	(1,755)	(1,525)	(1,451)	(1,760)	(1,226)	(1,113)	(1,124)	(1,416)
Starter $(BB+HBP/BFP)^2$ (-i, t)	57,857***	49,506***	29,639***	26,597***	12,237*	10,137	7,047	466.3
	(9,425)	(8,254)	(7,894)	(9,655)	(6,842)	(6,213)	(6,255)	(7,837)
Bullpen H-HR/BFP (-i, t)	-127.0	-131.3	21.90	-51.17	-39.98	115.6	214.8	112.6
	(178.3)	(155.9)	(151.1)	(151.9)	(463.5)	(513.1)	(538.5)	(690.3)
Bullpen $(H-HR/BFP)^2$ (-i, t)	178.7	128.3	-80.24	23.66	150.5	-201.8	-290.8	-168.7
	(249.3)	(216.7)	(216.2)	(218.2)	(1,050)	(1,215)	(1,277)	(1,655)
Bullpen HR/BFP (-i, t)	-394.4	-383.5	-277.4	34.84	-6.489	-33.83	463.2	457.1
	(419.4)	(353.7)	(360.7)	(382.4)	(370.4)	(336.5)	(351.4)	(530.2)
Bullpen $(HR/BFP)^2$ (-i, t)	-807.8	-1,028	-1,532	-3,724	497.9	1,492	-2,332	-4,209
	(3,846)	(2,836)	(3,042)	(3,250)	(4,112)	(3,254)	(3,840)	(7,983)
Bullpen K/BFP (-i)	-631.4***	-386.9**	-88.41	-162.3	-220.1	-181.8	-537.5**	128.9
	(215.6)	(187.2)	(191.0)	(204.7)	(228.0)	(227.1)	(260.4)	(374.1)
Bullpen $(K/BFP)^2$ (-i, t)	535.2	-100.2	-357.7	-319.6	-146.7	-0.680	1,698**	-179.6

	(728.9)	(634.6)	(656.2)	(717.6)	(637.4)	(627.9)	(713.9)	(1,014)
Bullpen BB+HBP/BFP (-i, t)	92.45	5.571	44.80	39.42	102.8	25.11	221.0	-13.37
	(111.9)	(99.08)	(96.21)	(108.0)	(135.5)	(131.0)	(134.9)	(171.7)
Bullpen $(BB+HBP/BFP)^2$ (-i, t)	-9.581	97.35	72.56	-0.466	-496.7*	-229.6	-611.1*	269.3
	(148.5)	(134.4)	(140.3)	(170.2)	(299.7)	(283.6)	(315.0)	(534.8)
Team R/G	54.55***	33.16***	5.300	-2.351	-0.503	-2.302	-3.389	-3.812
	(4.679)	(4.117)	(4.317)	(5.326)	(2.625)	(2.516)	(2.779)	(3.554)
BFP (i, t-1)		0.354***	0.333***	0.178***		0.244***	0.240***	0.0949***
		(0.00740)	(0.00725)	(0.00896)		(0.0107)	(0.0105)	(0.0147)
Age		-10.43**	-3.323	25.78***		3.168	4.259	13.05**
		(4.982)	(4.725)	(8.078)		(3.430)	(3.362)	(5.279)
Age^2		0.0593	-0.0340	-0.707***		-0.0846	-0.0978*	-0.240***
		(0.0808)	(0.0770)	(0.134)		(0.0537)	(0.0528)	(0.0735)
Career Average All-star Starting (t-1)		134.5**	151.8***	-89.52		-478.3**	-297.6	-2,999***
		(55.79)	(56.03)	(67.67)		(209.9)	(228.1)	(565.3)
Year	N	N	Y	Y	N	N	Y	Y
Player	N	N	N	Y	N	N	N	Y
Constant	2,836***	1,755***	577.1	15.15	504.4	144.7	-281.7	-922.4**
	(369.4)	(317.5)	(383.7)	(456.9)	(312.9)	(316.1)	(319.3)	(366.7)
Observations	12,170	12,170	12,170	12,170	4,904	4,904	4,904	4,904
R-squared	0.338	0.483	0.517	0.367	0.251	0.357	0.415	0.323
Number of players				2,918				1,655

Robust std. errors in (); *** p<0.01, ** $p < 0.05$, * $p < 0.1$.

Tables 6 is the BFP determination model results for the MLB starting and bullpen pitchers across different periods. Since the teams in early periods often let the starting pitchers complete all games and didn't really have relief pitchers, the earliest two periods for MLB bullpen are skipped. The results across the periods are quite similar: player performance matters, while teammate performance means little. Among the player performances, the chance of allowing home runs seems to be more strongly linked with working time than other performance indicators. For both starting and bullpen pitchers across all periods, although some of the first-order HR/BFP coefficients are insignificant, the HR/BFP squared-term coefficients are all strongly significant and negative. As for the teammate influence, however, almost none of the coefficients for the teammate performances across the periods are significant.

Table 6: MLB pitchers' BFP determination in different periods

	Starter					Bullpen	
	-1900	1901-1930	1931-1946	1947-1972	1973-	1947-1972	1973-
H-HR/BFP (i, t)	-19,366	8,180**	16,276***	10,522***	10,169***	282.6	2,343***
	(18,051)	(3,883)	(4,650)	(2,474)	(1,431)	(1,135)	(331.3)
$(H\text{-}HR/BFP)^2$ (i, t)	29,555	-23,874***	-40,901***	-33,745***	-29,450***	-2,403	-6,851***
	(36,841)	(8,082)	(10,090)	(5,723)	(3,255)	(2,642)	(796.8)
HR/BFP (i, t)	1,904	-861.6	10,165*	8,594***	6,279***	1,476	700.9*
	(30,074)	(4,171)	(5,258)	(2,633)	(1,279)	(1,346)	(370.5)
$(HR/BFP)^2$ (i, t)	-2,9280,00*	-381,980**	-478,512***	-341,239***	-193,942***	-70,221***	-39,099***
	(176,100)	(153,597)	(177,547)	(50,654)	(20,697)	(25,342)	(5,938)
K/BFP (i, t)	7,212	3,560***	4,871***	1,411**	1,962***	314.4	562.5***
	(6,323)	(1,186)	(1,142)	(705.9)	(436.7)	(594.4)	(145.8)
$(K/BFP)^2$ (i, t)	-35,513	-10,583*	-15,570***	-2,774	-5,171***	-157.4	-1,125***
	(27,511)	(5,444)	(5,060)	(2,274)	(1,250)	(1,983)	(318.1)
BB+HBP/BFP (i, t)	2,110	-2,975*	-2,463*	-2,559***	-1,571**	1,385	527.7**
	(12,745)	(1,520)	(1,359)	(970.4)	(656.6)	(908.0)	(238.3)
$(BB+HBP/BFP)^2$ (i, t)	-3,874	-9,866	-11,660*	-7,972*	-9,524***	-11,951***	-4,586***
	(61,180)	(7,093)	(6,544)	(4,649)	(3,048)	(4,204)	(982.2)
Starter H-HR/BFP (-i, t)	6,585	-6,896	-17,280	8,214	-1,007	-2,457	1,906
	(32,670)	(11,634)	(12,579)	(8,829)	(7,486)	(10,612)	(3,876)
Starter $(H\text{-}HR/BFP)^2$ (-i, t)	11,036	18,127	42,860	-10,998	4,734	11,006	-4,130

	(72,630)	(24,914)	(27,453)	(21,770)	(17,563)	(26,872)	(9,148)
Starter HR/BFP (-i, t)	-56,761	12,088	-23,937*	-6,857	3,788	-10,827	1,684
	(78,281)	(9,034)	(12,900)	(8,042)	(4,050)	(9,068)	(2,597)
Starter $(HR/BFP)^2$ (-i)	3,680,00	-147,321	1,060,000**	288,100	5,168	282,380	-6,862
	(5,763,000)	(416,051)	(452,811)	(181,368)	(77,121)	(210,877)	(48,608)
Starter K/BFP (-i, t)	-28,648**	-4,140	17.49	-5,779***	-774.1	-624.0	-780.6
	(11,779)	(2,860)	(3,746)	(1,828)	(1,223)	(2,867)	(803.9)
Starter $(K/BFP)^2$ (-i, t)	137,783**	11,496	-970.3	20,639***	3,028	3,113	2,141
	(53,720)	(15,303)	(19,811)	(6,095)	(3,863)	(9,016)	(2,430)
Starter BB+HBP/BFP (-i, t)	-25,173	2,829	-1,423	-2,986	-2,664	-2,730	837.3
	(23,742)	(4,644)	(4,585)	(2,984)	(2,438)	(4,476)	(1,483)
Starter $(BB+HBP/BFP)^2$ (-i, t)	170,185	7,252	23,357	30,511*	23,169*	21,396	-1,772
	(139,965)	(26,692)	(25,782)	(15,755)	(13,360)	(25,079)	(8,204)
Bullpen H-HR/BFP (-i, t)	-1,219	-9.595	-264.0	610.2	-1,326	-658.4	546.2
	(1,113)	(196.7)	(973.9)	(784.9)	(2,003)	(835.1)	(1,218)
Bullpen $(H-HR/BFP)^2$ (-i, t)	185.3	-12.98	97.28	-1,257	3,673	1,700	-1,178
	(2,541)	(248.9)	(1,860)	(1,837)	(4,830)	(1,915)	(2,987)
Bullpen HR/BFP (-i, t)	-7,696	-177.6	1,134	857.2	-1,428	891.1	-1,277
	(8,702)	(978.7)	(890.2)	(1,351)	(2,319)	(887.2)	(1,436)
Bullpen $(HR/BFP)^2$ (-i, t)	221,481	-8,284	-8,680	-15,963	31,962	-10,732	37,109
	(189,345)	(14,335)	(5,464)	(24,025)	(48,872)	(9,510)	(31,126)
Bullpen K/BFP (-i)	-4,091*	-278.8	-206.4	92.92	-185.3	-17.00	54.63
	(2,405)	(314.2)	(609.5)	(598.0)	(851.3)	(689.3)	(446.4)

Bullpen $(K/BFP)^2$ (-i, t)	18,392	439.4	-973.1	-1,114	-315.6	455.1	51.46
	(13,560)	(1,405)	(3,116)	(2,123)	(2,366)	(2,265)	(1,165)
Bullpen BB+HBP/BFP (-i, t)	1,174	-13.11	-131.9	237.4	1,763	-263.4	2,536**
	(1,499)	(147.7)	(358.7)	(345.3)	(1,989)	(590.8)	(987.6)
Bullpen $(BB+HBP/BFP)^2$ (-i, t)	-9,464*	67.63	578.8	-188.3	-6,385	1,136	-11,620**
	(4,953)	(192.7)	(1,074)	(783.9)	(9,302)	(1,949)	(4,627)
Team R/G	121.7*	-2.961	-33.79**	-5.370	6.352	-2.949	-4.062
	(62.63)	(13.96)	(14.36)	(10.68)	(7.987)	(11.91)	(3.694)
BFP (i, t-1)	0.138	0.111***	0.112***	0.203***	0.174***	0.0992**	0.0856***
	(0.0966)	(0.0252)	(0.0236)	(0.0161)	(0.0125)	(0.0430)	(0.0158)
Age	327.9	46.23	33.91	52.17***	19.10*	23.09*	6.058
	(238.8)	(35.23)	(23.44)	(17.21)	(9.963)	(12.92)	(5.125)
Age^2	-8.698*	-1.163**	-1.034***	-1.126***	-0.544***	-0.481***	-0.230***
	(4.582)	(0.586)	(0.371)	(0.293)	(0.167)	(0.183)	(0.0804)
Career Average			-325.1	6.398	-54.66	7,206	-3,055***
All-star Starting (t-1)[a]			(253.1)	(104.5)	(77.35)	(19,422)	(599.0)
Year & Player Dummies	Y	Y	Y	Y	Y	Y	Y
Constant	1,314	631.8	1,008	-1,393	-228.3	302.4	-378.3
	(4,668)	(1,614)	(1,439)	(954.9)	(814.9)	(1,085)	(432.8)
Observations	167	1,894	1,376	2,698	6,035	685	4,133
R-squared	0.621	0.328	0.433	0.411	0.374	0.388	0.327
Number of players	88	569	408	680	1,474	320	1,318

Robust std. errors in (); *** $p<0.01$, ** $p < 0.05$, * $p < 0.1$. [a]: the 1st All-stars game took place in the 3rd period (1933).

It is generally accepted that as working hours increase, productivity eventually drops (Barzel, 1973), but it is hard to test this theory on the baseball field because a drop in productivity will also lead to a reduction of a player's working time. In other words, an increase in working time decreases productivity, which in turn decreases a player's working time, and thus makes the net effect obscure. However, the influence of overwork on a player's productivity in the next season can be tested Tables 7 to 9 report the effects of overwork on a player's future working time and performance. In a nutshell, there seems to be a general reduction of working time for the overworked batters who play less in the next season and are more likely to get strikeouts. The future working time of the overworked pitchers is not affected, but they throw more walks, and the overworked starting pitchers also throw less strikeouts.

Tables 7 to 9 also report the results from the Cox hazard models in the last row of each table. In general, overwork increases the probability of retirement for the batters and bullpen pitchers, but not for the starting pitchers. Besides overwork, the significance of performance parameters (not shown) for both the batters and pitchers confirms the conclusion that better performance leads to lower exit rates (Spurr & Barber, 1994; Hoang & Rascher, 1999; Frick, Pieztner & Prinz, 2007). On the other hand, it is interesting to note that in the latest period, the influences of Career Average All-star for the batters and bullpen pitchers are positive, which means star players retire earlier. The fact that free agency was born in this period may have something to do with this result. Star players may be less willing to stay in MLB because they earn a lot of money. However, such an effect does not occur to the starting pitchers. Further research needs to be done pertaining to the relationship between a player's lifetime earning and his decision to retire.

Table 7: The influence of overwork on MLB batters

Teammate Influence (t-1) on:	All	-1900	1901-1930	1931-1946	1947-1972	1973-
PA	-0.227***	-0.167**	-0.215**	-0.128	-0.320***	-0.227***
	(0.0282)	(0.0816)	(0.0878)	(0.177)	(0.0690)	(0.0372)
1B/PA	-0.0000092	0.000022	0.000026	-0.000078*	-0.000027	-0.0000067
	(0.000077)	(0.000034)	(0.000027)	(0.000041)	(0.000021)	(0.0000098)
2B/PA	0.0000031	0.000030**	0.000020	-0.000027	-0.00000008	0.0000008
	(0.0000038)	(0.000013)	(0.000014)	(0.000025)	(0.0000083)	(0.0000082)
3B/PA	-0.0000011	-0.000012	0.0000051	-0.0000032	-0.0000005	-0.0000004
	(0.0000017)	(0.0000079)	(0.0000059)	(0.0000077)	(0.0000046)	(0.0000021)
HR/PA	-0.0000022	0.00002***	0.0000002	-0.0000002	-0.0000046	-0.0000043
	(0.0000026)	(0.000007)	(0.000005)	(0.000012)	(0.0000064)	(0.0000036)
K/PA	0.000022**	-0.000065	0.00008***	0.000135**	0.0000019	0.000018
	(0.000098)	(0.000042)	(0.000027)	(0.000066)	(0.000028)	(0.000012)
BB+HBP/PA	0.0000036	0.000012	-0.000019	-0.000059	0.000025	0.0000083
	(0.0000072)	(0.000028)	(0.000026)	(0.000043)	(0.000019)	(0.000009)
Retire[b]	0.00206***	0.00466**	0.00556***	0.00759***	0.00791***	0.000626
	(0.000553)	(0.00220)	(0.00143)	(0.00216)	(0.00132)	(0.000821)

Robust std. errors in (); *** p<0.01, ** p < 0.05, * p < 0.1.

The model estimating the influence on PA controls the player's current performance, capacity, structural variables, and current teammate performance. The other models control previous performance, capacity, and structural variables.

b: Cox's proportional hazard model

Table 8: The influence of overwork on MLB starting pitchers

Teammate Influence (t-1) on:	All	-1900	1901-1930	1931-1946	1947-1972	1973-
BFP	0.0610	1.147**	0.204	-0.117	0.0548	0.0403
	(0.0469)	(0.574)	(0.146)	(0.154)	(0.0874)	(0.0637)
H-HR/BFP	0.0000055	0.0000406	0.000031*	0.0000014	(0.0000027)	0.0000028
	(0.0000057)	(0.0000536)	(0.0000177)	(0.0000176)	(0.0000115)	(0.0000079)
HR/BFP	0.0000037*	-0.0000013	-0.0000004	0.0000059	0.0000015	0.0000029
	(0.0000022)	(0.0000058)	(0.0000026)	(0.0000054)	(0.0000043)	(0.0000034)
K/BFP	-0.000015**	(0.0000363)	-0.000026**	-0.0000242	-0.0000038	-0.0000127
	(0.0000061)	(0.0000388)	(0.0000111)	(0.0000179)	(0.0000129)	(0.0000096)
BB+HBP/BFP	0.000017***	0.0000229	0.000034***	0.000037**	0.000033***	0.0000016
	(0.0000051)	(0.0000291)	(0.0000130)	(0.0000153)	(0.0000112)	(0.0000069)
Retire[b]	0.000457	0.000008	-0.000111	-0.00185	0.00032	0.00161**
	(0.00046)	(0.00218)	(0.00079)	(0.00141)	(0.0013)	(0.00079)

Robust std. errors in (); *** p<0.01, ** p < 0.05, * p < 0.1.

The model estimating the influence on PA controls the player's current performance, capacity, structural variables, and current teammate performance. The other models control the previous performance, capacity, and structural variables.

b: Cox's proportional hazard model

Table 9: The influence of overwork on MLB bullpen pitchers

Teammate Influence (t-1) on:	All	1947-1972	1973-
BFP	0.0334	0.118	0.0319
	(0.0349)	(0.133)	(0.0370)
H-HR/BFP	0.000010	0.000053	0.000003
	(0.000016)	(0.000051)	(0.000017)
HR/BFP	0.000002	0.000023	-0.0000015
	(0.000007)	(0.000023)	(0.000007)
K/BFP	-0.000012	-0.000017	-0.000012
	(0.000018)	(0.000052)	(0.000020)
BB+HBP/BFP	0.000043***	0.000060	0.000043**
	(0.000016)	(0.000056)	(0.000017)
Retire[b]	0.0019***	0.0025*	0.00151*
	(0.00069)	(0.00142)	(0.000811)

Robust std. errors in (); *** p<0.01, ** p < 0.05, * p < 0.1.

The model estimating the influence on PA controls the player's current performance, capacity, structural variables, and current teammate performance. The other models control previous performance, capacity, and structural variables.

[b]: Cox's proportional hazard model

Tables 10 and 11 follow the discrete hazard model (Saint Onge, et al., 2008). The data are segmented by time period. However, the period from 1973 to the present is skipped, because most players from this period are still alive. Pitchers who started at least 5 games per season are counted as starting pitchers, while the others are viewed as bullpen pitchers. In addition, since the last period is removed, only one period and therefore one column is left for the bullpen pitchers. The first period for the starting pitchers is also removed because there are not enough samples.

Overwork doesn't seem to have a great influence on a player's lifespan. In Tables 10 and 11, only in two cases among all the interaction terms between overwork and age groups across all the periods does overwork have a positive influence on mortality.

There are even more cases in which overworked players have a lower mortality rate, but for the most part, overwork has nothing to do with a player's lifespan.

The results from the age groups are to some degree in line with the result concluded by Saint Onge et.al (2008) that mortality rate declines in more recent calendar periods. In the samples of starting pitchers, for the first 2 periods, even after controlling the mortality rate of the US population, the players still suffer a higher mortality rate as they age. In the 3rd period, the mortality rates of the starting pitchers in different age groups are not significantly different from the US population. However, starting pitchers in the 4th period show a decline in their mortality rate in their 70s and 80s. The sample for the batters shows similar but less obvious results. The batters from the latest period have a lower mortality rate for the age group of 75-79 and 85 and above. Another observation indicates that nearly all performance measures have no effect on a player's mortality rate, which corresponds to the result demonstrated by Saint Onge et.al (2008).

As for the influence of debut age, the results here do not support the precocity-longevity hypothesis proposed by McCann (2001) and Abel and Kruger (2007). Debut age almost have no effect on a player's mortality rate across all the periods, which goes against McCann’s argument of the shorter lifespan for early achievers, and may require more detailed inspection.

The healthy worker effect is not observed here on the part of baseball players, either. Career longevity is uncorrelated to a player's mortality rate except for starting pitchers from one period. Starting pitchers debuting between 1901 and 1930 have a smaller mortality rate the longer they play. This result from this period matches the report of Abel and Kruger (2006), who demonstrated that players during 1901 and 1939 lived longer as they played longer. However, such an effect does not occur in batters, bullpen pitchers, and starting pitchers from other periods, and the overall results cannot support the healthy worker effect. On the other hand, the results from Tables 10 and 11 do support the results by Able and Kruger (2004). The mortality rate of left-handed players is not significantly different from that of the right-handed players.

Table 10: Discrete hazard regression results for the MLB Batters

	All	Pre-1900	1901-1930	1931-1946	1947-1972
55-59	1.167	-0.821	4.812	9.719	0.423
	(1.606)	(3.926)	(4.065)	(10.21)	(4.831)
60-64	4.674***	8.487**	6.890*	10.02	2.514
	(1.618)	(3.304)	(3.727)	(10.20)	(3.965)
65-69	1.419	1.049	0.682	6.813	0.173
	(1.421)	(3.134)	(3.510)	(8.111)	(3.786)
70-74	1.777	3.237	1.551	-0.915	-3.017
	(1.563)	(3.255)	(3.113)	(8.180)	(3.999)
75-79	1.134	-0.255	0.426	6.299	-9.648*
	(1.653)	(3.641)	(3.179)	(8.040)	(5.411)
80-84	1.323	-1.311	1.100	9.313	-2.068
	(1.809)	(5.575)	(3.396)	(7.697)	(7.889)
85-	4.802**	7.824*	6.320	8.027	-28.44**
	(2.189)	(4.212)	(4.372)	(8.216)	(12.48)
Average Overwork	0.00124	7.29e-05	-0.00273	0.0135	-0.000553
	(0.00211)	(0.00512)	(0.00487)	(0.0120)	(0.00532)
55-59	-0.00225	0.00113	-0.00840	-0.0172	-0.00110
* Average Overwork	(0.00270)	(0.00719)	(0.00738)	(0.0176)	(0.00743)
60-64	-0.00784***	-0.0140**	-0.0129*	-0.0179	-0.00403
* Average Overwork	(0.00278)	(0.00615)	(0.00679)	(0.0176)	(0.00614)
65-69	-0.00123	8.04e-05	0.000208	-0.0110	-8.12e-05
* Average Overwork	(0.00240)	(0.00573)	(0.00625)	(0.0140)	(0.00587)
70-74	-0.00151	-0.00331	-0.000946	0.00248	0.00437
* Average Overwork	(0.00266)	(0.00599)	(0.00554)	(0.0140)	(0.00624)
75-79	-0.000109	0.00222	0.00154	-0.00911	0.0126
* Average Overwork	(0.00283)	(0.00656)	(0.00565)	(0.0138)	(0.00858)
80-84	-0.000281	0.00349	4.75e-05	-0.0138	-0.00300

* Average Overwork	(0.00311)	(0.00985)	(0.00602)	(0.0132)	(0.0133)
85-	-0.00632*	-0.0104	-0.00911	-0.0113	0.0376*
* Average Overwork	(0.00379)	(0.00793)	(0.00771)	(0.0141)	(0.0204)
Mortality Rate	10.35***	11.32*	8.489***	7.535***	118.2***
	(1.159)	(5.870)	(2.525)	(1.725)	(11.29)
Debut Age	-0.00829	-1.250**	0.210	0.0106	-0.168
	(0.140)	(0.614)	(0.352)	(0.278)	(0.338)
Debut Age^2	-0.000111	0.0278**	-0.00557	-0.000251	0.00379
	(0.00278)	(0.0129)	(0.00717)	(0.00550)	(0.00677)
Left-handed	0.0204	0.124	-0.267	0.0271	0.0445
	(0.104)	(0.400)	(0.210)	(0.201)	(0.221)
Years Played	-0.0171	-0.158	-0.0481	0.0753	0.0250
	(0.0317)	(0.117)	(0.0602)	(0.0624)	(0.0760)
Years Played^2	-0.000539	0.00387	0.000576	-0.00434	-0.00267
	(0.00139)	(0.00432)	(0.00270)	(0.00295)	(0.00322)
1B/PA	5.234	-34.64	-17.38	14.03	79.01*
	(16.47)	(118.0)	(29.25)	(34.60)	(40.73)
$(1B/PA)^2$	-9.248	117.6	56.42	-25.64	-247.0**
	(45.91)	(319.6)	(77.53)	(99.16)	(122.9)
2B/PA	-8.824	-43.60	29.38	-42.33	-86.23
	(15.64)	(71.93)	(27.52)	(44.24)	(61.48)
(2B/PA)^2	125.0	673.8	-322.3	569.5	1,317
	(184.6)	(957.1)	(294.2)	(559.0)	(900.9)
3B/PA	-18.65	108.5	-32.62	-110.3**	-20.57
	(20.32)	(106.1)	(38.84)	(51.94)	(58.37)
$(3B/PA)^2$	704.3	-2,278	852.1	5,343**	228.8
	(742.2)	(3,220)	(1,265)	(2,644)	(3,180)
HR/PA	22.10**	-97.51	-2.943	46.44**	14.19
	(10.93)	(116.0)	(26.83)	(21.91)	(25.21)
$(HR/PA)^2$	-190.7	8,551	472.8	-727.0	-120.3
	(226.8)	(6,081)	(848.0)	(455.3)	(456.6)
K/PA	1.861	14.11	10.30*	-6.968	-5.365
	(2.835)	(9.314)	(5.618)	(8.405)	(7.434)
$(K/PA)^2$	-1.381	-80.40*	-25.06	31.73	21.19
	(10.90)	(43.06)	(25.18)	(38.92)	(22.23)
BB+HBP/PA	-3.202	-44.21***	7.919	10.82	-16.46
	(5.023)	(16.71)	(11.32)	(9.866)	(14.30)
$(BB+HBP/PA)^2$	22.20	218.6**	-42.16	-26.30	86.91

	(24.68)	(89.66)	(62.27)	(48.13)	(62.05)
PA/Season	0.00205*	0.00219	0.00103	0.00298	0.000795
	(0.00119)	(0.00599)	(0.00212)	(0.00212)	(0.00296)
$(PA/Season)^2$	-3.13e-06*	-5.20e-06	-2.93e-08	-6.81e-06**	2.70e-06
	(1.83e-06)	(8.48e-06)	(3.26e-06)	(3.29e-06)	(4.42e-06)
Birth Year Dummy	Y	Y	Y	Y	Y
Constant	-6.681**	15.02	-5.604	-14.40*	-6.232
	(2.835)	(13.89)	(5.558)	(8.333)	(6.358)
Observations	41,974	3,248	8,484	11,270	16,578

Robust std. errors in (); *** p<0.01, ** p < 0.05, * p < 0.1.

Table 12: Discrete hazard regression results for the MLB Pitchers

	Starter				Bullpen
	All	1901-1930	1931-1946	1947-1972	All
55-59	0.326	-0.146	0.687	0.662	-46.21*
	(0.259)	(0.516)	(0.485)	(0.583)	(23.89)
60-64	0.191	-0.256	0.430	0.510	-31.05
	(0.267)	(0.519)	(0.497)	(0.574)	(23.15)
65-69	0.594**	1.024**	-0.351	0.444	-1.336
	(0.253)	(0.428)	(0.558)	(0.598)	(24.57)
70-74	1.057***	1.160***	0.845*	0.280	13.46
	(0.243)	(0.427)	(0.476)	(0.621)	(29.88)
75-79	0.919***	1.174**	0.911*	-1.576*	-6.610
	(0.263)	(0.484)	(0.486)	(0.845)	(28.40)
80-84	0.761***	1.387**	0.795	-4.470***	60.50
	(0.291)	(0.564)	(0.519)	(1.305)	(45.10)
85-	0.217	1.054	0.136	-9.090***	237.1
	(0.419)	(0.853)	(0.697)	(2.802)	(342.2)
Average Overwork	0.000472	-0.00202	0.00707	-0.00423	0.0133
	(0.00259)	(0.00310)	(0.00475)	(0.00658)	(0.0460)
55-59* Average Overwork	-0.00130	0.00616	-0.0150**	0.00917	0.0812*
	(0.00331)	(0.00487)	(0.00610)	(0.00727)	(0.0423)
60-64* Average Overwork	-0.00516	-0.00334	-0.0150**	0.00317	0.0572

	(0.00335)	(0.00567)	(0.00707)	(0.00748)	(0.0417)
65-69* Average Overwork	-0.00271	0.00177	-0.000500	0.00129	0.00493
	(0.00331)	(0.00395)	(0.00658)	(0.00847)	(0.0445)
70-74* Average Overwork	-0.000565	0.000455	-0.00395	-0.00195	-0.0223
	(0.00297)	(0.00378)	(0.00591)	(0.00761)	(0.0544)
75-79* Average Overwork	0.00119	0.00504	-0.00733	0.000222	0.0131
	(0.00283)	(0.00352)	(0.00540)	(0.00790)	(0.0525)
80-84* Average Overwork	-0.00286	0.00181	-0.0100*	-0.0117	-0.107
	(0.00295)	(0.00348)	(0.00532)	(0.0126)	(0.0833)
85-* Average Overwork	-0.00122	-0.00388	-0.00681	-0.00560	-0.428
	(0.00345)	(0.00641)	(0.00527)	(0.0138)	(0.613)
Mortality Rate	20.54***	13.21***	21.72***	150.9***	93.42
	(2.312)	(4.378)	(3.523)	(21.72)	(57.88)
Debut Age	0.108	-0.00791	0.505	-0.710	2.708
	(0.199)	(0.494)	(0.429)	(0.584)	(2.064)
Debut Age^2	-0.00328	-0.00194	-0.0113	0.0149	-0.0560
	(0.00408)	(0.0103)	(0.00881)	(0.0122)	(0.0421)
Left-handed	0.142	0.470**	-0.140	-0.226	0.185
	(0.121)	(0.191)	(0.238)	(0.334)	(0.518)
Years Played	-0.0182	0.0460	-0.124	-0.0877	-0.202
	(0.0537)	(0.0867)	(0.109)	(0.142)	(0.263)
Years Played^2	-0.00206	-0.00716*	0.00379	0.00382	0.00987
	(0.00240)	(0.00420)	(0.00501)	(0.00542)	(0.0120)
H-HR/BFP	89.55*	159.0	120.3	116.6	277.4

	(50.95)	(115.6)	(128.9)	(197.9)	(225.7)
$(H\text{-}HR/BFP)^2$	-205.6*	-339.3	-276.2	-284.7	-732.1
	(109.5)	(241.7)	(285.3)	(477.0)	(562.1)
HR/BFP	68.14	108.7	19.69	-40.44	519.7
	(46.78)	(73.20)	(124.1)	(159.8)	(402.4)
$(HR/BFP)^2$	-2,247	-2,812	-1,189	-185.4	-12,239
	(1,410)	(3,175)	(3,858)	(3,589)	(9,687)
K/BFP	-5.531	-21.10	10.00	-37.31	22.25
	(9.689)	(21.09)	(36.23)	(23.37)	(40.99)
$(K/BFP)^2$	37.68	144.6	-44.17	150.3*	-19.31
	(41.80)	(114.6)	(180.9)	(78.78)	(126.6)
BB+HBP/BFP	-9.359	-21.95	-18.61	9.468	-10.71
	(11.63)	(16.67)	(25.88)	(53.94)	(85.05)
$(BB+HBP/BFP)^2$	47.93	111.4	92.94	-51.05	20.99
	(53.77)	(74.59)	(117.6)	(257.0)	(384.7)
BFP/Season	0.000444	0.00219	0.00434	-0.00303	0.0128
	(0.000993)	(0.00249)	(0.00310)	(0.00425)	(0.0182)
$(BFP/Season)^2$	-1.17e-07	-8.17e-07	-3.64e-06	9.32e-07	-2.40e-05
	(7.08e-07)	(1.94e-06)	(2.76e-06)	(4.11e-06)	(3.57e-05)
Birth Year Dummy	Y	Y	Y	Y	Y
Constant	-15.36**	-21.52	-22.53	-6.012	-78.89*
	(6.555)	(14.93)	(15.35)	(21.51)	(44.32)
Observations	19,419	4,579	5,486	8,062	3,069

Robust std. errors in (); *** p<0.01, ** p < 0.05, * p < 0.1.

5. Actual Significance of Overwork on a Player's Career

The working time difference derived from teammate performance can be used to estimate the economic significance of the regression results. Specifically, comparisons of the working time differences and retirement probability are made between the average players and the overworked players to give an estimation of the actual harm caused by overwork. Table 12 reports the comparison results. The mean lagged working time influenced by teammate performance for the highest overworked players (assume to be those with the highest 10%) is retrieved to compare with the population average. This number is then multiplied by the coefficient in the working time model and the retirement probability model to see how the overworked players differ from the average players in terms of working time and retirement probability. The overworked batters will have 30 fewer plate appearances per year compared to the average players, which could be translated into 7 or 8 fewer games played for a regular starter. As for retirement, the overworked batters have 27.4% higher chance to retire for the next season, while the bullpen pitchers are about 17% more likely to retire.

Table 12: The overwork effect on the players' career

	Batter	Bullpen
Highest 10% Teammate Influence (t-1) - Average Teammate Influence (t-1)	133.244	91.06
Coefficient of Teammate Influence (t-1) in Working Time Model	-0.227	NA
Working Time Difference	**-30.25**	**NA**
Coefficient of Teammate Influence (t-1) in Retirement Model	0.00206	0.0019

Retirement Chance Difference	**0.274**	**0.17**

6. Conclusion and Discussion

This study aims at two goals. The first is to examine the working time of professional baseball players to see if there is a overwork phenomenon in the baseball field. The second is, if overwork exists, to make clear how overwork influences the career of MLB players.

It is not easy to judge if the phenomenon of overwork exists in professional baseball, since there is not even standard working hours for professional baseball players. In this research, I try to estimate the optimal working time based on a player's performance and capacity. However, a player's working time may also be influenced by his teammates' performance, due to either within-team competition or postseason race. Because such influence cannot be controlled by the player, this part of working time influence can be defined as unplanned working time and be regarded as a source of overwork. In MLB, a batter's current unplanned working time seems to be negatively related to the total working time for the next season. The batters who work more than their optimal working time tend to work less in the next season, while those who work under their optimal working time are inclined to work more in the next season, but this conclusion is not applicable to the pitchers. However, overwork does affect the performance of both the pitchers and the batters. Overworked batters are more inclined to strike out more. Overworked starting pitchers give up more home runs and walks and strike out the batters less often, and overworked bullpen pitchers give more walks. Moreover, having high unplanned working time will increase the probability of retirement for the batters and bullpen pitchers. The overworked batters have a 27.4% higher chance to retire, while the overworked bullpen pitchers have a 17% higher chance to retire in the following year. The influence of unplanned working time on the lifespan of the players is more ambiguous. In some cases, overwork is actually positively related to a player's lifespan, but for the most parts, overwork has no effect on a player's future mortality rate.

It is not surprising that overwork has little effect on a player's lifespan in view of the unusually brief career length on the baseball field. Given the fact that the career length in the professional leagues is much shorter than the span of normal employment, most of the professional players embark on a second career after their early retirement. After the players retire, some of them continue to work in some affiliated business with baseball, while others may switch to completely different careers. Only a few of them may stay home and enjoy their life after retirement. For most retired players, their second career is more likely to last longer than his first and may affect significantly on their health and their lifespan. Therefore, their life after retiring from the professional baseball league may count more in determining the lifespan of a player. However, it is quite difficult to track a player's career after his retirement. Some players left records as team managers, coaches, scouts, or amateur baseball players. It is easier to know how these players fared after their retirement, at least in a short while, since some of them would leave the baseball field within short years. For the other players who completely left the baseball field, it is hard to know what they did for a living. To get a more comprehensive and holistic understanding of the overwork impact on the lifespan of the players, the second career of the players is necessary to be taken into consideration.

Some other ways can also be employed to assess the workload of baseball players. Pitcher Abuse Point (PAP), a formula devised by Woolner and Jazayerli (2001), is usually considered a very popular method to measure a pitcher’s tendency to be abused, which means to be overworked, and the likeliness for him to cause arm troubles. In fact, PAP specifically focuses on the pitch counts by the starting pitcher and the accumulated effects of over 100 pitches. Besides these limitations, its credibility had been challenged by Bill James (2008), the Yoda of baseball statistician and the father of sabermetrics, who used 7 different control groups to prove that the pitchers identified as most abused performed better in the subsequent season. In view of these facts, the PAP may not serve my purpose in this study. Innings played is another way to estimate the workload of the position players. Instead of their batting chances, the working time of the batters can be more accurately captured by the amount of time they spent running on the field, which would be quite close to their innings played. However, innings played is not a traditional stat of the position players, so it is harder to compile or even find such data of the batters. Plus, innings played should be highly correlated to the PA of the batters, so using inning played may yield similar result to using PA.

Another question is that whether the time spent in the Minor Leagues, independent leagues, and foreign leagues should be included. MLB is not the sole baseball league in the world. Except for MLB, there are lots of opportunities for the players who failed to earn a spot in the Major League. There are Minor Leagues, semi-professional independent leagues, foreign leagues such as Nippon Professional Baseball or Korean Baseball Organization, and amateur leagues. Most MLB players have spent some time in the Minors during his career. Some Major League players even choose to join the independent league after the season is over to rehabilitate after a surgery or to show their capabilities to the scouts. Including the working time in these leagues may sound more comprehensive, but how to include these data is complicated and problematic. First, to get records from some of the leagues is quite difficult, especially the amateur leagues. Second, how to incorporate the records of different leagues involves very intricate analyses and considerations. The quantitative addition of the working time across different leagues together can be misleading because facing a batter in MLB may require more strength and concentration than in other leagues, and therefore be more tiresome. It will require a lot of work to sort out such differences between the various leagues.

The biggest problem of the model is that the estimation of overwork in this paper is *relative* overwork instead of *absolute* overwork. In contrast to the PAP as an absolute measure of overwork, the measure in this paper is a relative one; therefore, it is still possible that the overall players are all overworked or underworked. However, the estimation in this model won't be able to make such observation. Although it is not evidently enough to determine whether or not overwork exists in MLB, the results of this research indicate that players with relatively higher workload do perform worse and retire earlier than the others.

7 Reference

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2

Why Are There So Many Left-handed Players in MLB?[3]

1. Introduction

In baseball, batters are generally assumed to perform better when facing pitchers of the opposite handedness, as compared to facing pitchers of the same handedness. This prevailing belief is considered too self-evident to be disputed, as Casey Stegnel put it, "There is not much to it. You put a right-hand hitter against a left-hand pitcher and a left-hand hitter against a right-hand pitcher." (Albert & Bennet, 2003, p. 87) One of the oft-cited cases of the opposite-hand (OH) advantage in baseball is the miracle produced by the Boston Braves in 1914 when the team worked its way up from the bottom of the league table and, with the help of left-right platoon arrangements, eventually won the World Series.

There have been some qualitative explanations with regard to the origin of the OH advantage: the batter may have a slightly wider view when facing a pitcher throwing from the opposite side (Ryan et al., 1977, p. 66), be more observant, and hence make better swings. Or, a baseball thrown by a pitcher with the same handedness makes the batter feels like it is ”coming right at him” (Ryan et al., 1977, p. 67; Albert & Bennet, 2003, p. 87), which may keep him off kilter, and thus swing less effectively. It has also been proposed that curve balls thrown by pitchers tend to break ”away” from same-handed batters, and therefore make it more difficult for batters to make contact with (Adair, 1994).

Many studies involving opposite handedness in baseball have been devoted to the

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comparison of the stats, such as batting average or slugging average, between groups of players with different handedness (e.g., Lindsey, 1959; Thorn & Palmer, 1985; Grondin et al., 1999). However, OH advantage could alter the proportions of the left-handed players. Two frequently cited studies on the proportion of left-handed players in baseball and OH advantage are conducted by Goldstein and Young (1996) and Flanagan (1998). Both papers used game theory to derive the optimal percentage of left-handed players. Goldstein and Young used evolutionary stable strategy to predict the steady-state of the left-handed players and switch hitters, and their prediction is quite close to the actual numbers in MLB for the last four decades. Flanagan used a mixed-strategy game to elaborate the confrontations between pitchers and batters and derived the optimal percentages of the left-handed players. His model over-predicted the percentage of left-handed pitchers. This under-supply of left-handed pitchers, he concluded, may be due to biological constraints, which make right-handed pitchers difficult to train to throw with their left hand. Such under-supply may also result in the rise of right-pitch left-hit batters.

In the general population, about 10% of the people are left-handed (Groothuis et al., 2013). Some researchers find evidence of overrepresentation of left-handed players in interactive sports, such as tennis, cricket, volleyball and baseball (e.g., Raymond et al., 1996; Loffing, Hagemann, & Strauss, 2010). However, there are studies arguing that these findings are far from being conclusive (Wood & Aggleton, 1989). Our analysis was indeed motivated by the fact that the percentage of left-handed players in MLB in 2012 was 39.4% (219 out of 556) for batters[4] and 28.4% (188 out of 663) for pitchers. Even accounting for the fact that half of the left-handed batters are naturally right-handed players who chose to bat at the right side of the plate, this proportion of

[4] The left-handed player percentage does not include switch hitters, the players who choose to bat left-handed (right-handed) when facing right-handed (left-handed) pitchers.

left-handed players in MLB is still higher than in the general population or among other kinds of major league sports (NBA: 7%[5]; NFL: 7% for quarterbacks[6]; NHL is trickier, because a lot of hockey players choose to shoot with their left hand despite being natural right-handers[7]). Therefore, although people are always calling for the games to be played fairly, the game itself is not fair from the start. Baseball is greatly in favor of the left-handed players. Why, by simply being a lefty, your chance of playing in MLB is two to three times higher than the righties! The employment rate of left-handed baseball players is twice to three times higher than the right-handed players, yet no one seems to be complaining about that.

Furthermore, managers would often send left-handed (right-handed) pitchers to face powerful right-handed (left-handed) batters in later stages of games, or give some left-handed starting batters a break when the team is scheduled to face a left-handed pitcher. As a result, the statistics of hand-specific performance contain information of both players' ex ante OH advantage and ex post managerial strategies, which attenuates the apparent OH advantage to some extent. Here we provide a quantitative estimate of the OH advantage and an analysis that could sustain statistical scrutiny.

In addition to estimating the OH effect empirically, our analysis shed light on this issue in two more aspects. First, we disentangle the intrinsic ex-ante OH advantage and the ex-post PA choices by the manager. Second, we deal with the interaction and Nash equilibrium in baseball matchups. And because of the above two, we are able to answer the macro question: what percentage of left-handed players is explained by OH advantages? In other words, our motivation is not only to verify whether or not there is an OH advantage, but to identify the percentage of additional left-handed players

[5] See http://sports.espn.go.com/nba/dailydime?page=dime-091121-22

[6] See http://greatsportsnamehalloffame.blogspot.com/2009/07/there-have-been-only-32-left-handed.html

[7] In 2007 - 2008, 65% of NHL players shoot left. See http://en.wikipedia.org/wiki/Shot_%28ice_hockey%29

explained by OH advantage and determine how seriously MLB favors the left-handed players and influence their employment rate. To our knowledge, these have never been done before.

The remainder of this paper is arranged as follows. Section 2 provides some descriptive insights on baseball games. Sections 3 and 4 respectively describe the micro estimation setup and empirical estimation results. Sections 5 and 6 present the theoretical strategy and empirical results of player allocation, followed by a brief conclusion in section 7.

2. Some Facts in Professional Baseball Games

Suppose there is a world in which the OH advantage does not exist in baseball. In this world, the handedness of the players should have nothing to do with their performance, and the proportion of left-handed and right-handed players in MLB should be the same as the ratios found in the human population, which is about 10% and 90%, respectively.

In the real world, however, with the OH advantage being in effect, there should be more than 10% of left-handed batters in the league, mainly because they are capable of counteracting and taking advantage of the large proportion of right-handed pitchers in the league. When the number of left-handed batters goes up, the number of left-handed pitchers will also go up in order to counter the OH advantage from the left-handed batters. Thus, the OH advantage will increase the proportion of left-handed players to, say, 26%, and that of right-handed players will drop to 74%. But this also implies that the skill cut-off point will be different for the left-handed and right-handed players. Some left-handed pitchers not skillful enough to play in the hypothetical OH-less world will be selected, whereas some right-handed pitchers who are just skillful enough in the

OH-less world will be left out. As a result, the average skill level of right-handed pitchers in MLB should be higher than that of left-handed ones because "left handed pitchers do not have to be as good as right-handers to earn a roster spot in MLB" (Groothuis & Hill, 2008, p. 589). This argument also holds true to the batters. By the same token, in the NBA, the talent level of the over-represented taller players who have an inherent advantage is more dispersed than the smaller players (Berri et al., 2005).

Table 1 shows the on-base plus slugging (OPS), slugging percentage (SLG)[8], strikeouts per plate appearance (PA), and walks per PA by different kinds of players from 2000 to 2012. For right-(left-) handed batters, their OPS against the same-handed pitcher is 0.723 (0.698), and the number increases to 0.781 (0.787) when facing opposite-hand pitchers. The SLG, strikeouts per PA, and walks per PA also change from 0.408/0.174/0.085 to 0.440/0.158/0.102 for right-handed batters, and from 0.383/0.200/0.097 to 0.442/0.162/0.110 for left-handed ones. Two interesting observations emerge immediately. First, there seems to be an OH advantage on all these four stats. Batters get higher OPS and SLG, strike out less often, and draw more walks when facing an opposite-handed pitcher, but this advantage is not homogeneous between the left-handed and right-handed batters. By the handedness group average, the left-handed batters enjoy about 8% more on OPS and SLG and 13% more on strikeouts per PA compared to the right-handed batters, while the OH advantage in walks per PA for the left-handed batters is about 7% less than the right-handed ones Secondly, switch hitters do not appear to have any OH advantage in OPS and SLG, but there seems to be a small OH advantage in strikeouts per PA and disadvantage in walks per PA. Also, since the percentage of left-handed batters is higher than that of the left-handed pitchers, the skill cut-off for the left-handed batters must be lower. This can be shown in that

[8] OPS = OBP + SLG; OBP = [(Base Hits + Walks + Hit By Pitches)/Plate Appearances]; SLG = (Base Hits + Doubles + 2·Triples + 3·Homeruns)/At Bats

when facing pitchers with same handedness (RH vs. RP and LH vs. LP), right-handed batters perform better than left-handed ones in every aspect except for walks per PA.

Table 1: Pitcher and batting record by handedness,’00-’12

	OPS			SLG			Strikeouts per PA		
	RP	LP	All	RP	LP	All	RP	LP	All
RH	.723	.781	.740	.408	.440	.417	.174	.158	.170
SH	.729	.720	.727	.399	.395	.398	.160	.151	.158
LH	.787	.698	.766	.442	.383	.428	.162	.200	.171
All	.746	.749	.746	.418	.417	.418	.168	.169	.168

	Walks per PA			% of Samples		
	RP	LP	All	RP	LP	All
RH	.085	.102	.090	38%	15%	53%
SH	.101	.093	.099	11%	4%	15%
LH	.110	.097	.106	24%	7%	32%
All	.096	.099	.097	73%	27%	100%

The overall effect of left-handed players on team performance is somehow ambiguous, though. Table 2 is the regression results between team performance and the percentage of left-handed players during the modern baseball era (1976-present[9]). With the year dummies being controlled, the first column shows that having 1% more left-handed batters will increase the winning percentage by 0.095%, while having 1% more left-handed pitchers will decrease the winning percentage by 0.077%. The runs allowed and the runs scored show the same thing: left-handed pitchers allow more runs, while left-handed batters score more runs. Therefore, it is not clear whether having more left-handed players is good for the team or not.

Table 2: Team Performance and left-handed players (1975-2012)

	Winning%	Runs Allowed	Runs Scored
Left-handed Pitcher %	-0.077**	93.06***	
	(0.035)	(30.28)	
Left-handed Batter %	0.095**		72.58*
	(0.048)		(40.56)
Switch Hitter %	0.078		-91.99*
	(0.049)		(48.94)
Year Dummy	Y	Y	Y
Constant	0.52***	616.7***	665.7***
	(0.036)	(25.48)	(19.50)
Observations	1,054	1,054	1,054
R-squared	0.019	0.486	0.503

Robust std. errors in (); *** $p<0.01$, ** $p < 0.05$, * $p < 0.1$.

3. Data and Micro Estimation Setup

We use ordinary least squares as our benchmark model to estimate the

9 There weren't any significant changes on the rules of baseball after 1976, which is why we picked this year as the first year of modern baseball era.

opposite-hand effect. Data used in this research span the years from 2000 to 2012 and are retrieved from the Retrosheet website (2012) and the Lahman baseball database (2012). The Retrosheet website contains detailed play by play data for every batter vs. pitcher since 1940. The Lahman database provides additional information about each baseball player, such as the date of his major league debut, his throwing and batting hand, the teams and managers he played for in every season, games played at each defensive position, and so on.

In order to estimate the net effect of OH advantage, let $\beta_{i,j,t}$ be the OPS of batter *i* facing pitcher *j* at matchup *t*. We use OPS instead of batting average because OPS gives weight to both extra-base hits and walks and better captures the effectiveness of swings by batters described in section 1.[10] We assume that $\beta_{i,j,t}$ is composed of a group of variables:

$$\begin{aligned}\beta_{i,j,t} =& \propto_i + \theta_1 * E_{i,t} + \theta_2 E_{i,t}^2 + \rho OPSASH_{j,(t-1)} + \eta_1 BPA_{i,t} + \eta_2 Pos_{p(i),t} + C_m I_{m(i)} \\ &+ C_n I_{n(j)} + \mu_t Y_t + \gamma H_{i,j} + \eta_3 Day\ or\ Night\ Dummies_t \\ &+ \eta_4 Sky\ Dummies_t + \eta_5 Site\ Dummies_t + \eta_6\ Temperature_t \\ &+ \eta_7 Doubleheader_t + \varepsilon_{i,j,t} \qquad (1)\end{aligned}$$

In the above expression, $\propto_i$ is batter *i*'s skill fixed effect, while his experience effect is, following Mincer (1974), captured by $E_{i,t}$ and $E_{i,t}^2$, where $E_{i,t}$ is the number of years the batter played in MLB at matchup *t*. For pitchers, we control their status by their allowed OPS against same-handed batters in the previous season to matchup *t* (OPS$ASH_{j,(t-1)}$).[11] BPA_{it} is batter *i*'s total plate appearances in the season at matchup *t*. It captures the fact that managers tend to let good players bat more and reflects the skill level of the batter.

[10] Using batting average or SLG as a dependent variable yields similar results.

[11] A symmetric approach is to specify a pitcher's status as the sum of his fixed effect and experience effect as well. But when doing this, we will have a multi-collinearity problem: when the fixed effects for both batter *i* and pitcher *j* are specified, whether they are opposite hands or not ($H_{i,j}$) is also specified.

Term $Pos_{p(i),t}$ in (1) is the dummy for player i's defensive position p of the year at matchup t. Different positions require different defensive ability, which may be valued by the managers over batting performance. For instance, a manager is likely to demand the designated hitter to hit a certain number of home-runs, but unlikely to expect the same level of offense output from his catcher or shortstop, for their defensive ability may be as important as their batting performance. $I_{\mathrm{m(i)}} = 1$ stands for player i's manager name tag m, and $I_{\mathrm{n(j)}}$ is similarly defined for pitcher j's manager. C_m and C_n capture managers' fixed effects, revealing the possible influence of team-specific training differences. If a player played under two or more managers in the same year, we regard him as playing for his first manager for the entire season; the assumption is that no significant adjustments can be made once the season starts. While other team-related factors, such as batting coach and senior players' leadership, may have an effect, we assume that the "team manager" variable is sufficient to capture all such influences. To control other effects that could potentially influence the matchup, the game specific variables Day or Night Dummies, Sky Dummies, Site Dummies, Temperature, and Doubleheader are added. Day or Night Dummies specify if the game is played at day or night; Sky Dummies are the condition of the sky, such as sunny, cloudy, night, overcast, dome, or unknown; Site Dummies are the ballpark the matchup takes place; temperature is the temperature of the time the game is played; Doubleheader indicates if the game is a doubleheader, and if it is, which game of the doubleheader it belongs to.

In expression (1), Y_t is the dummy for the season at matchup t, and $H_{i,j}$ is a dummy for opposite-hand between i and j, which equals to 1 if i and j use opposite hands and 0 if otherwise. After controlling players' fixed and status effect, we use γ to capture the size of the OH advantage (measured from the batter's point of view).

Expression (1) evidently assumes that all effects are independent or can be approximated by linear functional forms and that the OH effect is experience-invariant. We found no violation of such assumptions from our estimation, hence skipped the related discussion. ε is the error term with subscripts neglected, satisfying the usual regularity assumptions.

Table 3 is the summary statistics of the relevant variables, and Table 4 is the correlation between the variables. Because we want to estimate the effect of the OH advantage on the proportions of the regular left-handed batters and pitchers, only starting pitchers and starting batters are used in this paper. There are about 1.3 million plays between batters and pitchers during 2000 and 2012. The correlation of the variables are all close to zero, except for those between $E_{i,t}$ and $BPA_{i,t}$. More experience is rewarded for more chances to bat, which reflects our assumption that experience could be an indicator of skill level, and players with higher skill level have more chance to play.

Table 3: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
$\beta_{i,j,t}$	1357580	0.716226	1.210222	0	5
$Experience(E_{i,t})$	1357580	7.041636	4.201426	1	25
$Experience^2(E_{i,t}^2)$	1357580	67.2366	74.79649	1	625
$OPS\ Against\ Same\ Handed\ Batters\ (t-1)\ (\mathrm{OPS}ASH)_{j,(t-1)}$	1357580	0.703258	0.1481	0	2.42308
$Batter\ Seasonal\ PA\ (BPA_{i,t})$	1357580	485.933	183.3823	1	783
$Year\ Dummy\ (Y_t)$	1357580	2006.008	3.738109	2000	2012
Opposite-handed matchup for LH vs. RP	1357580	0.255021	0.435873	0	1
Opposite-handed matchup for RH vs. LP	1357580	0.176956	0.381632	0	1
Opposite-handed matchup for SH vs. LP	1357580	0.040913	0.198089	0	1
Same handed matchup for LH vs. LP	1357580	0.061541	0.24032	0	1
Same handed matchup for SH vs. RP	1357580	0.109407	0.31215	0	1

Table 4: Correlations of the Variables

	$\beta_{i,j,t}$	$E_{i,t}$	$E_{i,t}^2$	$OPSASH_{j,(t-1)}$	$BPA_{i,t}$	Y_t	$H_{i,j}$*(LH)*	$H_{i,j}$*(RH)*	$H_{i,j}$*(SH vs. LP)*	*LH vs. LP*	*SH vs. RP*
$\beta_{i,j,t}$	1										
$E_{i,t}$	0.0108*	1									
$E_{i,t}^2$	0.0088*	0.9579*	1								
$OPSASH_{j,(t-1)}$	0.0126*	0.0008	0.0030*	1							
$BPA_{i,t}$	0.0445*	0.1373*	0.0734*	0.0050*	1						
Y_t	0.0054*	-0.0564*	-0.0454*	-0.0147*	-0.0421*	1					
$H_{i,j}$*(LH)*	0.0143*	-0.0204*	-0.0040*	0.0043*	-0.0048*	-0.0054*	1				
$H_{i,j}$*(RH)*	0.0067*	-0.0021	-0.0039*	-0.0191*	-0.0939*	0.0288*	-0.2713*	1			
$H_{i,j}$*(SH vs. LP)*	-0.0044*	-0.0030*	-0.0064*	-0.0105*	-0.0023*	0.0147*	-0.1208*	-0.0958*	1		
LH vs. LP	-0.0072*	-0.0014	0.0027*	-0.0034*	0.0884*	0.0278*	-0.1498*	-0.1187*	-0.0529*	1	
SH vs. RP	-0.0064*	0.0034*	-0.0023*	0.0034*	-0.0084*	-0.0115*	-0.2051*	-0.1625*	-0.0724*	-0.0898*	1

*: p<0.01

4. Empirical Results

1. Micro estimation

Table 5 reports the regression results of the model, using all the samples. We assign dummy variables for left-handed batters vs. right-handed pitchers, left vs. left, right vs. left, switch vs. left, and switch vs. right, while having right vs. right as the comparision group. In column 1, the OH advantage increases right-handed batter's OPS by 0.032 Compared to the right-handed batter, the left-handed batters have an advantage of 0.044 when batting against right-handed pitcher. However, 0.044 is not the OH advantage of left-handed batters. The OH advantage of left-handed batters should be based on left-handed batters vs. right-handed pitchers against left vs. left. We can derive this by calculating OPS (LH vs. RP) – OPS (LH vs. LP) = OPS (LH vs. RP – RH vs. RP) – OPS (LH vs. LP – RH vs. RP), which is the 0.056 (0.044 + 0.012). To better investigate the effect of OH advantage, we gradually added in variables described in equation (1). The OH advantage of left-handed and right-handed batters under full specification is 0.113 and 0.0517. Furthermore, the t-test we performed rejected that these two coefficients are equal.

Such a difference supports the renowned "fighting hypothesis," which focused on frequency-dependent effects (Raymond et al., 1996). This proposition emphasized, as a result of fewer number of left-handers in the human population, people have less experience fighting the left-handers, which serves as an advantage to the left-handers and increases their chance of winning. Lots of studies have been revolving around this hypothesis from various perspectives arguing for (Brooks, et. al 2004; Hagemann, 2009; Loffing et. al, 2012), or against (Wood & Aggleton, 1989; Groothuis, et. al, 2013; Pollet et. al, 2013) this left-handed advantage.

If fighting hypothesis is true in baseball, batters should hit better in the face of right-handed pitchers than facing left-handed pitchers. Likewise, pitchers should pitch better against right-handed batters. Therefore, the OH advantage could contain both the advantages from batting against a pitcher of different handedness and the advantage/disadvantage of batting against a more/less familiar right-handed/ left-handed pitcher. For a left-handed batter, batting against a right-handed pitcher will get advantage from opposite handedness and the unfamiliarity on the part of the pitcher. In contrast, for a right-handed batter batting against a left-handed pitcher, though, only the opposite handedness is advantageous to the batter, while the factor of unfamiliarity will put him at a disadvantage.

The OH advantage of switch hitters is weak and insignificant compared to their left-handed and right-handed fellows. Since they are able to grasp the advantage from sides of the home plate, directly comparing their OPS against left-handed and right-handed pitchers is not enough to observe their OH advantage. Note that the OH advantage increases after we control for batters' plate appearances and their fixed effects. It means the skill or status of batters must be negatively related to the OH advantage. We will discuss more of this in section 4.3. Moreover, concerning the distribution of the managers' effects on pitching and batting, both batting and pitching manager effects display normal distributions.

Table 5: Various OH advantage for all batters

	OPS	OPS	OPS	OPS	OPS
LH vs. RP	0.0437***	0.0473***	0.0486***	0.102***	0.113***
	(0.00272)	(0.00273)	(0.00274)	(0.00550)	(0.00890)
RH vs. LP	0.0318***	0.0473***	0.0459***	0.0461***	0.0517***
	(0.00305)	(0.00305)	(0.00312)	(0.00377)	(0.00605)
SH vs. LP	-0.0117**	-0.00661	-0.00778	0.00233	-0.00130
	(0.00522)	(0.00522)	(0.00529)	(0.00698)	(0.0115)
LH vs. LP	-0.0198***	-0.0357***	-0.0348***		
	(0.00442)	(0.00443)	(0.00450)		
SH vs. RP	-0.00801**	-0.00324	-0.00409		
	(0.00349)	(0.00349)	(0.00353)		
Pitchers' OPS vs.		0.103***	0.0818***	0.0829***	0.0802***
Same-handed Batters(t-1)		(0.00705)	(0.00735)	(0.00884)	(0.0144)
Batter Exper. (year)		-0.00166*	-0.00125		
		(0.000875)	(0.000888)		
Batter Exper.^{2}		0.000178***	0.000140***		
(year^2)		(4.91e-05)	(4.98e-05)		
Batter PA		0.000307***	0.000300***		
		(5.73e-06)	(5.79e-06)		
Constant	0.702***	0.477***	0.535***	0.624***	0.477***
	(0.00174)	(0.00640)	(0.0315)	(0.00641)	(0.0237)

Manager Dummy	N	N	Y	Y	Y
Year Dummy	N	N	Y	Y	Y
Pos. Dummy	N	N	N	Y	Y
Batter Dummy	N	N	N	Y	Y
Match Specific Variables	N	N	N	N	Y
Observations	1,357,580	1,357,580	1,357,580	1,357,580	1,357,519
R-squared	0.000	0.003	0.004	0.000	0.000
Number of Dummies[12]				105,957	341,225

Match Specific: includes Day or Night Dummies, Site Dummies, Sky Dummies, Temperature, and Doubleheader.

Robust std. errors in (); *** p<0.01, ** p < 0.05, * p < 0.1.

RH/LH/SH stands for right/left/switch hitting batter; RP/LP stands for right/left-handed pitcher.

[12] A Huasman test suggested that it is better to use the fixed-effect model than the random-effect model.

2. Opposite-hand advantages, various batter-pitcher combinations

Table 6 reports the OH advantage for different sample selection criteria. Here we use the full specification similar to column (5) in Table 5. The first row reports the OH advantage by regressing left-handed batters only. The second row shows that for a right-handed batter, the OH effect on OPS is 0.052 when he faces a left-handed pitcher. While still a positive number, it is smaller than the analogous number for a left-handed batter, which is 0.113. Moreover, the OH advantages from SLG and strikeouts per PA are also smaller for right-handed batters, while walks per PA are quite similar between the two kinds of batters. For the right-handed batters, the OH advantage takes up 7%, 9.5%, 7.4%, and 16.7% of the performance in their OPS, SLG, strikeouts per PA, and walks per PA, while the percentage for the left-handed batter is 14.8%, 21.2%, 16.9%, and 14.3%. Since switch hitters have the OH advantage from both sides of the plate, although some of the effects in row (3) appear significant, they are small compared to those of the left-handed and right-handed batters. Furthermore, we could also split the sample by the handedness of pitchers. Row (4) indicates that for the right-handed pitchers' sample, a left-handed batter's OPS would be 0.028 higher than a right-handed batter's. Switch hitters, on the other hand, have some disadvantage in OPS, SLG, and some advantage in strikeouts and walks per PA. Finally, row (5) also shows that when facing a left-handed pitcher, the right-handed batters and switch hitters have 0.101 and 0.029 higher OPS than the left-handed batters. They also have higher SLG and walks per PA, and lower strikeouts per PA against opposite-handed pitchers.

Table 6: Various OH advantage under different sample selections

	OPS	SLG	K/PA	BB/PA
Sample: Left-handed Batters				

vs. RP	0.113***	0.0909***	-0.0289***	0.0152***
	(0.00890)	(0.00704)	(0.00267)	(0.00212)
Sample: Right-handed Batters				
vs. LP	0.0518***	0.0397***	-0.0126***	0.0150***
	(0.00605)	(0.00473)	(0.00178)	(0.00142)
Sample: Switch Hitters				
vs. LP	-0.00142	-0.00194	-0.0126***	-0.00921***
	(0.0115)	(0.00876)	(0.00342)	(0.00273)
Sample: Right-handed Pitchers				
vs. RH	0.0276***	0.0126***	-0.0250***	0.0152***
	(0.00490)	(0.00382)	(0.00152)	(0.00114)
vs. SH	-0.0152**	-0.0245***	-0.0159***	0.0158***
	(0.00716)	(0.00550)	(0.00225)	(0.00170)
Sample: Left-handed Pitchers				
vs. LH	0.101***	0.0817***	-0.0169***	0.0140***
	(0.00841)	(0.00649)	(0.00274)	(0.00204)
vs. SH	0.0299**	0.0186**	-0.0296***	0.00485*
	(0.0118)	(0.00898)	(0.00378)	(0.00285)

Robust std. errors in (); *** $p<0.01$, ** $p < 0.05$, * $p < 0.1$.
RH/LH/SH stands for right/left/switch hitting batter; RP/LP stands for right/left-handed pitcher.

3. Opposite-hand advantages, various plate appearances

Table 5 shows that the OH advantage is negatively related to batters' PA. A closer examination is provided in Table 7, which reports the OH advantage on OPS, SLG, strikeouts per PA, and walks per PA. The players are split by the number of PAs, and the estimations are made under the full specification similar to column (5) in Table 5. The results show that the OH advantage of the stronger player is somewhat smaller. In Table 7, for the left-handed batters, those who bat the least have higher OPS and SLG advantage. However, they have no advantage in strikeouts and walks per PA. For the right-handed batters, although those who have the fewest PAs have little OH advantage, those whose PAs are between 162 to 324 have a higher OH advantage in OPS, SLG, and strikeout rates than those whose PAs are higher than 324. This may be due to the fact that those who do not have many chances to bat are also the young, inexperienced players who are more aggressive and prefer to prove themselves by their batting power, not by their batting eyes. Therefore, the players who bat less have a higher OH advantage in OPS and SLG, but have no such advantage in strikeouts and walks per PA. Those who bat more tend to be the good and experienced players who have better batting eyes and hit well against pitchers of either handedness and do not need a high OH advantage to survive in MLB. This is why in equilibrium the OH advantage is negatively related to a batter's batting skill, measured by PAs. Since there are more right-handed pitchers than left-handed pitchers, it makes sense that the difference is larger for left-handed batters.

Table 7: Opposite-hand Advantage by Number of Plate Appearances (PAs)

	OPS	SLG	K/PA	BB/PA
		162 > PA		
LH vs. RP	0.231***	0.170***	-0.0190	-0.0132
	(0.0668)	(0.0494)	(0.0236)	(0.0142)
RH vs. LP	0.0620*	0.0402	-0.0167	0.00788
	(0.0333)	(0.0247)	(0.0118)	(0.00770)

SH vs. LP	0.0161	0.0214	-0.0172	0.0184
	(0.0643)	(0.0468)	(0.0208)	(0.0163)
		324 > PA ≥ 162		
LH vs. RP	0.0978***	0.0706***	-0.0173	-0.00158
	(0.0334)	(0.0250)	(0.0120)	(0.00844)
RH vs. LP	0.0787***	0.0601***	-0.0213***	0.00735*
	(0.0187)	(0.0142)	(0.00588)	(0.00430)
SH vs. LP	0.00945	0.0101	-0.0169	-0.00880
	(0.0335)	(0.0248)	(0.0107)	(0.00775)
		PA ≥ 324		
LH vs. RP	0.112***	0.0908***	-0.0298***	0.0168***
	(0.00930)	(0.00739)	(0.00276)	(0.00222)
RH vs. LP	0.0483***	0.0372***	-0.0114***	0.0161***
	(0.00651)	(0.00511)	(0.00189)	(0.00153)
SH vs. LP	-0.00321	-0.00407	-0.0122***	-0.0100***
	(0.0124)	(0.00953)	(0.00366)	(0.00296)

Robust std. errors in (); *** p<0.01, ** p < 0.05, * p < 0.1.
RH/LH/SH stands for right/left/switch hitting batter; RP/LP stands for right/left-handed pitcher.

5. Game Theoretic Model and Its Macro Implications

In the previous sections, we found out that even after controlling the strength and experiences of the players, batters do have a significant advantage when facing opposite-handed pitchers. In this regard, game theory can be used to illustrate how the OH advantage influences the percentage of left-handed and right-handed players in MLB (Goldstien & Young, 1996; Flanagan, 1998), but the assumptions we made here are different from the others. First, both studies assumed that the distribution of the players will make the expected payoff against opponent left-handed and right-handed players equal. However, such proposition only works when both the batters and pitchers are sent to the field on a random basis. As a matter of fact, they are not. Since the pitching rotation is highly predictable, the batting lineup is definitely not assigned at random. Moreover, both studies used the average performances of the lateral groups to estimate the expected payoffs. This would be a proper method if players are drawn from normal distributions which have mean values equal to the average performances. As a matter of fact, they are not, either. Only the best players can enter the league, so, in theory, all the best players should be already playing in MLB. If a team wants to increase its proportion of left-handed players, it must select from players inferior to the current league level. Similarly, if a team wants to cut its proportion of left-handed players, it must cut the least performed players. Using the average performance would make the estimation biased.

In our game model, the goal of the teams is to recruit players under a roster limit, and then to control the playing time of the left-handed and right-handed players to achieve the highest payoff, given how many left-handed players are there in their rival teams. Therefore, a sub-game perfect Nash equilibrium of the numbers of left-handed players can be derived.

First, we specify the payoff function between a batter and a pitcher. In team *u*, a left-handed batter i has an individual status level of $\Delta_{bi,u}$ (which is equal to $\propto_i + \theta_1 E_{i,t} + \theta_2 E_{i,t}^2 + \eta_1 BPA_{i,t} + C_m I_{m(i)}$ in equation (1)), and a right-handed batter i' has an individual status level of $\Delta_{\mathrm{b'i',u}}$, but the year dummy, the defensive position, and the random disturbance term are neglected for the time being. A batter may face pitcher j in team *v*, with an individual effect of $\Delta_{\mathrm{pj,v}}$ (which is equal to $\rho OPSASH_{j,(t-1)} + C_n I_{n(j)}$

in equation (1)) if left-handed, or $\Delta_{\mathrm{p'j',v}}$ if right-handed. Players of various skills can be recruited by the team. For convenience, let $\Delta_{\mathrm{bi,u}} > \Delta_{\mathrm{b\tilde{\imath},u}}, \Delta_{\mathrm{b'i,u}} > \Delta_{\mathrm{b'\tilde{\imath},u}}$ for all $i < \tilde{\imath}$, and $\Delta_{\mathrm{p\tilde{\jmath},u}} > \Delta_{\mathrm{p\tilde{\jmath}u}}, \Delta_{\mathrm{p'j,u}} > \Delta_{\mathrm{p'\tilde{\jmath},u}}$ for all $j < \tilde{\jmath}$. We also assume that:

- There are no switch hitters.
- Team u is able to observe the fixed effect of the potential players they can recruit, which is $\Delta_{\mathrm{pj,u}}$ for left-handed pitcher for all j, $\Delta_{\mathrm{p'j',u}}$ for right-handed pitcher for all j', $\Delta_{\mathrm{bi,u}}$ for left-handed batter for all i, and $\Delta_{\mathrm{b'i',u}}$ for right-handed batter for all i'..
- Team u can also observe the fixed effect of the potential players of opponent team v, $\forall\, v \neq u$

The teams undergo five stages in this game model. The five stages are:

Stage 1: Team manager decides pitching rotation. It is a practice in MLB that teams announce the starting pitchers for their next few games, so the pitching rotation is quite predictable. Furthermore, since starting pitchers need several days to rest and prepare for their next game, they cannot be easily substituted without giving the replacement starting pitcher some days to prepare and the team will have to announce the replacement in advance too.

Stage 2: The batting lineup adjustments will be made according to the pitching rotation at every match. Since the starting rotation for the opponent is known information, the manager will send his players with the highest expected payoff to play against the specific pitcher.

Stage 3: Starting batters confront starting pitchers in the match.

Stage 4: During the match, both teams substitute their players in order to gain the highest expected payoff for the subsequent plays. Players will be substituted because of injury, weariness, or simply because they are having a bad day.

Stage 5: The outcome of the match is finalized, and the winner is decided.

From equation (1), the individual payoff function for the batter-pitcher confrontation in stage 3 and 4 is as follows.

Batter vs. Pitcher by Handedness	Expected Payoff
bi,u (LH) vs. *pj,v* (LP)	$(\Delta_{\mathrm{bi,u}} - \Delta_{\mathrm{pj,v}}, \Delta_{\mathrm{pj,v}} - \Delta_{\mathrm{bi,u}})$
bi,u (LH) vs. *p'j',v* (RP)	$(\Delta_{\mathrm{bi,u}} - \Delta_{\mathrm{p'j',v}} + \gamma_{\mathrm{l}}, \Delta_{\mathrm{p'j',v}} - \Delta_{\mathrm{bi,u}} - \gamma_{\mathrm{l}})$
b'i',u (RH) vs. *pj,v* (LP)	$(\Delta_{\mathrm{b'i',u}} - \Delta_{\mathrm{pj,v}} + \gamma_{\mathrm{r}}, \Delta_{\mathrm{b'i',u}} - \Delta_{\mathrm{pj,v}} - \gamma_{\mathrm{r}})$
b'i',u (RH) vs. *p'j',v* (RP)	$(\Delta_{\mathrm{b'i',u}} - \Delta_{\mathrm{p'j',v}}, \Delta_{\mathrm{p'j',v}} - \Delta_{\mathrm{b'i'u}})$

In the above expression, we allow OH advantages (γ_l and γ_r) to be different for left-handed and right-handed batters. In order to simplify the analysis, we also assume that OH advantage is constant among players with different fixed effects. Allowing OH advantage to vary across different players will not affect the following analysis. If a left-handed batter is batting against a left-handed pitcher, the batter's expected payoff would be his fixed effect, $\Delta_{\mathrm{bi,u}}$, minus the pitcher's fixed effect, $\Delta_{\mathrm{pj,v}}$, while the pitcher's expected payoff would be $\Delta_{\mathrm{pj,v}}$ minus $\Delta_{\mathrm{bi,u}}$. However, if the left-handed batter is facing a right-handed pitcher instead, the batter will gain an OH advantage, γ_{l}, in addition to the fixed effects, while the pitcher will take an OH disadvantage of $-\gamma_{\mathrm{l}}$.

Specifically, 4 kinds of situations may occur during a match:

1. Starting batter vs. starting pitcher, where the batter is arranged to extract the highest expected payoff against the scheduled starting pitcher.

2. Substitute batter vs. starting pitcher, where the batter comes up from the bench to replace the starting batter who didn't do well to gain the highest payoff against the pitcher.

3. Starting batter vs. substitute pitcher, where the pitcher comes up to gain the

maximum payoff for the next few plays or even just one play.

4. Substitute batter vs. substitute pitcher, where both sides try to counteract their opponent's strategy, or just to let the players gain some experience after the match is almost decided.

Situation 2 to 4 are more complicated because the affecting factors include not only the skill level of the player and the OH advantage, but also the unpredictable shocks that temporarily affect the players such as luck or tiredness, so our analysis focuses on situation 1.

In the first situation, since the batters are all facing the same pitcher, the batter's expected payoff lies only in his own skill and the OH advantage, which is:

$$\Delta_{\mathrm{bi,u}} + \mathrm{H_{i,j}} * \gamma_{\mathrm{l}}$$

where $\mathrm{H_{i,j}}$ = 1 if the batter's batting hand is different from the pitcher's pitching hand and $\mathrm{H_{i,j}}$ = 0 if otherwise.

Let $0 \leq i, i' \leq \mathrm{N_b}$, where $\mathrm{N_b}$ is the maximum of number of batters in a batting lineup. The strategy of the team is to maximize the expected payoff for the batting lineup. If the opponent pitcher is right-handed, the expected payoff of starting all the lineup with left-handed batters would be:

$$\int_{\mathrm{i}=0}^{\mathrm{N_b}} (\Delta_{\mathrm{bi,u}} + \gamma_{\mathrm{l}})\, \mathrm{di}$$

However, if your best right-handed batter is so good that he satisfies:

$$\Delta_{\mathrm{b'0,u}} > \Delta_{\mathrm{bN_b,u}} + \gamma_{\mathrm{l}}$$

then it will be strictly better to send one more right-handed batter. As a result, there will be a batter $k'\mathrm{N_b}$ $(0 \leq k' \leq 1)$ who satisfies:

$$\Delta_{\mathrm{b'k'N_b,u}} = \Delta_{\mathrm{b(1-k')N_b,u}} + \gamma_{\mathrm{l}} \qquad (2)$$

which means that it is still better to send the right-handed batter $k'\mathrm{N_b}$ than a left-handed batter, but the batters weaker than $k'\mathrm{N_b}$ will not have his chance. The team's expected payoff will be:

$$\int_{i'=0}^{k'N_b} (\Delta_{b'i',u})di' + \int_{i=0}^{(1-k')N_b} (\Delta_{bi,u} + \gamma_l)di$$

Similarly, when facing a left-handed pitcher, there will be a batter kN_b $(0 \le k \le 1)$ who satisfies:

$$\Delta_{bkN_b,u} = \Delta_{b'(1-k)N_b,u} + \gamma_r \qquad (3)$$

and the payoff for the team against a left-handed pitcher will be:

$$\int_{i'=0}^{kN_b} (\Delta_{bi,u})di + \int_{i'=0}^{(1-k)N_b} (\Delta_{b'i',u} + \gamma_r)di'$$

Now, it must be the case that $k \le 1 - k'$, so that $\Delta_{bkN_b,u} \ge \Delta_{b(1-k')N_b,u}$ and $\Delta_{b'kN_b,u} \ge \Delta_{b'(1-k')N_b,u}$, because if not, then a team will send *less* left-handed batters when they are playing against a right-handed pitcher than when they are facing a left-handed one, which contradicts the OH advantage.

From equation (2), if there is an increase in γ_l, k' must decrease in order to satisfy the equilibrium. Similarly, from (3), an increase in γ_r will cause a decrease in k. The interpretation is that the optimal percentage of batters facing left-handed and right-handed pitchers only depends on the magnitude of the OH advantage and the distribution of the batters' fixed effect, and nothing else. A change in the percentage of left-handed pitchers will not affect this optimal strategy. If there is a change in the OH advantage which made the left-handed batter more favorable when playing against right-handed pitchers, then it will be better to send more left-handed batters when facing right-handed pitchers.

The strategy for the team's starting batting lineup for a whole season will be:

$$
\begin{aligned}
&\max_{k+k'\leq 1}(1-\pi_{LP})\left[\int_{\mathrm{i}'=0}^{\mathrm{k}'\mathrm{N_b}}(\Delta_{\mathrm{b'i',u}})\,\mathrm{di}'+\int_{\mathrm{i}=0}^{(1-\mathrm{k}')\mathrm{N_b}}(\Delta_{\mathrm{bi,u}}+\gamma_{\mathrm{l}})\mathrm{di}\right] \\
&\qquad +\pi_{LP}\left[\int_{\mathrm{i}=0}^{\mathrm{kN_b}}(\Delta_{\mathrm{bi,u}})\mathrm{di}+\int_{\mathrm{i}'=0}^{(1-\mathrm{k})\mathrm{N_b}}(\Delta_{\mathrm{b'i',u}}+\gamma_{\mathrm{r}})\,\mathrm{di}'\right] \\
&\qquad =\max_{k+k'\leq 1}\left\{\int_{\mathrm{i}=0}^{\mathrm{kN_b}}[\Delta_{\mathrm{bi,u}}+(1-\pi_{LP})\gamma_{\mathrm{l}}]\,\mathrm{di}+\int_{\mathrm{i}'=0}^{\mathrm{k}'\mathrm{N_b}}(\Delta_{\mathrm{b'i',u}}+\pi_{LP}\gamma_{\mathrm{r}})\,\mathrm{di}'\right. \\
&\qquad \left.+(1-\pi_{LP})\int_{\mathrm{i}=\mathrm{k}}^{(1-\mathrm{k}')\mathrm{N_b}}(\Delta_{\mathrm{bi,u}}+\gamma_{\mathrm{l}})\,\mathrm{di}+\pi_{LP}\int_{\mathrm{i}'=\mathrm{k}'}^{(1-\mathrm{k})\mathrm{N_b}}(\Delta_{\mathrm{b'i',u}}+\gamma_{\mathrm{r}})\mathrm{di}'\right\}
\end{aligned}
$$

where π_{LP} is the percentage of left-handed pitchers in the opponent pitching rotation. For a team with $k=\tilde{k}$ and $k'=\tilde{k}'$, the chance of a left-handed batter to play is:

$$[\tilde{k}+(1-\pi_{LP})\big(1-\tilde{k}'-\tilde{k}\big)]\mathrm{N_b}$$

while the chance of a right-handed batter to play is:

$$[\tilde{k}'+\pi_{LP}\big(1-\tilde{k}'-\tilde{k}\big)]\mathrm{N_b}$$

How the percentage of the left-handed and right-handed batters is decided can be elaborated as follows.

1. If $\gamma_l=\gamma_r=0$, $\tilde{k}$ and $\tilde{k}'$ should be adjusted according to their skill level only. In this case, according to equation (2) and (3), $\tilde{k}$ and $\tilde{k}'$ are adjusted to the point that the fixed effects of these two players are equal. Since there are 8 times more people using right hand than the people using the left hand in the real word, for every left-handed people with a given skill level, there should be 9 right-handed people as well. Therefore, $\tilde{k}'$ will be equal to about 9 times of $\tilde{k}$. Moreover, the starting lineup when facing a left-handed pitcher will be the same as facing a right-handed one, which means $\tilde{k}'=1-\tilde{k}$ or $1-\tilde{k}'-\tilde{k}=0$. The optimal percentage of the left-handed batters will be the same as that in the general population, which is about 10%, and will not be influenced by the percentage of left-handed pitchers they are facing.
2. If $\gamma_l>0,\gamma_r>0$, then $\tilde{k}$ and $\tilde{k}'$ should depend on the magnitude of γ_l and γ_r.

Both $\tilde{k}$ and $\tilde{k}'$ will be smaller than the situation under $\gamma_l = \gamma_r = 0$, because the weaker batters can get some benefit from the OH advantage. In this case, a change of the opponent left-handed pitcher percentage will affect the batting chances of both left-handed and right-handed players. An increase in π_{LP} will increase $[\tilde{k}' + \pi_{LP}(1 - \tilde{k}' - \tilde{k})]\mathrm{N_b}$ and decrease $[\tilde{k} + (1 - \pi_{LP})(1 - \tilde{k}' - \tilde{k})]\mathrm{N_b}$

The interpretation of the batters' equilibrium is this: teams have two different lineups against left-handed and right-handed pitchers. There are some regular players who have positions in both lineups, and some marginal players who can only play against left-handed or right-handed batters. Without the OH advantage, some of these batters will not even have a chance to play, but with the OH advantage, these batters are able to face pitchers with opposite handedness and gain a better payoff than a stronger batter who uses the same hand as the pitcher and has no OH advantage. If there are more left-handed pitchers, the lineup against left-handed pitchers will be arranged more often, thus right-handed marginal batters will have more chance to play, while left-handed marginal batters will have less playing time. However, such change in the proportion of left-handed pitchers will not change the numbers of regular and marginal players within the lineup. The numbers will stay the same, only that the lineup against the left-handed pitchers will be used more times in the season.

Now, in stage 1, the expected payoff for a left-handed pitcher c $(0 \le c \le 1)$ will be:

$$\left[\int_{\mathrm{i}=0}^{\tilde{k}\mathrm{N_b}} (\Delta_{\mathrm{pc,v}} - \Delta_{\mathrm{bi,u}})\,\mathrm{d}i + \int_{\mathrm{i'}=0}^{(1-\tilde{k})\mathrm{N_b}} (\Delta_{\mathrm{pc,v}} - \Delta_{\mathrm{b'i',u}} - \gamma_\mathrm{r})\mathrm{d}i'\right]$$
$$= \mathrm{N_b}\Delta_{\mathrm{pc,v}} - \left[\int_{\mathrm{i}=0}^{\tilde{k}\mathrm{N_b}} (\Delta_{\mathrm{bi,u}})\,\mathrm{d}i + \int_{\mathrm{i'}=0}^{(1-\tilde{k})\mathrm{N_b}} (\Delta_{\mathrm{b'i',u}} + \gamma_\mathrm{r})\mathrm{d}i'\right]$$

and the expected payoff for a right-handed pitcher c' $(0 \le c' \le 1)$ will be:

$$\mathrm{N_b}\Delta_{\mathrm{p'c',v}} - \left[\int_{\mathrm{i'}=0}^{\tilde{k}'\mathrm{N_b}} (\Delta_{\mathrm{b'i',u}})\mathrm{d}i' + \int_{\mathrm{i}=0}^{(1-\tilde{k}')\mathrm{N_b}} (\Delta_{\mathrm{bi,u}} + \gamma_\mathrm{l})\mathrm{d}i\right]$$

The team wants to maximize the payoff of the starting rotation:

$$\max_{c+c'=1}\int_{j=0}^{c\mathrm{N_p}}\left\{\mathrm{N_b}\Delta_{\mathrm{pj,v}}-\left[\int_{\mathrm{i=0}}^{\tilde{k}\mathrm{N_b}}(\Delta_{\mathrm{bi,u}})\,\mathrm{d}i+\int_{\mathrm{i'=0}}^{(1-\tilde{k})\mathrm{N_b}}(\Delta_{\mathrm{b'i',u}}+\gamma_{\mathrm{r}})\mathrm{d}i'\right]\right\}\mathrm{d}j+\int_{j'=0}^{c'\mathrm{N_p}}\left\{\mathrm{N_b}\Delta_{\mathrm{p'j',v}}\right.$$
$$\left.-\left[\int_{\mathrm{i'=0}}^{\tilde{k}'\mathrm{N_b}}(\Delta_{\mathrm{b'i',u}})\mathrm{d}i'+\int_{\mathrm{i=0}}^{(1-\tilde{k}')\mathrm{N_b}}(\Delta_{\mathrm{bi,u}}+\gamma_{\mathrm{l}})\mathrm{d}i\right]\right\}\mathrm{d}j$$

In theory, the expected payoff for the worst starting pitcher $\tilde{c}=\tilde{\pi}_{LP}$ and $\tilde{c}'=1-\tilde{\pi}_{LP}$ should be the same. $\tilde{c}$ and $\tilde{c}'$ will be adjusted to the point that their expected payoffs against the marginal batters are the same:

$$\mathrm{N_b}\Delta_{\mathrm{p\tilde{c}N_pv}}-\left[\int_{\mathrm{i=0}}^{\tilde{k}\mathrm{N_b}}(\Delta_{\mathrm{bi,u}})\,\mathrm{d}i+\int_{\mathrm{i'=0}}^{(1-\tilde{k})\mathrm{N_b}}(\Delta_{\mathrm{b'i',u}}+\gamma_{\mathrm{r}})\,\mathrm{d}i'\right]$$
$$=\mathrm{N_b}\Delta_{\mathrm{p'\tilde{c}'N_p,v}}-\left[\int_{\mathrm{i'=0}}^{\tilde{k}'\mathrm{N_b}}(\Delta_{\mathrm{b'i',u}})\,\mathrm{d}i'+\int_{\mathrm{i=0}}^{(1-\tilde{k}')\mathrm{N_b}}(\Delta_{\mathrm{bi,u}}+\gamma_{\mathrm{l}})\mathrm{d}i\right]$$

$$\mathrm{N_b}\Delta_{\mathrm{p\tilde{c}N_p,v}}-\mathrm{N_b}\Delta_{\mathrm{p'\tilde{c}'N_p,v}}+\int_{\mathrm{i=\tilde{k}N_b}}^{(1-\tilde{k}')\mathrm{N_b}}\Delta_{\mathrm{bi,u}}\,\mathrm{d}i+(1-\tilde{k}')\mathrm{N_b}\gamma_{\mathrm{l}}-\int_{\mathrm{i=\tilde{k}'N_b}}^{(1-\tilde{k})\mathrm{N_b}}\Delta_{\mathrm{b'i',u}}\mathrm{d}i'$$
$$-(1-\tilde{k})\mathrm{N_b}\gamma_{\mathrm{r}}=0 \quad (4)$$

Differentiate both sides with γ_{l}:

$$\mathrm{N_b}\frac{d\Delta_{\mathrm{p\tilde{c}N_p,v}}}{d\tilde{\pi}_{LP}}\frac{d\tilde{\pi}_{LP}}{d\gamma_{\mathrm{l}}}-\mathrm{N_b}\frac{d\Delta_{\mathrm{p'\tilde{c}'N_p,v}}}{d\tilde{\pi}_{LP}}\frac{d\tilde{\pi}_{LP}}{d\gamma_{\mathrm{l}}}-\mathrm{N_b}\Delta_{\mathrm{b(1-\tilde{k}'),u}}\frac{d\tilde{k}'}{d\gamma_{\mathrm{l}}}+(1-\tilde{k}')\mathrm{N_b}-\frac{d\tilde{k}'}{d\gamma_{\mathrm{l}}}\mathrm{N_b}\gamma_{\mathrm{l}}$$
$$+\mathrm{N_b}\Delta_{\mathrm{b'\tilde{k}',u}}\frac{d\tilde{k}'}{d\gamma_{\mathrm{l}}}=0$$

$$\frac{d\tilde{\pi}_{LP}}{d\gamma_{\mathrm{l}}}=\frac{\left(\Delta_{\mathrm{b(1-\tilde{k}'),u}}+\gamma_{\mathrm{l}}-\Delta_{\mathrm{b'\tilde{k}',u}}\right)\dfrac{d\tilde{k}'}{d\gamma_{\mathrm{l}}}-(1-\tilde{k}')}{\dfrac{d\Delta_{\mathrm{p\tilde{c}N_p,v}}}{d\tilde{\pi}_{LP}}-\dfrac{d\Delta_{\mathrm{p'\tilde{c}'N_p,v}}}{d\tilde{\pi}_{LP}}}$$

However, from equation (2), it is shown that $\Delta_{\mathrm{b'\tilde{k}'N_b,u}}=\Delta_{\mathrm{b(1-\tilde{k}')N_b,u}}+\gamma_{\mathrm{l}}$. Thus, the above equation can be simplified into:

$$\frac{d\tilde{\pi}_{LP}}{d\gamma_{\mathrm{l}}}=\frac{-(1-\tilde{k}')}{\dfrac{d\Delta_{\mathrm{p\tilde{c}N_p,v}}}{d\tilde{\pi}_{LP}}-\dfrac{d\Delta_{\mathrm{p'\tilde{c}'N_p,v}}}{d\tilde{\pi}_{LP}}} \quad (5)$$

Since $\frac{d\Delta_{\mathrm{p\tilde{c},v}}}{d\tilde{\pi}_{LP}}<0,\frac{d\Delta_{\mathrm{p'\tilde{c}',v}}}{d\tilde{\pi}_{LP}}>0$, and $0\le\tilde{k}'\le1$, equation (5) should be positive. Likewise,

$$\frac{d\tilde{\pi}_{LP}}{d\gamma_{\mathrm{r}}} = \frac{\left(1-\tilde{k}\right)}{\frac{d\Delta_{\mathrm{p}\tilde{c}\mathrm{N_p,v}}}{d\tilde{\pi}_{LP}} - \frac{d\Delta_{\mathrm{p'}\tilde{c}'\mathrm{N_p,v}}}{d\tilde{\pi}_{LP}}} \quad (6)$$

should be negative. The economic interpretation is that when the left-handed batters become more favorable against right-handed pitchers, the teams send more left-handed pitchers. On the contrary, when the right-handed batters are more advantageous against left-handed pitchers, the teams send less left-handed pitchers.

From (2), (3), and (4), the equilibrium number of both left-handed and right-handed batters and pitchers for every team can be derived, given the population distribution of the players' talent pool. First, the team chooses $\tilde{k}$ and $\tilde{k}'$ according to the OH advantage γ_r and γ_l. Then, the opponent team chooses $\tilde{c}$ and $\tilde{c}'$ according to $\tilde{k}, \tilde{k}'$ and the OH advantage. The choice of $\tilde{k}$ and $\tilde{k}'$ is independent of $\tilde{c}$ and $\tilde{c}'$, but there will be two different batting lineups against left-handed and right-handed batters. If there are more left-handed pitchers pitching, then the lineup against left-handed pitchers will be used more often, and more right-handed batters will be batting.

A t-test shows that when a team faces left-handed pitchers, the batting chance for the left-handed batters is significantly less than when the team faces right-handed pitchers, which serves to reject that the left-handed and right-handed batters are randomly sent to play, because if they are, their batting chances should not be significantly different. However, another t-test also shows that the batting chance of left-handed batters is significantly larger than 0, which validates our basic assumption of the game model above that teams let some good left-handed batters face the left-handed pitchers even if they don't have the OH advantage.

Table 8 shows the relationship between a starting batter's percentage of facing a left-handed starting pitcher and percentage of the overall percentage of left-handed pitchers faced by his team. Batters are grouped into three levels according to their fixed effects from the lowest to the highest year by year. Based on our explanation above, the marginal batters are more inclined to face pitchers with opposite handedness to extract his OH advantage. The results in Table 8 tell us that this is indeed true. When the team faces more left-handed pitchers, the strongest left-handed batters will have more chance to play than the average or weakest players, while the average and weakest right-handed batters will have more playing time than the strongest right-handed batters.

Table 8: The percentage of left-handed pitchers faced by a batter and the percentage of the team's chance of facing left-handed pitchers.

	Batter *i* P(LP, *t*)	Batter *i'* P(LP, *t*)
P(Team vs. LP, *t*)	0.773***	1.136***
	(0.0492)	(0.0662)
P(Team vs. LP, *t*)* Average 1/3	-0.123***	0.148***
	(0.0199)	(0.0263)
P(Team vs. LP, *t*)* Weakest 1/3	-0.162***	0.147***
	(0.0230)	(0.0286)
Constant	-0.0473***	0.0601***
	(0.0134)	(0.0182)
Observations	2,557	4,643
R-squared	0.089	0.078

Robust std. errors in (); *** $p<0.01$, ** $p < 0.05$, * $p < 0.1$.

6. Percentage of Left-handed Players Explained by OH Advantage

We have shown in the previous sections the existence of the OH advantage, and also verified the manager’s strategic adjustment on hand-specific proportion of the players according to the OH advantage. The next logical question to ask is: how many percentage points of the left-handed players come from the OH advantage?

Again, we adopted the same model specification in column (5) of Table 5, but left out the batter's PA effects. We obtain the fixed effects of the left-handed and right-handed batters who started at least one game during 2000 and 2012 from our estimation. Then the fixed effects of the players are adjusted by the player's experience year by year. We also ruled out switch hitters, because they enjoy the OH advantage from both sides of the plate.

Recall from equations (2) and (3) that

$$\Delta_{\mathrm{b}'\mathrm{k}'\mathrm{N_b},\mathrm{u}} = \Delta_{\mathrm{b}(1-\mathrm{k}')\mathrm{N_b},\mathrm{u}} + \gamma_{\mathrm{l}} \quad (2)$$

$$\Delta_{\mathrm{bkN_b},\mathrm{u}} = \Delta_{\mathrm{b}'(1-\mathrm{k})\mathrm{N_b},\mathrm{u}} + \gamma_{\mathrm{r}} \quad (3)$$

From Table 5, we know that $\gamma_{\mathrm{l}} = 0.113, \gamma_{\mathrm{r}} = 0.0517$. Since by the assumptions in section 5, the teams are able to observe all the fixed effects of the batters and then choose the best ones, it will not serve our purpose to make a simulation and draw samples from the distributions of the players. Instead, we set up an estimation that would allow the teams to observe the full distribution of the players and recruit the best players first. An estimation of the fixed effects of the batters with respect to the numbers of the batters can be derived by regressing each batter's fixed effect on his rank in the year. The estimations would be:

$$\text{LH: } FE_i = 0.5082185 - 0.0037816 * Batter\ Rank_i$$

$$\text{RH: } FE_{i'} = 0.5031287 - 0.0027068 * Batter\ Rank_{i'}$$

where *Batter Rank* is the yearly fixed effect ranking of left-handed batter *i* or right-handed batter *i'* in the league. These two estimations imply the good players are signed first, and the numbers of the batters in the league reflect the fixed effects of the average and marginal batters. By substituting the fixed effect estimations into the equilibrium, the optimal percentages of the batters can be obtained:

$$0.5082185 - 0.0037816 * (1 - k')\mathrm{N_b} + 0.113 = 0.5031287 - 0.0027068 * k'\mathrm{N_b}$$

$$0.5031287 - 0.0027068 * (1 - k)\mathrm{N_b} + 0.0517 = 0.5082185 - 0.0037816 * k\mathrm{N_b}$$

Simplifying the above equations leads to:

$$0.0064884 * k'\mathrm{N_b} = -0.1180898 + 0.0037816 * \mathrm{N_b}$$

$$0.0064884 * k\mathrm{N_b} = -0.0466102 + 0.0027068 * \mathrm{N_b}$$

There are currently 30 teams in MLB. Each team has an active roster limit of 25 players[13]. Suppose 13 of the 25 players are batters, which means there should be 390 batters in the whole league. Substituting $\mathrm{N_b}$ = 390 into the above equations, and results would be k = 0.399, k'=0.536. Thus, the percentage of left-handed batters who starts against pitchers with both handedness should 39.9%, while the percentage of right-handed batters who start against pitchers with both handedness should be 53.6%. The percentage of the players whose chance of playing depends on the opponent pitcher's handedness will be 1 - 0.399 - 0.536 = 0.065.

With the same method, the optimal percentage of the left-handed pitchers can also be obtained. From equation (4),

$$\Delta_{\mathrm{p}\tilde{c}\mathrm{N_p,v}} - \Delta_{\mathrm{p'}\tilde{c}'\mathrm{N_p,v}} + \int_{\mathrm{i}=\tilde{k}\mathrm{N_b}}^{(1-\tilde{k}')\mathrm{N_b}} \Delta_{\mathrm{bi,u}}\,\mathrm{d}i + (1-\tilde{k}')\mathrm{N_b}\gamma_\mathrm{l} - \int_{\mathrm{i}=\tilde{k}'\mathrm{N_b}}^{(1-\tilde{k})\mathrm{N_b}} \Delta_{\mathrm{b'i',u}}\mathrm{d}i'$$

$$- (1-\tilde{k})\mathrm{N_b}\gamma_\mathrm{r} = 0 \quad (4)$$

Same as the above, an estimation of the relationship between the fixed effects of the pitchers and their ranking gives us an estimation of the optimal percentage of left-handed pitchers. However, as mentioned above, the fixed effects of the pitchers cannot be estimated in the same model with the batters' fixed effects due to multi-collinearity. Therefore, the pitchers' OPS against the same-handed batters in the previous season multiplying the coefficient in column 5 in Table 5 (0.0802) is used as an approximation of the pitchers' fixed effects. The estimations of the relationship between pitchers' fixed effects and rankings are:

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[13] The active roster limit will increase to 40 after September 1st each season, but here we only discuss the regular 25-man roster limit..

$$\text{LP: } FE_{\,j} = -0.0328549 - 0.0007446 * Pitcher\ Rank_j$$

$$\text{RP: } FE_{\,j'} = -0.0384887 - 0.0002293 * Pitcher\ Rank_{j'}$$

Suppose all the 30 teams in MLB uses a 5-pitcher starting rotation, that is, $\mathrm{N_p} = 150$. Substituting the numbers of $\tilde{k}, \tilde{k}', \mathrm{N_b}, \mathrm{N_p}, \gamma_l, \gamma_r$, and the pitchers' fixed effect estimations into equation (4) gives us $\tilde{c} = 0.27$, and $\tilde{c}' = 0.73$. From this ratio, the proportion of left-handed batters is 0.399 + 0.73*0.065 = 0.446.

In order to estimate the excess left-handed players in MLB, we need to find out three different ratios of left-handed players under different assumptions. 1) If there is no OH advantage, then $\gamma_l = \gamma_r = 0$. In this case, the proportion of left-handed batters and pitchers should be the same as the general population, which is 10%. 2) If the OH advantage exists and is the only consideration for the managers in adjusting the plate appearances, the above estimation shows that the optimal equilibrium should be 44.6% for the left-handed batters and 27% for the left-handed pitchers. 3) The final scenario concerns the numbers from the MLB data. After ruling out the switch hitters and focusing on starting players only, the left-handed batters take up 37.1% of the plate appearances while the left-handed pitchers take up 27%.

The above analysis implies that while the percentage of left-handed pitchers is at the optimal, there should be more left-handed batters in MLB. There are some reasons for the lower percentage of the actual left-handed batters. The first reason is the defensive side. Catchers, second-basemen, third-basemen, and shortstops are usually right-handed players because they can pass the ball more easily to the first base than the left-handed players. Thus, an average right-handed shortstop may have a position in the regular starting lineup, while a good left-handed outfielder has to compete with other left- and right-handed players.

Also, a left-handed pitcher is more likely to succeed than a left-handed batter. In addressing the absence of left-handed catchers, Bill James (2001) emphasized the biggest reason for having no left-handed catchers is “natural selection.” He remarked that catchers “need good throwing arms,” but asked, “If you have a kid on your baseball team who is left-handed and has a strong arm, what are you going to do with him?” (p. 41) It is most probable that this kid will be trained as a left-handed pitcher. By the same token, this reasoning may be applied to other position players. Left-handed players may either choose to face competition from both left-handed and right-handed batters in the first base, outfield, and the DH, or they can give up batting and become a pitcher instead.

7. Conclusion

In this paper, we tried to explore the commonly accepted OH advantage in the baseball field by using statistical method, and determine how this OH advantage created an imbalance on the employment rate of left-and right-handed players. Our regression results show that in MLB, the OH advantage for left-handed batters explains about 15% of their OPS, while for right-handed batters, it only explains about 7% of their OPS. Such difference may lend support to the fighting hypothesis, in view of the advantage of the minority of left-handers in the baseball games. There seems to be no such advantage for switch hitters. On the other hand, pitchers throw better to batters of the same handedness, as compared to opposite-handed batters. We then used OH advantage and game theory to estimate the optimal percentage of left-handed players in MLB. However, our approach is different from Goldstein and Young (1996) in that we assume the teams can observe the talent of every possible player and sign the best ones. The estimation of our model shows that while our estimation of the percentage of the left-handed pitchers is close to the number in MLB, there should be more left-handed batters playing in MLB.

Although our model partly explained the in-field management decision of sending which kind of batters to the plate, it is far from perfect. For example, we can't explain why the left-handed batters have a larger OH advantage. We also completely omitted the effect of defensive characteristics. In the baseball field, catchers, second-basemen, third-basemen, and shortstops are usually right-handed players. Plus, we didn't put too much emphasis on switch hitters. Neither did we distinguish the right-pitching left-handed batters with the natural left-handed batters, simply because the results are mostly the same when we split them apart. We also ruled out the substitute batters and the relief pitchers in the theoretical model, because they would make the model way too complicated to analyze. Moreover, although OPS is the most accepted baseball stat when evaluating player performance, using OPS as the dependent variable may give too much weight to base hits and too little to walks. There might be ways to make improvements in these aspects. However, this model not only explains how the batters and pitchers are arranged in accordance with the OH advantage to play against the opponent's deployment, but also serves as a fair estimation to the practical operations of the teams.

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3

Are Players More Valuable for Winning a World Series? A Regression Analysis of MLB Players' Salaries from 1997 to 2013

1. Introduction

For the baseball fans around the world, the competition between teams in the course of the pennant race and the postseason is the most eye-catching part. For the players and managers, the experience of playing in the postseason, or even of winning a World Championship, is highly deemed and eagerly pursued.

On April 17th, 2012, the veteran outfielder Johnny Damon signed a contract with the Cleveland Indians, who believed that Damon would be able to help them win more games in view of the fact that he was "entering his 17th season with an impressive resume of postseason experience."[14] The importance of postseason experience is displayed in this move. Another example goes to Derek Lowe, in whose case the value of postseason experience is encapsulated. Before the 2010 National League Division Series, it was thought that this Atlanta Braves pitcher's "postseason experience… will give Lowe a chance to match [Tim] Lincecum pitch for pitch."[15] This speculation is based on the fact that Lowe finished the season with 16 wins and a 4.00 ERA, but Lincecum finished with 16 wins and a 3.43 ERA, and also led the National League in strikeouts. It was obvious that Lowe's postseason experience was regarded as an advantage for the 37-year-old pitcher.

Is previous successful experience advantageous? Do people benefit from the experiences accumulated in the past? In arguing that confidence built up from past

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[14] See http://www.usatoday.com/sports/baseball/al/indians/story/2012-04-17/johnny-damon-contract/54351208/1

[15] See http://suite101.com/article/mlb-posteason-the-atlanta-braves-face-tough-playoff-road-a294427

achievements will enhance performance, Compte and Postlewaite (2004) proposed a model showing that a person's future success rate is affected by his previous experience of success and failure, which is termed as “bias” by the authors, and concluded that such “bias” is welfare improving. In a similar vein, Feltz (2007) pointed out that performance accomplishments and vicarious experience will enhance self-efficacy and lead to better performance. What is emphasized in these arguments is that performance in the past counts a lot in future accomplishments. By the same token, in theory, the players’ postseason experience in the past may exert great effects on their performance. In fact, empirically, Tarlow (2012) found that past postseason experience of NBA players can increase the chance of the team to enter the playoff.

From practical viewpoints, how is the postseason experience accumulated in the past seasons reflected on the value of the professional baseball players? The "invariance principle" proposed in 1956 by Simon Rottenberg indicated that players always end up with the teams in which they are most valued. This proposition anticipates the famous Coase Theorem, published four years later. In fact, the value of players is commonly recognized as their marginal revenue product, which is a commonly used concept in economics. It is Scully (1974) who first applied this concept to the baseball field by connecting the revenue of the team with its winning percentage, which in turn was linked to the performances of the players.

Suppose players do end up with teams they are highest valued, and suppose players are paid according to their marginal revenue product. If postseason experience is valuable to the teams, then the players should be able to get a higher salary, because their postseason experience stands for a higher marginal revenue product. In scholarly discussion on baseball players’ salaries, little has been given to the factors related to the postseason experience. This paper focuses on whether or not the postseason and World

Series (WS) experience contribute to the salary enhancement of professional baseball players. In this study, a linear regression of MLB player salary from 1997 to 2013 is made to see if players who participated in the postseason or won a WS received better salaries than those who did not.

The remainder of this paper is organized as follows: Sections 2 briefly examines related studies. Section 3 focuses on the relationship between postseason experience and team achievement. Section 4 presents the data and the model used in this study. Section 5 is devoted to the discussion of the results from the regression model. The connection between the player's chance of employment and his postseason experience is dealt with in Section 6, followed by the conclusion in the last section.

2. Literature Review

Lots of researches on baseball economics have been focused on salary issues. Simon Rottenberg's paper in 1956 has been regarded as the first scholarly work touching upon the connection between the salary and the baseball players. Rottenberg discussed the labor market at a time when free agency hasn't started and the team literally owned the players and had full power in trading or terminating the players' contracts. He concluded that although the richer teams were able to recruit more powerful players than the poorer teams, this would not happen in reality because the richer teams also intended to keep the whole league competitive enough in order to attract larger attendance. Thus, the distribution of the players' talent among the teams would be similar to the distribution under a free player's labor market.

On the other hand, Scully (1974) aimed at measuring if the salary of the players really matched their marginal revenue product. He concluded that the players generally received lower payment than their marginal revenue product. Krautmann (1999) and

MacDonald and Reynolds (1994) also compared the marginal revenue product of the players to their salaries. But at that time, the reserve clause was dropped, and the rules of free agency were installed, so the players were being paid more reasonably. In contrast, Blass (1992) argued that experienced players were often overpaid, which contradicted the human capital model of investment.

Lots of researches have focused on the salary discrimination for MLB players (Pascal and Rapping, 1972; Hill and Spellman, 1984; Holmes, 2010). Some dealt with contract length (Kahn, 1993; Krautmann and Oppenheimer, 2002; Link and Yosifov, 2012)., while others addressed structural changes (Sommers and Quintonm, 1982; Raimondo, 1983; Marburger, 1994). As for the influence of past success or postseason experience on the players' salary, very few studies have been conducted. The research conducted by Krautmann and Ciecka (2009) suggested that in order to earn the extra profits from the postseason, a contending team will recruit elite players with salary beyond their worth to increase the team's chance of heading into the postseason. Mirabile and Witte (2012) found out that college football coaches' past success will influence their future salary.

3. Postseason Experience

This section tries to shed light on the relationship between previous postseason experiences and the achievement of the teams. The current MLB postseason structure follows a three-round structure, starting with the American League and National League determining the champions of each league separately, then determining a joint championship for the whole MLB. Only the winners of the three conferences and one wild card team[16] in each league are qualified to play in the postseason. In the first round,

[16] Since 2012, the wild card seats increased from one team to two teams per league. The two wild card

the League Division Series (DS), the four teams in each league are split into two groups to play a best-of-five series. The two teams in each league then engage with each other in the League Championship Series (CS), a best-of-seven series. The winner of the CS in each league then enters the best-of-seven WS, the winner of which will become the World Championship.

Table 1 is a simple summary of the percentage of the players who had postseason experience in the previous season. The first row is the average percentage of players for the teams which clinched postseason from 1996 to 2013, the second row is for the teams failed to make the postseason. The third row and the fourth row are similar to the first and the second, only that the conditions are changed into teams which won the World Championships and those which failed to win it. It is clearly shown that the amount of postseason experience is related to the final achievement of the teams. For the teams which clinched the postseason, 30% of its pitchers and 28% of its batters have postseason experience in the previous season. For the teams which failed to make the postseason, the number went down to 12% and 13%. The difference still exists when the teams are sorted by the championship and non-championship teams. Furthermore, there are more players with postseason experience in World Championship teams, than in the non-championship ones, with the winners having about 8% more players with postseason experience. The phenomenon still exists in the newly signed players. 30% of the pitchers and 29% of the batters newly signed by the World Championship teams have previous postseason experience. It is clear that the most successful teams tend to sign players with postseason experience. Recruiting players with postseason experience could be a good way to increase the team's winning percentage and perhaps its chance

teams in each league will engage a single-elimination tournament. However, in this paper, this stage of the postseason is ignored, because the players who failed to advance only played one postseason game, which may not be really a valuable experience. Moreover, only players in 2012 and 2013 have the possibility to experience this round, so the sample is quite small and is hard to be compared with the players playing in the period when such round didn't exist.

of being in the postseason. So here comes the question: how much would the teams pay for the postseason experience?

Table 1: Team Percentage of players with previous postseason experience, stratified by the achievement of the teams, 1996-2013.

Team Achievement	Pitchers	Batters	Newly Signed Pitchers	Newly Signed Batters
Clinched Postseason	0.306	0.281	0.254	0.266
Failed to Make Postseason	0.124	0.136	0.137	0.177
Won World Championship	0.250	0.250	0.300	0.293
Failed to Win World Championship	0.169	0.173	0.164	0.199

4. Data & Method

The basic concept of estimating the value of the players in this study follows Wallace's salary determination model for NBA players. According to Wallace (1988), "[T]he earning process in basketball or any labor market can be conceptualized as a consequence of returns to three sets of resource: *human capital*, *performance or merit*, and *structural characteristics* of the worker's job." (p. 296, italics mine) "Human capital" means the training or job experience, "performance or merit" indicates the productivity of the workers, and "structural characteristics" is the different structures of the labor market, product market, or government regulations. In terms of the model used, the baseball salary determination model set up by Harder (1992) is adopted with some minor modifications. Harder's model includes the above-mentioned three features:

$$
\begin{aligned}
ln(Real\ Salary)_{i,t} \\
&= \theta_0 + \theta_1 RC_{Career} + \theta_2 RC/YR + \theta_3 AB_{t-1} + \theta_4 YR + \theta_5 YR^2 \\
&+ \theta_6 YR200 + \theta_7 All\ Stars_{t-1} \\
&+ \sum_p \theta_{8,p} Defensive\ Position\ Dummies_p + \theta_9 Minority \\
&+ \theta_{10} Free\ Agent + \theta_{11} Arbitration\ Eligable + \theta_{12} Arbitration\ Won \\
&+ \theta_{13} Arbitration\ Lost
\end{aligned}
$$

where RC is the runs created by the players, YR indicates the years played by the players in MLB, and YR200 is an indicator variable that equals to 1 if the player's at bats that season is more than 200. In his model, human capital variable (YR), performance variable (RC, YR200) and structural variables (defensive positions, free agent, etc.) are all present. Based on this model, the structural form is modified into:

$$
\begin{aligned}
ln(Real\ Salary)_{i,t} \\
&= f(Postseason\ Experience_{i,p,t-k}, Experience_{i,t}, Performance_{i,l,t-1} \\
&\quad Structural\ Variables_{i,m}) + \varepsilon_i
\end{aligned}
$$

$ln(Real\ Salary)_{i,t}$	Player *i*'s nature log of real salary at year *t*.
Postseason Experience:	
$Won\ the\ WS_{i,t-1}$	If the player *i* won the WS games in the previous season.
$Eliminated\ in\ the\ WS_{i,t-1}$	If the player *i* was outmatched in the WS games in the previous season.
$Eliminated\ in\ the\ CS_{i,t-1}$	If the player *i* was outmatched in the CS games in the previous season.
$Eliminated\ in\ the\ DS_{i,t-1}$	If the player *i* was outmatched in the DS games in the previous season

$Average\ Champion\ per\ Year_{i,t-2}$	Player i's career number of championships won divided by his years of experience in season t-2.
$Average\ WS\ Elimination\ per\ Year_{i,t-2}$	Player i's career number of eliminations in the WS divided by his years of experience in season t-2.
$Average\ CS\ Elimination\ per\ Year_{i,t-2}$	Player i's career number of eliminations in the CS divided by his years of experience in season t-2.
$Average\ DS\ Elimination\ per\ Year_{i,t-2}$	Player i's career number of eliminations in the DS divided by his years of experience in season t-2.
$Experience_i$	Player *i*'s years of service in MLB.
Performance Variables:	
$\frac{H-HR}{BFP}_{i,t-1}$	Non-home run base hits per batter faced allowed by pitcher *i* in the previous season.
$\frac{HR}{BFP_{i,t-1}}$	Home runs per batter faced allowed by pitcher *i* in the previous season.
$\frac{BB+HBP}{BFP}$	Walks plus hits by pitch per batter faced allowed by pitcher *i* in the previous season.
$\frac{K}{BFP_{i,t-1}}$	Strikeouts per batter faced earned by pitcher *i* in the previous season.
$BFP_{i,t-1}$	Total batters faced by pitcher *i* in the previous season.
$\frac{Singles}{PA}_{i,t-1}$	Singles per plate appearance hit by batter *i* in the previous season.
$\frac{Doubles}{PA}_{i,t-1}$	Doubles per plate appearance hit by batter *i* in the

	previous season.
$\frac{Triples}{PA}_{i,t-1}$	Triples per plate appearance hit by batter *i* in the previous season.
$\frac{HR}{PA_{i,t-1}}$	Home runs per plate appearance hit by batter *i* in the previous season.
$\frac{BB+HBP}{PA}_{i,t-1}$	Walks plus hits by pitch per plate appearance earned by batter *i* in the previous season.
$\frac{K}{PA_{i,t-1}}$	Strikeouts per plate appearance earned by batter *i* in the previous season.
$PA_{i,t-1}$	Total plate appearances of batter *i* in the previous season.
Structural Variables:	
$Career\ All-stars\ per\ Season_{t-1}$	Player *i*'s career All-stars games starting appearances per season in season *t-1*.
$Year_t$	Dummy variable for year *t*.
$Team_n$	Dummy variable the player's team *n*.
$Defensive\ Position_{i,d,t}$	Defensive position dummy *d* for the batter *i* at year *t*.
$Regular\ Player_{i,t-1}$	If the pitcher *i* started 15 games or above or relieved 45 games or above, or batter *i* played 80 games or above in season *t-1*.
$Career\ Regular\ Player_{i,t-}$	If the pitcher *i* started 15 games or above or relieved 45 games or above per season, or batter *i* played 80 games or above per season in his career until season *t-2*.

$ln(Real\,Salary)_{i,t}$is applied in order to estimate the percentage change of a player's real salary and to control the skewness of salary data. The MLB salary data are heavily skewed to the right, with lots of players earning lower than a small amount of money, and few people earning a lot of money. The $Postseason\ Experience_{i,t-k}$ are dummies to capture players who achieved different stages of the postseason. The MLB postseason structure is composed of three rounds: the DS, the CS, and the WS. Therefore, there should be four different stages in terms of team achievement: eliminated in the DS, won the DS but eliminated in the CS, won the CS but eliminated in the WS, and won the WS. Players who participated in the postseason shall be allocated to one of these four groups. In this paper, all the records of a player's postseason experience are used to estimate his current salary changes, but the postseason experience of the most recent season is extracted and estimated, independent of the other past postseason experience, since the most current experience should be more influential than the others. There are four dummy variables to estimate the most recent postseason experience, that is, for $k = 1$. For all the other previous postseason experiences, that is, $k = 2, 3, ...$, each round of past postseason experiences is combined into four parameters to estimate a player's average past experience for each of the four kinds of postseason experiences in his career. With other variables being controlled, the effect of postseason experience on salary is then determined from this model. The variables in the model shall be different for pitchers and batters.

The regressions are made by applying OLS. The $Experience_i$ variable follows the wage equation of Mincer (1974), where the experience is viewed as the in-job training human capital in the professional baseball field. The performance variables for pitchers are the average base hits, walks, and strikeouts allowed by the pitcher. Although other stats could be used, such as ERA or WHIP, the goal of this research is not to develop an ultimate statistic that could perfectly capture the performance and the rankings of the players. Therefore, it should be more appropriate to use the raw stats of the pitchers' performance. The same reasoning goes to the batters' stats, which are singles, doubles, triples, home runs, walks, and strikeouts per plate appearance, instead of OBP or SLG. The $BFP_{i,t-1}$ and $PA_{i,t-1}$ measures the consistency of the player. When the two players have similar stats, the one who is able to play more games would be preferred. Players with low $BFP_{i,t-1}$ and $PA_{i,t-1}$ may either have an injury problem in the previous season, which may be more risky for the teams, or they didn't prove that they are able to maintain their own stats when they are given more opportunities to play, which is not rare in the Major League.

The structural variables are the year dummies, team dummies, and defensive position dummies. The year dummies are added to capture the structural variation across different years. The team dummies are added because some team owners are really rich and prefer to pay big bucks to the players, while other owners tend to limit their team budget in an acceptable range. The defensive position dummies are present to capture the different characteristics and defensive skills of the defensive positions. Outfielders and first-base men are less valued for their defensive skill, so their salary would be highly related to their performance on the offensive side. The shortstop, on the other hand, is a key to the infield defense, and is required to be highly skilled on their defensive side. Therefore, it would be misleading to solely consider their batting performance.

In the model, several interaction terms are added to capture the possible different influences of postseason experiences between regular players and non-regular players. $Regular\ Player_{i,t-1}$ is a dummy to indicate if the batter played 80 games or more, or if the pitcher started 15 games or more or relieved 45 games or more in the previous season. $Career\ Regular\ Player_{i,t-2}$ is a dummy to indicate if the batter played 80 or more games per season, or if the pitcher started 15 or more games or relieved 45 or more games per season in his career. There will be 4 interaction terms to capture the regular players' postseason in the previous season, and another 4 interaction terms to capture the regular players' career postseason experience. Since regular players have more playing time, their postseason experiences should be more influential than the non-regular players, and thus more valuable.

Table 2 and 3 are the summary statistics of the sample used in this study. The correlations between the postseason experiences and the performance stats are mostly not significant at the 1% level. The sample consists of the data for players who were granted free agency before each season began from 1997 to 2013 and played at least two seasons, including 606 seasonal pitching and 1148 seasonal batting data. The 1997 season is chosen because the first DS was held in 1995, and at least two years of data are needed to calculate the career average DS per season. In testing the effects of postseason experience, two factors are considered: the performance data and financial data of MLB players from 1997 to 2013 seasons. Both data are retrieved from Lahman's Database, which preserves all historical seasonal data of MLB, including a player's birth year, defensive position, batting or pitching records, and his annual salary. Moreover, according to the analysis by Krautmann (1992), although the baseball players are supposed to be paid for his marginal revenue product, the truth is that only free agents face competitive bidding from all MLB teams. If postseason experience is indeed valuable, it should be reflected only on the salaries of the players directly coming from the free agent market, because their salary is more closely related to their marginal revenue product. Therefore, only players that are granted free agency before each season are included in the sample.

Table 2: Summary statistics for pitchers

Variable	N	Mean	Std. Dev.	Min	Max
Real Salary	606	1470328	1579047	115264.8	9216590
ln (Real Salary)	606	13.697	1.019	11.65	16.04
Won the WS (t-1)	606	0.031	0.174	0	1
Won the WS * Regular Player (t-1)	606	0.028	0.165	0	1
Eliminated in the WS (t-1)	606	0.043	0.203	0	1
Eliminated in the WS * Regular Player (t-1)	606	0.035	0.183	0	1
Eliminated in the CS (t-1)	606	0.063	0.243	0	1
Eliminated in the CS (t-1) * Regular Player (t-1)	606	0.058	0.233	0	1
Eliminated in the DS (t-1)	606	0.124	0.330	0	1
Eliminated in the DS (t-1) * Regular Player (t-1)	606	0.111	0.314	0	1
Average WS Champion (t-2)	606	0.023	0.061	0	0.5
Average WS Champion (t-2) * Career Regular (t-2)	606	0.019	0.057	0	0.5
Average WS Elimination (t-2)	606	0.024	0.058	0	0.375
Average WS Elimination (t-2) * Career Regular (t-2)	606	0.019	0.053	0	0.375
Average CS Elimination (t-2)	606	0.049	0.084	0	0.5
Average CS Elimination (t-2) * Career Regular (t-2)	606	0.037	0.073	0	0.5
Average DS Elimination (t-2)	606	0.076	0.105	0	0.667
Average DS Elimination (t-2) * Career Regular (t-2)	606	0.055	0.096	0	0.625
Years Played	606	11.107	4.136	3	26
Years Played^2	606	140.45	107.24	9	676

(H-HR)/BFP (t-1)	606	0.206	0.036	0	0.5
HR/BFP (t-1)	606	0.026	0.013	0	0.111
(BB+HBP)/BFP (t-1)	606	0.101	0.038	0.027	0.5
K/BFP (t-1)	606	0.172	0.052	0	0.4
BFP (t-1)	606	420.78	282.40	2	1071
Career All-stars per Season	606	0.006	0.026	0	0.2

Table 3: Summary statistics for batters

Variable	N	Mean	Std. Dev.	Min	Max
Real Salary	1148	1190386	1494359	93457.95	13000000
ln (Real Salary)	1148	13.458	0.987	11.445	16.381
Won the WS (t-1)	1148	0.036	0.186	0	1
Won the WS * Regular Player (t-1)	1148	0.030	0.170	0	1
Eliminated in the WS (t-1)	1148	0.037	0.190	0	1
Eliminated in the WS * Regular Player (t-1)	1148	0.032	0.177	0	1
Eliminated in the CS (t-1)	1148	0.071	0.258	0	1
Eliminated in the CS (t-1) * Regular Player (t-1)	1148	0.064	0.244	0	1
Eliminated in the DS (t-1)	1148	0.151	0.358	0	1
Eliminated in the DS (t-1) * Regular Player (t-1)	1148	0.131	0.337	0	1
Average WS Champion (t-2)	1148	0.027	0.063	0	0.667
Average WS Champion (t-2) * Career Regular (t-2)	1148	0.015	0.048	0	0.4

Average WS Elimination (t-2)	1148	0.024	0.056	0	0.5
Average WS Elimination (t-2) * Career Regular (t-2)	1148	0.015	0.042	0	0.333
Average CS Elimination (t-2)	1148	0.051	0.079	0	0.5
Average CS Elimination (t-2) * Career Regular (t-2)	1148	0.029	0.062	0	0.5
Average DS Elimination (t-2)	1148	0.078	0.108	0	0.8
Average DS Elimination (t-2) * Career Regular (t-2)	1148	0.046	0.092	0	0.667
Years Played	1148	10.95	3.60	3	24
Years Played^2	1148	132.90	87.80	9	576
Singles/PA (t-1)	1148	0.156	0.036	0	0.375
Doubles/PA (t-1)	1148	0.046	0.017	0	0.25
Triples/PA (t-1)	1148	0.004	0.005	0	0.048
HR/PA (t-1)	1148	0.025	0.018	0	0.125
(BB+HBP)/PA (t-1)	1148	0.093	0.037	0	0.333
K/PA (t-1)	1148	0.169	0.070	0	1
PA (t-1)	1148	368.80	192.00	1	778
Career All-stars per Season	1148	0.029	0.092	0	0.75

5. Regression Results

Table 4 is a regression of a pitcher’s nature log of real salary against his postseason experience. Overall, the test below shows that pitchers who participated in the postseason don't really have high salaries. Even in column 1, under the simplest specification without any other variables except for the postseason experiences, the pitchers who participated in the postseason do not seem to receive a much higher salary. When pitchers’ performance, years of service, All-stars experience, year dummies and team dummies are added to the regression, the value for postseason experience almost totally disappeared. Column 3 shows that the only pitchers who won the previous World Series have a 58% higher salary, while other postseason experiences give no premium in salary to the pitchers. On the other hand, the performance stats are quite important in determining a pitcher's salary as expected. More home runs and walks allowed per batter faced by the pitcher will lead to a lower salary, while more strikeouts given will bring him a higher paycheck. Consistency is also an important factor for the pitcher. More batter faced in the last season will lead to a higher salary, but a pitcher's experience will not affect his salary. Pitchers who started more often in the All-stars games do not have a higher salary, either.

Table 4: The effect of past postseason experiences on a pitcher’s real salary, 1997-2013.

	ln (Real Salary)	ln (Real Salary)	ln (Real Salary)
Won the WS (t-1)	0.535	0.727	0.579**
	(0.705)	(0.442)	(0.259)
Won the WS	0.263	-0.430	-0.307
* Regular Player (t-1)	(0.738)	(0.461)	(0.291)
Eliminated in the WS (t-1)	-0.0378	-0.0643	0.135
	(0.250)	(0.261)	(0.158)

Eliminated in the WS	0.392	-0.0863	-0.103
* Regular Player (t-1)	(0.310)	(0.312)	(0.232)
Eliminated in the CS (t-1)	-0.928**	-0.488	-0.222
	(0.388)	(0.350)	(0.402)
Eliminated in the CS	1.582***	0.786**	0.515
* Regular Player (t-1)	(0.404)	(0.360)	(0.412)
Eliminated in the DS (t-1)	-0.510*	-0.112	-0.0218
	(0.274)	(0.240)	(0.197)
Eliminated in the DS	1.210***	0.419*	0.313
* Regular Player (t-1)	(0.287)	(0.250)	(0.208)
Average WS Champion (t-2)	0.888	0.0500	0.107
	(1.503)	(1.173)	(1.131)
Average WS Champion	0.750	0.858	0.456
* Career Regular (t-2)	(1.683)	(1.304)	(1.232)
Average WS Elimination (t-2)	-0.625	-0.111	0.637
	(1.610)	(1.324)	(1.118)
Average WS Elimination	2.551	0.948	0.0294
* Career Regular (t-2)	(1.805)	(1.425)	(1.233)
Average CS Elimination (t-2)	1.162	0.345	0.577
	(0.827)	(0.535)	(0.394)
Average CS Elimination	0.529	0.231	0.464
* Career Regular (t-2)	(0.984)	(0.651)	(0.557)
Average DS Elimination (t-2)	0.382	0.390	0.399
	(0.552)	(0.363)	(0.415)
Average DS Elimination	1.268**	0.893**	0.557
* Career Regular (t-2)	(0.617)	(0.414)	(0.456)
Years Played		0.0648*	0.0447
		(0.0332)	(0.0310)
Years Played^2		-0.00207	-0.00155
		(0.00130)	(0.00122)
(H-HR)/BFP (t-1)		-8.644*	-7.229
		(4.854)	(4.728)
[(H-HR)/BFP (t-1)]^2		11.72	9.386
		(10.27)	(9.975)
HR/BFP (t-1)		-11.71*	-17.45***
		(6.005)	(5.368)
[HR/BFP (t-1)]^2		65.99	151.1***
		(64.28)	(56.97)

(BB+HBP)/BFP (t-1)		-8.095***	-7.175***
		(1.705)	(1.680)
$[(BB+HBP)/BFP\ (t-1)]^2$		12.36***	11.22**
		(4.751)	(4.878)
K/BFP (t-1)		5.909*	6.989**
		(3.287)	(2.881)
$[K/BFP\ (t-1)]^2$		-2.843	-5.668
		(8.966)	(7.792)
BFP (t-1)		0.00131**	0.00182***
		(0.000585)	(0.000582)
$[BFP\ (t-1)]^2$		4.46e-07	1.63e-08
		(5.16e-07)	(5.25e-07)
Career All-stars		1.732	2.315
per Season (t-1)		(1.303)	(1.450)
Year Dummy	N	N	Y
Team Dummy	N	N	Y
Constant	13.31***	13.67***	13.37***
	(0.0565)	(0.768)	(0.767)
Observations	606	606	606
R-squared	0.221	0.564	0.659

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5 uses the same regression model as Table 4, except that the data are from batters instead of pitchers. Plus, the dummies for the batters' defensive position are also included. On the batters' table, the premiums for the postseason experience are somewhat more significant than those for the pitchers. The previous postseason experience does not affect a batter's salary, either for a regular batter or a non-regular one. However, their career postseason experience is still valuable to the teams, as the coefficients for the average career postseason experiences are mostly significant and positive. Batters with more WS eliminations and DS eliminations have higher salaries. Regular batters who got eliminated more often in the CS in their career earn more money, too. It is interesting that winning more Championships in a batter's past career do not help him to get a higher salary, but losing more often in the postseason does. It could be that batters who failed to win a World Championship may be more eager to win one and thus play harder than those who won Championships before.

In addition to the postseason experience, performance and years of experience are also main references in determining a batter’s salary. Singles are not valued, but all other performance parameters have significant effects on a batter's salary. The trend of the salary is uprising in a decreasing order as the batters gain experience. Contrary to the pitchers' part, the All-star batters do earn higher salaries, even after controlling their performances.

Table 5: The effect of past postseason experiences on a batter’s real salary, 1997-2013.

	ln (Real Salary)	ln (Real Salary)	ln (Real Salary)
Won the WS (t-1)	0.0297	0.378***	0.203
	(0.159)	(0.116)	(0.154)
Won the WS	0.656***	-0.234	-0.129
* Regular Player (t-1)	(0.231)	(0.157)	(0.188)
Eliminated in the WS (t-1)	-0.429***	-0.0752	-0.0477
	(0.112)	(0.0678)	(0.170)
Eliminated in the WS	0.763***	0.141	0.152
* Regular Player (t-1)	(0.177)	(0.126)	(0.190)
Eliminated in the CS (t-1)	-0.355**	-0.00581	-0.0316
	(0.153)	(0.140)	(0.101)
Eliminated in the CS	0.801***	0.0943	0.121
* Regular Player (t-1)	(0.190)	(0.154)	(0.117)
Eliminated in the DS (t-1)	-0.177	0.133	0.138
	(0.145)	(0.122)	(0.122)
Eliminated in the DS	0.729***	-0.00712	0.0241
* Regular Player (t-1)	(0.163)	(0.132)	(0.130)
Average WS Champion (t-2)	0.0815	0.359	0.372
	(0.453)	(0.309)	(0.314)
Average WS Champion	1.582**	-0.267	-0.273
* Career Regular (t-2)	(0.713)	(0.487)	(0.470)

Average WS Elimination (t-2)	0.0324	0.691*	0.715**
	(0.561)	(0.361)	(0.339)
Average WS Elimination	1.016	-0.784	-0.487
* Career Regular (t-2)	(0.964)	(0.668)	(0.592)
Average CS Elimination (t-2)	-0.686	-0.192	-0.157
	(0.435)	(0.289)	(0.267)
Average CS Elimination	3.061***	0.974**	0.730*
* Career Regular (t-2)	(0.638)	(0.439)	(0.405)
Average DS Elimination (t-2)	0.616**	0.709***	0.379**
	(0.291)	(0.195)	(0.189)
Average DS Elimination	1.989***	0.449	0.408
* Career Regular (t-2)	(0.403)	(0.278)	(0.258)
Years Played		0.173***	0.157***
		(0.0278)	(0.0282)
Years Played^2		-0.00728***	-0.00678***
		(0.00118)	(0.00121)
1B/PA (t-1)		-2.061	0.151
		(2.808)	(3.118)
[1B/PA (t-1)]^2		15.02*	8.559
		(7.926)	(9.322)
2B/PA (t-1)		8.406***	4.791***
		(1.832)	(1.855)
[2B/PA (t-1)]^2		-20.10*	-1.348
		(12.13)	(11.38)
3B/PA (t-1)		18.99**	22.90***
		(7.702)	(6.655)
[3B/PA (t-1)]^2		-323.4	-434.4
		(364.2)	(275.7)
HR/PA (t-1)		13.70***	16.39***
		(4.581)	(4.306)
[HR/PA (t-1)]^2		6.676	-23.62
		(74.89)	(69.29)
(BB+HBP)/PA (t-1)		3.681**	4.000**
		(1.739)	(1.981)
[(BB+HBP)/PA (t-1)]^2		-6.700	-5.816
		(7.696)	(9.503)
K/PA (t-1)		-2.258***	-2.109***
		(0.595)	(0.531)

[K/PA (t-1)]^{2}		3.692***	2.546***
		(0.916)	(0.637)
PA (t-1)		0.000437	0.000350
		(0.000431)	(0.000457)
[PA (t-1)]^{2}		2.97e-06***	2.63e-06***
		(5.38e-07)	(5.72e-07)
Career All-stars		0.954***	0.925***
per Season (t-1)		(0.269)	(0.272)
Position Dummy	N	Y	Y
Year Dummy	N	N	Y
Team Dummy	N	N	Y
Constant	13.10***	10.87***	11.46***
	(0.0405)	(0.301)	(0.312)
Observations	1,148	1,148	1,141
R-squared	0.215	0.655	0.729

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

It is interesting to note how different teams value the postseason experience, because different teams may have different demands for various players. Table 6 sorts the pitching data based on three categories: the winning percentage, the revenue and the income of the teams. In the first two columns, the players are sorted by the previous season winning percentage of the team they belong to. Teams with higher winning percentage are closer to the postseason, and may have higher demand for players with past postseason experiences to help them win a Championship. The next two columns stratify the players by the previous revenue of the teams. The column "Large Revenue" includes teams which had revenue higher than the seasonal league average, while the column "Small Revenue" contains the rest of the teams. The last two columns sort the players by the teams’ income in the previous season. Teams with larger revenue or positive income may have more money to spend on players with postseason experience.

From this table, it can be noted that, first, the teams with winning percentage less than 50% are willing to give a huge 69% raise in the salary of a non-regular pitcher who won a World Championship in the previous season. The teams which won more are only willing to pay more for the players who got eliminated in the DS in the previous season. Secondly, the small revenue teams have a higher demand for the pitchers who won the championship in the previous season, but they have no demand for players with other kinds of postseason experience. The large revenue teams, on the other hand, have greater demands for players who are eliminated in the previous DS and CS. Thirdly, both teams with negative and positive income have higher demand for pitchers who won the previous World Series. However, having won the previous World Series benefits those non-regular pitchers only. For regular pitchers, being eliminated in the WS has no value to any team. In row 2 of columns 5 and 6, the negative coefficients for the regular pitchers are almost as large as the overall effects in row 1. Lastly, across all kinds of teams, being eliminated in the World Series does not affect a pitcher's salary. Other kinds of postseason experiences influence a pitcher's salary either in the short or the long term, but being eliminated in the World Series does not.

Table 6: The effect of past postseason experience on a pitcher's real salary, stratified by winning percentage, revenue and income, 1997-2013.

	Win % (t-1) <0.5	Win % (t-1) ≧0.5	Small Revenue (t-1)	Large Revenue (t-1)	Income (t-1) < 0	Income (t-1) ≧0
Won the WS (t-1)	0.692**	0.601	0.932***	0.180	1.705**	1.011***
	(0.300)	(0.368)	(0.335)	(0.374)	(0.851)	(0.241)
Won the WS	NA	-0.520	-0.546	0.0595	-1.654*	-0.703**
* Regular Player (t-1)		(0.399)	(0.408)	(0.383)	(0.946)	(0.317)
Eliminated in the WS (t-1)	0.399	-0.278	0.187	-0.141	-0.0241	0.298
	(0.286)	(0.234)	(0.318)	(0.177)	(0.318)	(0.238)
Eliminated in the WS	-0.594	0.387	-0.363	0.241	-0.351	-0.268
* Regular Player (t-1)	(0.639)	(0.287)	(0.550)	(0.258)	(0.395)	(0.316)
Eliminated in the CS (t-1)	0.105	-0.332	-0.296	0.273**	0.283	-0.208
	(0.199)	(0.448)	(0.373)	(0.126)	(0.317)	(0.406)
Eliminated in the CS	NA	0.633	0.365	NA	NA	0.533
* Regular Player (t-1)		(0.467)	(0.418)			(0.419)
Eliminated in the DS (t-1)	-0.354	0.613***	-0.351	0.464**	0.343	0.00662
	(0.264)	(0.224)	(0.465)	(0.189)	(0.378)	(0.240)
Eliminated in the DS	0.471	-0.355	0.459	-0.262	-0.420	0.347
* Regular Player (t-1)	(0.296)	(0.243)	(0.493)	(0.208)	(0.504)	(0.259)
Average WS Champion (t-2)	1.449	0.809	0.557	-0.142	1.043	-1.544
	(2.447)	(1.220)	(2.124)	(1.419)	(2.271)	(1.671)
Average WS Champion	-0.993	-0.123	0.644	0.554	-1.144	1.937

* Career Regular (t-2)	(3.048)	(1.316)	(2.643)	(1.462)	(2.468)	(1.835)
Average WS Elimination (t-2)	-1.130	0.0432	1.234	-0.612	1.250	0.689
	(1.751)	(1.386)	(2.067)	(1.557)	(4.138)	(1.183)
Average WS Elimination	1.627	0.757	-1.814	1.971	-0.145	0.158
* Career Regular (t-2)	(1.967)	(1.630)	(2.170)	(1.726)	(4.067)	(1.389)
Average CS Elimination (t-2)	1.026	-0.152	-0.440	0.894*	0.0991	0.691
	(0.785)	(0.501)	(0.676)	(0.536)	(1.041)	(0.482)
Average CS Elimination	0.295	0.869	1.740*	-0.785	0.413	0.282
* Career Regular (t-2)	(1.092)	(0.722)	(0.933)	(0.760)	(1.629)	(0.683)
Average DS Elimination (t-2)	0.271	0.345	0.108	0.647	1.599	0.370
	(0.729)	(0.766)	(0.514)	(0.952)	(1.024)	(0.494)
Average DS Elimination	0.675	0.375	0.996	0.154	-1.119	0.659
* Career Regular (t-2)	(0.806)	(0.743)	(0.691)	(0.924)	(0.960)	(0.568)
Performance Variables	Y	Y	Y	Y	Y	Y
Year Dummy	Y	Y	Y	Y	Y	Y
Team Dummy	Y	Y	Y	Y	Y	Y
Observations	272	334	263	319	155	451
R-squared	0.686	0.711	0.662	0.734	0.859	0.620

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7 analyzes different salary offers to the batters in terms of the team's winning percentage, revenue and income. The results are somewhat different from those acquired in Table 6. Overall, batters who have postseason experience in the previous season are not met with higher demand from any teams sorted by winning percentage, revenue or income. For the postseason experience in the previous season, only teams which on more than half of the games and teams with negative income have a higher demand for batters who are eliminated in the previous DS. On the other hand, career postseason experience seems to be more important. In particular, teams with positive income have higher demand for batters with more World Series experiences and regular batters who are eliminated in the DS and CS more often. In comparison, teams with negative income have almost no demand for batters with postseason experience. This may indicate that batters' postseason experience is not a necessity for the teams. Only teams having spare money will place a higher value on postseason experiences.

Table 7: The effect of past postseason experience on a batter's real salary, stratified by winning percentage, revenue and income, 1997-2013.

	Win % (t-1) <0.5	Win % (t-1) ≧0.5	Small Revenue (t-1)	Large Revenue (t-1)	Income (t-1) < 0	Income (t-1) ≧0
Won the WS (t-1)	0.419	0.0551	0.223	0.345	0.722	-0.0142
	(0.449)	(0.160)	(0.173)	(0.245)	(0.574)	(0.150)
Won the WS	-0.392	0.0236	-0.354	-0.137	-0.271	-0.000207
* Regular Player (t-1)	(0.542)	(0.194)	(0.320)	(0.268)	(0.629)	(0.193)
Eliminated in the WS (t-1)	0.211	-0.269	-0.0517	0.0109	0.105	-0.109
	(0.144)	(0.301)	(0.164)	(0.180)	(0.177)	(0.278)
Eliminated in the WS	-0.00450	0.335	NA	0.313	-0.0563	0.219
* Regular Player (t-1)	(0.231)	(0.315)		(0.205)	(0.225)	(0.294)
Eliminated in the CS (t-1)	-0.279	0.00478	-0.128	-0.0108	-0.0621	-0.0883
	(0.189)	(0.172)	(0.141)	(0.191)	(0.187)	(0.157)
Eliminated in the CS	0.306	0.118	0.00526	0.161	0.0118	0.228
* Regular Player (t-1)	(0.229)	(0.187)	(0.181)	(0.206)	(0.248)	(0.170)
Eliminated in the DS (t-1)	0.103	0.288**	0.139	0.218	0.866*	0.0276
	(0.180)	(0.141)	(0.205)	(0.175)	(0.440)	(0.128)
Eliminated in the DS	0.134	-0.156	-0.00921	-0.0523	-0.568	0.0976
* Regular Player (t-1)	(0.194)	(0.154)	(0.219)	(0.179)	(0.461)	(0.139)
Average WS Champion (t-2)	0.191	0.198	0.542	0.155	0.0642	0.776**
	(0.606)	(0.422)	(0.461)	(0.513)	(0.570)	(0.375)
Average WS Champion	-0.190	-0.0602	-0.0758	-0.327	-0.0387	-0.596

* Career Regular (t-2)	(0.873)	(0.600)	(0.812)	(0.702)	(1.082)	(0.521)
Average WS Elimination (t-2)	0.307	0.970	1.264***	0.423	-0.0919	0.802*
	(0.523)	(0.593)	(0.444)	(0.533)	(0.824)	(0.430)
Average WS Elimination	-0.392	-0.788	-0.964	-0.874	0.443	-0.473
* Career Regular (t-2)	(0.864)	(0.890)	(0.904)	(0.803)	(1.419)	(0.677)
Average CS Elimination (t-2)	0.149	-0.498	-0.249	-0.314	0.438	-0.291
	(0.405)	(0.383)	(0.405)	(0.396)	(0.553)	(0.302)
Average CS Elimination	0.474	1.082*	0.181	1.240**	-0.684	1.064**
* Career Regular (t-2)	(0.667)	(0.554)	(0.674)	(0.536)	(0.910)	(0.449)
Average DS Elimination (t-2)	0.0126	0.735**	0.324	0.448	0.368	0.236
	(0.300)	(0.294)	(0.303)	(0.274)	(0.487)	(0.213)
Average DS Elimination	0.514	0.283	0.152	0.612*	0.198	0.569*
* Career Regular (t-2)	(0.403)	(0.374)	(0.452)	(0.357)	(0.622)	(0.291)
Performance Variables	Y	Y	Y	Y	Y	Y
Defensive Position Dummy	Y	Y	Y	Y	Y	Y
Year Dummy	Y	Y	Y	Y	Y	Y
Team Dummy	Y	Y	Y	Y	Y	Y
Observations	514	627	499	588	300	841
R-squared	0.718	0.780	0.690	0.787	0.804	0.741

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

6. Chance of Employment and Postseason Experience

In investigating a player's postseason experience, the chance of employment should also be taken into consideration. A career duration analysis of the players is the major concern in this section. In order to estimate the relationship between postseason experience and the chance of employment, I use Cox's (1972) proportional hazard model, which is adopted by Ohkusa (2001) and Frick, Pieztner and Prinz (2007) in examining the connection between sports players' performance and his chance of exiting the league. The basic form of the Cox model is:

$$h(t) = h_0(t)e^{\beta X_i}$$

where $h(t)$ is whether the player at age t and $h_0(t)$ is the probability of retiring at age t when all the independent variables are 0. X_i is a list of independent variables that may influence the probability of retirement of the players. The variables in X_i are the same as those in the performance indicator prediction models above.

Table 8 shows that regular pitchers who won the World Series or lost in the CS are less likely to retire, while non-regular pitchers who lost in the CS are more likely to retire. Table 5 shows pitchers have higher salary for having won the World Championship in the previous season, which may increase their willingness to stay in the league. On the other hand, batters who lost in the previous DS are also less likely to retire. Also, batters who achieved higher stages in the postseason more often in his career are more likely to retire, and those who won the Championships more often are much less likely stay in the league. This could indicate that batters who had fewer chances in the postseason are more likely to stay in the league to fight for a Championship, while those who had higher achievement have less motivation to stay in the league. Furthermore, batters who hit more doubles and home runs per PA are less likely to retire (not shown in the table), which confirms the conclusion that better performance leads to lower exit rates (Hoang & Rascher, 1999; Frick, Pieztner & Prinz, 2007). However, the influences of pitchers' performance are all insignificant. The cause of such difference between the batters and the pitchers may arise from the different occupational productivity patterns (Ohkusa, 2001). Further analysis is required on this issue.

Table 8: The effect of past postseason experience on a player's chance of unemployment, 1997-2013

	Retire, Pitchers	Retire, Batters
Won the WS (t-1)	0.819	0.138
	(0.632)	(0.601)
Won the WS	-2.464**	0.0899
* Regular Player (t-1)	(1.218)	(0.754)
Eliminated in the WS (t-1)	-0.696	0.228
	(0.869)	(0.673)
Eliminated in the WS	-0.979	-0.909
* Regular Player (t-1)	(1.552)	(0.822)
Eliminated in the CS (t-1)	0.904***	0.0977
	(0.314)	(0.290)
Eliminated in the CS	-2.926***	-0.757
* Regular Player (t-1)	(0.916)	(0.513)
Eliminated in the DS (t-1)	-0.571	-0.876**
	(1.029)	(0.401)
Eliminated in the DS	-1.083	0.466
* Regular Player (t-1)	(1.153)	(0.471)
Average WS Champion (t-2)	-1.685	-0.553
	(1.441)	(1.058)
Average WS Champion	2.696	4.346***
* Career Regular (t-2)	(1.967)	(1.304)
Average WS Elimination (t-2)	1.336	-1.104
	(2.963)	(1.434)
Average WS Elimination	-4.204	3.221*
* Career Regular (t-2)	(3.406)	(1.691)
Average CS Elimination (t-2)	-2.110	-1.109

	(2.160)	(0.919)
Average CS Elimination	2.392	0.758
* Career Regular (t-2)	(2.278)	(1.172)
Average DS Elimination (t-2)	-0.494	0.852*
	(0.860)	(0.478)
Average DS Elimination	0.100	-0.128
* Career Regular (t-2)	(1.016)	(0.749)
Performance	Y	Y
Defensive Position Dummy	-	Y
Year Dummy	Y	Y
Log pseudolikelihood	-1814.1464	-1803.7676
N of retirement	378	400
Observations	1,476	1,993

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

7. Conclusion and Discussion

This research shows that the teams prioritize the batters' postseason experience over the pitchers' and are more willing to offer a better contract to a batter with postseason experience. For the pitchers with previous World Championship experience, they generally get a 58% raise in payment, but other postseason experiences will not boost their salaries. As for the batters, the postseason experience in the previous season is insignificant, but their career postseason experience still counts. Batters who have more experiences being eliminated from the postseason receive higher salaries, which means their career postseason or championship experience to can be used to ask for higher salaries when they are negotiating with the teams. In other words, the immediate Championship experience is advantageous for the pitchers in negotiating the salaries, while the batters benefit from their career experience for a salary raise.

Furthermore, several interesting facts came into view. First, teams without winning records in the previous season are more inclined to offer a higher salary for the pitcher with higher achievement in the postseason, while the better performed teams tend to offer higher salaries to batters who experienced losing in the postseason. Moreover, the teams with positive income have higher demand for batters with postseason experience than the teams with negative income.

Second, the decision for a player to leave or to stay in MLB may have something to do with his recent postseason experience. A pitcher who wins a championship ring in the previous season will have a higher propensity to stay in the league. Since they are offered with higher salaries, such decision is not really surprising. In contrast, batters who are better achieved in the postseason stages tend to retire early, and those who won Championships more often throughout their career are most likely to retire. This may indicate that the less achieved batters are prone to striving for honor and success. However, as for why such a yearning for prestige only appears in the batters, further study is needed.

Some problems may occur with regard to the estimation in this paper. The first problem concerns the postseason performance. A batter who hits well in the postseason is obviously different from a batter who cannot make even a single hit in the postseason. Teams will place more value on the first kind of batter, but in the model of this research, such value differences are omitted. It is because if postseason performance is included, only players who played postseason can be compared. It is not possible to compare them with the players who did not play in the postseason.

Another problem involves the long-term contracts. For example, if a player with postseason experience signed a 4-year contract, his bonus salary gained from postseason experience may spread across 4 years. It won't be proper to estimate his postseason experience value with the salary for the next season only. A closer scrutiny on the contract length of every player is required to make the estimation more accurate.

Finally, since it can be concluded that the postseason experience has some value to the teams, and teams pay higher salaries to sign players with some kinds of postseason experiences, the next question arises: is it worth it? Will buying postseason experience be rewarded with positive earnings? It is not easy to answer this question. For the teams, the value of postseason experience lies in the chance of advancing to higher stages of the postseason and earns higher revenue. However, no data are available for the revenue of the postseason. It's obvious that large revenue comes from the postseason, but no one knows how big it is. If the data on the postseason revenue are available, estimation can be made to see if the revenues generated from postseasons are enough to cover higher cost of signing players with postseason experience.

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