ESTIMATING ECONOMIC IMPACTS

OF TOMMY JOHN SURGERY ON

MAJOR LEAGUE BASEBALL PITCHERS

by

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TABLE OF CONTENTS

1. INTRODUCTION 1

2. BACKGROUND 3

History of Tommy John Surgery 3

Wins Above Replacement (WAR) 4
Baseball-Reference: BR-WAR 6
FanGraphs: FG-WAR 9
Two WAR Measures: Discussion 12

Chapter Two Figures and Tables 13

3. RELATED LITERATURE 15

Medical Literature 15

Economic Literature on Marginal Revenue Product 19

Wins Above Replacement (WAR) Literature 23

Chapter Three Figures and Tables 27

4. IMPACT OF TOMMY JOHN SURGERY ON PITCHER MARGINAL PRODUCT 29

Estimating the Impact of TJS on Pitcher Productivity 30
Empirical Specification 30
Data 33
Results 35

Estimating the Marginal Product of Pitcher WAR on Team Wins 42

Chapter Four Figures and Tables 47

5. ESTIMATING MARGINAL REVENUE OF A WIN 65

Theory and Empirical Specification 65

Data 68

Results 69

Chapter Five Figures and Tables 72

TABLE OF CONTENTS (CONTINUED)

6. MARGINAL REVENUE PRODUCT CALCULATION 78

General Estimate for Average Pitcher 79

Specific Estimates for Three Hypothetical Pitchers 83

Pitcher A Estimation: 84

Pitcher B Estimation: 85

Pitcher C Estimation: 87

Discussion 88

7. CONCLUSION 90

REFERENCES CITED 94

APPENDICES 97

A. ADDITIONAL DETAILS ON ESTIMATION OF WAR FOR POSITION PLAYERS 98

Appendix A Tables 102

B. ATTEMPT AT REPLICATING MEDICAL STUDY METHODS AND RESULTS 103

Appendix B Tables 106

C. ESTIMATION OF MARGINAL REVENUE USING GATE REVENUE INSTEAD OF TOTAL REVENUE 108

Appendix C Figures and Tables 110

LIST OF TABLES

Table — Page

1. Comparison of Medical Journal Analyses of Tommy John Surgery 27
2. Summary Statistics – Pitchers 1996-2016 47
3. Summary Statistics – All Pitcher-years 1996-2016 48
4. Summary Statistics – All TJS Pitcher-years 1996-2016 48
5. Summary Statistics – Non-TJS Pitcher-years 1996-2016 49
6. Impact of TJS on WAR 51
7. Age Subsamples (Young = Age < 28, Old = Age >= 28) 52
8. Starter and Reliever Sub-samples 53
9. Impact of TJS of ERA, WHIP and Innings Pitched for Starting Pitchers 54
10. Impact of TJS of ERA, WHIP and IP for Relief Pitchers 55
11. Breakdown of WAR into standard pitching statistics 56
12. Impact of TJS on Games Pitched, Innings Pitched and ERA for All Pitchers 57
13. Impact of TJS on WHIP, Strikeouts, Walks and Homeruns Allowed for All Pitchers 58
14. Summary Statistics – Pitchers and Position Player-years 59
15. Team Wins as a Function of Individual FG-WAR 61
16. Team Wins as a Function of Individual BR-WAR 62
17. Team Wins as a Function of Team FG-WAR 63
18. Team Wins as a Function of Team BR-WAR 64
19. Summary Statistics by Team 74

LIST OF TABLES (CONTINUED)

Table Page

20. MR of a Win, Quantile Regression with Time Trend and Team Fixed Effects 75

21. MR of a Win, Quantile Regression with Team and Year Fixed Effects 76

22. MR of a Win, Quantile Regression with Time Trend and Yankee Dummy 77

23. Positional Adjustment Runs 102

24. Summary Stats for Case (TJS) Group (343 pitchers) 106

25. Summary Stats for Control Group (595) 107

26. Comparison of Means for Case and Control Groups 107

27. MR of a Win, Quantile Regression with Time Trend and Team Fixed Effects 112

28. MR of a Win, Quantile Regression with Team and Year Fixed Effects 113

29. MR of aWin, Quantile Regression with Time Trend and Yankee Dummy 114

LIST OF FIGURES

Figure Page

1. Number of Tommy John Surgeries in MLB by Year 13

2. Ratio of Players who Return to Same Level after TJS 13

3. Average Months to Return to the Same Level after TJS 14

4. Distribution of FG-WAR Values 49

5. Distribution of BR-WAR Values 50

6. Variation is Wins over Time for 10 Teams 60

7. Mean Total and Gate Revenues by Year 72

8. Real Total Revenues by Season for Four Teams 72

9. Mean Wins and Revenue by Team 1996-2016 73

10. Gate Revenues by Season for Four Teams 110

11. Mean Annual Wins and Gate Revenue by Team 111

ABSTRACT

Tommy John Surgery is a common elbow surgery among baseball pitchers that has become more prevalent over the last two decades. In this thesis, I estimate the impact of Tommy John Surgery on Major League Baseball pitcher productivity and value to the team, measured through Marginal Revenue Product. Tommy John Surgery requires a rehabilitation period of over a year on average, and it is important for the team to be able to predict the pitcher's post-surgery performance. The estimated productivity impact of Tommy John Surgery is a decrease in pitchers' performance for at least two seasons following their return to play. The combined magnitude of this decrease in performance translates to about one team win and over an $800,000 decrease in Marginal Revenue Product for the team. I estimate the entire cost to a team resulting from lost productivity related to Tommy John Surgery to be about $2 million. With an average of 25 Tommy John Surgeries a season in Major League Baseball over the last five seasons, these costs total approximately $50 million league wide every year. Other components of this thesis include analyses of Wins Above Replacement as a productivity statistic in baseball and the impact of Tommy John Surgery on pitcher performance, measured through both Wins Above Replacement and standard pitching statistics, such as innings pitched and earned run average.

CHAPTER ONE

INTRODUCTION

This thesis is about the impact of injury, and its treatment, on winning and the subsequent impact on team revenues. The particular research focus is elbow injury to Major League Baseball (MLB) pitchers and its treatment through what is now commonly known as “Tommy John Surgery” (TJS). Twenty-five percent of all current pitchers in Major League Baseball (MLB) have had Tommy John Surgery (TJS) at some point in their career, and over 95 percent of the pitchers who have the surgery are able to return to pitch at a professional level again (Keri 2015).

Team owners use hitting and pitching talent to produce wins and then generate part of their revenues selling those wins to fans at the gate and through media outlets. An injury to a player, specifically one that requires surgery and a long rehabilitation process, will affect the player’s value to the team. The goal of this thesis is to quantify the impact of TJS on a pitcher’s future performance and their resulting value to the team.

The outcome of interest is the impact of TJS on Marginal Revenue Product (MRP). Here, as in other contexts, MRP is marginal product (MP) multiplied by the marginal revenue (MR) collected from the sale of that MP. In sports, MP is typically measured by a player’s contribution to his team’s wins and MR is estimated from a team revenue function that depends on wins.

I estimate the impact of TJS on a pitcher’s MP in terms of the difference in the number of wins that pitcher contributes to his team after the surgery. The performance measure I use for pitcher MP is Wins Above Replacement (WAR). WAR is designed to capture all aspects of a player's contribution to his team, compared to that of an available replacement level player.

I estimate MR at the team level by regressing each team's total revenue on the determinants of revenue, including their wins for that season. Theoretically, in professional sports leagues, MR varies across teams with different total revenue potential across a league. To incorporate the theory, the quantile regression technique is employed to allow MR to vary for teams in different-sized markets.

This thesis adds to the literature on MRP, using WAR and TJS to estimate changes in MRP. My results provide valuable information to MLB teams attempting to predict the future value of pitchers who have to undergo TJS. These results indicate a decrease in productivity for a pitcher in the first two seasons following his return to MLB. In addition, the analysis informs the sports analytics community on how individual player WAR values translate into team wins. The MP of one unit of pitching WAR is significantly larger than one unit of hitting WAR.

The remainder of this thesis proceeds as follows. Chapter two presents background on the history of TJS and WAR. Chapter three presents the relevant literature to this thesis. Chapter four contains the estimates of the impact of TJS on pitcher MP, measured by WAR. The estimated quantiles of MR are in chapter five. Combining the estimates from chapters four and five, chapter six contains the calculation of the impact of TJS on MRP. A summary of results, implications and suggestions for future research conclude the thesis in chapter seven.

CHAPTER TWO

BACKGROUND

This chapter includes the history of TJS and an explanation of WAR, the measure of pitcher MP used in this thesis.

History of Tommy John Surgery

TJS repairs damage to the ulnar collateral ligament (UCL), one of the thick ligaments connecting the humerus (upper arm) to the ulna (lower, or forearm). Due to the stress put on this ligament during the act of throwing, baseball pitchers are particularly susceptible to UCL injuries.

Dr. Frank Jobe performed the first UCL reconstruction surgery in 1974 on pitcher Tommy John, hence the name "Tommy John Surgery." In the 44 years since that first UCL reconstruction, thousands of the surgeries have been performed on baseball players at all levels, from high school through MLB. Figure 1 shows the increasing incidence of TJS in MLB over the years. The annual number of surgeries has been increasing over time, with a dramatic increase during the 1990s and 2000s. The MLB peak occurred in 2012 with 36 total surgeries.[1]

The average TJS recovery time is 12 to 18 months for pitchers and about half that for position players. This recovery time is measured as the amount of time to return to

[1] There are a few position players who have to undergo TJS, but very few compared to the number of pitchers who require the surgery. There have been 16 total TJS on MLB position players in the last 10 years.

pitching again at any level, and most pitchers require at least a few rehabilitation starts at the minor league level. Some pitchers who were borderline MLB pitchers prior to TJS may spend years working their way back to the major-league level. In my analysis, the time to return to the same level of competition ranges from nine months to almost five years, even though the majority of players are pitching again at some level within two years. Figure 2 shows the ratio of pitchers who get TJS that are able to return to MLB each year over the course of the sample, and figure 3 shows the average time to return to the same level of play by year. Both figures show a downward trend over time, but that trend is not statistically significant at the 5 percent level.[2] The rate of return to MLB is decreasing at a rate of approximately 1 percent per year, but this does not mean that the surgery has gotten less effective over the past 20 years. The low return rate in recent years is primarily due to those players not having sufficient time to recover and return, and may also be related to more pitchers undergoing TJS in the later seasons of the sample than in the early seasons. There is a variety of opinions on the actual performance impacts of TJS, and this thesis uses econometric regression methods to actually estimate the performance impacts of TJS.

Wins Above Replacement (WAR)

Wins Above Replacement (WAR) is a fairly new and widely used statistic in the world of baseball.[3] As I explain below, the process of estimating WAR values is a

[2] The trend is statistically significant at the 10 percent level with a P-value = 0.074.
[3] Baseball-Reference began calculating and reporting WAR in 2010 and they credit Sean Smith with the original formula used for their calculations.

complicated and technical procedure. The purpose of WAR is to be a productivity estimate that encapsulates everything a player contributes to his team's success on the field and presents it as a single value. For pitchers, WAR is relative to contributing to wins by preventing opponent runs. The "replacement" player is viewed as the cheapest available alternative, typically a AAA minor-league player. Thus, the use of WAR is relevant to the actual problem confronting management when a player is injured. They could always turn to a minor league alternative to replace the injured player. WAR is also calculated so that comparisons between players of different positions are possible. The time period can be a single season, multiple seasons, or an entire career, and players are compared over that period based on their WAR values.

There are four steps to the calculation of any WAR value:

1. Define the replacement level.
2. Calculate the runs stopped for any given pitcher.
3. Translate runs stopped into wins.
4. Calculate wins relative to the replacement level.

In this section, the actual derivations of WAR by Baseball-Reference and FanGraphs are presented only for pitchers.[4] The WAR values from these two sources constitute the WAR data used in the analysis chapters. Position player WAR is calculated using similar steps as pitcher WAR, but uses position player statistics to estimate runs created instead of runs stopped (more details are shown in appendix A). Pitchers also have hitting WAR values calculated for them and that discussion is in appendix A as well

[4] The information for this section is from https://www.fangraphs.com/library/war/calculating-war-pitchers/ and https://www.baseball-reference.com/about/war_explained_pitch.shtml

as later on in chapter four, because it is separate from their pitching WAR value and only used in one small section of the analysis.

Baseball-Reference: BR-WAR

Step 1: The first step in developing the Baseball-Reference version of WAR, BR-WAR, is to identify the replacement level of performance. The replacement level is based on the contribution of a player to team performance if all the players were replacement players (AAA). This replacement level is currently set at a winning percentage of 0.294, meaning that a team of all replacement players would be expected to win about 48 games in a 162-game season.

This replacement level corresponds to a total of 1000 available WAR allocated across all MLB players for each season.[5] Baseball-Reference assigns 59 percent of WAR to position players and 41 percent to pitchers (a total of 410 WAR for all pitchers). Baseball-Reference bases this on the distribution of total free agent salaries between pitchers and hitters over the last four seasons. This consistent distribution of total WAR allows for the comparison of players over different eras, where one is more hitter or pitcher friendly than the other.

For pitchers, Baseball-Reference calculates the difference between the league average and the replacement level in terms of runs allowed per out (RpO_replacement). The league average runs allowed per out is simply the total runs scored divided by total outs recorded across the league, and the replacement level runs per out is estimated using

[5] Teams in MLB: 30, Games in a season: 162, Average winning percentage: 0.500, Replacement level winning percentage: 0.294. So, 30*162*(.500-.294) = 1001 which is rounded to 1000 WAR per season.

the designated replacement level in order to generate a total of 410 WAR for pitchers. The runs per out replacement level is then multiplied by the number of outs each pitcher records in the season to get his total replacement level for the season.

Step 2: The next step is to use a comprehensive array of baseball performance statistics designed to capture a pitcher's contribution to runs stopped against opponents. Baseball-Reference states that the basic measure of a pitcher's value to his team is the number of runs he allows. They use Runs Allowed per Nine Innings Pitched (RA/9) as their primary statistic and then adjust for defensive performance and level of opposition. The statistics used for defensive performance adjustments include team defensive runs saved weighted by the number of balls in play allowed by the pitcher.

Baseball-Reference also adjusts for ballpark factors, league and year differences, as well as a leverage multiplier. The leverage multiplier adjusts for the relative importance of relief pitchers by putting more weight on some relief innings than others depending on the situation of the game when the pitcher enters. Coming into a close game or with runners on base would result in a high leverage multiplier for a relief pitcher. Starting pitchers automatically have a leverage multiplier of one. After all these adjustments, the resulting value is Runs Allowed Above Average. The remaining steps in calculating a pitcher's WAR value convert Runs Allowed Above Average from runs to wins, adjusted by replacement level.

Step 3: Converting runs to wins is another aspect of WAR that is somewhat arbitrary and not easily understood by non-sabermatricians. Until recently, converting from runs to wins was as simple as dividing by 10 runs per win, that is, the average number of runs per win over MLB's 140 seasons. This means that every additional 10 runs added to a team's total runs over the course of a season adds one win. However, this choice of historical runs per win for all players and years has been one of the most criticized componenets of the calculation of WAR.

Baseball-Reference now employs a more advanced and player specific runs-to-wins conversion technique. The general idea is that the runs-per-win can vary by year and league and even the individual player based on the value of an additional run in a given situation. For example, a better pitcher will allow fewer average runs per game in the games they pitch in than in an average game. This means that each run saved for that dominant pitcher is a higher percentage of the total runs in the game and translates to more wins.

Specifically, Baseball-Reference calculates "RA"; the pitcher's mean adjusted number of runs allowed (above or below average). Then RA is used in the PythagenPat formula to estimate the team's winning percentage while that pitcher is pitching.[6]

$$\text{Team PythagenPat W-L\%} = (RS^x) / (RS^x + RA^x),$$

Where Team PythagenPat W-L% is an estimated win percentage for pitcher i against an average team; RS = league average runs scored per game; RA = pitcher i's mean adjusted runs allowed per game; and $x = (\text{total runs/gm})^{.285}$.

The difference between this expected winning percentage and the league average winning percentage (0.500) is multiplied by the games pitched by pitcher i to get his resulting number of Wins Above Average.

[6] The PythagenPat formula was created by David Smyth as an adjustment to Clay Davenport's Pythagenport formula.

Step 4: To calculate BR-WAR, the Wins Above Average estimate from step 3 is added to the difference between league average wins and replacement level wins. I will use Baseball-Reference's example of Roy Halladay's 2011 season to illustrate this process. In 2011, the National League average was 4.14 runs/game for each team and Halladay allowed 1.866 fewer runs per game than average and pitched in 32 games. So, the RS = 4.14 and RA = 2.27 for the PythagenPat formula and the resulting estimated winning percentage for Halladay is 0.735. Therefore, WAA = (0.735-0.500) * 32 games = 7.52. The difference between the average and replacement level, weighted by Halladay's innings pitched was 1.7 wins so Baseball-Reference's estimation of Halladay's WAR for 2011 was 9.22 = 7.52 + 1.7.

FanGraphs: FG-WAR

Step 1: As with BR-WAR, the first step toward the FanGraphs version, FG-WAR, is to identify the replacement level of performance. Using the same winning percentage of 0.294 and 48 replacement wins, the FanGraphs' split of the 1000 replacement points is 57 percent to position players and 43 percent to pitchers (430 WAR total for all pitchers). FanGraphs claims that this matches the total payroll split between the two, as opposed to the free agent salary split that Baseball-Reference uses. FanGraphs uses this to calculate the difference between an average pitcher and a replacement level pitcher. This difference (Replacement Level) ends up being 0.03 wins per game for relievers and 0.12 wins per game for starters.[7]

[7] If the pitcher splits time as a starter and a reliever then their Replacement Level is a weighted average based on their games starting and games in relief.

Step 2: To estimate runs stopped by a particular pitcher, FanGraphs calculates fielding independent pitching (FIP), which is a weighted average of all the pitching outcomes that do not result in a ball in play:

$$FIP = ((13*HR)+(3*(BB+HBP))-(2*K))/IP + \text{FIP Constant}$$

These include home runs allowed (HR), walks (BB), hit by pitches (HBP), strikeouts (K), all on a per innings pitched (IP) basis. The FIP Constant is the difference between the league average ERA and league average FIP, which normalizes the individual FIP values around the league average ERA.

FanGraphs also has a park adjustment based on the average FIP in a given park and a leverage multiplier. FanGraphs leverage multiplier is averaged with a value of one to account for bullpen “chaining.” Chaining means that if the closer gets injured, he is replaced by the set-up man, who is replaced by the next person in the bullpen and on down. So, the replacement player from the highest minor league level (AAA) enters the back end of the bullpen and does not get slotted into the closer’s role.

FanGraphs converts the FIP value onto a RA/9 scale (comparable to the RA used by Baseball-Reference) by adding an adjustment to FIP that is equal to the league average RA/9 minus the league average ERA. This value (pFIPR9) is subtracted from the league average pFIPR9 for the appropriate league, resulting in a Runs Above Average per nine innings pitched. One thing to note about this process from FIP to Runs Above Average is that it converts the value (FIP) from an interpretation where smaller is better, like the interpretation of ERA, to a value (Runs Above Average) where bigger is better, which is the interpretation of WAR. This Runs Above Average per nine innings pitcher measure is converted to wins and adjusted for replacement level, as described below.

Step 3: To translate runs into wins, FanGraphs calculates Dynamic Runs per Win, which is specific for each pitcher based on how many innings per game he pitches and the number of runs scored while he is pitching. Simply put, this is the average of the runs per game while the given pitcher is pitching and the league average runs per game, weighted by the innings per game pitched by the given pitcher. In a much simpler method than Baseball-Reference uses, FanGraphs divides Runs Above Average by Dynamic Runs per Win to get a pitcher's Wins Per Game Above Average.

Step 4: Finally, the Wins Per Game Above Average is added to the replacement level and scaled by the number of innings pitched to get the pitcher's FG-WAR value. Adding the Replacement Level from step 1 to Wins Per Game Above Average, we get a pitcher's Wins Per Game Above Replacement. This value is then multiplied by the number of nine-inning games pitched (innings pitched divided by nine innings per game) to get an unadjusted FG-WAR value. A small adjustment is made to everyone's unadjusted FG-WAR value, based on innings pitched, in order to get the total FG-WAR across all MLB players for the season to be 1000 and the split between pitchers and position players to be 430 and 570, respectively. Once this small adjustment is made, the result is the final FG-WAR.

For example, assume a starting pitcher has a Runs Above Average of 2.0 and a Dynamic Runs Per Win of 8.8. This pitcher would have Wins Per Game Above Average of 0.23. Then adding the replacement level of 0.12, this pitcher has Wins Per Game

Above Replacement of 0.35. If this pitcher pitched 135 innings (15 full games), then this pitcher's unadjusted FG-WAR value is 5.25. The final FG-WAR value after adjustments based on all other player's FG-WAR values will be very close to this number.

Two WAR Measures: Discussion

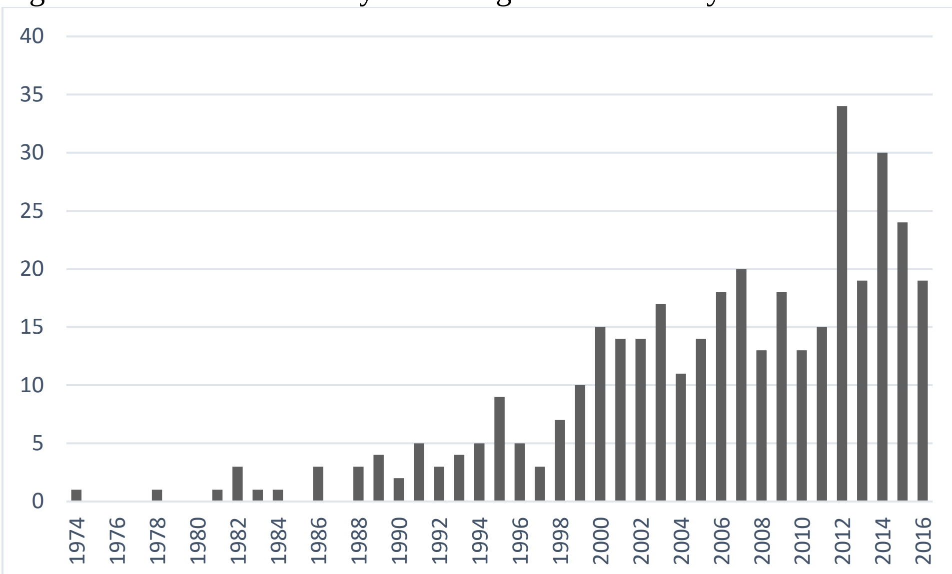
The two WAR estimates, BR-WAR (Baseball-Reference) and FG-WAR (FanGraphs) are similar, and both clearly differentiate between an all-star player and role player. However, the two WAR values for the same pitcher will not be identical. FanGraphs and Baseball-Reference derive their respective "wins above average" estimates for any given pitcher differently. Further, Baseball-Reference determines replacement wins using the split of total free agent salaries between pitchers and position players, while FanGraphs uses total league payrolls resulting in a total of 410 BR-WAR and 430 FG-WAR across all pitchers each season.

The results of these differences are clearly present in the data. For example, in 2016, Baseball-Reference rated Justin Verlander as the top pitcher in terms of BR-WAR with a value of 6.6 and Noah Syndergaard 10th with 5.3. FanGraphs had Syndergaard at the top with an FG-WAR value of 6.4, while Verlander was fifth with 5.3.

In my sample of all pitchers from 1996-2016, the correlation between FG-WAR and BR-WAR is 0.85. If position players were included in the sample, the correlation would be higher, because the formulas for position player WAR are very similar for FanGraphs and Baseball-Reference. While the process for calculating WAR can be difficult for non-fans to understand and it is not an exact measure, WAR is widely regarded by baseball insiders as the best overall measure of a player's productivity.

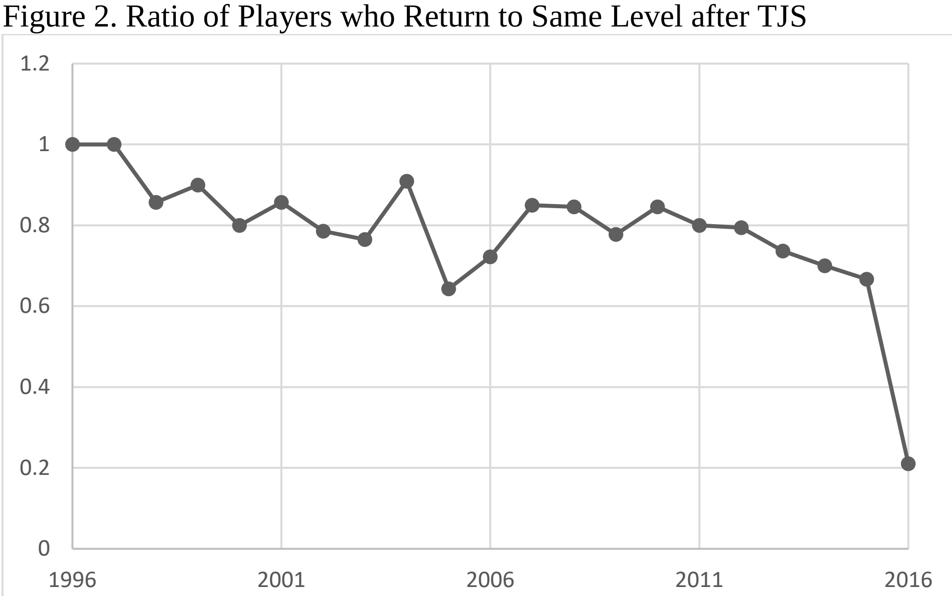
Chapter Two Figures and Tables

Figure 1. Number of Tommy John Surgeries in MLB by Year



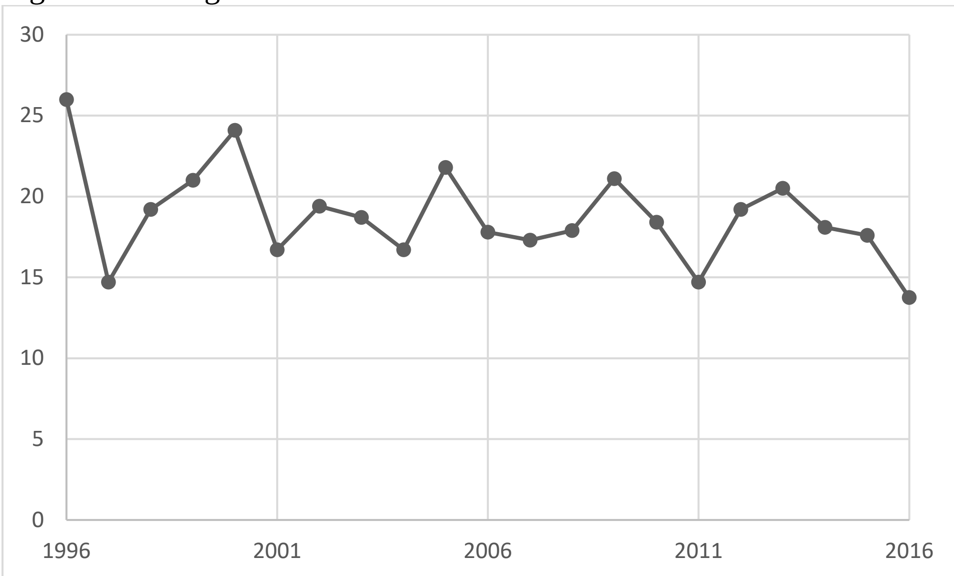
Note: This figure shows the number of surgeries on pitchers who were in MLB at the time of the injury. The graph would look the very similar with position players included because there are only one or two position players to get TJS each season.

Figure 2. Ratio of Players who Return to Same Level after TJS



Note: This figure shows the percentage of MLB pitchers to get TJS is in each season who have successfully returned to MLB.

Figure 3. Average Months to Return to the Same Level after TJS



Note: This figure shows the average number of months to return to MLB for pitchers who get TJS in MLB.

CHAPTER THREE

RELATED LITERATURE

Previous literature related to the impact of TJS on MLB pitcher MRP can be broken into three categories: Medical literature on the performance impacts of TJS, economic studies estimating MRP, and papers that explore the makeup of WAR, and its effectiveness as a statistic. [8] Identifying the impact of TJS on MRP shows the value loss to the organization. Therefore, this literature review includes a brief overview of the salary and MRP relationship, but does not extensively review the literature on salary. Each of the identified relevant literature areas is discusses in this chapter.

Medical Literature

Medical studies have looked at the time to return to play and success rates of TJS, as well as the impact of the surgery on performance. These studies use similar methods and samples, but report varying results. Table 1 shows summaries of these articles and the different methods and results are displayed side-by-side.

Gibson et al. (2007) attempt to determine the performance impacts of TJS using a comparison of means between a case and control group. They chose their control group randomly by picking every fifth name on an alphabetical roster of pitchers who had not had TJS. Their case group is 68 pitchers and their control group is 112 with a higher

[8] There is also a related literature on salary determination in MLB. One could also examine the impact of TJS on pitcher salary in order to identify the effects on the player, rather than ownership. The focus in this thesis is on the impact on ownership through MRP so there is no attention to salary determination.

proportion starting pitchers in the case group than in the control group. In their case group, 82 percent on pitchers returned to MLB and took an average of 18.5 months to return. They find improved performance compared to the control group in terms of ERA and WHIP post-surgery.

Erickson et al. (2014) estimate the impact of TJS on MLB pitcher performance and calculate the time to return to pitch after getting the surgery. To do this, they use a matched control study with 179 pitchers who had TJS and a control group of players without UCL tears. The control group was chosen to match the treatment group based on age, body mass index (BMI), position, handedness, MLB experience and performance measures, but whether the control group is matched on an individual basis, or based on the group means as a whole, is not clear in the paper. An index year is implemented for the control players to match the year of TJS for the players in the treatment group. This index year allows there to be a matching before and after period for both the case and control group.

They find that 97.2 percent of the pitchers who got TJS were able to return to pitch in professional baseball, and 83 percent of them were able to return to the majors. In the comparison with the control group, they find that after returning from TJS, these pitchers had significant performance improvement in winning percentage, ERA, and walks and hits per inning pitched (WHIP). They conclude that TJS results in a high rate of return among Major League pitchers, and that pitchers' performance declines immediately prior to the surgery and improves after the surgery.[9] These results and conclusions are based on the comparison of means using t-tests and not the use of any rigorous econometric techniques.

Keller et al. (2014) use the same method as Gibson (2007) for 168 case players from 1982-2010. They specify that the control group is created randomly with the only exclusion criteria being age and no previous TJS. Similar to Gibson, Keller's case group has a higher percentage of starting pitchers than the control group but Keller finds that performance declined in ERA, WHIP and innings pitched, which is the opposite of Gibson's reported results.

Lansdown and Feeley (2014) conducted a case series study to compare the fastball velocity of pitchers before and after undergoing TJS. They have 80 pitchers with pre- and post-surgery pitching data from years 2002-2012 and no control group. They find the average fastball velocity prior to TJS to be 91.3 mph, compared to 90.6 mph after the surgery.

Makhni et al. (2014) use 147 players who underwent TJS between 1999 and 2011, compared with 192 control players. They define this control group as age-matched controls who pitched at least 10 innings in both 2008 and 2009, and find that for ERA, WHIP, batting average against and innings pitched, performance declined after returning from the surgery.

[9] The decline in performance was most likely due to the pitchers missing some portion of that season once they were injured, so naturally, their performance in statistics such as games, innings pitched and wins will be lower the season prior to getting the surgery.

DeFroda et al. (2016) use a case and control study to try to identify a difference between pitchers who get TJS and pitchers who do not. A case group of 118 established major league players who tore their UCL is matched with a control group of players who never tore their UCL. Similar to other medical studies, the methods for choosing the control players are not clear, but they do use a similarity scores algorithm that accounts for players' pitching statistics and time in MLB. They find that the mean fastball velocity was higher in the tear group than the non-tear group (91.7 mph vs. 91.0 mph), and based on this, they conclude, "small increases in fastball velocity are a main contributor to an increased rate of UCL tears in MLB." This paper also reported that 62 percent of UCL tears occur in the first three months of the season.

The only consistent finding of the medical journal articles is that about 80 percent of Major League pitchers who undergo TJS return to pitch in the majors following the surgery. The performance impact results vary based on the sample, the methods used to create the control group and which two means are being compared. Some papers reported results comparing pre-TJS performance with post-TJS performance for just the pitchers who got TJS, while other papers compared the performance of TJS pitchers after surgery with the control group after a designated index year.

Methodologically, the small sample sizes in these studies raise questions about the statistical power of the findings.[10] Any results of the comparison of means technique can be questioned due to the differences between the case and control groups that are not being controlled for. My econometric approach, that utilizes panel data regression

[10] In appendix B, I construct my own case and control groups and compare means to see how the results compare those in the medical studies.

techniques on a larger and more complete sample, estimates causal relationships with economic implications. My thesis also goes well beyond the recovery and performance impacts of TJS and onto the economics of it and impact of TJS on the value of players.

Economic Literature on Marginal Revenue Product

Articles most closely related to my topic in the economic literature estimate the relationship between value and performance in baseball and attempt to estimate MRP of individual players. None of this literature has examined the impact of TJS from an economic perspective or using an econometric model. The literature on MRP and how it is determined by performance and marginal revenue (MR) starts with Scully (1974).

Scully (1974) discusses how salaries are determined in the pre-free-agency period of baseball when the reserve clause was still in place. He acknowledges that in a competitive labor market, players would earn a salary equal to their MRP. However, in MLB at the time of his writing, there was no free agency and the teams still had monopsony power. So, players earned a salary less than their MRP, and the remainder of their MRP went to the team in the form of monopsony rents. In the current state of the Collective Bargaining Agreement (CBA), with arbitration and free agency, the MLB labor market is not a competitive market either, but the player's union has more bargaining power than it did in 1970.

Scully's approach follows the definition of MRP. Since MRP = MP x MR, he estimated MP from a team win production function, that is, the contribution of hitting and pitching statistics to winning. Then, he estimated MR from a team revenue function specification. Each player has performance statistics that contribute to wins. The product of a player's statistics, the MP estimate and the MR estimate is the resulting MRP for the given player. There is other work following this original approach introduced by Scully.

Burger and Walters (2003) use MLB data from 1995-1999 to estimate the impact of market size and expected team performance on MR and then on player values. They find that large market teams can potentially value a given player up to six times more than small market teams. In addition, the difference between contending for the playoffs and World Series can have a similar positive effect on a player's value. For my thesis, this suggests that marginal revenues are also different across different larger- and smaller-revenue teams. The empirical method suggested is the quantile regression approach.

Bradbury (2011) introduces a modern and clearly defined method for estimating individual player's MRP by using their run-differential for a season to estimate MP and calculating the marginal revenue of an additional run for a team.[11] He finds that there is a positive and increasing return to run-differential for a team, that is, a team increasing from 70 to 75 wins is less impactful on fans' willingness to pay than a team increasing from 85 to 90 wins. Run-differential and wins are highly correlated and using runs instead of wins at both the team and player level should theoretically result in the same estimates as using wins. However, fans demand wins, not runs, in both the theory of sports and the actuality of sports. Therefore, estimates based on MP as contributions to wins, not runs, is the appropriate method for this thesis.

[11] Run-differential is defined as total runs scored minus total runs allowed.

Pearce (2016) uses a similar approach to Bradbury to estimate players MRPs. She estimates the effect of team-level performance statistics on winning percentage and the impact of team winning percentage on team revenue. An interesting control variable Pearce uses to control for the national popularity of a team is the number of twitter followers each team has. Similar to Scully and Bradbury’s results, Pearce finds that younger players are paid significantly less than their MRP. She also finds that older players are sometimes paid more than their MRP.

There are problems with Pearce’s approach. She uses a more simplified and less sophisticated process than either Scully or Bradbury, which relies on some additional assumptions. One assumption she has to make is that the impact of a team level change in on-base percentage (OBP) is the same as the impact of a change in an individual’s OBP. Additionally, OBP is only one aspect of a player’s value to his team and does not include all contributions a player makes to team wins.

Fort et al. (2017) is a working paper that employs a quantile regression strategy to estimate the MRP for players on various teams. The quantile regression strategy allows teams in different size markets, based on total revenue, to have different marginal revenues of an additional win, as earlier suggested in Burger and Walters (2003). For this reason, the same player could have a different MRP playing for one team than they would with the same level of performance for a different team. I use this quantile regression approach in my own MR model to account for different teams’ market sizes in my estimation of MRP. Fort finds that an additional win for a team in Q75 is worth approximately $635,000, which is almost double the MR of a win for a team in Q50.

Krautmann introduces an alternative to Scully's approach that deserves coverage because it helps reinforce the choice of Scully's approach in this thesis. Krautmann (1999) uses an alternate approach to estimate players' marginal revenue products and claims that his method produces superior estimates to Scully's. Krautmann uses total bases created as the measure of a player's marginal product and has a sample of 215 position player free agents from 1990-1993.[12] Another adjustment Krautmann made to the calculation of MRP was using turnstile revenues as the dependent variable instead of total revenues, because he claims that turnstile revenue is the only revenue source directly influenced by team success. Krautmann's method attempts to estimate the free market return (FMR) to performance for players, which should be synonymous with MRP, but his estimates are much lower than Scully's. Using the FMR approach, Krautmann finds that the "average journeyman" is paid about 85 percent of his MRP, while Scully's method suggests those players only receive 25 percent of their MRP.[13] Distinguishing between these methods, and identifying the strengths and flaws of each, is essential for understanding my estimation of players' MRPs.

Krautmann et al. (2009) employ the FMR approach to determine how much the reserve clause is restricting pay in the National Football League (NFL), National Hockey League (NHL) and MLB. Their findings are consistent with economic theory; owners use their monopsony power as much as possible to pay players less than their free market value. For baseball players, they use on-base percentage plus slugging average (OPS) as

[12] Total bases = 1*singles + 2*doubles + 3*triples + 4*home runs. Similar to slugging percentage except does not divide by the number of at-bats so it is a cumulative measure and not an average.
[13] Krautmann defines players who have reached free agency as journeyman and players who have not as apprentices.

the productivity measure. They only include position players in their sample, just as Krautmann did is his 1999 paper. Consistent with Krautmann (1999), Journeyman are paid 85 percent of their MRP and Apprentices earn less than 20 percent of their MRP.

Krautmann (2013) re-examines the Scully estimates and his own free-market approach estimates of MRP. He addresses some criticisms and shortcomings of the FMR approach and discusses some of his issues with the Scully approach. In conclusion, he states that the two approaches are not competing and that each has its own pros and cons. He claims that the Scully approach is appropriate for identifying efficiency issues related to contract length and whether or not a player "earned" his salary, while the FMR approach is better suited for estimating the determinants of a player's salary or identifying discrimination in the arbitration process.

Scully's approach is the clear choice for my dissertation. I am interested in the impact of TJS on MP, and subsequently on MRP. The FMR approach does not directly assess that impact. For my purpose of estimating the impact of TJS on a player's MRP, an approach similar to Scully's is more appropriate.

Wins Above Replacement (WAR) Literature

The fact that I am interested in the change in MRP, as opposed to the total MRP value, allows WAR to be used as the performance statistic in the player production function without having to worry about or add on the replacement level associated with WAR. WAR is a productivity measure in baseball that is widely accepted and used by teams and media to analyze and compare players. This section reviews previous literature related to WAR and its use in previous empirical analyses.

Furnald (2012) uses WAR as his dependent variable to estimate the impact of aging on performance in MLB and the impact of the steroid era on the age at which player performance peaks. He uses BR-WAR from Baseball-Reference, because other sources change their formulas over time.[14] The peak age of players is estimated to be 27.655 for all non-steroid era years and 29.057 during the steroid era. Furnald does not include pitchers in his sample and only includes hitters with at least 5,000 career at-bats, so these results are specific to starting position players with lengthy careers. Thus, even though pitchers are excluded, Fernauld provides an interesting approach to the impact of outside forces on player productivity that is directly relevant to the assessment of TJS in this thesis.

Baumer et al. (2015) propose a new version of WAR, openWAR, that they claim is more repeatable and transparent than the existing measures, such as FG-WAR and BR-WAR. Their biggest criticism of WAR is that the data and methods used to calculate it are not all publicly available and that it cannot be used to distinguish players down to its typically reported number of significant decimal places (usually one); it cannot be concluded that a player with 3.6 WAR is better than a player with 3.4 WAR.

Comparing FG-WAR, BR-WAR and openWAR, the correlation between FG-WAR and openWAR is 0.875, the correlation between BR-WAR and openWAR is 0.881,

[14] In my research of WAR formulas, I found that both FanGraphs (FG-WAR) and Baseball-Reference (BR-WAR) frequently update and refine their calculation methods to try to develop the most accurate estimations possible.

and the correlation between FG-WAR and BR-WAR is 0.918. OpenWAR employs a very different replacement level than the constant and arbitrary level used in the FG-WAR and BR-WAR calculation. Baumer justifies that most teams have 13 active position players and 12 active pitchers every day, so the top 390 position players (13*30 teams) and top 360 pitchers (12*30 teams) in terms of playing time are designated as major league players and the rest are replacement players. This appears to be a more intuitive way to calculate the replacement level, and it allows the replacement level to change from one season to the next. This new estimation of WAR could potentially be used in future analysis, but it has not yet been accepted in the baseball analytics world.

Cameron (2017) emphasizes that the main point of WAR is to estimate an individual's contribution to their team and the statistics used to do that focus on factors in the individual's control. As part of the discussion, Cameron addresses criticism from Bill James that WAR does not directly translate to team wins and that it does not consider situational hitting in the calculation. According to Cameron, including situational factors that would be reliant on the performance of other team members would result in a statistic that does not serve the intended purpose of WAR.

King (2017) proposes a new productivity statistic, zWins, as a better alternative to WAR. While zWins appears to perform better than WAR in predicting actual wins, it is just a proposed statistic and not widely used yet. In his analysis, King evaluates FG-WAR and BR-WAR and finds that they both have an R^2 value of about 0.81 when used to explain team wins. I expand this analysis by splitting FG-WAR and BR-WAR into pitching and hitting WAR, and analyzing this relationship at the individual level in addition to the team level.

Ng (2017) uses WAR as his dependent variable to estimate the impact of age and experience on performance for both pitchers and hitters in MLB. His sample is a panel dataset that includes 562 hitters and 489 pitchers with a total of 5,754 hitting seasons and 4,767 pitching seasons. To control for talent, Ng creates weighted averages of a players' WAR values for their first six seasons in the majors. Ng finds that hitters peak at an average age of 29, while pitchers peak at about 28. Using the estimates from his model, Ng attempts to predict players' future performance and their corresponding salaries once they hit free agency.

Given these various attempts to reinvent WAR or propose a new calculation that is better that WAR, it is clear that WAR has its shortcomings as a measure of player MP. While some of these proposed measures appear to perform better than WAR in some uses, WAR is still the most widely used statistic to estimate a player's overall contribution and the most trusted measure by baseball organizations and analysts.

Chapter Three Figures and Tables

Table 1. Comparison of Medical Journal Analyses of Tommy John Surgery

Title	Authors	Data	Control Group/Methods	Results	Conclusions
Ulnar collateral ligament reconstruction in major league baseball pitchers	Gibson, B. W. et al. (2007)	68 MLB pitchers who pitched in at least 1 MLB game prior to surgery from 1998-2003 compared with 112 controls	Controls chosen randomly, every fifth name on alphabetical roster. T-tests run on means for case and control groups	Higher percentage of starting pitchers in case group than control group and 82 percent of pitchers returned to MLB play at average of 18.5 months.	Improved performance in terms of ERA and WHIP for reconstructed pitchers compared to controls.
Performance, Return to Competition, and Reinjury After Tommy John Surgery in Major League Baseball Pitchers A Review of 147 Cases	Makhni, E. C. et al. (2014)	147 pitchers from 1999 to 2011 who had one UCL reconstruction, 192 control players	Control group chosen randomly from matching age groups from pitchers who threw 10+ innings in 2008 and 2009.	80 percent of cases returned to Majors, 67 percent returned to established play. Only significant difference between cases and controls: increase in pitches thrown per season and a decrease in K/9.	Performance declined post surgery in ERA, BA against, WHIP, IP.
The effects of medial ulnar collateral ligament reconstruction on Major League pitching performance	Keller, R. A. et al. (2014)	168 MLB pitchers with at least 1 major league game prior to surgery from 1982-2010. 178 age-matched random controls from 2004-2005 MLB rosters	Controls chosen randomly, every fifth name on alphabetical roster. Index year based on median year of MUCL reconstruction.	Significant difference between cases and controls for weight and BMI. Higher percentage of starting pitchers in case group (63.7%) than in control group(35.4%).	Performance declined after surgery in ERA, WHIP and Innings pitched.
Rate of Return to Pitching and Performance After Tommy John Surgery in Major League Baseball Pitchers	Erickson B. J. et al. (2014)	148 of 179 pitchers with UCL tears able to return to play in MLB.	Controls matched based on age, BMI, experience, pitching performance and handedness. Index year matches year of surgery.	83% returned to play in MLB with a mean time to return of 20.5 months. Case pitchers had lower ERA and WHIP and fewer losses than control pitchers following the surgery and index year.	"Performance declined before surgery and improved after surgery" for pitchers who got TJS.

Table 1. Comparison of Medical Journal Analyses of Tommy John Surgery (continued)

Title	Authors	Data	Control Group/Methods	Results	Conclusions
The effect of ulnar collateral ligament reconstruction on pitch velocity in Major League Baseball pitchers.	Lansdown, D. A. et al. (2014)	Total of 129 players who had surgery limited to 80 or final analysis due to lack of pre or post surgery data. Data from 2002-2012 seasons.	No control group to match with	Pitchers threw fewer innings and pitches following surgery than prior to surgery.	Against popular belief, mean fastball velocity decreased from 91.3 to 90.6 MPH and percent of fastballs thrown decreased as well.
Risk Stratification for Ulnar Collateral Ligament Injury in Major League Baseball Players: A Retrospective Study From 2007 to 2014.	DeFroda, S. F. et al. (2016)	Total of 170 UCL tears in MLB from 2007-2014. 118 players who tore UCL after 100+ IP were matched with control group with no tears.	Matched based on similarity scores algorithm. Compared with tear group using paired t-test.	Mean fastball velocity greater in tear group than non-tear group (91.7 vs 91.0 mph). Relief pitchers made up a greater percentage of early tear group than the later tear group.	Small increases in fastball velocity are a main contributer to increased rate of UCL tear in MLB.

CHAPTER FOUR

IMPACT OF TOMMY JOHN SURGERY ON PITCHER MARGINAL PRODUCT

The primary objective of this thesis is to estimate the impact of TJS on an MLB pitcher's MRP. Following Scully (1974), MRP = MP * MR. In this case, we are interested in the MP of a pitcher's performance in terms of his contribution to his team's wins and the MR of a team's wins in terms of team revenue. The impact of TJS on a pitcher's a pitcher's performance is measured through WAR. In this context, total revenue is impacted by TJS as follows:

$$\frac{\partial TR}{\partial TJS} = \frac{\partial TR}{\partial W} * \frac{\partial W}{\partial WAR} * \frac{\partial WAR}{\partial TJS}$$

Where $\frac{\partial TR}{\partial TJS}$ is the impact of TJS on TR, $\frac{\partial WAR}{\partial TJS}$ is the impact of TJS on the productivity of a player measured through WAR, $\frac{\partial W}{\partial WAR}$ is the MP of a unit of WAR in terms of team wins, and $\frac{\partial TR}{\partial W}$ is the MR associated with a team win. Theoretically, $\frac{\partial W}{\partial WAR}$ = 1 by the definition of WAR, but one component of this thesis is determining whether this holds in actuality.

This chapter focuses on estimating the impact of TJS on the marginal product of pitchers, which is the product of $\frac{\partial W}{\partial WAR}$ and $\frac{\partial WAR}{\partial TJS}$. I calculate $\frac{\partial WAR}{\partial TJS}$ in the first section of this chapter and $\frac{\partial W}{\partial WAR}$ in the second section. As discussed in chapter two, the two different measures of WAR, FG-WAR from FanGraphs and BR-WAR from Baseball Reference have the same purpose, to provide an estimate of wins contributed to the team above what a replacement level player would contribute. However, the two processes rarely generate the exact same value for a given player. In my dataset they have a correlation of 0.85 and can differ by as many as two WAR units (wins) for the top pitchers in a given year. For this reason, I use both FG-WAR and BR-WAR for comparative purposes in the empirical analysis.

Estimating the Impact of TJS on Pitcher Productivity

This section estimates the impact of TJS on player productivity, $\frac{\partial WAR}{\partial TJS}$. This process is broken down into three subsections – an empirical specification, a data description and results.

Empirical Specification

The model I use to estimate the impact of TJS on player productivity, $\frac{\partial WAR}{\partial TJS}$, regresses WAR on TJS dummy variables of interest as well as other control variables:

(1) $WAR_{it} = \beta_0 + \beta_1 {*} PreTJS1_{it} + \beta_2 {*} Injury\ Season_{it} + \beta_3 {*} Months\ Missed_{it} + \beta_4 {*} PostTJS1_{it} + \beta_5 {*} PostTJS2_{it} + \beta_6 {*} PostTJS3_{it} + \beta_7 {*} PostTJS4_{it} + \beta_8 {*} PostTJS5_{it} + \beta_9 {*} Age_{it} + \beta_{10} {*} Age^2_{it} + \beta_{11} {*} Experience_{it} + \beta_{12} {*} Experience^2_{it} + \beta_{13} {*} Starting\ Pitcher_{it} + \beta_{14} {*} American\ League_{it} + \delta_i + \varepsilon_{it}$

Where δ_i represents player fixed effects.

For pitcher i in season t, the TJS binary variables identify the last full year of performance prior to the surgery, **PreTJS1**, a dummy for the season of the injury, **Injury Season**, separate dummies for each of the first four years after returning from surgery, **PostTJS1 - PostTJS4,** and for five or more years following a player’s return,

PostTJS5.[15] To account for variation in within year timing of torn UCLs and the corresponding time missed in the season of the injury, I include a **Months Missed** variable that is equal to 10 (for the end of baseball season in October) minus the month of the player's TJS. A pitcher only has a non-zero value for **Months Missed** if the **Injury Season** dummy equals one, and **Months Missed** is equal to zero for all other observations. For example, if a pitcher tears his UCL and gets TJS in August then he will be missing August and September (two months) so **Months Missed** = 10 – 8 = 2.

Additional controls are included for other factors expected to be correlated with a player's WAR measure for a season, with the caveat that these controls must be independent of performance. The goal is to identify the impact of the TJS on a player's contribution to the team's wins, through the mechanism of the impact on his performance. For that reason, we do not want to control for any measure of performance that explains the variation in WAR.

My controls include variables that I expect to be correlated with a player's performance and likelihood to have undergone TJS, such as **Age** and **Experience**.[16] **Age** and **Experience** are included in quadratic form with a linear and squared term for each. **Starting Pitcher** is a binary variable that differentiates starters from relief pitchers. **American League** is a binary variable that allows for differences in pitching use in the

[15] The **Injury Season** dummy variable is only equal to one if the pitcher got TJS in the same calendar year as that season of performance. Pitchers who are injured in the offseason or do not get the surgery right away, and end up getting TJS in January to March will not have an observation with a value of one for **Injury Season**, but will have a value of one for **PreTJS1** season.

[16] **Starting Pitcher** is equal to one if a pitcher starts at least half of the games he appears in and zero otherwise.

league with the designated hitter. Finally, player fixed effects, $\boldsymbol{\delta_i}$, control for unquantifiable characteristics specific to each player. [17]

For the sake of comparison, and to inform the literature on production functions in MLB, I run the model (equation 1) with a variety of standard pitching statistics as dependent variables. These standard pitching statistics are **Games, Games Started**, **Innings Pitched**, **Saves**, earned run average (**ERA**), strikeouts per 9 IP (**K/9**), walks per 9 IP (**BB/9**), home runs allowed per 9 IP (**HR/9**), and walks plus hits per inning pitched (**WHIP**).

As a final attempt to inform the literature on MLB production functions, I also estimate WAR on the same set of traditional pitching statistics (to conserve notation, the estimated coefficients here are not related to the estimated coefficients in (1), above):

(2) $WAR_{it} = \beta_0 + \beta_1{*}Games_{it} + \beta_2{*}Games\ Started_{it} + \beta 3{*}Innings\ Pitched_{it} + \beta_4{*}Saves_{it} + \beta_5{*}ERA_{it} + \beta_6{*}K/9_{it} + \beta_7{*}BB/9_{it} + \beta_8{*}HR/9_{it} + \beta_9{*}WHIP_{it} + \beta_{10}{*}Starting\ Pitcher_{it} + \beta_{11}{*}American\ League_{it} + \varepsilon_{it}$

The purpose of equation (2) is to determine the relative importance of these standard pitching stats in the calculation of WAR. This provides some intuition behind the underlying, but irreproducible formulas used by FanGraphs and Baseball-Reference. I also split the dataset into subsets of relief and starting pitchers to test for different results based on a pitcher’s role on the team.

[17] I ran the model with individual year dummies as well as a time trend, but these specifications did not result in significantly different coefficients on the TJS dummy variables, and caused a strange issue with the age coefficient. Even though **Age** and the **Time Trend** are not highly correlated overall (0.02), in the BR-WAR model when the **Time Trend** was included, the coefficient on Age decreased by about two, which was the same magnitude as the coefficient on the **Time Trend**. In the FG-WAR model, this did not happen and the **Time Trend** was not significantly different from zero.

Data

Data on all known TJS performed on baseball players are publicly available in a Google document updated and managed by @MLBPlayerAnalys. This dataset includes all professional players and some college players who have received the surgery, but I only use pitchers who underwent surgery while in the majors from 1996-2016. Details on every surgery include the age of the player, date of the surgery, date of return to play, team, MLB ID, FanGraphs ID and others that I did not use.[18] I use this dataset and merge it with performance data for all pitchers in MLB from 1996-2016.[19] I did not go back farther than 1996, because I wanted to focus on the years since TJS became more prevalent (more than 10 per year) and have a sufficient representation of players with TJS in my sample. My dataset has 3,108 pitchers in it, with 343 of them having TJS during their MLB career.

Table 2 shows summary statistics for all the pitchers in the dataset, split into non-TJS pitchers and TJS pitchers. TJS pitchers have longer average career length and higher average career WAR values than the non-TJS pitchers. There is also a higher percentage of starting pitchers in the TJS-player group. The means of the TJS variables of interest (**PreTJS1-PostTJS5**) indicate the fraction of TJS pitchers that have a season for that variable. For example, 72 percent of TJS pitchers have a **PostTJS1** season, meaning that 28 percent of them do not make it back to the majors following the surgery.[20] The decreasing mean values for **PostTJS1** to **PostTJS4** is a result of some pitchers only

[18] Other variables in the dataset for some, but not all, players include college, high school state, and surgeon.
[19] All performance data are collected from FanGraphs and Baseball-Reference.
[20] The pitchers who underwent TJS is 2015 or 2016 have not had sufficient time to return to MLB yet.

having one season after returning from TJS and some having two seasons and so on. **PostTJS5** has a higher mean than **PostTJS4** because **PostTJS5** is equal to one for five or more years after TJS. This means some pitchers will have **PostTJS5** turned on for multiple season while the other TJS dummy variables are one turned on for a maximum of one season for each pitcher who had TJS. The average **Months Missed** for the TJS players is 1.52, but it is important to remember that pitchers receiving TJS in the offseason have zero months missed, as well as zero for **Injury Season**.

Tables 3, 4 and 5 show summary statistics for all player-years, first for the whole sample, and then broken down by TJS pitchers and non-TJS pitchers. The higher mean FG-WAR and BR-WAR values for TJS pitchers indicate that on average, pitchers who get TJS are more productive on a yearly basis than pitchers who do not. The two-tailed t-tests comparing these means for the two groups confirmed that they are statistically different at the 5 percent level. This finding presents the potential issue of TJS being endogenous and not random. My use of player fixed effects in the model controls for any baseline talent difference between pitchers and any constant variation over time. This accounts for the majority of the potential issues for this thesis, but the endogeneity of TJS and potential for some pitchers to be at a higher risk than others deserves further research in the future.[21]

[21] The one example of this I have seen is Woodrum (2016), who attempts to predict the relative risk of UCL injuries and the resulting TJS for individual MLB pitchers using pitcher characteristics, previous injury data, and pitch and performance statistics. He finds that the number of days missed due to injury the previous season, the number of hard pitches thrown (fastballs), and age are the primary factors in determining the likelihood of TJS.

Figures 4 and 5 show the distributions of both measures of WAR. These distributions are not normal but instead skewed to the right, with the majority of the WAR values concentrated around zero. For both FG-WAR and BR-WAR, the largest two bins are -0.5 to zero and zero to 0.5. One contributing factor to this concentration around zero is the inclusion of all pitchers for each season that appeared in at least one game. WAR is heavily dependent on playing time, so pitchers who throw very few innings in a season are going to have a WAR value of close to zero, no matter how well or poorly they play for those limited innings. Another contributor to all the WAR values around zero is the high level of talent and the intense competition across professional baseball. The difference in ability between a MLB starter and a replacement level pitcher is often very slim, so the majority of players hover around that designated replacement level.

Results

The results for this section can be found in tables 6 through 13. The primary results of interest are presented first, followed by subsamples and other specifications to address questions that arose from the initial results.

Table 6 shows the results of an OLS estimation of equation (1) with either **BR-WAR** or **FG-WAR** as dependent variables. Columns (1) and (2) show the results without player fixed effects, which clearly are significantly different from the fixed effect model results in columns (3) and (4). Notably, the magnitudes of the coefficients on **PostTJS1** and **PostTJS2** are smaller without player fixed effects. The F-test on the player fixed effects indicate joint significance at the 1 percent level, so I proceed with player fixed effects. Hausman tests also verified the use of fixed effects over random effects.[22]

For the fixed effect results in columns (3) and (4) of table 6, the coefficient estimates for **PreTJS1** are statistically insignificant, indicating that a pitcher has no statistical change in performance in his last full season prior to injury. This provides evidence that future changes in performance are related to having the injury and TJS as opposed to systematic differences in players.

The coefficient on **Injury Season** is -0.311 for the **FG-WAR** regression and -0.469 for the **BR-WAR** regression and significant at the 5 percent level for both. This result indicates a decline in performance in the season that TJS occurs, and this decline in performance is independent of the portion of the season missed following the injury, because I control for the number of months missed that season. The coefficient on **Months Missed** is -0.121 and significant at the 1 percent level for the **FG-WAR** model and -0.0805 and significant at the 10 percent level (one-sided p-value = 0.055) for the **BR-WAR** model. The combination of the results for **Injury Season** and **Months Missed** indicates that a player has decreased productivity in the season he tears his UCL, and this decreased productivity is due to both time missed once he is injured and a decrease in performance leading up to the injury.[23]

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[22] For the Hausman test, the Chi-squared test-statistic is 7387.14 for FG-WAR and 4067.89 for BR-WAR.

[23] Looking specifically at individual game logs for some players, this decline in performance appears to be concentrated in the last few starts before a player is injured, and often times the start where they are injured is especially bad. This is only speculation, but it explains why there is no significance on the **PreTJS1** coefficient. A more rigorous test of this theory could be done with individual game performance data instead of annual data, as I use for my analysis.

The coefficients of primary interest are on the post TJS dummy variables (**PostTJS1 – PostTJS5**). The estimated coefficient on **PostTJS1** is -0.516 for the **FG-WAR** model and -0.575 for the **BR-WAR** model**,** which is large compared to the mean **FG-WAR** and **BR-WAR** for TJS pitchers of 0.86 and 0.79, and close to half of one standard deviation of **FG-WAR** and **BR-WAR** (1.29 and 1.44). For **PostTJS2,** the magnitudes of the coefficients decrease to -0.231 for the **FG-WAR** specification and -0.395 for the **BR-WAR** specification**.**

For the **BR-WAR** model, both **PostTJS1** and **PostTJS2** are statistically significant at the 1 percent level, while for **FG-WAR, postTJS1** is statistically significant at the 1 percent level and **PostTJS2** is statistically significant at the 5 percent level. **PostTJS3** through **PostTJS5** are insignificant for both **FG-WAR** and **BR-WAR**. These results provide evidence that pitchers have a decline in productivity following TJS, and this effect diminishes over time following the surgery, with a significant impact for the first two years. After those first two years, there is no statistically significant difference between the pitcher's post-TJS performance and what his performance would have been with no injury or resulting TJS.

The coefficients on the control variables, **Age** and **Age^2**, are similar for the **FG-WAR** and **BR-WAR** models; WAR increases at a decreasing rate in each case. For **FG-WAR**, the coefficient on **Age** is 0.545 and on **Age^2** is -0.0087. For **BR-WAR**, the coefficient on **Age** is 0.633 and on **Age^2** is -0.0094. The two results suggest that a pitcher's WAR increases until the player is 31 to 33 years old and then begins to decrease.[24]

FG-WAR and **BR-WAR** reveal different behavior for experience; decreasing at a decreasing rate. For **FG-WAR**, the coefficient on **Experience** is -0.0087 (insignificant at 5 percent) and on **Experience^2** is -0.006. For **BR-WAR**, the coefficient on **Experience** is -0.0871 and on **Experience^2** is -0.0045.

The technical interpretation is that for two players with the same talent level and age, the more experienced one is less productive. This may seem strange, especially when considering younger players. In Table 7, I split the sample into players older than average, 28 years, and players younger than average. The coefficient on experience is positive and significant for the younger sample, while for the older sample, the coefficient on experience is negative and significant. Based on the results in table 7, the older players in the sample are driving the negative coefficients. This is most likely due to players wearing out with more experience. For two older pitchers of the same age and talent level, the one who has pitched less over his career, still has more left in his arm and is more productive.[25]

The **American League** binary variable has an insignificant coefficient in the **BR-WAR** regressions, but a negative and significant coefficient in the **FG-WAR** regressions (-0.097). This suggests that Baseball-Reference's WAR calculation technique is correctly

[24] Peak Age using the FG-WAR model coefficients on Age = .545 / (2*0.0087) = 31.3. Note that these peak ages are all controlling for experience and baseline talent (player fixed effects) and are higher than the peak ages without experience in the model (about 27 to 28 years).
[25] Pitchers in the minor leagues generally throw fewer innings on average than in the major leagues, because the season is shorter and innings are more evenly distributed among all pitchers in the minors.

accounting for any league differences, while FanGraphs' formula does not fully eliminate the advantage that National League pitchers have over American League pitchers.[26]

The coefficient on the **Starting Pitcher** variable is 0.532 in the **FG-WAR** regression and 0.216 in the **BR-WAR** regression, meaning that pitchers who start the majority of their games have a higher WAR on average than pitchers who enter as a reliever in the majority of their games. This is most likely due to the higher number of innings that starting pitchers throw in the course of a season relative to relief pitchers and that teams use their best pitchers as starters and not relievers. This difference leads to the question of whether starting pitchers and relief pitchers may be impacted differently by TJS. To investigate that possibility, I split the dataset into subsamples of starting and relief pitchers to compare the results.

Table 8 shows the results for the split sample regressions on starting and relief pitchers. With the split, **PostTJS1** is the only PostTJS variable that is significant for starters, while all five are significant for relievers. This means that starting pitchers generally take about one season of pitching to regain their pre-surgery level of performance, while relievers deal with the negative impacts of the surgery for the remainder of their career. Another difference between starters and relievers is that the **Injury Season** dummy variable is significant for relievers but **Months Missed** is not significant, while the opposite is true for starters. These results are both strange and difficult to explain, and I tried to gain more insight by running these regressions with other pitching statistics as the dependent variable.

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[26] The designated hitter in the American League forces pitchers to face a more talented line-up on average than in the National League, where pitchers have a spot in the lineup and hit.

Tables 9 and 10 show the results for equation (1) with **ERA, WHIP** and **Innings Pitched** as the dependent variable (rather than either WAR variable) for starters and relievers. These results show a significant relationship between **Months Missed** and **ERA** and between **Months Missed** and **WHIP** for relievers, but not for starters. In addition, there is a significant negative impact of both **Injury Season** and **Months Missed** on **Innings Pitched** for relievers, while only the coefficient on **Months Missed** is significant for starters. The coefficients on **Age** and **Age^2** also differ between starters and relievers with larger magnitudes and a much younger peak age (29 vs. 36) for starters. For relievers, none of the three regressions has significant coefficients on all five PostTJS variables, so these results do not provide a clear explanation for the unexpected results in table 8.

Table 11 shows results for equation (2), which is designed to explain the variation in **FG-WAR** and **BR-WAR** at the individual level, using standard pitching statistics. The variables included are **Games**, **Games Started**, **Innings Pitched**, **Saves**, **ERA**, **K/9**, **BB/9**, **HR/9**, and **WHIP**. In addition, **American League** and **Starting Pitcher** are included to control for the related calculation adjustments in the WAR formulas. These results indicate the implicit weight that each performance statistic has in determining a pitcher's WAR.

The coefficients on **Games** and **Games Started** are negative, which at first glance are different than the intuitive expectation. However, **Innings Pitched** is also in the model, so the negative coefficients on **Games** and **Games Started** suggest that a pitcher who throws 100 innings in 20 games has a lower WAR value than a pitcher who throws

100 innings in only 15 games. This makes intuitive sense, especially for starting pitchers, where the more effective a pitcher is, the more innings they get to pitch per start. Similar situations occur for other variables, such as the coefficients on **ERA** in the **FG-WAR** model and **BB/9** in the **BR-WAR** model being the opposite of expected.

Tables 12 and 13 present the results of models estimating the impact of TJS on the various standard pitching statistics that were used as explanatory variables in table 11. A few interesting results from these tables relate to the coefficients on the pre-surgery dummy variables (**PreTJS1**, **Injury Season** and **Months Missed**). First, as expected, the **Months Missed** coefficient is negative and significant for **Games** and **Innings Pitched.** Clearly, the more months of a season a pitcher misses, the fewer innings and games they will pitch.

Another noteworthy result in tables 12 and 13 is that the coefficient on **Injury Season** is also negative and significant for both **Games** and **Innings Pitched**, meaning that **Months Missed** is not fully controlling for the decrease in pitching. Other factors in addition to the month when they get TJS are contributing to pitchers throwing fewer innings in that season. One possible factor is pitchers missing additional time due to other injuries or attempting to rehab their elbow prior to getting TJS, but the available data do not allow examination of that possibility. Another factor relates to the significance of the **Months Missed** coefficient in the **ERA**, **WHIP**, **K/9** and **BB/9** regressions. The signs on all these coefficients indicate a decline in performance prior to getting TJS, and a decline in performance can coincide with a decrease in innings pitched.

The most important result in tables 12 and 13 is the significant negative coefficient on **PostTJS1** in the **Innings Pitched** column, combined with all PostTJS coefficient estimates being insignificant for all of the pitching quality dependent variables **(ERA, WHIP, K/9, BB/9, HR/9)**. This indicates that pitchers throwing fewer innings after returning from TJS is the primary mechanism through which TJS results in a decrease in WAR. There is no evidence that pitchers' performance, measured through **ERA**, **WHIP**, **K/9, BB/9** or **HR/9** decreases following TJS. This can be thought of as a decrease in pitching quantity not quality. Pitchers who return to MLB partway through the season following their TJS recovery will naturally have fewer innings pitched that season, but even pitchers who return at the beginning of the season can be limited to throwing fewer innings. Anecdotal evidence suggests that pitchers can be on strict pitch counts and innings limits to lower the risk of re-injury in the first year returning after TJS (MLB.com).[27]

Estimating the Marginal Product of Pitcher WAR on Team Wins

The second step in estimating the impact of TJS on MP of a pitcher is estimating the marginal product of an additional unit of WAR for a pitcher in terms of team wins, $\frac{\partial W}{\partial WAR}$. In simple terms, the marginal product of a player is defined as the change in wins from a change in a player's performance. The marginal product for pitchers and hitters

[27] In 2012, Stephen Strasburg, the number one overall pick in the 2009 MLB draft, was shut down after less than 160 innings his first year back from TJS, and in 2015, Matt Harvey had a 180 inning limit advised by his surgeon. There are other situations of pitchers not being limited and there is not significant evidence supporting the effectiveness of innings limits, but it only takes limits on some of the returning pitchers to generate a significant coefficient.

can differ and are estimated using a team-level production function. Let W = Team Wins, P = Generic Pitching Performance, H = Generic Hitting Performance, and Q = Team Quality. A descriptive production function for W is:

$$W = W(P, H; Q)$$

For my question, I am interested in the MP of pitchers' productivity on the total team wins in a season, $\frac{\partial W}{\partial P} = MP_P$. In estimating this MP, I use WAR as the productivity measure for both hitters and pitchers, and control for persistent differences in team quality using team fixed effects. For player i on team j in season t, the empirical specification is:

(3) $Wins_{jt} = \beta_0 + \beta_1 * pitcherWAR_{ijt} + \beta_2 * pitcherWAR^2_{ijt} + \beta_3 * hitterWAR_{ijt} + \beta_4 * hitterWAR^2_{ijt} + \beta_5 * Pitcher_{ijt} + \gamma_j + \varepsilon_{ijt}$

Where γ_j represents team fixed effects.

I run this model at the individual level in a seemingly unrelated regression (SUR), because the dependent variable, **Wins**, is the same for all players on a given team in a given year, but the WAR values are specific to each player and separated by pitchers (**pitcherWAR**) and hitters (**hitterWAR**).[28] Squared terms allow for non-linearity and a **Pitcher** binary variable allows pitchers and position players to have different constant terms. Team fixed effects are the γ_j. Because WAR is defined as an estimate of wins contributed by a player, theoretically β_1 and β_3 should be one and β_2 and β_4 should be zero

[28] For comparison, I also run the model aggregated to the team level, so there is one observation for each team-season with the total pitching WAR and hitting WAR aggregated across all team members for that team-season.

in this specification. One additional unit of WAR, whether it comes from a pitcher or a hitter corresponds to an additional team win in a linear fashion.

The dataset for this model includes individual annual FG-WAR values from FanGraphs and BR-WAR values from Baseball-Reference for all players who appeared in at least one major league game in at least one year for the 1996-2016 seasons. The resulting dataset contains 28,650 total observations for 5,533 players on 31 teams. Summary statistics for pitchers and position players in this dataset are shown in table 14. Figure 6 shows the variation from year to year in wins for specific teams. This within team variation is being explained by the variation in individual WAR values in the model.

Pitchers in the sample have both a pitching and hitting WAR value if they had plate appearances, and their hitting WAR is equal to zero if they did not hit at all. Note that hitting WAR for pitchers is calculated so the average is zero, meaning that pitchers who are above average hitters (relative to other pitchers) will have a small positive WAR value, while pitchers who are below average hitters will have a small negative WAR value.[29] This is important because pitchers are valued for their pitching ability, not their hitting ability, but a pitcher who is a relatively good hitter provides additional value to the team beyond his pitching ability. Position players in the sample have pitching WAR values of zero.

Results for the SUR analysis of equation (3) are shown in tables 15 (FG-WAR) and 16 (BR-WAR). It is pretty clear that the hypotheses that β_1 and β_3 should be one and

[29] No pitcher gets enough at-bats or is a good enough hitter to have a very large hitting WAR value (maximum hitting WAR of 1.43 for pitchers and 11.85 for hitters in the sample).

β_2 and β_4 should be zero are rejected. In column 1 of table 15, without the squared WAR terms included, **Hitter FG-WAR** is statistically different from one at the 10 percent level, and statistically different from **Pitcher FG-WAR** at the 5 percent level. When the squared terms are included (column 2), **Pitcher FG-WAR** is statistically different from one at the 1 percent level and statistically different from **Hitter FG-WAR** at the 1 percent level. Similarly for the BR-WAR model (columns 1 and 2 of table 16), Pitcher BR-WAR is statistically different from Hitter BR-WAR at the 1 percent level.

The result here with the most significant potential implications is the significantly larger magnitude of **Pitcher WAR** than **Hitter WAR** in explaining **Team Wins.** My interpretation of this is that in the calculation of WAR by FanGraphs and Baseball-Reference, pitchers are not receiving a share of the total WAR distributed throughout the league that is proportional to the wins they actually contribute to their teams.

The significant and negative values of all the squared terms indicate that teams observe a decreasing marginal benefit of WAR from each individual player. For example, from a team's perspective, it is better to have four players' WAR values improve from one to two than it is to have a star player's WAR value improve from five to nine. This is another result that has not been recognized in previous WAR literature and could have significant implications on the reliable uses of WAR.

The **Pitcher** dummy is not significant at the 5 percent level for any of the specifications. While they are not statistically significant, the coefficient on **Pitcher** for all four models is about -0.25 with a p-value of slightly greater than 0.10. The interpretation of this negative coefficient on the **Pitcher** dummy is that if an average pitcher on a team is replaced with a replacement level pitcher (WAR = 0), that team will win about 0.25 games fewer than if an average position player is replaced with a replacement level player. This reinforces that the WAR formula undervalues pitchers relative to position players.

Columns (3) and (4) of tables 15 and 16 show the results with pitcher WAR broken up into starting pitcher WAR and relief pitcher WAR. For both FG-WAR and BR-WAR, the coefficient estimates for relief pitcher WAR are larger than the estimates for starting pitcher WAR. These differences are statistically significant without the squared terms included in column (3) but are not statistically significant with the squared terms in column (4). Similar to the comparison between pitcher and hitter WAR, the larger coefficients on relief pitcher WAR suggest that the WAR formulas under value relief pitcher's WAR relative to starting pitcher's WAR. The difference is larger for FG-WAR, indicating that FanGraphs' WAR formula under values relief pitchers more than Baseball-Reference's does.

For comparison with the individual WAR specification, I aggregate the individual WAR values into team level values of pitcher and hitter WAR. The resulting dataset has 626 team-season observations with the total pitching WAR and hitting WAR for each team-season. The results for this model, in table 17 for FG-WAR, are very comparable to the results at the individual level in table 15. For BR-WAR however, the team level results in table 18 are significantly different from the individual level results in table 16. The team level coefficients on Pitcher BR-WAR and Hitter BR-WAR are both very close to one and are not statistically different from one another. This suggests that at the team level, BR-WAR is placing the appropriate values on pitching and hitting WAR. It is unclear why this changes at the individual level, which is something that deserves more analysis in future research.

Chapter Four Figures and Tables

Table 2. Summary Statistics – Pitchers 1996-2016

Variable	N (players)	Mean	St. Dev	Minimum	Maximum
Non-TJS Pitchers					
Career Length	2765	3.98	3.37	1	20
Career FG-WAR	2765	2.54	7.27	-2.9	78.8
Career BR-WAR	2765	2.45	7.08	-4.2	75.7
Starting Pitcher	2765	0.32	0.41	0	1
American League	2765	0.48	0.42	0	1
TJS Pitchers					
Career Length	343	6.61	3.86	1	17
Career FG-WAR	343	5.66	8.62	-2.4	53.1
Career BR-WAR	343	5.22	7.88	-3.1	57.2
Starting Pitcher	343	0.41	0.43	0	1
American League	343	0.45	0.38	0	1
PreTJS1	343	0.85	0.37	0	1
Injury Season	343	0.54	0.50	0	1
Months Missed	343	1.52	1.94	0	6
PostTJS1	343	0.72	0.45	0	1
PostTJS2	343	0.55	0.50	0	1
PostTJS3	343	0.41	0.49	0	1
PostTJS4	343	0.29	0.46	0	1
PostTJS5	343	0.70	1.69	0	9

Note: These summary statistics were created by collapsing all the seasons for each pitcher into one career level observation. Career Length is the number of observations for a pitcher (seasons in MLB). Career WAR is the sum of all season WAR values. For PreTJS1, Injury Season, and PostTJS1-PostTJS4, the mean is the fraction of TJS players that have each of those observations. None of these equal 1 because some players get TJS in their first season in MLB (15 percent) and some do not return after TJS (28 percent).

Table 3. Summary Statistics – All Pitcher-years 1996-2016

Variable	n (observations)	Mean	Std. Dev.	Minimum	Maximum
FG-WAR	13,260	0.68	1.30	-1.7	11.6
BR-WAR	13,260	0.65	1.46	-3.2	11.9
Age	13,260	28.07	4.19	19	49
Experience	13,260	4.09	3.15	1	20
Starting Pitcher	13,260	0.40	0.49	0	1
American League	13,260	0.48	0.50	0	1

Note: Statistics for players who switched teams mid-season are combined into one observation, so n is the number of player-years in the sample. There are 3108 total players.

Table 4. Summary Statistics – All TJS Pitcher-years 1996-2016

Variable	n (observations)	Mean	Std. Dev.	Minimum	Maximum
FG-WAR	2,266	0.86	1.29	-1.5	8.4
BR-WAR	2,266	0.79	1.44	-2.46	8.53
Age	2,266	28.5	4.48	19	49
Experience	2,266	4.93	3.39	1	17
Starting Pitcher	2,266	0.45	0.50	0	1
American League	2,266	0.44	0.50	0	1

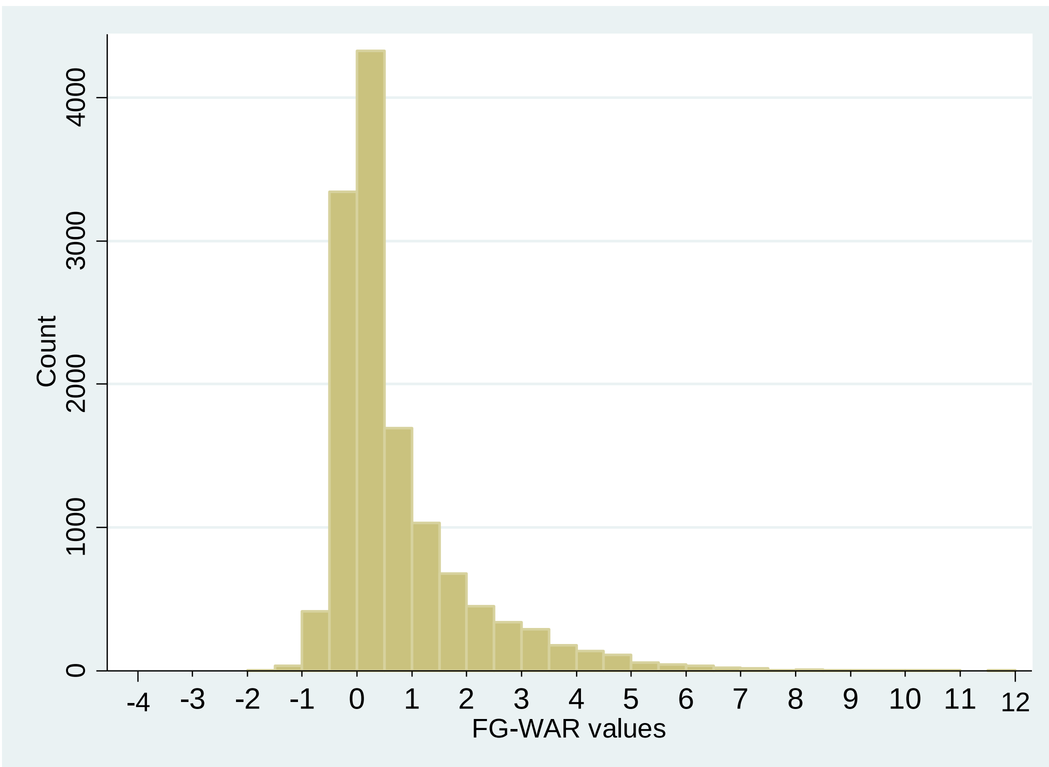
Note: Statistics for players who switched teams mid-season are combined into one observation, so n is the number of player-years in the sample. There are 343 total players.

Table 5. Summary Statistics – Non-TJS Pitcher-years 1996-2016

Variable	N	Mean	Std Dev	Minimum	Maximum
FG-WAR	10,994	0.64	1.30	-1.7	11.6
BR-WAR	10,994	0.62	1.47	-3.19	11.93
Age	10,994	28.0	4.13	19	46
Experience	10,994	3.92	3.07	1	20
Starting Pitcher	10,994	0.39	0.49	0	1
American League	10,994	0.49	0.50	0	1

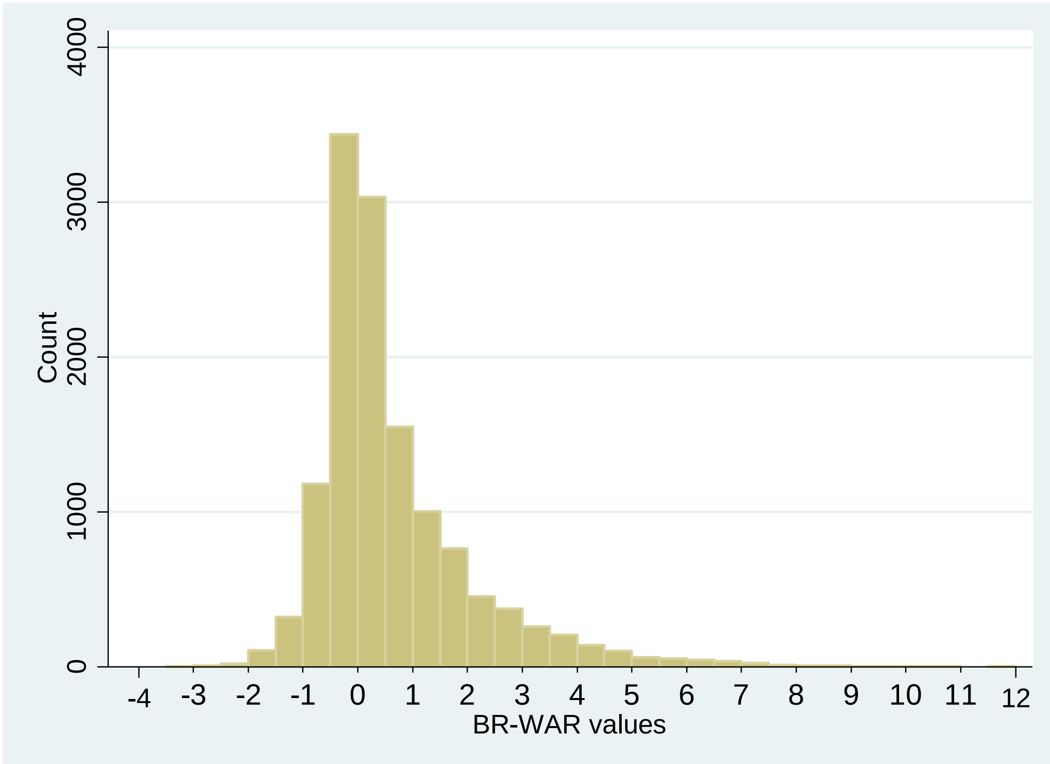
Note: Statistics for players who switched teams mid-season are combined into one observation, so n is the number of player-years in the sample. There are 2,765 total players.

Figure 4. Distribution of FG-WAR Values



Note: This figure includes all pitcher-seasons from 1996-2016 and each bar has a width of 0.5.

Figure 5. Distribution of BR-WAR Values



Note: This figure includes all pitcher-seasons from 1996-2016 and each bar has a width of 0.5.

Table 6. Impact of TJS on WAR

	(1)	(2)	(3)	(4)
VARIABLES	FG-WAR	BR-WAR	FG-WAR	BR-WAR
PreTJS1	0.132**	0.158**	-0.00740	-0.00130
	(0.0621)	(0.0760)	(0.0677)	(0.0890)
Injury Season	-0.191	-0.322*	-0.311**	-0.469**
	(0.152)	(0.171)	(0.150)	(0.203)
Months Missed	-0.139***	-0.104**	-0.121***	-0.0805
	(0.0404)	(0.0433)	(0.0399)	(0.0503)
PostTJS1	-0.393***	-0.416***	-0.516***	-0.575***
	(0.0541)	(0.0657)	(0.0829)	(0.0991)
PostTJS2	-0.130	-0.276***	-0.231**	-0.395***
	(0.0936)	(0.107)	(0.111)	(0.132)
PostTJS3	-0.0202	-0.120	-0.0773	-0.186
	(0.0979)	(0.115)	(0.115)	(0.135)
PostTJS4	-0.105	-0.129	-0.159	-0.158
	(0.105)	(0.137)	(0.124)	(0.157)
PostTJS5	-0.106	-0.236**	-0.0822	-0.161
	(0.0748)	(0.0936)	(0.160)	(0.193)
Age	-0.00207	-0.0147	0.545***	0.633***
	(0.0291)	(0.0355)	(0.0595)	(0.0686)
Age_sq	0.000141	0.000445	-0.00871***	-0.00940***
	(0.000486)	(0.000594)	(0.000994)	(0.00110)
Experience	0.201***	0.199***	-0.00872	-0.0871**
	(0.0122)	(0.0145)	(0.0300)	(0.0407)
Experience_sq	-0.0122***	-0.0122***	-0.00608***	-0.00453**
	(0.000943)	(0.00113)	(0.00163)	(0.00182)
American League	0.0154	0.114***	-0.0966***	-0.00487
	(0.0198)	(0.0240)	(0.0291)	(0.0371)
Starting pitcher	1.152***	0.813***	0.532***	0.216***
	(0.0247)	(0.0291)	(0.0347)	(0.0421)
Constant	-0.325	-0.143	-7.545***	-9.125***
	(0.422)	(0.512)	(0.888)	(1.071)
Individual Fixed Effects	No	No	Yes	Yes
Observations	13,260	13,260	13,260	13,260
R-squared	0.230	0.108	0.117	0.063
Number of Pitchers	3,108	3,108	3,108	3,108

Robust standard errors in parentheses
Significance Levels: *** p<0.01, ** p<0.05, * p<0.1
Estimates generated using OLS. Columns (1) and (2) do not include any fixed effects while columns (3) and (4) contain player fixed effects.

Table 7. Age Subsamples (Young = Age < 28, Old = Age >= 28)

VARIABLES	(1) FG-WAR Young	(2) BR-WAR Young	(3) FG-WAR Old	(4) BR-WAR Old
PreTJS1	-0.102	-0.182	-0.0591	0.00294
	(0.102)	(0.134)	(0.103)	(0.136)
Injury Season	-0.116	-0.460	-0.547***	-0.715**
	(0.267)	(0.339)	(0.190)	(0.300)
Months Missed	-0.204***	-0.136	-0.0736*	-0.0261
	(0.0717)	(0.0878)	(0.0435)	(0.0691)
PostTJS1	-0.688***	-0.752***	-0.536***	-0.574***
	(0.153)	(0.186)	(0.131)	(0.152)
PostTJS2	-0.254	-0.452	-0.382***	-0.505***
	(0.241)	(0.284)	(0.148)	(0.170)
PostTJS3	-0.235	-0.517	-0.187	-0.203
	(0.281)	(0.345)	(0.163)	(0.175)
PostTJS4	-0.333	0.0870	-0.232	-0.230
	(0.336)	(0.455)	(0.188)	(0.221)
PostTJS5	-0.949**	-0.859**	-0.0402	-0.0564
	(0.408)	(0.345)	(0.193)	(0.220)
Age	1.397***	1.219***	0.250*	0.416***
	(0.258)	(0.315)	(0.128)	(0.141)
Age_sq	-0.0299***	-0.0263***	-0.00200	-0.00377*
	(0.00527)	(0.00642)	(0.00197)	(0.00205)
Experience	0.355***	0.367***	-0.235***	-0.319***
	(0.0646)	(0.0996)	(0.0512)	(0.0706)
Experience_sq	-0.0210***	-0.0254***	-0.00322*	-0.00210
	(0.00779)	(0.00893)	(0.00187)	(0.00220)
American League	-0.0635	0.00210	-0.119***	-0.000156
	(0.0450)	(0.0600)	(0.0382)	(0.0489)
Starting pitcher	0.497***	0.230***	0.479***	0.104
	(0.0427)	(0.0532)	(0.0576)	(0.0726)
Constant	-16.42***	-14.17***	-3.654*	-6.580***
	(3.190)	(3.982)	(2.100)	(2.408)
Individual Fixed Effects	Yes	Yes	Yes	Yes
Observations	6,860	6,860	6,400	6,400
R-squared	0.107	0.044	0.188	0.119
Number of Pitchers	2,528	2,528	1,757	1,757

Robust standard errors in parentheses
Significance Levels: *** p<0.01, ** p<0.05, * p<0.1
Estimates generated using OLS with individual fixed effects for all columns.

Table 8. Starter and Reliever Sub-samples

VARIABLES	(1) FG-WAR Relievers	(2) BR-WAR Relievers	(3) FG-WAR Starters	(4) BR-WAR Starters
PreTJS1	-0.111*	-0.113	0.189	0.206
	(0.0606)	(0.0877)	(0.136)	(0.171)
Injury Season	-0.362***	-0.569***	-0.0216	-0.198
	(0.125)	(0.181)	(0.282)	(0.380)
Months Missed	-0.0147	-0.00763	-0.274***	-0.182*
	(0.0319)	(0.0438)	(0.0708)	(0.0940)
PostTJS1	-0.420***	-0.520***	-0.577***	-0.563***
	(0.0657)	(0.0946)	(0.172)	(0.211)
PostTJS2	-0.375***	-0.504***	0.111	-0.0903
	(0.0765)	(0.110)	(0.237)	(0.290)
PostTJS3	-0.264***	-0.438***	0.379	0.373
	(0.0779)	(0.112)	(0.265)	(0.311)
PostTJS4	-0.350***	-0.474***	0.231	0.417
	(0.103)	(0.136)	(0.255)	(0.331)
PostTJS5	-0.271***	-0.317**	0.161	0.0737
	(0.101)	(0.157)	(0.335)	(0.383)
Age	0.268***	0.448***	0.803***	0.850***
	(0.0412)	(0.0577)	(0.141)	(0.167)
Age_sq	-0.00371***	-0.00587***	-0.0137***	-0.0144***
	(0.000664)	(0.000919)	(0.00227)	(0.00230)
Experience	-0.0512**	-0.135***	-0.0167	-0.0894
	(0.0205)	(0.0289)	(0.0873)	(0.131)
Experience_sq	-0.00306***	-0.000691	-0.00668**	-0.00354
	(0.00112)	(0.00139)	(0.00304)	(0.00341)
American League	-0.0352*	0.0102	-0.211***	-0.0341
	(0.0183)	(0.0289)	(0.0756)	(0.0940)
Constant	-4.018***	-6.983***	-9.726***	-10.58***
	(0.629)	(0.898)	(2.242)	(2.961)
Individual Fixed Effects	Yes	Yes	Yes	Yes
Observations	7,979	7,979	5,281	5,281
R-squared	0.080	0.054	0.122	0.087
Number of Pitchers	2,532	2,532	1,419	1,419

Robust standard errors in parentheses

Significance Levels: *** p<0.01, ** p<0.05, * p<0.1

Estimates generated using OLS with individual fixed effects for all columns.

Table 9. Impact of TJS of ERA, WHIP and Innings Pitched for Starting Pitchers

	(1)	(2)	(3)
VARIABLES	ERA	WHIP	Innings Pitched
PreTJS1	-0.745**	-0.105***	7.823
	(0.312)	(0.0390)	(6.287)
Injury Season	-0.261	-0.0791	-13.10
	(0.560)	(0.0784)	(11.44)
Months Missed	0.226	0.0347	-17.00***
	(0.198)	(0.0231)	(2.915)
PostTJS1	0.259	0.00322	-46.81***
	(0.274)	(0.0375)	(8.258)
PostTJS2	-0.107	-0.0492	3.553
	(0.263)	(0.0432)	(9.706)
PostTJS3	-0.353	-0.0840*	2.395
	(0.283)	(0.0442)	(11.90)
PostTJS4	-0.681**	-0.129***	10.11
	(0.298)	(0.0473)	(12.48)
PostTJS5	-0.0494	-0.0435	0.188
	(0.358)	(0.0580)	(13.45)
Age	-0.736***	-0.0917***	26.16***
	(0.143)	(0.0273)	(6.096)
Age_sq	0.00768***	0.00135***	-0.528***
	(0.00193)	(0.000306)	(0.0920)
Experience	0.443***	0.0306	8.507**
	(0.111)	(0.0227)	(4.255)
Experience_sq	-0.00606*	-0.000700	-0.386***
	(0.00312)	(0.000478)	(0.122)
American League	0.283***	0.0352**	-2.892
	(0.0878)	(0.0137)	(3.094)
Constant	17.52***	2.837***	-217.1**
	(2.598)	(0.535)	(104.4)
Individual Fixed Effects	Yes	Yes	Yes
Observations	5,281	5,281	5,281
R-squared	0.023	0.020	0.109
Number of Pitchers	1,419	1,419	1,419

Robust standard errors in parentheses
Significance Levels: *** p<0.01, ** p<0.05, * p<0.1
Estimates generated using OLS with individual fixed effects for all columns.

Table 10. Impact of TJS of ERA, WHIP and IP for Relief Pitchers

	(1)	(2)	(3)
VARIABLES	ERA	WHIP	Innings Pitched
PreTJS1	-0.219	-0.0463	1.976
	(0.303)	(0.0489)	(2.070)
Injury Season	-1.266	-0.154	-13.39***
	(1.759)	(0.252)	(4.606)
Months Missed	1.851**	0.288**	-4.471***
	(0.922)	(0.121)	(1.152)
PostTJS1	0.862*	0.0855	-19.55***
	(0.517)	(0.0777)	(2.480)
PostTJS2	0.251	0.0477	-5.388*
	(0.463)	(0.0754)	(2.922)
PostTJS3	1.457	0.207	-5.623*
	(1.102)	(0.193)	(3.124)
PostTJS4	0.664	0.123	-4.684
	(0.676)	(0.109)	(3.624)
PostTJS5	2.024	0.224	-6.186
	(1.520)	(0.176)	(4.260)
Age	-1.697***	-0.244***	14.58***
	(0.456)	(0.0639)	(1.646)
Age_sq	0.0205***	0.00284***	-0.223***
	(0.00682)	(0.000802)	(0.0247)
Experience	0.870***	0.127***	-1.164
	(0.308)	(0.0490)	(0.966)
Experience_sq	-0.0240***	-0.00316***	-0.0874**
	(0.00743)	(0.000954)	(0.0408)
American League	0.294	0.0272	-2.011**
	(0.266)	(0.0361)	(0.877)
Constant	33.83***	5.766***	-185.7***
	(8.208)	(1.241)	(27.44)
Individual Fixed Effects	Yes	Yes	Yes
Observations	7,979	7,979	7,979
R-squared	0.018	0.023	0.085
Number of Pitchers	2,532	2,532	2,532

Robust standard errors in parentheses

Significance Levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Estimates generated using OLS with individual fixed effects for all columns.

Table 11. Breakdown of WAR into standard pitching statistics

VARIABLES	(1) FG-WAR	(2) BR-WAR
Games	-0.0317***	-0.0429***
	(0.00113)	(0.00143)
Games Started	-0.105***	-0.205***
	(0.00560)	(0.00719)
Innings Pitched	0.0371***	0.0542***
	(0.00110)	(0.00137)
Saves	0.0222***	0.0238***
	(0.000963)	(0.00132)
ERA	0.0151***	-0.0129**
	(0.00504)	(0.00543)
K/9	0.0915***	0.0634***
	(0.00325)	(0.00319)
BB/9	-0.0269***	0.0231***
	(0.00401)	(0.00656)
HR/9	-0.130***	-0.0478***
	(0.0120)	(0.0104)
WHIP	0.0117	-0.139***
	(0.0352)	(0.0433)
Starting Pitcher	-0.0891***	-0.0753***
	(0.0179)	(0.0248)
American League	0.00715	0.0905***
	(0.0123)	(0.0167)
Constant	-0.596***	-0.475***
	(0.0463)	(0.0581)
Individual Fixed Effects	No	No
Observations	13,260	13,260
R-squared	0.711	0.569

Robust standard errors in parentheses
Significance Levels: *** p<0.01, ** p<0.05, * p<0.1
Estimates generated using OLS with no fixed effects.

Table 12. Impact of TJS on Games Pitched, Innings Pitched and ERA for All Pitchers

VARIABLES	(1) Games	(2) Innings Pitched	(3) ERA
PreTJS1	1.226	3.001	-0.518***
	(1.151)	(2.944)	(0.199)
Injury Season	-4.898*	-15.98***	-0.981
	(2.522)	(6.087)	(1.030)
Months Missed	-4.669***	-10.01***	1.139**
	(0.689)	(1.740)	(0.522)
PostTJS1	-13.60***	-32.35***	0.374
	(1.499)	(3.940)	(0.314)
PostTJS2	-3.094*	-5.170	-0.0502
	(1.707)	(4.518)	(0.265)
PostTJS3	-4.452**	-6.097	0.365
	(1.858)	(5.065)	(0.633)
PostTJS4	-2.512	-2.372	-0.302
	(2.064)	(6.152)	(0.349)
PostTJS5	-3.295	-3.185	0.572
	(2.334)	(6.704)	(0.710)
Age	7.632***	23.89***	-0.996***
	(0.855)	(2.379)	(0.214)
Age_sq	-0.124***	-0.410***	0.0127***
	(0.0129)	(0.0387)	(0.00298)
Experience	1.183**	3.173**	0.506***
	(0.567)	(1.396)	(0.180)
Experience_sq	-0.0896***	-0.280***	-0.0154***
	(0.0237)	(0.0598)	(0.00367)
American League	-2.391***	-2.606**	0.246
	(0.520)	(1.233)	(0.157)
Starting pitcher	-8.754***	51.08***	-0.355*
	(0.718)	(1.802)	(0.192)
Constant	-82.38***	-295.8***	21.45***
	(14.44)	(37.84)	(4.196)
Individual Fixed Effects	Yes	Yes	Yes
Observations	13,260	13,260	13,260
R-squared	0.094	0.200	0.011
Number of Pitchers	3,108	3,108	3,108

Robust standard errors in parentheses

Significance Levels: *** p<0.01, ** p<0.05, * p<0.1

Estimates generated using OLS with individual fixed effects for all columns.

Table 13. Impact of TJS on WHIP, Strikeouts, Walks and Homeruns Allowed for All Pitchers

VARIABLES	(1) WHIP	(2) K/9IP	(3) BB/9IP	(4) HR/9IP
PreTJS1	-0.0803***	0.248**	-0.317**	-0.0818
	(0.0293)	(0.126)	(0.130)	(0.0624)
Injury Season	-0.161	0.663**	-0.141	-0.105
	(0.145)	(0.329)	(0.608)	(0.150)
Months Missed	0.178***	-0.281**	0.515**	0.0828
	(0.0688)	(0.125)	(0.239)	(0.0721)
PostTJS1	0.0400	0.113	0.00626	0.127
	(0.0450)	(0.201)	(0.237)	(0.102)
PostTJS2	-0.00215	-0.0336	-0.0101	0.00284
	(0.0421)	(0.190)	(0.202)	(0.0812)
PostTJS3	0.0606	0.237	0.142	-0.0901
	(0.109)	(0.211)	(0.436)	(0.0965)
PostTJS4	-0.00989	0.276	0.185	-0.107
	(0.0559)	(0.236)	(0.295)	(0.0985)
PostTJS5	0.0690	0.367	0.384	-0.0311
	(0.0845)	(0.301)	(0.440)	(0.103)
Age	-0.158***	0.552***	-0.515***	-0.197***
	(0.0320)	(0.0994)	(0.145)	(0.0502)
Age_sq	0.00197***	-0.00879***	0.00714***	0.00292***
	(0.000373)	(0.00149)	(0.00177)	(0.000610)
Experience	0.0755***	-0.170**	0.131	0.0992***
	(0.0278)	(0.0676)	(0.131)	(0.0384)
Experience_sq	-0.00210***	0.00544***	-0.00529**	-0.00400***
	(0.000508)	(0.00210)	(0.00223)	(0.000919)
American League	0.0260	-0.425***	-0.0716	0.103***
	(0.0214)	(0.0583)	(0.0885)	(0.0304)
Starting pitcher	-0.0636***	-0.873***	-0.622***	0.0891*
	(0.0243)	(0.0789)	(0.102)	(0.0501)
Constant	4.162***	-0.456	12.71***	4.035***
	(0.651)	(1.754)	(3.027)	(0.976)
Individual Fixed Effects	Yes	Yes	Yes	Yes
Observations	13,260	13,260	13,260	13,260
R-squared	0.014	0.034	0.012	0.007
Number of Pitchers	3,108	3,108	3,108	3,108

Robust standard errors in parentheses

Significance Levels: *** p<0.01, ** p<0.05, * p<0.1

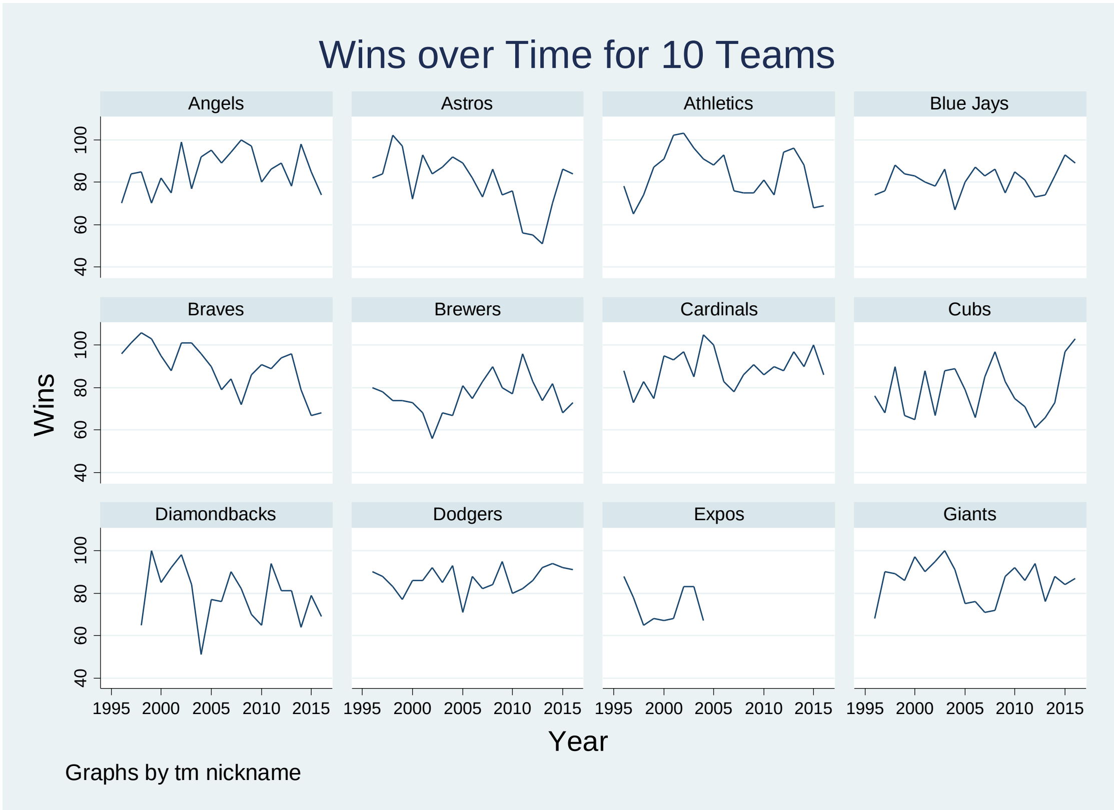
Estimates generated using OLS with individual fixed effects for all columns.

Table 14. Summary Statistics – Pitchers and Position Player-years

Variable	N	Mean	St. Dev.	Minimum	Maximum
All Pitchers					
Team Wins	14,493	80.4	11.3	43	116
Pitcher BR-WAR	14,493	0.59	1.40	-3.19	11.93
Pitcher FG-WAR	14,493	0.62	1.24	-1.7	11.6
Relief Pitchers					
Relief Pitcher BR-WAR	9,396	0.29	0.84	-2.72	5.01
Relief Pitcher FG-WAR	9,396	0.20	0.60	-1.4	4.7
Starting Pitchers					
Starting Pitcher BR-WAR	5,097	1.17	1.96	-3.19	11.93
Starting Pitcher FG-WAR	5,097	1.39	1.68	-1.7	11.6
Position Players					
Team Wins	14,157	80.7	11.4	43	116
Hitter BR-WAR	14,157	0.87	1.73	-3.27	11.85
Hitter FG-WAR	14,157	0.84	1.68	-3.1	12.7

Note: Seasons are split by team for players who are traded mid-season, meaning there can be two observations for a given player in a given season (one for each team they are on). N is number of observations. There are 3,138 pitchers and 2,543 position players.

Figure 6. Variation is Wins over Time for 10 Teams



Note: The Expos ceased to be a team after 2004. The variation in wins for any given team appears to be random, reducing the concern for time persistent shocks in errors.

Table 15. Team Wins as a Function of Individual FG-WAR

VARIABLES	(1) Team Wins	(2) Team Wins	(3) Team Wins	(4) Team Wins
Pitcher BR-WAR	1.118***	1.474***		
	(0.115)	(0.140)		
Pitcher BR-WARsq		-0.0832***		
		(0.0194)		
Hitter BR-WAR	0.855***	0.993***	0.855***	0.993***
	(0.0781)	(0.120)	(0.0781)	(0.120)
Hitter BR-WARsq		-0.0279		-0.0278
		(0.0171)		(0.0171)
Starting Pitcher BR-WAR			1.362***	1.870***
			(0.144)	(0.198)
Starting Pitcher BR-WARsq				-0.100***
				(0.0270)
Relief Pitcher BR-WAR			2.062***	2.297***
			(0.257)	(0.380)
Relief Pitcher BR-WARsq				-0.156
				(0.202)
Pitcher	-0.223	-0.265	0.185	0.224
	(0.154)	(0.159)	(0.152)	(0.165)
Starting Pitcher			-1.848***	-2.094***
			(0.252)	(0.273)
Constant	79.94***	79.91***	79.94***	79.91***
	(0.0866)	(0.0912)	(0.0888)	(0.0931)
Team Fixed Effects	Yes	Yes	Yes	Yes
Observations	28,650	28,650	28,650	28,650
R-squared	0.020	0.020	0.024	0.025
Number of Teams	31	31	31	31

Robust standard errors in parentheses
Significance Levels: *** p<0.01, ** p<0.05, * p<0.1
Estimates are calculated using OLS with team fixed effects for the 31 teams in the sample.

Table 16. Team Wins as a Function of Individual BR-WAR

	(1)	(2)	(3)	(4)
VARIABLES	Team Wins	Team Wins	Team Wins	Team Wins
Pitcher BR-WAR	1.081***	1.205***		
	(0.106)	(0.117)		
Pitcher BR-WARsq		-0.0294**		
		(0.0129)		
Hitter BR-WAR	0.746***	0.710***	0.744***	0.701***
	(0.0640)	(0.0795)	(0.0638)	(0.0788)
Hitter BR-WARsq		0.00717		0.00883
		(0.00998)		(0.00992)
Starting Pitcher BR-WAR			1.126***	1.385***
			(0.112)	(0.134)
Starting Pitcher BR-WARsq				-0.0545**
				(0.0215)
Relief Pitcher BR-WAR			1.515***	1.491***
			(0.194)	(0.192)
Relief Pitcher BR-WARsq				0.0149
				(0.0231)
Pitcher	-0.292*	-0.303*	0.0388	0.0209
	(0.167)	(0.167)	(0.179)	(0.183)
Starting Pitcher			-1.217***	-1.222***
			(0.204)	(0.206)
Constant	80.03***	80.03***	80.03***	80.03***
	(0.0840)	(0.0844)	(0.0845)	(0.0847)
Team Fixed Effects	Yes	Yes	Yes	Yes
Observations	28,650	28,650	28,650	28,650
R-squared	0.020	0.020	0.022	0.022
Number of Teams	31	31	31	31

Robust standard errors in parentheses
Significance Levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Estimates are calculated using OLS with team fixed effects for the 31 teams in the sample.

Table 17. Team Wins as a Function of Team FG-WAR

VARIABLES	(1) Wins	(2) Wins
Pitcher FG-WAR	1.130***	1.481***
	(0.0430)	(0.204)
Pitcher FG-WARsq		-0.0121*
		(0.00671)
Hitter FG-WAR	0.850***	0.875***
	(0.0199)	(0.0785)
Hitter FG-WARsq		-0.000780
		(0.00200)
Constant	48.59***	46.21***
	(0.662)	(1.425)
Team Fixed Effects	Yes	Yes
Observations	626	626
R-squared	0.765	0.766
Number of Teams	31	31

Robust standard errors in parentheses
Significance Levels: *** p<0.01, ** p<0.05, * p<0.1
Estimates are calculated using OLS with team fixed effects for the 31 teams in the sample. Team-level War values are aggregated totals of the individual players' WAR values.

Table 18. Team Wins as a Function of Team BR-WAR

VARIABLES	(1) Wins	(2) Wins
Pitcher BR-WAR	1.000***	1.028***
	(0.0274)	(0.116)
Pitcher BR-WARsq		-0.00107
		(0.00389)
Hitter BR-WAR	0.957***	1.060***
	(0.0237)	(0.0765)
Hitter BR-WARsq		-0.00256
		(0.00198)
Constant	48.24***	47.24***
	(0.679)	(1.068)
Team Fixed Effects	Yes	Yes
Observations	626	626
R-squared	0.823	0.823
Number of Teams	31	31

Robust standard errors in parentheses
Significance Levels: *** p<0.01, ** p<0.05, * p<0.1
Estimates are calculated using OLS with team fixed effects for the 31 teams in the sample. Team-level War values are aggregated totals of the individual players' WAR values.

CHAPTER FIVE

ESTIMATING MARGINAL REVENUE OF A WIN

In the previous chapter, through a two-step process, I estimated the impact of TJS on the MP of a pitcher in terms of team wins. In this chapter, I estimate the MR for a team of an additional win, $\frac{\partial TR}{\partial W}$. Combining these estimates, I get an estimate for the impact of TJS on MRP of a pitcher.

Theory and Empirical Specification

Many factors influence a team's total revenue for a season. Because revenues are simply price multiplied by quantity sold, most of the determinants of revenue are the determinants of the underlying demand function. Fans demand winning according to the usual elements—price, available substitutes, expectations, and preferences. Preferences in sports, from a fan's perspective, usually include team quality and preferences toward outcome uncertainty and competitive balance.

I am interested in the impact of on-field success, the quality aspect in team wins, on team revenue. One aspect that complicates this estimation is that a team's revenue in year t is not only dependent on the team's wins in year t. Season ticket sales, endorsements and some television contracts are based on the team's expected wins, which are largely based off the number of wins the year before, and to a lesser extent additional previous years.[30] In addition, making the playoffs provides the opportunity to earn significant additional revenue through additional ticket sales and revenue sharing. Another factor that can provide a big shock to a team's revenue, independent of the team's wins, is opening a new stadium. This is referred to as the honeymoon effect in other literature (Fort et al. 2017) and has been found to have an effect on revenues up to four years following the opening of the new stadium.

There are two logical options for the revenue measure to use in the model: Total Revenue and Gate Revenue. Both measures have been previously used to estimate the MR of an additional win. Krautman (1999) used gate revenues while the other authors have primarily used total revenues. The measure of revenue most directly tied to a team's on-field success is gate revenue, but there are additional revenue sources such as merchandise sales and concession sales that are dependent on team success and not included in gate revenue. While total revenue includes sources of revenue that are not dependent on year-to-year team success, such as revenues from long-term television contracts, the annual variation in total revenue should be driven by those sources of revenue that are dependent on team success. An issue with the gate revenue is that the revenue data are split up differently in different years so the gate revenue does not necessarily contain the same sources of revenue in all years. Also, I do not have data on gate revenue for 1997, 1998 or 2001. The total revenue data are available for all years

[30] I tried including additional lags and multiple lags were significant out to t-3 but the magnitudes of the coefficients were distributed among the three lags and the sum was similar to that on t-1. Also, with the inclusion of t-4, the results returned to being similar to only including t-1 with the additional lags being insignificant. In the end, for the theoretical reasons, supported by the results, I only included **Team Wins** and **Team Wins(t-1)** in the model.

and I am more confident in their accuracy, so I use total revenue for my estimation of MR.[31]

Equation (4) presents my empirical specification of revenues for team j in season t as:

(4) $Revenue_{jt} = \beta_0 + \beta_1 * Team\ Wins_{jt} + \beta_2 * Team\ Wins_{jt-1} + \beta_3 * Playoffs_{jt} + \beta_4 * New\ Stadium1_{jt} + \beta_5 * New\ Stadium2_{jt} + \beta_6 * New\ Stadium3_{jt} + \beta_7 * New\ Stadium4_{jt} + \beta_8 * Time\ Trend_t + \gamma_j + \varepsilon_{ijt}$

Revenue is a function of **Team Wins** in the current season (t), **Team Wins** in the previous season (t-1), whether the team made the **Playoffs** in the current season, and whether they occupied a new stadium in the past four seasons (**New Stadium1 – New Stadium4**). Figure 7 shows the fairly linear increase in real revenues over time, both for total revenues and gate revenues, which is effectively controlled for with the **Time Trend.** Total revenues are increasing at a much faster rate than gate revenues, primarily due to the rapid increase in television revenues over time. Figure 8 shows similar trends for four teams with very different revenue levels. Figure 9 illustrates the correlation between wins and revenue among teams in the sample, calculated at 0.76, and the need for team fixed effects, γ_j, to isolate the marginal revenue of an additional win for a given team. Fixed effects also account for variation due to different costs of attendance and access to media across locations.

[31] For comparison, I also calculate the MR of a win using teams' gate revenues and those results are reported in appendix C.

The variation in average revenue among teams also raises the question of whether the marginal revenue of a win is the same for all teams. Burger and Walters (2003) determined that large market teams value some players up to six times more than small market teams. To address the possibility of different MR for different teams, I follow Fort et al (2017) and use a Quantile Regression approach, which allows for different estimates for different quantiles in the distribution of revenue. Quantile Regression generates estimates based on the median of the dependent variable (or other designated points in the distribution), while OLS regression generates the estimates based on the mean of the dependent variable. I also report results using an OLS fixed effects specification for comparison.

I also run the model without team fixed effects to see how the between team variation in revenue and wins impacts the estimates for the marginal revenue of a win. For example, the Yankees average revenue is $100 million higher than any other team, and they win an average of five more games per year than any other team. I include a **Yankee Dummy** variable to control for this difference between the Yankees and other teams, but allow the variation between the other teams to contribute to the estimates.

Data

The data for this model are annual team level data for the same seasons as the marginal product dataset, 1996-2016. With the Montreal Expos moving and becoming the Washington Nationals in 2005, there are 31 teams in the dataset and 626 observations. Teams that changed their team name, but remained the same organization and in the same location (Angels, Rays and Marlins), are treated as a single team throughout the dataset. Total annual revenue data for each team are reported by Forbes and were provided at Rodney Fort's Sports Business Data website.[32]. Annual win data, playoff appearances, and new stadium data are collected from Baseball-Reference.

There is a wide distribution of revenues (both total revenues and gate revenues) among teams resulting from different market sizes and fan bases, as can be seen in table 19. The nature of baseball, without a salary cap and the consistent success of some large market teams, such as the Yankees, results in this high level of inequality in both revenue and wins. Figure 9 shows the relationship between the average revenue and average wins for each team from 1996-2016. The low average revenue for the Expos in table 19 is partially the result of the Expos only being in the dataset for the first nine years of the sample and the increase in all revenues over time, and partially due to poor ownership and a lack of interest in the team.[33] After the Montreal Expos were moved to Washington and became the Nationals in 2005, they began generating more revenue. For the 12 years that the Nationals are in the sample, they are near the middle of the distribution of teams in terms of average revenue.

Results

Table 20 shows the Quantile Regression and OLS results for equation (4). The coefficients on **Team Wins** and **Team Wins(t-1)** are not statistically different between

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[32] The URL for Rodney Fort's Sports Business Data website is https://umich.app.box.com/folder/320019395

[33] With the sample restricted to those nine years for the entire sample, the Expos still have the lowest average revenue.

the different quantiles.[34] This suggests that the marginal revenue of a win does not significantly differ between teams with different average total revenues, but I still use the Quantile Regression results for the MR portion of the MRP estimation.[35] The results suggest that an additional win in year t has an effect on revenue of $0 to $200,000 in year t, but results in an increase in revenue of about $500,000 in year t+1. In comparison with the previous literature (Fort 2017), my results are more similar across the quantiles and have larger magnitudes. I attribute these differences to the team fixed effects controlling for between team variations.

The control variables, **Playoffs**, **New Stadium1-New Stadium4** and the **Time Trend** all have positive and significant coefficients. The coefficient estimates on the **New Stadium** dummies decrease in magnitude for each additional season the stadium is open, but mostly stay significant through the fourth season (**New Stadium4**). The impact of opening a new stadium is less for the Q75 teams than the smaller market teams (statistically different for **New Stadium2** and **New Stadium3**). A possible reason for this is that large market teams, such as the Yankees and Red Sox, have high attendance totals every season, so a new stadium has a limited potential impact on attendance. In contrast, a small market team, such as the A's or Marlins, have very low attendance in most seasons, so there is a low more room for a new stadium to impact attendance totals.

[34] The P-values for the t-tests between the estimated coefficients across all quantiles are 0.44 for Team Wins and 0.91 for Team Wins(t-1). The sums of Team Wins and Team Wins(t-1) are also not statistically different between quantiles (p-value: 0.41).

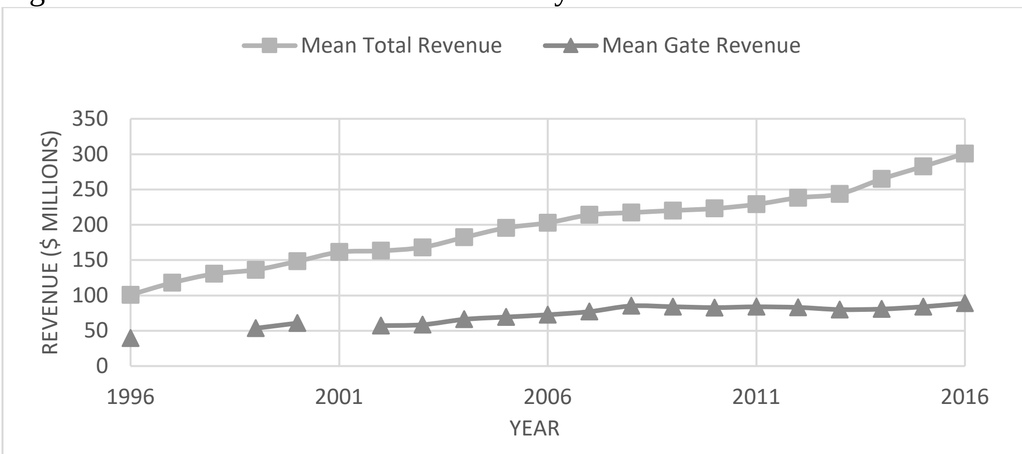
[35] The Quantile Regression results also allow for comparison across quantiles with the results in appendix C, where I use gate revenue instead of total revenue as the dependent variable.

For comparison, I also include results for the model with year fixed effects instead of the **Time Trend,** as well as results for the model with just the **Time Trend** and a **Yankee Dummy** and no other team fixed effects (tables 21 and 22). Table 21 shows that the results are very consistent when year fixed effects are used instead of a **Time Trend**. Naturally, the R-squared values are slightly higher with the year fixed effects than the **Time Trend** and some coefficients are a bit different, but there are no notable changes among the coefficients of interest. Removing the team fixed effects, however, increases the magnitudes of all the **Team Win** coefficients and causes the coefficients to be significantly larger for the larger quantiles. This makes theoretical sense, because the model is now using between team variation in wins to explain the between team variation in revenue instead of just the within team variation. The strong correlation between average team revenue and average team wins is driving these results. This variation overestimates the marginal revenue of an additional win for a given team, so I use the results from column 2 in table 20 for my MRP estimation. For a median revenue team, the total MR of a win, $\frac{\partial TR}{\partial W}$, is approximately \$720,000 split between the current season and following season.[36]

[36] The calculation to get this total is 0.219 + 0.501 = 0.720, and the total revenue measures are in millions so that is \$720,000.

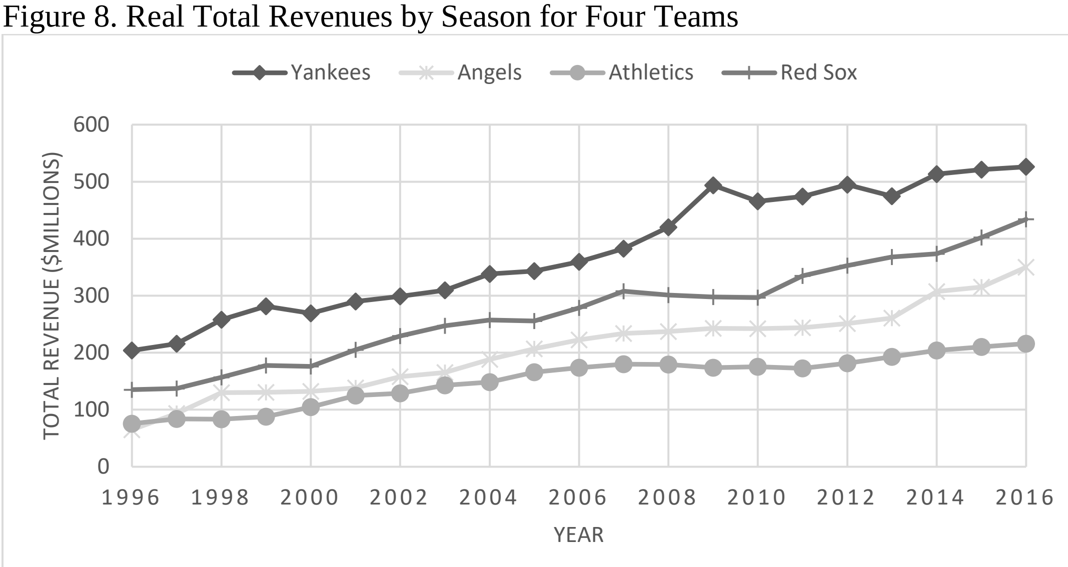
Chapter Five Figures and Tables

Figure 7. Mean Total and Gate Revenues by Year



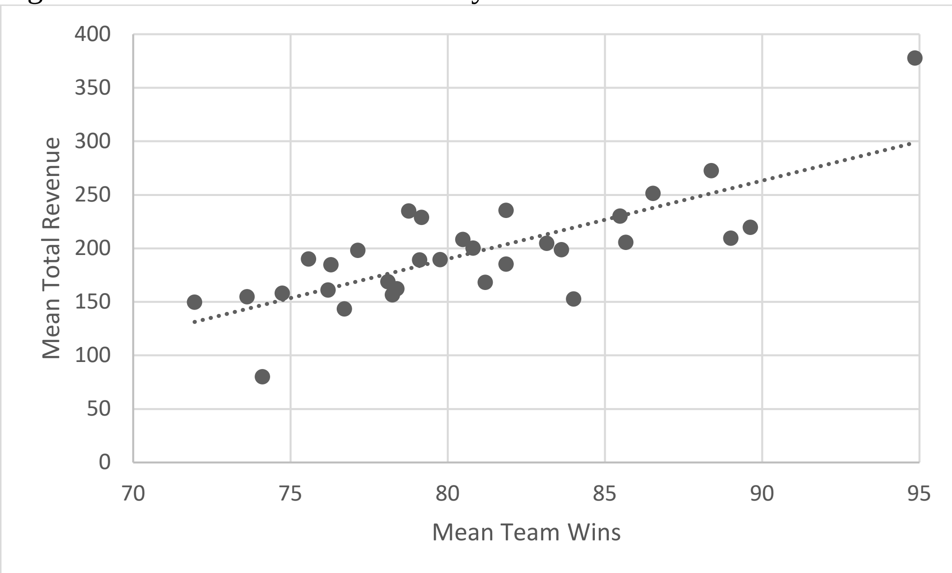
Note: Total revenues are increasing at a much faster rate than gate revenues. The primary cause of this increase in total revenues is the increase in television revenue both at the national and regional levels. I include the Time Trend variable in the model to control for this linear increase in total revenue. The rate that average total revenue is increasing is almost $10 million per year.

Figure 8. Real Total Revenues by Season for Four Teams



Note: The Yankees got a new stadium in 2009, which explains that jump in revenue and is an example of why I include the New Stadium dummy variables in my model. These four teams have similar trends in total revenue over the 21-year period, despite being in very different size markets.

Figure 9. Mean Wins and Revenue by Team 1996-2016



Note: Mean total revenues and wins are calculated for each of the 31 teams for 1996-2016. Correlation (Mean Total Revenue, Mean Wins) = 0.76
Equation of the trendline: Revenue = -394.85 + 7.31*Wins

Table 19. Summary Statistics by Team

Team	N	Average Revenue ($ millions)	Average Gate Revenue ($ millions)	Average Team Wins
Expos	9	80.1	17.3	74.1
Marlins	21	143.5	31.7	76.7
Royals	21	149.7	42.1	72.0
Athletics	21	152.7	37.8	84.0
Pirates	21	154.9	45.3	73.6
Twins	21	156.6	54.5	78.2
Rays	19	158.2	31.5	74.7
Brewers	21	161.0	55.4	76.2
Reds	21	162.3	48.6	78.4
Blue Jays	21	168.4	49.5	81.2
Padres	21	168.8	51.7	78.1
Tigers	21	184.7	67.5	76.3
White Sox	21	185.2	56.9	81.9
Diamondbacks	19	189.2	51.5	79.1
Astros	21	189.6	71.0	79.8
Rockies	21	190.1	61.4	75.6
Orioles	21	198.0	72.8	77.1
Indians	21	198.8	61.5	83.6
Phillies	21	200.2	53.6	80.8
Rangers	21	204.7	89.0	83.1
Angels	21	205.5	62.8	85.7
Mariners	21	208.4	79.3	80.5
Cardinals	21	209.4	68.6	89.0
Braves	21	219.6	101.7	89.6
Nationals	12	228.9	64.2	79.2
Giants	21	230.2	75.4	85.5
Cubs	21	235.0	106.1	78.8
Mets	21	235.4	116.7	81.9
Dodgers	21	251.4	99.0	86.5
Red Sox	21	272.6	97.0	88.4
Yankees	21	377.8	156.8	94.6
Total	**626**	**170.7**	**72.8**	**81.0**

Note: N is the number of seasons each team is in the sample. The mean revenue for Expos is artificially low relative to other teams due to only being in the sample for 1996-2004. The opposite is true for the Nationals because they are only in the sample for 2005-2016.

Table 20. MR of a Win, Quantile Regression with Time Trend and Team Fixed Effects

VARIABLES	(1) Real Revenue Q25	(2) Real Revenue Q50	(3) Real Revenue Q75	(4) Real Revenue OLS
Team Wins	0.151**	0.219***	0.0435	0.0841
	(0.0635)	(0.0835)	(0.101)	(0.138)
Team Wins(t-1)	0.536***	0.501***	0.501***	0.613***
	(0.0384)	(0.0632)	(0.0673)	(0.113)
Playoffs	10.62***	10.12***	13.31***	13.98***
	(1.803)	(2.011)	(2.412)	(4.020)
New Stadium1	37.74***	32.83***	30.23***	33.64***
	(2.881)	(2.149)	(8.255)	(5.494)
New Stadium2	27.49***	25.50***	16.40***	22.17***
	(1.821)	(2.628)	(2.779)	(4.789)
New Stadium3	17.53***	17.74***	8.471***	19.57***
	(1.530)	(2.706)	(2.659)	(5.073)
New Stadium4	17.60***	16.23***	11.94**	16.90***
	(5.806)	(5.848)	(4.945)	(5.941)
Time Trend	8.432***	8.408***	8.365***	8.675***
	(0.0830)	(0.140)	(0.127)	(0.245)
Constant	40.14***	46.06***	66.38***	47.72***
	(9.462)	(7.883)	(12.44)	(13.37)
Team Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No
Observations	595	595	595	595
R-squared	0.696	0.674	0.690	0.885

Robust standard errors in parentheses
Significance levels: *** p<0.01, ** p<0.05, * p<0.1
Estimates generated using quantile regression for columns (1), (2), and (3) while column (4) estimates are generated using OLS. All columns include team fixed effects and a time trend and do not include year fixed effects. Revenue values are in millions of 2016 dollars.

Table 21. MR of a Win, Quantile Regression with Team and Year Fixed Effects

VARIABLES	(1) Real Revenue Q25	(2) Real Revenue Q50	(3) Real Revenue Q75	(4) Real Revenue OLS
Team Wins	0.241***	0.222*	-0.0358	0.0892
	(0.0598)	(0.118)	(0.108)	(0.131)
Team Wins(t-1)	0.499***	0.486***	0.501***	0.610***
	(0.0423)	(0.0892)	(0.0835)	(0.110)
Playoffs	9.458***	9.207***	15.55***	13.88***
	(1.392)	(2.406)	(2.074)	(3.802)
New Stadium1	31.80***	33.04***	28.47***	34.78***
	(2.056)	(4.254)	(2.509)	(5.813)
New Stadium2	18.84***	18.24***	18.70***	22.68***
	(2.056)	(4.570)	(4.370)	(4.800)
New Stadium3	11.97***	14.62***	10.19**	20.94***
	(2.755)	(3.556)	(3.955)	(5.453)
New Stadium4	4.370**	7.371	10.79**	18.41***
	(2.081)	(9.461)	(4.210)	(6.228)
Constant	0.241***	0.222*	-0.0358	0.0892
	(0.0598)	(0.118)	(0.108)	(0.131)
Team Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	595	595	595	595
R-squared	0.735	0.697	0.711	0.896

Robust standard errors in parentheses
Significance levels: *** p<0.01, ** p<0.05, * p<0.1
Estimates generated using quantile regression for columns (1), (2), and (3) while column (4) estimates are generated using OLS. All columns include team fixed effects and year fixed effects and no time trend. Revenue values are in millions of 2016 dollars.

Table 22. MR of a Win, Quantile Regression with Time Trend and Yankee Dummy

VARIABLES	(1) Real Revenue Q25	(2) Real Revenue Q50	(3) Real Revenue Q75	(4) Real Revenue OLS
Team Wins	0.409**	0.644***	0.713***	0.576***
	(0.177)	(0.209)	(0.241)	(0.195)
Team Wins(t-1)	0.704***	0.938***	1.219***	1.007***
	(0.140)	(0.159)	(0.173)	(0.162)
Playoffs	18.22***	16.73***	11.57*	14.93***
	(5.552)	(5.577)	(6.992)	(5.622)
New Stadium1	39.65***	31.26***	16.64***	29.05***
	(10.37)	(3.710)	(4.868)	(7.508)
New Stadium2	26.58***	24.92***	11.30*	16.61***
	(3.150)	(7.195)	(6.109)	(5.919)
New Stadium3	21.68***	21.49**	4.460	13.09**
	(4.627)	(9.032)	(3.538)	(5.586)
New Stadium4	20.51***	8.844	-1.212	10.82*
	(7.258)	(5.846)	(5.716)	(6.458)
Yankee Dummy	135.9***	154.3***	192.4***	158.8***
	(8.244)	(34.13)	(23.76)	(13.69)
Time Trend	8.365***	8.314***	7.859***	8.688***
	(0.248)	(0.280)	(0.363)	(0.321)
Constant	-22.90*	-39.76**	-35.35**	-37.72***
	(13.34)	(16.27)	(16.65)	(14.51)
Team Fixed Effects	No	No	No	No
Year Fixed Effects	No	No	No	No
Observations	595	595	595	595
R-squared	0.492	0.456	0.462	0.726

Robust standard errors in parentheses

Significance levels: *** p<0.01, ** p<0.05, * p<0.1

Estimates generated using quantile regression for columns (1), (2), and (3) while column (4) estimates are generated using OLS. All columns include a time trend and do not include team fixed effects nor year fixed effects. Revenue values are in millions of 2016 dollars.

CHAPTER SIX

MARGINAL REVENUE PRODUCT CALCULATION

To get the final estimate for the impact of TJS on a player's MRP, I combine the marginal product estimates and the marginal revenue estimates. The value of interest, $\frac{\partial TR}{\partial TJS}$, is the product of $\frac{\partial TR}{\partial W}$, $\frac{\partial W}{\partial WAR}$ and $\frac{\partial WAR}{\partial TJS}$. I estimated these three values in the previous two chapters with $\frac{\partial WAR}{\partial TJS}$ in the first half of chapter four, $\frac{\partial W}{\partial WAR}$ in the second half of chapter four and $\frac{\partial TR}{\partial W}$ in chapter five. Clearly, the actual cost to the team in a specific situation is heavily dependent on the team and pitcher involved. To help illustrate the range of potential costs, I generate general estimates for an average pitcher on a median revenue team and then provide estimates for three specific hypothetical pitchers on different teams and in different roles.[37]

To provide some context for these estimates, I also estimate the total career MRP for these pitchers. The career MRP for a pitcher is based on his career WAR value, which is simply the sum of all his annual WAR values. Therefore, a pitcher can accumulate a high career WAR by pitching for many seasons, having a high per season WAR value, or both. For some estimates, I also use partial career WAR values, such as a pitcher's career WAR prior to TJS. Intuitively, these WAR values are calculated as the sum of the pitcher's annual WAR values in the seasons prior to his TJS.

[37] Note that these estimates are not discounted to present value. Due to the multi-step process of calculating the cost estimates, I felt discounting would make understanding the process unnecessarily difficult and hard to follow. Also, the discounted estimates would be similar to these non-discounted estimates, because the costs are distributed over a relatively short period(about five years),

General Estimate for Average Pitcher

We get $\frac{\partial WAR}{\partial TJS}$ from the coefficients on **PostTJS1-PostTJS5** in columns 3 and 4 of table 6 (chapter four). The **PostTJS1** value is -0.516 for the first year back after TJS for FG-WAR and -0.575 for BR-WAR. This is saying that a pitcher who gets TJS will have a loss in productivity of slightly more than one-half WAR value on average in the season he returns to pitch, compared to that season had he not been injured. The coefficients of **PostTJS2** are equal to -0.231 for FG-WAR and -0.395 for BR-WAR and are statistically different from zero. While the coefficients on **PostTJS3-PostTJS5** are not statistically different from zero, they are the best estimates we have for those seasons and for this application are not treated as zero. The average number of seasons pitched after returning from TJS in my sample is 3.7, so for this estimate I use the sum of the first four **PostTJS** coefficients as the total impact of TJS on pitcher performance, $\frac{\partial WAR}{\partial TJS}$. This value is estimated to be -0.983 for FG-WAR and -1.314 for BR-WAR.[38]

From column 1 of tables 15 and 16 (chapter four), $\frac{\partial W}{\partial WAR} = 1.12$ for FG-WAR and 1.08 for BR-WAR. Multiplying these estimates by the estimates for the impact of TJS on WAR, gives us the impact of TJS on MP in terms of team wins, $\frac{\partial W}{\partial TJS}$. This value is -1.101 for FG-WAR and -1.419 for BR-WAR.[39]

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[38] The calculation for FG-WAR is -0.983 = -0.516 – 0.231 – 0.077 – 0.159. The calculation for BR-WAR is -1.314 = -0.575 – 0.395 – 0.186 – 0.158.

[39] The calculation for FG-WAR is -1.101 = -0.983 * 1.12. The calculation for BR-WAR -1.419 = -1,314 * 1.08.

To convert this estimation of the impact of TJS on marginal product to the impact of TJS on MRP, I multiply it by the estimation of marginal revenue from chapter five. Using the results from column (2) in table 20, the total marginal revenue of an additional win for a given team is $\frac{\partial TR}{\partial W}$ = \$720,000.[40] Therefore, the impact of TJS on MRP is $\frac{\partial TR}{\partial TJS}$ = -1.101 * \$720,000 = -\$792,720 using FG-WAR and $\frac{\partial TR}{\partial TJS}$ = -1.419 * \$720,000 = -\$1.022 million using BR-WAR. This is the estimated cost to the team due to a decrease in productivity after the pitcher returns to the major leagues and does not include the costs of the surgery itself, the cost of the time the pitcher misses while recovering from the surgery or the potential cost if the pitcher does not return at all.

The medical costs associated with the surgery (about \$50,000) are negligible in comparison with the value and salaries of MLB pitchers, and the cost if a pitcher is unable to return at all is dependent upon how long he would have continued to play and who he is replaced with. I am able to provide some rough estimates of these costs under assumptions for his expected performance and career length and that he is replaced with a replacement level pitcher. I generate this estimate at the end of this section for comparison with the costs if the pitcher does return to play.

I estimate the cost to the team while the pitcher is in rehabilitation using the assumption that a replacement level player replaces them for that time period. The average time to return to MLB following TJS is about 18 months, which typically includes the remainder of the season in which the pitcher was injured and one more entire

[40] This calculation is 0.219 in year t plus 0.501 in year t +1 = 0.720, and revenue is in millions of dollars, so this is \$720,000.

season. I have estimates for the lost productivity in the season in which they are injured, using the coefficients on **Injury Season** and **Months Missed** in columns 3 and 4 of table 6 (chapter four).

The average number of months missed for pitchers who are injured during the season is about three so the estimated total loss in the Injury Season is -0.674 FG-WAR and -0.711 BR-WAR.[41] To estimate the lost productivity for a full season missed due to TJS, I use the pitcher's expected WAR value because his replacement's average WAR value should be zero by the definition of a replacement player. For this general estimate, I use the average WAR value of a TJS pitcher before TJS, which is 0.96 for FG-WAR and 0.93 for BR-WAR. Therefore, the estimate for total lost productivity due to missed seasons for TJS is -1.634 = -0.674 – 0.96 for FG-WAR and -1.671 = -0.711 – 0.93 for BR-WAR. Using the same estimates for $\frac{\partial W}{\partial WAR}$ and $\frac{\partial TR}{\partial W}$ as above, the estimated cost to the team of this missed time is approximately $1.318 million using FG-WAR and $1.299 million using BR-WAR.[42] Combining these estimates with the estimates for lost MRP after a pitcher returns from TJS, my general estimate for the total cost of TJS in terms of decreased productivity experienced by the team is $2.111 million ($792,720 + $1.318 million) for FG-WAR and $2.321 million ($1.022 million + $1.299 million) for BR-WAR.

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[41] The calculation for FG-WAR is -0.311 + 3*-0.121 = -0.674, and for BR-WAR it is -0.469 + 3*-0.0805 = -0.711. This estimated loss is for a pitcher who is injured halfway through the regular season. Some pitchers are injured in spring training and then miss the entire season and a portion of or the entire next season.

[42] The calculation using FG-WAR is -1.634 * 1.12 * $720,000 = -$1.318 million. The calculation using BR-WAR is -1.671 *1.08 *$720,000 = -$1.299 million.

For comparison, the average career WAR values for TJS pitchers who return to MLB after TJS is 6.99 FG-WAR or 6.44 BR-WAR with an average of 4.11 FG-WAR and 3.94 BR-WAR coming prior to TJS. This translates to a total career MRP estimate of $5.637 million using FG-WAR and $5.008 million using BR-WAR.[43] These career average MRP values are accounting for the lost MRP due to TJS, so the expected average MRP without the injury at all would be $5.637 million + $2.111 million = $7.748 million using FG-WAR and $5.008 million + $2.321 million = $7.329 million using BR-WAR. This suggests that the average cost of TJS in terms of MRP is about 30 percent of the pitcher's expected career MRP.

If a pitcher does not return at all from TJS, then he does not generate any MRP after his injury. The estimate for this pitcher's career MRP, using the average career WAR up to the point of TJS is $3.314 million using FG-WAR and $3.064 million using BR-WAR.[44] Using these estimates for pre-TJS career MRP, we can say the cost of not getting TJS, or the expected benefit of getting TJS is the MRP generated by the pitcher after returning from TJS. Using these estimates, that value is $5.637 – $3.314 = $2.323 million using FG-WAR and $5.008 – $3.064 = $1.944 million using BR-WAR. Note that these values are very similar to the estimated costs of having to get TJS, but that is just a coincidence specific to this example and does not necessarily hold for specific pitchers.

[43] The calculation using FG-WAR is 6.99 * 1.12 * $720,000 = $5.637 million. The calculation using BR-WAR is 6.44 * 1.08 * $720,000 = $5.008 million.
[44] The calculation for FG-WAR is 4.11 * 1.12 * $720,000 = $3.314 million. The calculation for BR-WAR is 3.94 * 1.08 * $720,000 = $3.064 million.

Specific Estimates for Three Hypothetical Pitchers

For this section, I will estimate the impact of TJS on MRP for three different pitchers on different teams.

Pitcher A: All-Star, starting pitcher on high revenue team, who gets TJS at age 26 after five seasons in MLB, misses four months in his injury season and the entire following season, and then pitches for six seasons following TJS. His average WAR value pre-TJS was 5.0.

Pitcher B: Quality, bullpen pitcher on a median revenue team, who gets TJS at age 32, after eight seasons in MLB, misses one month in his injury season and the entire following season and then pitches two more seasons following TJS. His average WAR value pre-TJS was 2.5.

Pitcher C: Back of the rotation, starting pitcher on a low revenue team, who gets TJS at age 24 after two seasons in MLB and tearing his UCL in spring training. He misses two full seasons recovering and then pitches for four more total seasons following TJS. His average WAR value pre-TJS was 0.4.

For each pitcher, I use the appropriate estimate for $\frac{\partial WAR}{\partial TJS}$ based on if they are a starter or reliever (table 8, chapter four). For the $\frac{\partial W}{\partial WAR}$ estimate, I use column 2 from tables 15 and 16 (chapter four), because each pitcher has a specific expected WAR value that can be plugged in. I use each pitcher's average pre-TJS WAR value as his expected WAR value in the calculation of lost productivity while they are rehabbing. The MR of a win, $\frac{\partial TR}{\partial W}$, for each pitcher is estimated based on the team they are on (column 1, 2, or 3 in table 20, chapter 5).

Pitcher A Estimation:

Pitcher A is a starting pitcher, so using the coefficients on PostTJS1-PostTJS5 in columns 3 and 4 of table 8, the estimate for $\frac{\partial WAR}{\partial TJS}$ = 0.466 for FG-WAR and 0.284 for BR-WAR.[45] These values are positive because **PostTJS1** is negative, indicating a decrease in productivity the first year back, but after that the coefficients are positive, indicating an increase in productivity.[46] The lost productivity to the team while Pitcher A is out is -1.118 for FG-WAR and -0.926 for BR-WAR for the season he was injured and 5.0 WAR for the full season he missed.[47] Adding these impacts of TJS on productivity together, the total impact from the season he is injured through his last season in the league is -5.65 for FG-WAR and -5.64 for BR-WAR. Even though his performance improved slightly following return from TJS, the lost productivity to the team of the time he missed greatly outweighed the improved productivity from **PostTJS2** forward.

[45] Because Pitcher A pitches six seasons after TJS, I use the coefficient on PostTJS5 for both the fifth and sixth seasons following return to MLB. The calculation for FG-WAR is -0.577 + 0.111 + 0.379 + 0.231 + 0.161 + 0.161 = 0.466. The calculation for BR-WAR is -0.563 – 0.0903 + 0.373 + 0.417 + 0.0737 + 0.0737 = 0.284.

[46] PostTJS2-PostTJS5 are not significantly different from zero so it is possible that there is no impact after the first season back in MLB, but to remain consistent with the general estimation last section, I include these values because they are the best estimates we have for those seasons.

[47] The calculation for FG-WAR is -0.0216 + 4*-0.274 = -1.118. The calculation for BR-WAR is -0.198 + 4*-0.182 = -0.926.

The season missed is 5.0 for both FG-WAR and BR-WAR because it is just his expected WAR value (5) minus the replacement player's expected WAR value (0).

To calculate the $\frac{\partial W}{\partial WAR}$ estimate for Pitcher A, I plug his expected WAR value of 5.0 into $\frac{\partial W}{\partial WAR}$ = 1.476 – 2*0.0845*WAR for FG-WAR (column 2 of table 15) and $\frac{\partial W}{\partial WAR}$ = 1.205 – 2*0.029*WAR for BR-WAR (column 2 of table 16). These estimates are 0.631 for FG-WAR and 0.915 for BR-WAR. Multiplying these estimates by the estimated impact of TJS on productivity from above, $\frac{\partial W}{\partial TJS}$ = -3.57 for FG-WAR and -5.16 for BR-WAR.

The estimate for $\frac{\partial TR}{\partial W}$ for Pitcher A is $544,500 from column 3 of table 20, because Pitcher A is on a high revenue team (Q75).[48] Multiplying this estimate times the estimates for $\frac{\partial W}{\partial TJS}$, the estimated cost of TJS in terms of lost MRP is approximately $1.944 million using FG-WAR and $2.810 million using BR-WAR.

In estimating the total career MRP for pitcher A, I assume and average WAR value of 5.0 per season over the course of a 12-year career if he had never been injured. This does not mean a constant performance level over the course of his career, because the expected trend would be an increase and then decrease in performance with an increase in age. The expected total career WAR for Pitcher A without injury and TJS is 60, which translates to an expected MRP of $20.615 million using FG-WAR and $29.893 million using BR-WAR. In this example, the lost MRP due to TJS is less than 10 percent of the total expected WAR value due to Pitcher A’s long and very productive career.

<u>Pitcher B Estimation:</u>

[48] The MR estimation using the coefficients on wins in year t and in year t-1 is 0.501 + 0.0435 = 0.5445 *1,000,000 = $544,500

Pitcher B is a relief pitcher and he only pitches two seasons after returning from TJS, so using the coefficients on PostTJS1 and PostTJS2 in columns 1 and 2 of table 8, the estimate for $\frac{\partial WAR}{\partial TJS}$ = -0.795 for FG-WAR and -1.024 for BR-WAR.[49] The lost productivity to the team while Pitcher B is out is -0.377 for FG-WAR and -0.577 BR-WAR for the season he was injured and 2.5 WAR for the full season he missed.[50] Adding these impacts of TJS on productivity together, the total impact from the season he is injured through his last season in the league is -3.67 for FG-WAR and -4.10 for BR-WAR.

I use the same process as above for estimating $\frac{\partial W}{\partial WAR}$ for Pitcher B, but with an expected WAR value of 2.5. These estimates are 1.054 for FG-WAR and 1.058 for BR-WAR. Multiplying these estimates by the estimated impact of TJS on productivity from above, $\frac{\partial W}{\partial TJS}$ = -3.87 for FG-WAR and -4.34 for BR-WAR. The estimate for MR is the same as was used in the general estimate in the first section of this chapter ($720,000), because Pitcher B is on a median revenue team. The product of this MR and the estimated $\frac{\partial W}{\partial TJS}$ is the estimated cost of TJS in terms of lost MRP and is approximately $2.786 million using FG-WAR and $3.123 million using BR-WAR.[51]

Using the same process as was used above for Pitcher A, Pitcher B's expected career WAR if he had remained healthy is 27.5 (11 seasons with an average of 2.5 WAR

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[49] The calculation for FG-WAR is -0.420 – 0.375 = -0.795. The calculation for BR-WAR is -0.520 – 0.504 = -1.024.

[50] The calculation for FG-WAR is -0.362 + 1*-0.0147 = -0.377. The calculation for BR-WAR is -0.569 + 1*-0.00763 = -0.577.

[51] The calculation for FG-WAR is -3.87 * $720,000 = -$2.786 million. The calculation for BR-WAR is -4.34 * $720,000 = -$3.123 million.

per season). This career WAR translates to a career MRP of $20.869 million using FG-WAR and $20.948 million using BR-WAR.[52] In this case, Pitcher B having to undergo TJS cost the team just under 14 percent of his expected career MRP.

<u>Pitcher C Estimation:</u>

Pitcher C is a lower quality, starting pitcher with an expected WAR value of just above replacement level. This adds a few wrinkles to the estimation of the cost to the team of TJS. Starting with the two seasons that Pitcher C misses while recovering from TJS, that is a lost productivity of 0.8 WAR. Then in the first season when he returns to pitch, the estimate on PostTJS1 of -0.577 for FG-WAR or -0.563 for BR-WAR would put him below replacement level. In this case, I would expect the team to use a replacement pitcher and leave pitcher C in the minors for that season. This results in a lost productivity to the team of 0.4 WAR again. This gives us a total loss of 1.2 WAR up to this point when Pitcher C makes it back to the majors and pitches three more seasons in the majors.

For Pitcher C's final three years, I use the coefficients on PostTJS2-PostTJS4 in columns 3 and 4 of table 8. These estimates suggest a total increase in productivity over those three seasons of 0.721 for FG-WAR and 0.700 for BR-WAR. Subtracting off the lost productivity of the three years prior, the net impact of TJS on productivity is -0.479 for FG-WAR and -0.500 for BR-WAR. Using the same process as for Pitchers A and B,

[52] The calculation for FG-WAR is 27.5 * 1.054 * $720,000 = $20.869 million. The calculation for BR-WAR is 27.5 * 1.058 * $720,000 = $20.948 million.

$\frac{\partial W}{\partial WAR}$ for Pitcher C is 1.408 for FG-WAR and 1.181 for BR-WAR. Therefore, the total impact of TJS on team wins is -0.674 for FG-WAR and -0.591 for BR-WAR. Using column 1 in table 20, because Pitcher C is on a low revenue team, the MR of a win is $687,000.[53] Multiplying this MR estimate times the estimate for the impact of TJS on team wins, the cost of TJS is approximately $463,000 using FG-WAR and $493,000 using BR-WAR.

Pitcher C's expected career WAR, without injury, is 3.2 (8 seasons with an average of 0.4 WAR per season). The resulting MRP generated over the course of his career is $3.095 million using FG-WAR and $2.596 million using BR-WAR.[54] Using these calculations the estimated cost of Pitcher C having to undergo TJS is about 15 to 19 percent of his expected career MRP.

Discussion

The primary takeaway from these different estimates is that the majority of the cost associated with TJS is due to the time missed and the lost productivity in this time. An injury to a high quality pitcher is much more costly to the team than an injury to a lower quality pitcher, but in terms of the percentage of total career MRP generated, the lost MRP for a high quality pitcher can be less. The lost MRP due to a pitcher having to undergo TJS ranges from 10 to 30 percent of the pitcher's total career MRP depending on

[53] The MR of a win calculation is 0.151 + 0.536 = 0.687 *$1,000,000 = $687,000

[54] The calculation for FG-WAR is 3.2 * 1.408 * $687,000 = $3.095 million. The calculation for BR-WAR is 3.2 * 1.181 * $687,000 = $2.596 million.

pitcher quality and career length. The benefit of a successful TJS, or the cost of a pitcher not being able to return following TJS, is also dependent on the quality of the pitcher and the length of time they are able to pitch after returning from the surgery.

It is important to note that teams are able to buy insurance on player contracts to cover a portion of the remaining money owed to a player who suffers a serious injury. However, insurance companies have the right to refuse to cover pitchers with a history of previous injury, and they charge very high premiums to cover the hundred million dollar contracts that teams are most likely to insure. This insurance option would help decrease the cost to the team in the event that a pitcher is unable to return from TJS, but the cost of the insurance and limitations set by the insurance companies make this situation only applicable to a few top pitchers.[55]

Teams do not always replace an injured player by bringing up a replacement level player from the minors. They can also trade for a higher quality player or sign a higher quality free agent to avoid the cost associated with lost productivity. In these cases, the cost of the injury is transferred from lost MRP to what it costs the team to replace that player's productivity; either minor league prospects in a trade or money in a free agent signing. No matter how a team chooses to handle it, an injury, especially one that requires surgery such as TJS, is very costly to the team and the league as a whole. Using the general estimate for an average pitcher from section one of this chapter and the average number of TJS over the last five years (about 25), the estimated total cost across all teams, due to the lost productivity associated with TJS, is over $50 million per season.

[55] FanGraphs discusses the high costs and details of teams buying insurance on player contracts: https://www.fangraphs.com/community/insurance-in-baseball-is-like-a-black-hole/

CHAPTER SEVEN

CONCLUSION

This thesis estimates economic impacts of Tommy John Surgery (TJS). Prior medical studies have estimated the performance impacts of TJS and there is an extensive literature estimating the Marginal Revenue Product (MRP) of players in MLB, but this thesis is the first to combine the two and estimate the impacts of TJS on team revenues. This thesis also contributes new findings to the Sabermetric literature related to Wins Above Replacement (WAR) and the relationship between individual WAR values and team wins.

Three primary empirical models are employed in this thesis. The first is an OLS, fixed effects model on all MLB pitchers from 1996-2016 to estimate the impact of TJS on pitchers' WAR values, $\frac{\partial WAR}{\partial TJS}$. The second model is a Seemingly Unrelated Regression on all MLB pitchers and position players from 1996-2016 to estimate the relationship between individual pitching WAR and team wins, $\frac{\partial W}{\partial WAR}$. Finally, a quantile regression is employed on all MLB teams from 1996-2016 to estimate the MR of a win, $\frac{\partial TR}{\partial W}$. The product of these three estimates, $\frac{\partial TR}{\partial TJS}$, is the outcome of interest.

The primary results of this thesis provide evidence that TJS has a negative impact on a pitcher's productivity and his resulting value to the organization. My empirical results suggest that this loss of productivity is primarily driven by fewer innings pitched in the first two seasons after returning to play. The effect is the largest in the pitcher's first year back in MLB, with the loss in productivity estimated to be over half a win. This effect decreases to about a third of a win in the second year after returning and then is smaller and not statistically significant for the remainder of the pitcher's career. The total estimated decrease in productivity over the remainder of at pitcher's career is slightly more than 1.1 wins. The estimated MR of a win for a median revenue team is $720,000, so the estimated impact of TJS on a team's MRP after the pitcher returns to play is about -$800,000.

TJS also results in lost productivity to the team while the pitcher is recovering from surgery. The lost productivity during the recovery time is very dependent on the quality of the pitcher and his expected productivity if he were pitching. Using the average TJS-pitcher prior to undergoing TJS, this lost productivity is estimated to be over one and a half games and the corresponding cost to the team is about $1.2 million in lost revenues. Therefore, the total cost of TJS from lost productivity is estimated to be over $2 million for an average pitcher. With an average of 25 TJS per season the last five years, the total league cost is about $50 million per year.

These results do not suggest that teams are better off not keeping a player after he injures his UCL and requires TJS, although in some cases that may be the appropriate interpretation. In most cases, any pitcher whose typical WAR value is over 0.5 for a season will still be above "replacement level" after returning from the surgery.[56] These results do provide some evidence as to what teams can expect from a pitcher following TJS and may assist them in their valuation process.

[56] This does not take into account player's relative salaries and the possibility of the team being able to get a similarly productive player at a cheaper price.

The results of the team wins and individual WAR model provides evidence that the current formulas for calculating WAR are valuing hitters and pitchers disproportionately to their respective contributions to team wins. My results suggest that with the current WAR values, one unit of pitching WAR contributes more to team wins than one unit of hitting WAR. The simple solution to this would be to change the distribution of total WAR each season, and provide more units of WAR to pitchers and fewer to position players. The current distribution is 430 WAR for pitchers and 570 for position players (FanGraphs), or 410 for pitchers and 590 for position players (Baseball-Reference), so something closer to 450 WAR for pitchers and 550 for position players might be more representative.

The primary limitations of my approach relate to the fact the pitchers who get TJS may be different from pitchers who do not get TJS in a way that is correlated with their performance over the course of their career. The summary statistics suggest that TJS pitchers are better pitchers and have longer careers on average than non-TJS pitchers. My approach uses player fixed effects to control for the talent level differences between pitchers but there are opportunities for future work relating to the endogeneity of TJS. Future work to help address this should include a model to estimate the impact of pitcher characteristics and performance measures on their likelihood to undergo TJS.

The results of this thesis, and the methods I use to estimate these results, are applicable to other common injuries in other professional sports, such as anterior cruciate ligament (ACL) tears or concussions in football, basketball and soccer. It would be interesting to compare the lost team revenues between various injuries in different sports.

This thesis is relevant to both the sports economics literature and the baseball analytics literature. There is the potential for at least two different papers to come out of this thesis; an economics paper on the impact of TJS on MRP, and an analytics paper on the relationship between WAR and team wins.

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APPENDICES

APPENDIX A

ADDITIONAL DETAILS ON ESTIMATION OF WAR FOR POSITION PLAYERS

Specifics on FanGraphs' and Baseball-Reference's Methods for Calculating WAR for Position Players

Chapter two contains a summary of the step-by-step process to calculate pitcher WAR values for both FanGraphs and Baseball-Reference. Because my thesis focused on pitcher performance, the processes for calculating position player WAR values was not included in that chapter. The purpose of this appendix is to include details specific to position player WAR calculations that were not included in the main text. The steps to calculate position player WAR are the same as those for calculating pitcher WAR, with the exception of step 2. For pitchers, this step is to calculate the number of runs stopped by a given pitcher, while for position players, this step is to calculate the number of runs added or created by a given position player. This appendix describes the statistics that FanGraphs and Baseball-Reference use in this process.

The total number of runs contributed by a given position player is a combination of batting runs created, base running runs created and defensive runs saved. Both FanGraphs and Baseball-Reference use weighted runs above average (wRAA) as the primary measure for Batting Runs with some added adjustments for league and park factors. FanGraphs computes Base Running Runs as combination of Ultimate Base Running (UBR), which is non-stolen base related base running, and Weighted Stolen Base Runs (wSB), which is stolen bases and caught stealing measures. FanGraphs also includes Weighted Grounded into Double Play Runs (wGDP) in the base running category. Baseball-Reference uses the same or similar components of base running runs but refer to it as Rbr (Baserunning Runs). UBR and wGDP are calculated using specific play outcomes and video tracking data, but wSB is calculated according to the following formula:

wSB = SB * runSB + CS * runCS – lgwSB * (1B + BB + HBP – IBB)

For Defensive Runs Above Average, FanGraphs uses Ultimate Zone Rating (UZR) for non-catchers, which is calculated using video tracking data. For catchers, FanGraphs uses Stolen Base Runs (rSB) and Runs Saved on Passed Pitches (RPP). One limitation for catcher’s defensive measures is the lack of a pitch framing measure in the calculation. Baseball-Reference uses Total Zone Rating (TZR), which is very similar to the UZR that FanGraphs uses and Defensive Runs Saved (DRS) to calculate their defensive runs above average metric. DRS includes measures for Fielding Range, Outfield throwing, infield double plays, a good play-bad play value, bunt fielding and stolen base/caught stealing data for pitchers and catchers. In contrast to FanGraphs, Baseball-Reference includes data for catchers on handling the pitching staff, including pitch calling and pitch framing. In addition to the runs saved due to defensive performance, FanGraphs and Baseball-Reference both have positional adjustments based on each position’s relative importance of offense and defense. The positional adjustments are slightly different for FanGraphs and Baseball-Reference and are shown in table 23.

One final WAR value that I did not include in chapter two is hitting WAR for pitchers. Most pitchers hit at some point over the course of the season, with National League starting pitchers getting multiple at-bats every week. While pitchers are valued based on their pitching ability and generally expected to provide zero contribution hitting, a pitcher that is a good hitter provides additional value to their team (and the opposite for especially poor hitters).

FanGraphs does not calculate a hitting WAR for pitchers, or they include it in the pitching WAR, but Baseball-Reference explains their approach. It is not appropriate to compare pitchers' hitting ability to a replacement position player, because pitchers are valued based on their pitching ability and any hitting ability is considered a bonus. For that reason, Baseball-Reference incorporates a pitcher position adjustment that results in the sum of hitting WAR for all pitchers being equal zero. Therefore, pitchers who are above average hitters (for pitchers) will have positive hitting WAR values and pitchers who are below average will have negative hitting WAR values. Due to their relatively few at-bats, most pitcher's hitting WAR values are very close to zero.

Appendix A Tables

Table 23. Positional Adjustment Runs

Position	FanGraphs runs	Baseball-Reference runs
Catcher	+12.5	+9
Shortstop	+7.5	+7
Second base	+2.5	+3
Center field	+2.5	+2.5
Third base	+2.5	+2
Right field	-7.5	-7
Left field	-7.5	-7
First base	-12.5	-9.5
Designated hitter	-17.5	-15

Notes: These runs are added to (or subtracted from) a player's calculated runs above replacement based on the defensive value of the position they play.
FanGraphs runs are based on 162 games at 9 innings per game while Baseball-Reference bases them on 150 games, or 1350 total innings.
Sources: FanGraphs, Baseball-Reference

APPENDIX B

ATTEMPT AT REPLICATING MEDICAL STUDY METHODS AND RESULTS

Replicating Medical Study Methods and Results

The majority of medical studies on Tommy John Surgery use similar methods of comparing means between a case and control group. Although the studies all use different time periods and sample sizes, most of them use the same method of randomly selecting the control group by taking every fifth player from a list of players who did not get TJS.[57] I replicate this strategy using my own dataset to see how the results compare to those reported in the various medical articles.

The component of the medical studies that I replicate is the comparison of TJS pitchers before and after the surgery with control pitchers before and after a generated index year. Following the procedure used in the medical studies, I calculate an index year for the control group that represents the expected timing of Tommy John Surgery, and allows both pre- and post- comparison between the case and control groups. I generate a **Post Index Year** variable for the control group based on the average experience level in the case group at the time of TJS. This mean level of experience for pitchers in the TJS group in their first year back in the majors was 4.96, so the **Post Index Year** variable is zero for pitchers with four or less years of experience and it is one for five or more years of experience.

My case group includes data for 342 pitchers from 1996-2016, who got Tommy John Surgery while in the Major Leagues. My control group includes 595 pitchers from the same period who did not get Tommy John Surgery while they were in the Major

[57] A full summary and comparison of these medical studies can be found in table 1 at the end of chapter three.

Leagues. This control group is a subset of all the pitchers who did not get TJS (all MLB ID numbers that are evenly divisible by five). The relative size of my case and control group (more pitchers and observations for the control group than case group) is similar to the medical studies, although my dataset includes more years and total pitchers than any of the medical studies do.

Tables 21 and 22 show the summary stats for the case (TJS) and control groups respectively. The average age and experience for the TJS group is slightly higher than for the control group. From a performance standpoint, the average **WAR** values, **Innings Pitched**, **ERA** and **WHIP** are all lower for the TJS group than the control group. For **WAR** and **Innings Pitched**, this represents lower average production for TJS pitchers, but for **ERA** and **WHIP**, the lower value represents better performance.

Comparison of the **pre-Index Year** performance with the **post-Index Year** performance for the control group yields an improvement in performance in terms of **WAR, Innings Pitched, ERA** and **WHIP**. For the case group, performance declined from the **pre-TJS** period to the **post-TJS** period in terms of **WAR** and **Innings Pitched,** and was not statistically different for **ERA** and **WHIP**. These results are somewhat similar to the results reported by Makhni et al. (2014) and Keller et al. (2014), but totally contradictory to those reported by Gibson et al. (2007) and Erickson et al. (2014). These results using the comparison of means method also support by my results using econometric methods, where I also find a decrease in productivity of pitchers following TJS. An unexpected result that I find, which is not mentioned in the medical literature, is the magnitude of improvement in performance for non-TJS pitchers from before the index year to after it. This finding suggests that players experience a dramatic improvement from the first half of their career to the second but I suspect there is a different explanation for this entirely. Pitchers who pitch more than four years in the major leagues are going to be better pitchers on average than those who do not. In my control group, the only pitchers who are in the **post-Index Year** have pitched at least five years in the majors while, there are less talented pitchers included in the **pre-Index Year** group who do not reach four or five years of experience.

Appendix B Tables

Table 24. Summary Stats for Case (TJS) Group (343 pitchers)

Variable	N	Mean	Std Dev	Minimum	Maximum
Age	2266	28.4699912	4.4747247	19	49
Experience	2266	4.9267432	3.3861058	1	17
SP	2266	0.4448367	0.4970574	0	1
AL	2266	0.4373345	0.4961670	0	1
FG-WAR	2266	0.8568844	1.2853767	-1.5	8.4
BR-WAR	2266	0.7899647	1.4350879	-2.5	8.5
IP	2266	75.8813769	63.9912267	0	265.2
ERA	2266	4.9098853	5.2456440	0	135.0
WHIP	2266	1.4829876	0.7445652	0	15.0

Notes: N is all observations (pitcher-years) for pitchers who get TJS in their MLB career. This includes seasons prior to and following TJS.

Table 25. Summary Stats for Control Group (595)

Variable	**N**	**Mean**	**Std Dev**	**Minimum**	**Maximum**
Age	2434	28.1002465	4.2742762	19	45
Experience	2434	4.0184881	3.1823708	1	19
SP	2434	0.3866064	0.4870722	0	1
AL	2434	0.5061627	0.5000648	0	1
FG-WAR	2434	0.7271159	1.4451629	-1.7	11.6
BR-WAR	2434	0.7264215	1.6073717	-3.19	11.9
IP	2434	68.1732539	64.4555184	0	271.2
ERA	2434	5.1466311	4.0050464	0	67.5
WHIP	2434	1.5382046	0.6420092	0	10.0

Notes: N is the number of observations (pitcher-years) for members of the control group, which is a random subset of all pitchers who did not get TJS while in MLB.

Table 26. Comparison of Means for Case and Control Groups

	Case Group (342 Pitchers)			**Control Group (595 Pitchers)**		
Variable	Pre-TJS mean	Post-TJS mean	Change	Pre-Index mean	Post-Index mean	Change
FG-WAR	0.96	0.70	-0.26***	0.52	1.13	0.61***
BR-WAR	0.93	0.59	-0.34***	0.52	1.14	0.62***
Innings Pitched	80.6	69.0	-11.6***	56.3	91.6	35.3***
ERA	4.81	5.06	0.25	5.47	4.50	-0.97***
WHIP	1.47	1.50	0.03	1.60	1.41	-0.19***

*** p<0.01, ** p<0.05, * p<0.1 using Pooled t-test

Notes: The Change for the case group is between Pre-TJS mean and Post-TJS mean, and for the control group, it is between Pre-Index mean and Post-Index mean. The comparison between the Change values for the two groups is the estimate for the productivity impact of TJS using this method.

APPENDIX C

ESTIMATION OF MARGINAL REVENUE USING GATE REVENUE INSTEAD OF TOTAL REVENUE

Estimating the Marginal Revenue of a Win using Gate Revenue

This appendix replicates the model used in chapter five to estimate the marginal revenue of a win, using gate revenues as the dependent variable instead of total revenues. The argument for gate revenues is that not all components of teams' total revenues, specifically television revenues, are dependent on the team's annual win totals. Each team receives an equal share of the national television revenue and signs a 10-plus year regional television contract. Gate revenue is solely the revenue generated through ticket sales (both individual game and season tickets) and does not include television revenues, merchandise sales, or concession revenues. The variation in gate revenues is more directly related to year-to-year team success than the variation is total revenues is.

Gate revenues have also not increased over time as fast as total revenues have, as can be seen in figure 7 in chapter five. Figure 10 shows the gate revenues for four different teams and can be compared to figure 8 in chapter five. Figure 11 shows the correlation of mean annual wins and gate revenue by team and is comparable to figure 9 in chapter five.

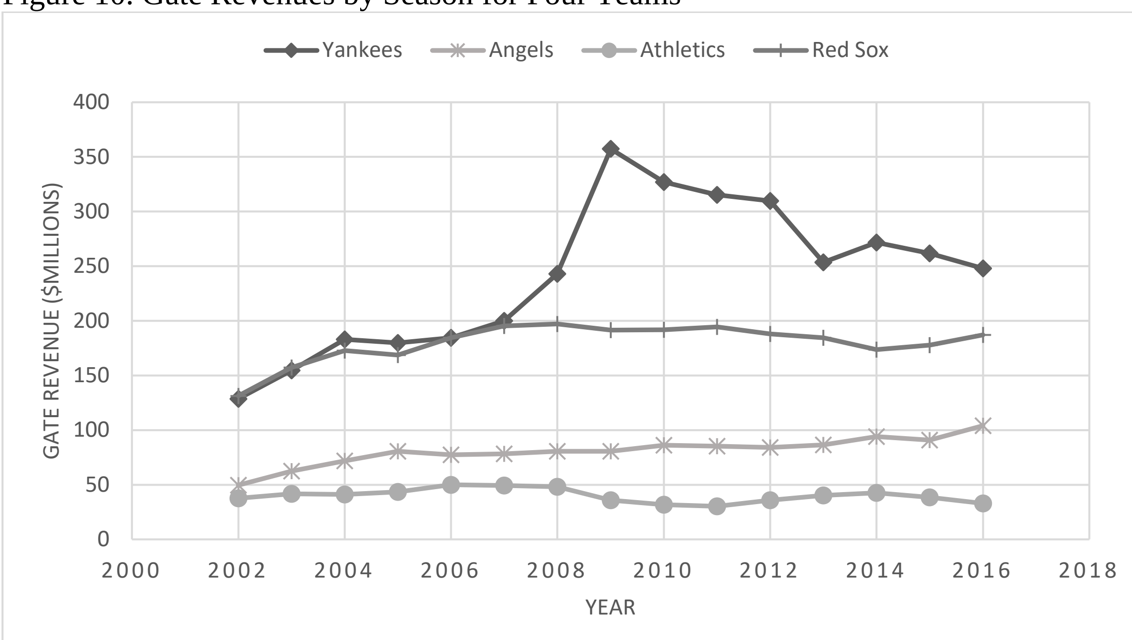
Table 27 shows the quantile regression and OLS results for equation (3) with **Gate Revenue** as the dependent variable and a **Time Trend** and team fixed effects. These results suggest the marginal gate revenue from an additional win increases with the average revenue of the team. The sum of the coefficients on Team Wins and Team Wins(t-1) are not statistically different between all three quantiles (columns 1-3) but they are statistically different between Q25 and Q75. Also, the coefficient on Team Wins(t-1) is statistically greater in Q75 than in Q50. These differences are unique to the Gate

Revenue specification and were not present in table 20 in chapter five. However, the magnitudes of these coefficients are relatively similar in tables 20 and 27, which means my estimation of the cost of TJS would not change very much using Gate Revenues instead of Total Revenues.

Tables 28 and 29 show the alternative specifications with year fixed effects instead of a Time Trend (table 28) and with a Yankee Dummy variable instead of all team fixed effects (table 29). The results in these tables can be compared to, and are similar to, the results in tables 21 and 22 in chapter 5.

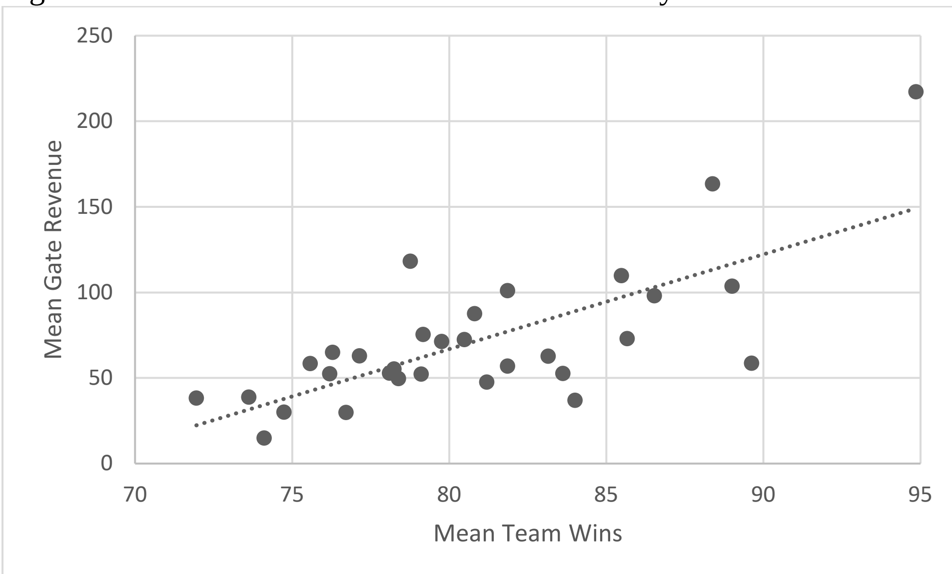
Appendix C Figures and Tables

Figure 10. Gate Revenues by Season for Four Teams



Note: The huge jump in Gate Revenue for the Yankees coincides with them opening a new stadium.

Figure 11. Mean Annual Wins and Gate Revenue by Team



Note: Mean gate revenues and wins calculated for each of the 31 teams for (1996-2016) with the exception of 1997, 1998 and 2001.
Correlation (Mean Total Revenue, Mean Wins) = 0.72
Equation of the trendline: Revenue = -352.79 + 5.25*Wins

Table 27. MR of a Win, Quantile Regression with Time Trend and Team Fixed Effects

VARIABLES	(1) Real Gate Revenue Q 25	(2) Real Gate Revenue Q 50	(3) Real Gate Revenue Q 75	(4) Real Gate Revenue OLS
Team Wins	0.143**	0.315***	0.163*	0.299**
	(0.0635)	(0.0945)	(0.0892)	(0.122)
Team Wins(t-1)	0.467***	0.464***	0.742***	0.500***
	(0.0485)	(0.0726)	(0.0608)	(0.0941)
Playoffs	7.791***	5.424**	9.745***	5.879**
	(1.831)	(2.676)	(2.277)	(2.991)
New Stadium1	28.78***	27.21***	42.33***	44.22***
	(5.359)	(9.028)	(15.25)	(9.679)
New Stadium2	26.31***	25.35***	24.03***	32.05***
	(8.542)	(4.176)	(3.063)	(6.306)
New Stadium3	10.45***	12.16***	8.358*	19.38***
	(3.387)	(2.123)	(4.624)	(5.523)
New Stadium4	4.672**	3.704*	7.257	14.18**
	(1.956)	(1.914)	(7.480)	(5.982)
Time Trend	1.720***	1.609***	1.272***	2.210***
	(0.0966)	(0.120)	(0.141)	(0.230)
Constant	-8.611	-13.51	-15.94**	-24.70**
	(5.901)	(8.297)	(7.902)	(10.41)
Team Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No
Observations	509	509	509	509
R-squared	0.546	0.599	0.634	0.838

Robust standard errors in parentheses
Significance levels: *** p<0.01, ** p<0.05, * p<0.1
Estimates generated using quantile regression for columns (1), (2), and (3) while column (4) estimates are generated using OLS. All columns include team fixed effects and a time trend and do not include year fixed effects. Revenue values are in millions of 2016 dollars.

Table 28. MR of a Win, Quantile Regression with Team and Year Fixed Effects

VARIABLES	(1) Real Gate Revenue Q 25	(2) Real Gate Revenue Q 50	(3) Real Gate Revenue Q 75	(4) Real Gate Revenue OLS
Team Wins	0.215***	0.319***	0.212	0.298**
	(0.0545)	(0.0929)	(0.130)	(0.121)
Team Wins(t-1)	0.488***	0.499***	0.682***	0.500***
	(0.0507)	(0.0658)	(0.0747)	(0.0943)
Playoffs	7.191***	5.319**	8.451***	5.928**
	(1.396)	(2.294)	(2.143)	(2.986)
New Stadium1	35.27***	33.78***	40.70***	43.17***
	(6.377)	(4.583)	(15.66)	(9.282)
New Stadium2	26.09***	27.81***	22.15*	31.98***
	(3.586)	(5.842)	(12.37)	(6.108)
New Stadium3	14.91***	12.04***	8.186*	19.98***
	(3.853)	(4.421)	(4.957)	(5.389)
New Stadium4	7.015***	6.190***	6.757**	15.02**
	(2.616)	(2.355)	(2.863)	(6.048)
Constant	20.03***	16.39	14.15	-1.739
	(4.569)	(10.00)	(11.60)	(10.72)
Team Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	509	509	509	509
R-squared	0.570	0.609	0.679	0.844

Robust standard errors in parentheses

Significance levels: *** p<0.01, ** p<0.05, * p<0.1

Estimates generated using quantile regression for columns (1), (2), and (3) while column (4) estimates are generated using OLS. All columns include team fixed effects and year fixed effects and no time trend. Revenue values in millions of 2016 dollars.

Table 29. MR of aWin, Quantile Regression with Time Trend and Yankee Dummy

VARIABLES	(1) Real Gate Revenue Q 25	(2) Real Gate Revenue Q 50	(3) Real Gate Revenue Q 75	(4) Real Gate Revenue OLS
Team Wins	0.162	0.223	0.472*	0.428**
	(0.108)	(0.173)	(0.267)	(0.190)
Team Wins(t-1)	0.562***	0.855***	1.055***	0.857***
	(0.0948)	(0.0974)	(0.227)	(0.151)
Playoffs	9.639**	17.44***	19.96**	13.27***
	(4.225)	(5.143)	(7.800)	(5.030)
New Stadium1	47.15***	35.94***	36.65***	45.70***
	(5.068)	(10.29)	(4.692)	(10.22)
New Stadium2	21.81***	21.48*	19.83**	26.99***
	(4.262)	(11.21)	(8.296)	(7.653)
New Stadium3	17.40**	13.75*	12.33	15.74**
	(7.930)	(7.127)	(10.45)	(6.099)
New Stadium4	18.11**	16.27***	-1.832	11.73**
	(7.227)	(2.393)	(9.779)	(5.781)
Yankee Dummy	118.7***	171.1***	175.5***	128.9***
	(29.99)	(38.56)	(6.887)	(15.42)
Time Trend	1.391***	1.856***	2.102***	2.236***
	(0.184)	(0.263)	(0.451)	(0.301)
Constant	-34.64***	-55.24***	-73.24***	-69.17***
	(7.097)	(12.08)	(20.79)	(14.11)
Team Fixed Effects	No	No	No	No
Year Fixed Effects	No	No	No	No
Observations	509	509	509	509
R-squared	0.213	0.261	0.312	0.520

Robust standard errors in parentheses

Significance levels: *** p<0.01, ** p<0.05, * p<0.1

Estimates generated using quantile regression for columns (1), (2), and (3) while column (4) estimates are generated using OLS. All columns include a time trend and do not include team fixed effects nor year fixed effects. Revenue values are in millions of 2016 dollars.