A Study of Sabermetrics in Major League Baseball:

The Impact of *Moneyball* on Free Agent Salaries

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Honors in Management

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Abstract

Using contract and player statistic data for Major League Baseball free agents, this paper estimates the relative effects of player attributes on player salaries over different periods of time. *Moneyball* is the analytical, evidence-based approach to baseball, utilizing various statistics as an indicator of player performance. Estimating a hedonic pricing model, our results show a lasting impact of *Moneyball* in shifting the emphasis on player valuation from observable traits to more advanced statistical analysis.

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1. Introduction

Traditionally in Major League Baseball (MLB), a baseball player's relative worth was gauged according to recent successes such as his batting average and number of strikeouts, and the qualitative opinions of scouts, who have seen these players in action (Lewis 2003). During the 2002 season, a cash-strapped Oakland Athletics team, led by general manager Billy Beane argued that current player valuation was highly inaccurate and inefficient, and that the use of new "analytical gauges" of player performance were more telling of player contribution, effectively unleashing hidden value from overlooked players – hence the introduction of *Moneyball* to the game of baseball. As a result, sabermetrics, the specialized analysis of baseball through objective evidence, has been accepted into the game and continues to impact different aspects of player valuation through its continual evolution and search for other undervalued traits in order to more accurately measure a player's relative worth.

Ever since *Moneyball* was first popularized in the early 2000s, sabermetrics, the "search for objective knowledge about baseball" (Grabiner, 1994), has continuously evolved as more advanced statistical metrics were developed to better evaluate individual player contribution to team wins. Previously overlooked statistics such as on-base percentage (OBP), which takes the number of times a batter reaches base (regardless of how) over the number of plate appearances, has now become a commonplace metric.

Given the popularization of *Moneyball* and the claims of unleashed hidden value resulting from pricing mismatches in the MLB, we aim to determine if the use of sabermetrics has impacted free-agent player salaries by comparing data from the era before *Moneyball*, after *Moneyball* (post), and in the most recent period available (post post). Through running the regression model for each respective time period, we are able to account for the time lag in the adjustment of prices. Utilizing Rosen's (1974) hedonic model as a revealed preference method of estimating true value for various player statistics, we believe a player can be reduced to various characteristics and traits that the market of MLB teams value. This also allows us to take into consideration the possibilities of multiple interactions between various player traits.

1.1 Major League Baseball as a Market for Player Salaries

In the MLB, the season structure is broken down into spring training, the regular season, and the postseason. Spring training serves as a series of practices and exhibition games that do not impact the overall win/loss record, while allowing new players to audition for roster spots. During the 162 game regular season, teams compete for one of the five playoff spots in their respective leagues (American or National) and can do this through winning their division or capturing a wild card spot. During the postseason, teams compete through four rounds of series in order to win the title of World Series Champion, the goal of every team. Franchises attempt to do this by surrounding their teams with the best facilities, coaches, and fans, but most importantly, by assembling the optimal player roster on their team.

Price theory suggests that in an environment with perfect market information and competition, there should be a strong correlation between player attributes and pay. The market for players in The MLB is an example of this, as player statistics have been tracked since the early 1900s and counting various metrics has been a major part of the game (Depken 1999), while salary data is much more transparent than for comparable information of workers in an office setting (Kahn 1993). In the MLB, free agents are not bound by an existing contract and after a minimum experience requirement of six years, can market their services to other teams

(Dworkin 1981, Scully 1989) and this allows for a significant amount of freedom for players to move to other teams.

1.2 Previous Economic Analyses of the *Moneyball* Hypothesis

Hakes and Sauer's (2006) study contests the claim that Lewis (2003) brought forth with his *Moneyball* hypothesis at the individual team level. They proposed that an efficient labor market for players would reward on-base percentage (OBP) and slugging percentage (SLG) in the same proportions that those statistics contribute to winning, which in turn drives team revenue, which are in turn, funneled back towards increased wages. By setting the dependent variable as the logarithm of annual salary on the aforementioned statistics, they were able to confirm that OBP and SLG were undervalued at the beginning of the 2000s in the MLB as it pertained to salary from a revenue maximization standpoint. However, this does not account for the possibility that fans prefer watching home runs rather than walks and scoring runs through "small ball" therefore increasing willingness to pay while disregarding win percentage.

Beneventano, Berger, and Weinberg (2012) conducted a similar study using stepwise multiple regression models analyzing the specific impact of sabermetric statistics on offensive run production, as well as defensive run saving measures (incorporating pitching as well as fielding statistics) on a team level. Their final model focused only on the production of position players and combined the sabermetric stats of weighted on-base average (wOBA) and strikeout percent with the traditional stats of slugging percentage and on-base percentage and resulted in a R^2 of 95.3% for the number of runs scored. However, they were not able to completely confirm the original contention of the paper, as the sabermetric variables did not dominate the explanation power in the variation of the final model's independent variable.

2. Data

An important decision was choosing the appropriate seasons that would enable a comparison of the pre-*Moneyball*, post-*Moneyball*, and post post-*Moneyball* periods during a timespan in which the game of baseball did not change too drastically. Therefore we selected the free agent signings for the 2001, 2005, and 2011 seasons. 2001 represents the last year prior to the introduction of *Moneyball* in 2002 - the pre-*Moneyball* period; 2005 was selected to reflect the successful implementation and adoption of the theory in the MLB - the post-*Moneyball* period[2]; and the most recent era from 2011, highlighting the continued emphasis on quantitative analysis - the post post-*Moneyball* period. All productivity variables are calculated based on performance in the prior year, because salary is determined prior to performance as a function of expected productivity given observed performance in previous years (Hakes & Sauer 2006).

As mentioned previously, MLB statistics are readily available through a number of databases. We selected two primary sources of data: one regarding player statistics and another for player contracts. Because the sources use the same unique player identification code, we are able to merge the player contract data with the player statistics data using Stata. The data and descriptive statistics are outlined below.

[2] The Boston Red Sox won the 2004 World Series and attributed their success largely to the hiring of various sabermetricians and statistical analysts

2.1 Key Metrics Explained

Contract Length

Players and teams can agree to contracts of any length and value above the league minimum of one year and the lower bounds on values that change each season without any upper limits. Players strive to secure long-term contracts to secure their long-term financial security. Teams, on the other hand, would rather commit to smaller sums of shorter length to maintain future financial flexibility and avoid being locked into a large contract of an underperforming player. Thus, the players who are successfully able to secure a long-term contract are those with above-average-to-great recent performance with teams that have the financial backing to commit to such an agreement.

Players who were previously above-average with recent struggles in performance or injuries, as well as players who are merely average or below average players, with the potential for future development typically sign shorter contracts. They understand the teams' lack of willingness to take a large risk and therefore, are willing to accept these contracts in order to establish themselves as a stable producer in the long run. As a result, these players typically accept the instability associated with a higher priced short-term contract, rather than being locked into a long-term contract in which they would feel underpaid.

Teams are reluctant to guarantee one of the 25 major league roster spots to a severely underperforming player and have the option to offer these players minor league contracts attached with an invitation to the major league team's spring training. There remains the potential for these players to make the major league roster, in the future, without any guarantee.

Height

In our dataset, player height is measured in inches. The strike zone of a batter has changed since the inception of baseball, but is defined as any pitch between the batter's shoulders and at least one foot from the ground that is also over the plate for all years in our sample (MLB rulebook). As such, a shorter batter, or a batter with a lower batting stance would have a smaller strike zone, making it more difficult for opposing pitchers. However, a short batter would typically have shorter arms and therefore a worse ability to protect the plate and reach to make contact on moving pitches. Taller batters are able to gain more leverage and bat speed than shorter batters.

Stolen Bases (SB)

Stolen bases are a counting statistic measuring the number of times a baserunner safely advances to the next base during the time the pitcher is delivering the ball to home plate. Only 2nd, 3rd, and home base can be stolen - provided that the base is open. In the event that the defense makes no attempt to throw the base-stealer out, no stolen base is credited to the runner. In addition to absolute speed, a successful base-stealer also needs good base-running instincts and a good understanding of the timing of a pitcher's windup. Typically, power hitters and speed do not go together, but the combination of those two skill sets is valued as seen in the exclusive 40 - 40 club, which consists of only four players[3] who have had 40 home runs and 40 bases in a single season as of the time of this paper.

[3] The only players to achieve this feat are: Jose Canseco with the Oakland As in 1988 with 42 HR and 40 SB, Barry Bonds with the San Francisco Giants in 1996 with 42 HR and 40 SB, Alex Rodriguez with the Seattle mariners in 1998 with 42 HR and 46 SB, and Alfonso Soriano with the Washington Nationals in 2006 with 46 HR and 41 SB

On-Base Plus Slugging Percentage (OPS)

OPS consists of two aspects: on-base percentage (OBP) and slugging percentage (SLG). OBP is a measure of how often a batter actually reaches base, regardless of how they got on base (with the exception of fielder errors or obstructions) and is calculated for each player in each season as:

$$OBP = \frac{Hits + Walks + Hit\ By\ Pitch}{At\ Bats + Walks + Hit\ By\ Pitch + Sacrifice\ Flies}$$

Ideally, you would want a leadoff batter to have a high OBP, such that power hitters could bring him home. Slugging percentage, on the other hand, is a measure of batter power and is calculated for each player in each season by weighting the number of bases gained on a hit over total at bats as follows:

$$SLG = \frac{Total\ Bases}{At\ Bats} = \frac{(1 \times B) + (2\ \times 2B) + (3 \times 3B) + (4\ \times 4B)}{At\ Bats}$$

Notice that walks are excluded, as only the batter's skill of putting a ball into play is accounted for. As the name suggests, OPS is the sum of these two factors, serving as a sabermetric stat measuring a batter's ability to hit for power and to get on base:

$$OPS = OBP + SLG$$

Ground into Double Plays (GDP)

GDP is a counting statistic that measures the times when a batter hits a ground ball that leads to a double play, resulting in two outs. This statistic has been around for a long time - since 1919; however, it was not valued until after *Moneyball*, as the impact of two outs from one batting play is severely detrimental to the offensive efforts of a team. Note that only double plays that are the results of a ground-out are accounted for here; rare double plays such as a flyout-throw-out or a strikeout-throw-out are not counted, as that these do not reflect the hitters putting a ground ball into play.

Wins Above Replacement (WAR)

The most advanced metric in use today is WAR. The theory behind WAR is to measure a player's contribution by comparing his performance to that of a *replacement player*, a below average, readily available player either in the minor leagues or on the waiver wire. The concept is such that the sum of every player on a team's individual WAR should equal the teams total wins above a team of replacement players (scaled to a floor of 51.84 wins, calculated from a 32% win rate resulting from a team of replacement players). Different sabermetricians have unique, but very similar WAR calculations. Our data uses Sean Smith's computation found on the Baseball-Reference website.

The main benefit of WAR is that other advanced metrics, such as on-base percentage and slugging percentage are most useful for the estimation of batting run creation (Winston, *Mathletics*). However, batting runs is just one of many factors to solve for true net contribution to the team for WAR.

WAR is composed of 6 different components that correlate to runs produced and runs saved: (1) batting runs, (2) baserunning runs (3) grounded into double plays runs, (4) fielding runs, (5) positional adjustment runs, and (6) replacement level runs scaled based on player's playing time (Smith, 2010). The first five components are relative comparisons to the league average, encompassing one half the WAR formula; the sixth component of replacement level measures the replacement level player's contribution. The net calculation of WAR is simplified to:

$$WAR_i = Player_i wins - replacement\ player\ runs$$

(1) Batting Runs: Uses a linear weights approximation, known as the weighted average on-base average, or wOBA, to output the true value of a hitter. The regression formula uses the total runs scored against the weighted average of the offensive categories of walks, hit by pitch, singles, doubles, triples, and homeruns divided by plate appearances (Tango, 2007).

(2) Baserunning Runs: Baserunning contributions come via stolen bases, as well as from the ability to advance an extra base on a hit (i.e., turning a single into a double or scoring from second on a single). Players' ability to steal or advance in a particular situation on a specific type of batted ball is compared to the league average with regards to extra bases attained on top of additional outs compiled. Statistically, extra bases add 0.20 runs and extra outs cost 0.48 runs. Under this framework, baserunning runs are calculated. (Smyth 1990, Tango 2007)

(3) *Grounded into Double Play Runs*: Grounding into a double play lowers expected runs scored; likewise a player having the ability to beat out double plays increases expected runs scored. Double play opportunities occur when there is a runner on 1st base and less than two outs. Comparing how often a player hits into a double play relative to the average player can

reveal a gain/loss in expected runs. The difference between grounding into a double play and avoiding the double play is roughly 0.44 runs. As such, a run saved/cost metric can show the net impact on run creation the player had on his team (Tango, 2007).

(4) Fielding Runs: Play-by-play data for hit velocity and speed off the bat, hit type (line drive, fly ball, or ground ball), and hit location exist for every play. The individual event files are aggregated and based on the resulting play, fielders can be compared to the expected average outs caused by that specific event. Thus, various statistics can be quantified such as: outfielder arm strength based on the number of times baserunners advanced compared to the average fielder, an infielder's ability to turn a double play, a fielder's ability to field a bunt, catcher stolen base to caught stealing rating adjusted for the pitcher, and 28 positive defensive plays (i.e., robbing a home run) and 54 adverse defensive plays (i.e., overthrowing the cutoff man). Comparing all advanced statistical factors determines the net run effect of a positional player's defensive ability. Some of the data used are not readily available to the public (Dewan, 2012).

(5)Positional Adjustment: In baseball nomenclature, teams are willing to substitute offense for defense at the tougher defensive positions. As such, lower expected offensive production is to be expected from the tougher positions. A ranking of positions from easiest to most difficult is: First baseman - Left fielder - Right fielder - Third baseman - Center fielder - Second baseman - Shortstop - Catcher. Thus, equivalent fielding runs from positions at the left end of the spectrum are not equal. Therefore positional adjustment based on relative difficulty of the position are required to compare and identify true defensive ability of positional players (Tango, 2008).

(6) Replacement Level: The previously discussed metrics were used to calculate net runs above average; however WAR ultimately compares a player to a replacement level player.

Logically, replacement level is below average. Setting a team of replacement level players to a win percentage of 0.320 (51.84 wins), and given the average MLB team with a 0.500 win percentage and a won-lost record of 81-81 implies a 29.16 wins above replacement. Hence, for all 30 MLB teams there are 875 wins above replacement total, 59% of which are attributed to positional players and 41% to pitchers. Under that framework, an average player, based on 650 plate appearances, would have 20 runs above replacement – this 20 is the Replacement Level Multiplier. Replacement Level Multiplier varies slightly annually based on American League or National League. Taking the total runs above average from the first 5 factors, and scaling player contribution to 650 plate appearances using the Multiplier outputs the total runs above replacement (Smith, 2010). Runs are converted to wins at roughly an 8.8 : 1 runs : wins ratio (Smyth, 1990).

2.2 Player Contracts

The source for data on player contracts was obtained from Buzzdata.com and USA today. Any free agent that was able to sign with any team and was signed in the given period was included in the dataset. Minor-league free-agent signings were dropped from the dataset, as the study pertains solely to performance in the MLB. Because of the multi-period nature of the study, contracts were adjusted for contract *length*, as well as for inflation using the Bureau of Labor Statistics' Consumer Price Index, such that final salary amounts are reflected in 2010 dollars. The 2001 contracts were inflated by 1.27 times the original amount and the 2005 contracts were inflated by 1.15 their 2005 nominal dollars.

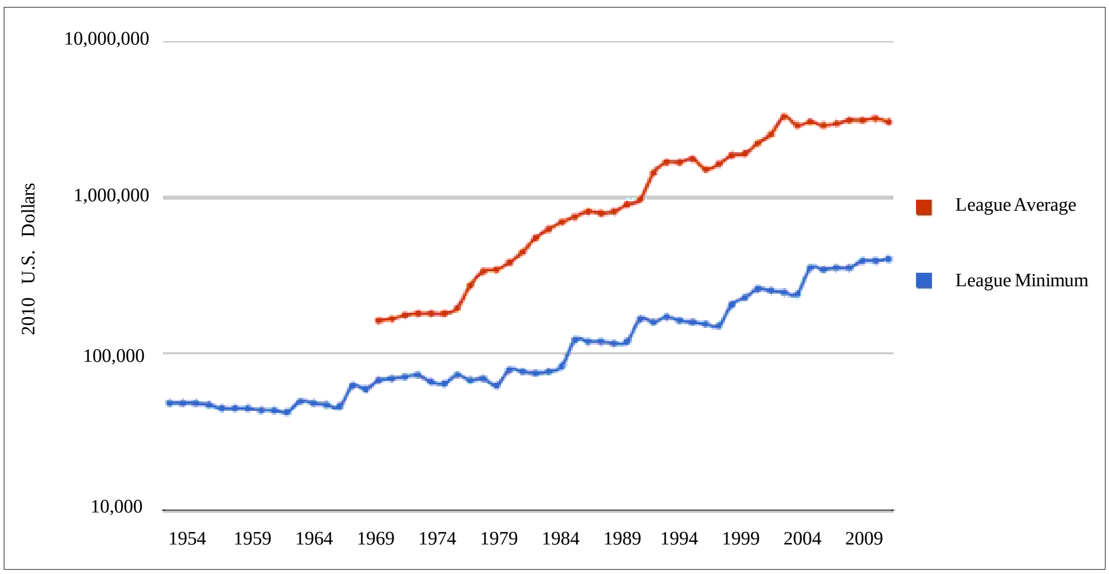
Table 1: Inflation Adjusted Player Salaries

Contract Season	Sample Size	Std. Dev.	Min.	Max.	Mean
2001	65	5,211,581	254,000	32,100,000	6,751,483
2005	76	4,452,757	488,750	18,900,000	3,768,293
2011	74	4,585,868	500,000	20,300,000	3,969,363

Prices are expressed in constant 2010 dollars.

Table (1) provides the summary statistics for the salaries in the pre-*Moneyball* period of 2001, post-*Moneyball* period of 2005, and post post-*Moneyball* period of 2011 for the selected free agents. In 2001, Alex Rodriguez signed the largest sports contract in the MLB, resulting in the larger salary range shown above. This sample will be used in the analysis as the dependent variable in the hedonic model.

Figure 1: MLB Salaries Over Time[4]



[4] Data collected from www.baseballanalysts.com

Figure (1) provides a picture of the overall increasing trend in both the league minimum and the league average salaries in the MLB since the 1950s until the 2011 season, albeit at differing rates. There is no league maximum – only what teams are willing to pay, which may lead to team discrepancies in overall team salary amounts, as some teams have more financial resources than others. In our selected time span, salaries have remained relatively flat over time.

2.3 Player Statistics

We acquired a complete dataset on player statistics in the prior season to the players' free agency from the MLB player statistic database[5]. In addition to standard counting statistics, the MLB player statistic database also has the advanced sabermetric statistics which we incorporated into this study. Furthermore, player characteristics that remain relatively stable over time, such as height, weight, and left-handedness or right-handedness were also retrieved from this source. Any player who did not compete in a comparable environment to the MLB, namely players that have played in other leagues, such as playing in the minors or internationally were dropped from the set. Additionally, because of our focus on run production and *Moneyball*, only position players were incorporated, and all pitchers were discarded.

[5] Available for download from www.baseball-reference.com

Table 2: 2001 Free Agent Statistics

	2001 Sample (*n* = 65)			
Variable	Mean	Std. Dev.	Min.	Max.
Contract Length *(Length)*	1.7538	1.6011	1	10
Height	72.5385	2.1292	68	77
Stolen Bases (*SB*)	4.5781	6.2534	0	30
On-Base Plus Slugging (*OPS*)	0.7830	0.1197	0.5550	1.1540
Ground into Double Play (*GDP*)	8.3438	4.6538	1	25
Wins Above Replacement (*WAR*)	1.0203	1.9323	-1.40	10.1

Table 3: 2005 Free Agent Statistics

	2005 Sample (*n* = 76)			
Variable	Mean	Std. Dev.	Min.	Max.
Contract Length *(Length)*	1.8421	1.3171	1	7
Height	72.6579	2.4361	67	80
Stolen Bases (*SB*)	4.7105	7.0594	0	42
On-Base Plus Slugging (*OPS*)	0.7438	0.1352	0.2540	1.0170
Ground into Double Play (*GDP*)	8.0263	4.9477	0	23
Wins Above Replacement (*WAR*)	1.1461	1.8700	-1.10	9.3

Table 4: 2011 Free Agent Statistics

	2011 Sample (*n* = 74)			
Variable	Mean	Std. Dev.	Min.	Max.
Contract Length *(Length)*	1.5676	1.2723	1	7
Height	72.7568	2.1759	68	78
Stolen Bases (*SB*)	4.5946	7.0476	0	47
On-Base Plus Slugging (*OPS*)	0.7349	0.1035	0.5280	1.0390
Ground into Double Play (*GDP*)	8.5405	6.0685	0	25
Wins Above Replacement (*WAR*)	1.0851	1.6514	-1.70	7.4

Tables (2), (3), and (4) reflect the summary statistics for the traditional counting statistics, *Moneyball* sabermetric statistics, and modern day sabermetrics. Over this decade-long period, we can see that player performance has not drastically shifted over time, as the summary statistics indicate. Thus, any major altercation in player pricing should be the result of differing valuation of these player traits, rather than an actual improvement of the quality of free agent players available on the market.

Figure 2: Free Agent Signings by Team

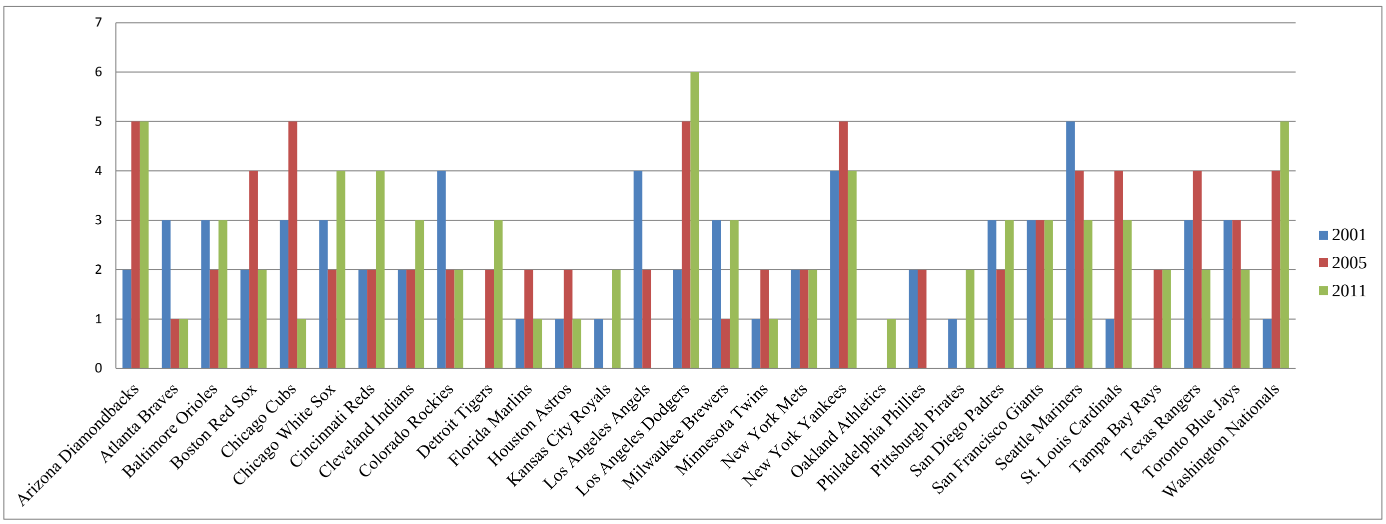


Figure (2) illustrates the breakdown of free agent signings during the study period by team, with respect to each season. Some teams are more active in their free agent signings, as a result of a larger expendable salary as well as a larger need for free agents (due to player attrition). During our study period, the team that invented *Moneyball*, the Oakland Athletics, only signed one free agent from the applicable universe.

3. Model & Estimation

We perform a hedonic analysis on player salaries to evaluate how player valuation metrics changes across three periods: the period prior to the popularization of *Moneyball* statistical techniques, the period after the release and subsequent popularization of these methods, and most recent period. To quantify such changes, we run a regression of player salaries on relevant valuation metrics for each of the three unique years.

One of the main characteristics of baseball before the release of *Moneyball* was team's reliance on scouts to evaluate players. Scouts tended to be experienced individuals who lived and breathed baseball, whether as players themselves, coaches, or association with the sport since childhood. Scouts tended to look beyond the basic or even advanced statistics of the players being evaluated and analyzed more subjective traits, such as whether the player's body could withstand the rigors of the game, structural batting form and throwing technique, as well as "makeup," an analysis of the player's family and personal ambition.

3.1 The General Model

The dependent variable is the natural logarithm of adjusted contract amount, where adjusted contract amount (*Salary*) is the average salary per year of the contract. The independent variables used to describe this amount are contract length (*Length*), player height in inches (*Height*), stolen bases (*SB*), on-base percentage plus slugging percentage (*OPS*), number of times grounded into double play (*GDP*), and wins above replacement (*WAR*). All independent variable statistics were collected from the season prior to the free-agent signing, taking the total contract amount divided by the number of years in the contract to arrive at an annual salary. Contract *length* is included to observe whether a longer contract drove a higher salary or a smaller salary.

$$Salary_{i,t} = B_{o,t} + B_{1,t}Length_{i,t} + B_{2,t}Height_{i,t} + B_{3,t}SB_{i,t} + B_{4,t}OPS_{i,t} + B_{5,t}GDP_{i,t} + B_{6,t}WAR_{i,t} + e_{i,t}$$

The natural logarithm is used to control for the skewed distribution of the residuals, as seen through "superstar" free-agent signings. We find that the relationship between salary and corresponding statistics is best described as exponential. In doing so, the results are simplified and the coefficients are interpreted as the percentage change in salary appropriate to each variable.

Three seasons of free agent contract data are analyzed – 2000, 2005, and 2011. We run the above regression equation for each of the three seasons. The statistics that are used in the regression are from the previous season (i.e., the 2000 regression is run using the player's characteristics in 1999). In our regressions, we find the previous season data is to have more explanatory power than a combination of previous years, whether a simple or a weighted average. The purpose of the model is to show the changing tendencies of player valuation. As such, we would expect the regression for the 2000 season to show a larger impact for the pre-*Moneyball* statistics, such as *height* and *SB* variables, than for the most recent sabermetric statistic of *WAR*. We would also expect the opposite effect in the regression of the 2011 season, in that the metrics developed just prior to the 2011 season would yield the largest coefficients.

3.2 Independent Variables

Not including the season-specific constant, we include six independent variables on the right-hand side of our hedonic regression. We expect that the season-specific coefficients will vary greatly across the three regressions: 2000, 2005, and 2011.

For the pre-*Moneyball* period, 2000, we expect *height* and *SB* to have the strongest effect. *Height* represents the essence of scout analysis as it completely ignores the accompanying player statistics and seamlessly fits into the subjective mold of determining a player's baseball anatomic structure. *SB* represents a previously accepted simple counting metric of player speed. In its simplicity, *SB* measures only the amount of times a player successfully stole any base, ignoring the success rate, who the opposing pitcher was, and the situational factors surrounding the steal.

For the immediate post-*Moneyball* period, 2005, we expect *OPS* and the number of times *GDP* to have the strongest effect. *OPS* has a higher causal relationship to runs produced than the traditional counting statistics (hits, home runs) due to their efficiency nature, as it accounts for actual runs produced. *Moneyball's* thesis revolves around scoring runs while limiting outs, and illustrates the Oakland Athletics' use of *OPS* in place of the outdated evaluation techniques. To control for the second half of the *Moneyball's* theorem, we chose to look at the frequency that a player grounded into a double play (*GDP)*, a situation in which one play results in two outs. Though this statistic is more of a counting metric as opposed to measuring frequency, its relative significance would reflect a shift in how outs are valued, thus illustrating an inherent subtle yet substantial modification in valuation methodology.

For the post post-*Moneyball* period evaluation of modern valuation times, 2011, we expect the *WAR* statistic to have the strongest impact. As previously mentioned, *WAR* is an all-encompassing statistics that accounts for a player's run contribution above that of a low-level replacement player. Relevant factors analyzed include the six factors outlined in Section 2.1. As a new statistic, we would expect this to have a limited effect for the earlier periods.

This model has minimal colinearity concerns, as each variable analyzes a unique aspect of the game. Though *WAR* consists of several similar underlying player traits, *WAR* is calculated using different derivations with more explanatory power. For instance, *OPS* has a positive correlation with batting runs produced. However, for the batting runs aspect of *WAR*, a more advanced metric based on the league average called the weighted on-base average is used. As such, it deviates from using *OPS* directly and uses a different weighting system based on the league runs environment.

3.3 Alternative Specifications

While the intention was to measure the shift in valuation metrics, various forms of the regression were run. Variables such as position, league, right or left-handedness, or switch hitter, weight, and player age were included in alternative specifications. Interestingly, when combined with the advanced metrics, none were remotely significant for any given year. Other than stolen bases and double plays, basic counting statistics were ignored, as their impact would be included in the OPS calculation. Furthermore, the components of OPS identify both the frequency that a player gets on base as well as the magnitude of the player's hits, thus encompassing both hitting ability and power.

4. Results & Discussion

In this section, we discuss the results from the estimation of our log-linear hedonic salary function, using the aforementioned model. For each pre-*Moneyball*, post-*Moneyball*, and post post-*Moneyball* period, in the years (2000, 2005 and 2011, respectively), we estimate the model described in Section 3. The regression analysis reveals that recent valuation methods have evolved towards a more advanced statistical foundation and away from observable player traits and counting statistics. Furthermore, these results show that the *Moneyball* theory has had a tangible, lasting impact on player valuation in The MLB.

4.1 Pre-*Moneyball*

Table (5) shows the results from the estimation for the free agents signed in the pre-*Moneyball* era (2000). In the regression of this period, the traditional observable traits of *height* and *SB*, a proxy for player speed, are statistically significant, as we would expect. However, the run-producing *OPS* variable and the out-preserving *GDP* variable also achieve statistical and economic significance, suggesting that these factors were also accounted for through other counting statistics. As expected, *WAR* is small and insignificant, as this metric had not yet been created.

Table 5: Pre-*Moneyball* regression results

Source	SS	df	MS
Model	57.1464	6	9.5244
Residual	17.8586	58	0.3133
Total	75.0050	64	1.1906

F (6 , 58)	30.4
Prob > F	0.0000
R - Squared	0.7619
Adj R-Squared	0.7368
Root MSE	0.5597

	Pre-*Moneyball* 2001 Sample (*n* = 65)					
$Salary_{i,t}$	Coefficient	Standard Error	t - value	p > | t |	[95% Confidence Interval]	
Contract Length (*Length*)	0.1701	0.0634	2.68	0.009	0.0432	0.2970
Height	0.1177	0.0358	3.29	0.002	0.0460	0.1893
Stolen Bases (*SB*)	0.0400	0.0135	2.97	0.004	0.0130	0.0670
On-Base Plus Slugging (*OPS*)	0.0343	0.0095	3.63	0.001	0.0154	0.0532
Ground into Double Play (*GDP*)	0.0775	0.0159	4.87	0.000	0.0456	0.1094
Wins Above Replacement (*WAR*)	0.0588	0.0757	0.78	0.440	-0.0927	0.2103
Constant	1.8815	2.7389	0.69	0.495	-3.6031	7.3662

Interestingly, *length* has a positive relationship on salary, illustrating that the longer contracts are also the more lucrative ones. From this, it can be deduced that the players getting signed to long-term deals are the more successful players that teams want for longer periods and that the players sees no negative tradeoff in salary with regards to financial security. Likewise, it shows that teams do not pay more for short-term contracts. Thus, the short-term contracts tend to be players with less negotiating leverage. This could be because the players who sign the shorter teams are of inferior quality or considered more risky "prospects" with fewer interested parties in their services. Because of this, there is no presence of a bidding war and narrow incentives for teams to offer such players financial security in the form of a larger salary or longer length.

OPS has the largest coefficient. This is due to the fact that it is the run-producing variable in the regression. Though the measurable player traits of *height* and *SB* are significant ($p < 0.05$), they do not impact performance the way *OPS* does, as an extra inch of height or another stolen base is not as predictive as another run. Thus, it is logical that *OPS* would have a large, positive impact. Given the percentage nature of *OPS*, the highest single-season figure in MLB history is

Barry Bond's 2004 *OPS* of 1.4217, an increase in the coefficient of one represents an extreme amplification of the previous number. To illustrate, an *OPS* of 1.0000 has only been achieved 395 times in MLB history, thus the increase itself would turn a below-average replacement player into a probable all-star.

GDP, which results in an extra out, has a negative sign. This, however, may not be counterintuitive. The factors that contribute to a double play go far beyond that of the batter, including infield position, location of the batted ball, and the defense's ability to turn the double play. And considering batters have limited control over the ultimate location of non-home runs batted balls (McCracken, 2001), it is understandable that teams do not look unfavorably to the novice statistic of total ground ball double plays. Meanwhile, *WAR*, in addition to being statistically insignificant also exhibits miniscule economic significance with a logarithmic coefficient of merely 5.8%, the second smallest coefficient in this regression.

Table 6: Pre-*Moneyball* Dollar Impact on Average Salary

Pre-*Moneyball* 2001 Sample (*n* = 65, average salary = $6,751,483)		
Impact on Salary	Coefficient	Dollar Impact
Contract Length (*Length*)	0.1701	1,148,389
Height	0.1177	794,390
Stolen Bases (*SB*)	0.0400	270,067
On-Base Plus Slugging (*OPS*)	0.0343	231,701
Ground into Double Play (*GDP*)	0.0775	523,147
Wins Above Replacement (*WAR*)	0.0588	396,965

The logarithmic estimation outputs a percentage change in salary. Table (6) converts the percentage change to reveal the monetary impact of increasing each coefficient by a one unit, based on the sample average salary of $6.751 million during this period. According to the regression analysis, for instance, increasing the average player's contract *length* by one year would increase his annual salary by $1.148 million. An added inch to *height* would increase his annual salary by $794,000. An additional *SB* would yield an increase of $270,000. A 1% increase in *OPS* would increase salary by $232,000. Another *GDP* would increase a player's salary by $523,000. An increase of one win in *WAR* would result in an increase of $397,000 in salary.

4.2 Post-*Moneyball*

The post-*Moneyball* 2005 season regression results are consistent with our hypothesis. The *height* and *SB* variables lose their significance, *WAR* maintains its statistical and economic insignificance, and *OPS* and *GDP* stay statistically significant with changes in economic significance. However, the coefficients of *OPS* actually decreases, presenting a contrary view to the theory that statistics played a larger, not a smaller, role in determining player value after the release of *Moneyball*. The regression results are shown in Table (7).

Table 7: Post-*Moneyball* regression results

Source	SS	df	MS
Model	57.2713	6	9.5452
Residual	21.3308	69	0.3091
Total	78.6021	75	1.0480

F (6 , 69)	30.88
Prob > F	0.0000
R - Squared	0.7286
Adj R-Squared	0.705
Root MSE	0.5560

	Post-*Moneyball* 2005 Sample (*n* = 76)					
$Salary_{i,t}$	Coefficient	Standard Error	t - value	p > | t |	[95% Confidence Interval]	
Contract Length (*Length*)	0.4370	0.0691	6.33	0.000	0.2992	0.5747
Height	0.0228	0.0295	0.78	0.441	-0.0359	0.0816
Stolen Bases (*SB*)	0.0012	0.0124	0.10	0.923	-0.0235	0.0259
On-Base Plus Slugging (*OPS*)	0.0146	0.0062	2.34	0.022	0.0022	0.0270
Ground into Double Play (*GDP*)	0.0470	0.0141	3.34	0.001	0.0189	0.0751
Wins Above Replacement (*WAR*)	0.0539	0.0552	0.98	0.332	-0.0562	0.1640
Constant	10.4478	2.1055	4.96	0.000	6.2474	14.6482

What we have described as a *Moneyball* statistic in *OPS* has a large and statistically significant coefficient in both 2000 (the pre-*Moneyball* season) and 2005. While the general trend between these periods was expected, the coefficient deviation is due to the inherent nature of the regression. The pre-*Moneyball* variables only analyze height and speed, thereby ignoring actual run production. Traditional power metrics, such as home runs, extra base hits, and runs batted in, are used to observe player power. As home runs and other extra base hits factor linearly into the *OPS* calculation where the slugging percentage component is the sum total bases (weighting a home run as four times as much as a single), this variable does contain intrinsic relevant run production explanatory power. However, given the limited sample size of roughly seventy observations per season, the additional variables of home runs and extra base hits that would help narrow down the true driver of run production on player valuation in the pre-*Moneyball* framework could only be added at the expense of the player makeup variables.

As *Moneyball* represented the shift away from the input of scouts towards "hard" statistics, we believed it was more informative to reveal that shift away from scouts between 2000 and 2005 followed by the statistical shift that was taking place continued through to 2011, and rise of sabermetric statistics. *Height* has a small coefficient and 95% confidence interval [-0.0359,0.0816], consistent with its statistical insignificance. The decrease in the *OPS* coefficient illustrates the shift away from scoutable traits as the game has progressed. Contract *length* takes on additional economic impact (43% versus 17%). However, contract lengths are a function of the free agent class and ability, the better the free agent class, the higher their valuation, and the longer length.

Table 8: Post-*Moneyball* Dollar Impact on Average Salary

Post-*Moneyball* 2005 Sample (n = 76, average salary = $3,738,293)		
Impact on Salary	Coefficient	Dollar Impact
Contract Length (*Length*)	0.4370	1,646,597
Height	0.0228	86,053
Stolen Bases (*SB*)	0.0012	4,503
On-Base Plus Slugging (*OPS*)	0.0146	54,936
Ground into Double Play (*GDP*)	0.0470	177,179
Wins Above Replacement (*WAR*)	0.0539	203,072

The actual dollar impact is shown in Table (8). The monetary amounts described are based on the average salary of the sample or the average salary of the free agents signed. The average salary in 2005 was significantly less than the average salary in 2000 ($3.738 million versus $6.751 million). According to the regression analysis, for instance, increasing the average player's contract *length* by one year would increase his annual salary by $1.646 million. An added inch to a player's *height* would increase his annual salary by $86,000. An additional *SB* would yield an increase of only $4,000. A 1% increase in *OPS* would increase salary by $55,000. An extra *GDP* would increase a player's salary by $177,000. An increase of one win in *WAR* would result in an increase of $203,000 in salary.

4.3 Post Post-*Moneyball*

In 2011, *OPS* becomes statistically insignificant while achieving the lowest economic significance of the 3 periods. Meanwhile, *WAR* becomes very relevant, achieving a statistically significant coefficient of 0.2073 (compared to coefficients of .0588 and .0539 in 2000 and 2005, respectively). The scouting variables of *height* and *SB* show limited economic impact and were not estimated to be statistically significant. This shows a dramatic change in how production was measured – no longer is the easy-to-calculate *OPS* relevant, rather the iterative statistic of *WAR* data achieves significance without impairing the adjusted R^2 in the modern era of baseball as illustrated in Table (9) below.

Table 9: Post post-*Moneyball* regression results

Source	SS	df	MS
Model	53.1640	6	8.8607
Residual	19.8492	67	0.2963
Total	73.0132	73	1.0001

F (6 , 67)	29.91
Prob > F	0.0000
R - Squared	0.7281
Adj R-Squared	0.7038
Root MSE	0.5443

	Post Post-*Moneyball* 2011 Sample (*n* = 74)					
$Salary_{i,t}$	Coefficient	Standard Error	t - value	p > | t |	[95% Confidence Interval]	
Contract Length (*Length*)	0.2031	0.7524	2.70	0.009	0.0530	0.3533
Height	0.0549	0.0360	1.53	0.132	-0.0169	0.1267
Stolen Bases (*SB*)	(0.0090)	0.0108	-0.83	0.407	-0.0305	0.0125
On-Base Plus Slugging (*OPS*)	0.0115	0.0096	1.20	0.235	-0.0077	0.0307
Ground into Double Play (*GDP*)	0.0549	0.1154	4.76	0.000	0.0319	0.0779
Wins Above Replacement (*WAR*)	0.2073	0.0694	2.99	0.004	0.0688	0.3457
Constant	8.8588	2.3522	3.77	0.000	4.1639	13.5538

Not only has *WAR* become significant, but also the traditional speed metric of *SB* has become negative. Traditional baseball theory would suggest that the number of stolen bases would have a positive relationship to player salary, but it appears that in this most modern era of baseball, teams have begun to implement the valuation of efficiency ratings over counting statistics, as seen through the statistical insignificance of *SB*, as well as how the 95% confidence interval containing both positive and negative values. The *GDP* metric has almost become an out-preserving metric for gauging player speed.

Table 10: Post Post-*Moneyball* Dollar Impact on Average Salary

Post Post-*Moneyball* 2011 Sample (*n* = 74, average salary = $3,969,363)		
Impact on Salary	Coefficient	Dollar Impact
Contract Length (*Length*)	0.2031	806,357
Height	0.0549	217,869
Stolen Bases (*SB*)	(0.0090)	(35,637)
On-Base Plus Slugging (*OPS*)	0.0115	45,623
Ground into Double Play (*GDP*)	0.0549	217,966
Wins Above Replacement (*WAR*)	0.2073	822,700

Table (10) illustrates the dollar impact seen during this period. The average salary in 2011 was $3.969 million. According to the regression analysis, increasing the average player's contract *length* by one year would increase his annual salary by $806,000. An added inch to a player's *height* would increase his annual salary by $218,000. An extra *SB* would yield an decrease of $36,000. A 1% increase in *OPS* would increase salary by $46,000. Another *GDP* would increase a player's salary by $218,000. An increase of one win in *WAR* would result in an increase of $823,000 in salary.

Of all the factors, *WAR* has the largest monetary impact on salary, achieving more than twice the economic salary compared to prior years and nearly four times the economic impact. This post post-*Moneyball* period highlights the importance that teams now place on advanced sabermetric statistics, illustrating the permanent shift that *Moneyball* has brought to the game, emphasizing the power of aggregating data. This also suggests the possible continual evolution towards a "more perfect" statistic that better predicts a player's impact on run production in the MLB. In those future periods, we would venture that *WAR* would become replaced by the newer, more advanced statistics.

4.3 General Trends

For all three regressions, the adjusted R^2 show an explanatory power above 70%. The lack of a dramatic change in the explanation power suggests that the six variables included in the model consistently accounts for a significant portion of the factors that go into the valuation of free agents. Thus, the yearly differences in player salaries are explained through a shift in the explanatory power of the dependent variables, thereby enforcing the overarching claim of a *Moneyball* shift to player valuation. Given the logarithmic nature of the regression, the dependent variables explain salary increases in percentage, and not linear, terms. Also note that contract *length* has maintained a positive and statistically significant coefficient throughout this decade-long period, suggesting that it is only the superstars that get the security of a long-term contract.

5. Conclusion

In this paper, we estimate the effect of quantifiable analytics on how MLB players are valued in the open market. *Moneyball* is used as the framework to baseline our analysis due to its impact in popularizing statistical thought in baseball. We employ a logarithmic regression on three seasons of free agent contract data to illustrate how valuation techniques evolved through the adaptation of new statistics. The three seasons used were the 2000, 2005, and 2011, each pertaining to a period before *Moneyball*, immediately after *Moneyball*, and in the modern day.

Not including the constant, the hedonic model uses six coefficients: *length*, *height*, *stolen bases*, *on-base plus slugging percentage*, *ground into double plays*, and *wins above replacement*.

The variables were chosen to reflect the metrics used to value players in each period. Through the examination of the shift in statistical and economic significance of the variables, we find a shift in valuation techniques away from the observable player traits and novice statistics towards a more advanced statistical approach.

The chronological progression of *WAR*, the most current advanced metric, sees a positive shift in the coefficient, describing a large increase in monetary effect, and an increase in statistical significance. In 2011, *WAR* achieved a coefficient of 0.2073, with a p-value of 0.004 for a monetary impact of $823,000 per year of one increased win. In 2005, the same trait achieved 0.0539, 0.332, and $203,000, respectively; while in 2000 *WAR* achieved 0.0588, 0.440, and $397,000, respectively. The greatest economic impact occurs in 2011, consistent with our hypothesis of a positive shift in *WAR*'s influence. *Height*, on the other hand, exhibits an opposite trend, as it loses the statistical and economic impact it had in 2000 entirely by 2011. In 2000, *height* revealed a coefficient of 0.1177 with a p-value of 0.002 for a monetary impact of $794,000. In 2011, the coefficient drops to 0.0549, the p-value loses significance at 0.132 and there is minimal monetary impact of merely $218,000. The 95% confidence interval for monetary effects of *height* is [-67,082.23, 502,918.29]. The change in the impact of variables is consistent from both statistical and economic significance standpoints and help reveal how player valuations evolved and become more statistically-focused after the release of *Moneyball*.

References

Beneventano, Philip, Paul D. Berger, and Bruce D. Weinberg. "Predicting Run Production and Run Prevention in Baseball: The Impact of Sabermetrics."

Depken II, Craig A. "Free-agency and the competitiveness of major league baseball." *Review of Industrial Organization* 14.3 (1999): 205-217.

Dewan, John, and Ben Jedlover. *The Fielding Bible*. ACTA Sports, 2012.

Dworkin, James B. *Owners versus players: Baseball and collective bargaining*. Boston, Mass: Auburn House Publishing Company, 1981.

Grabiner, David. "The Sabermetric Manifesto." *SeanLahman.com*. N.p., 1994. Web. 14 Apr. 2013.

Hakes, Jahn K., and Raymond D. Sauer. "An economic evaluation of the Moneyball hypothesis." *The Journal of Economic Perspectives* 20.3 (2006): 173-185.

Kahn, Lawrence M. "Free agency, long-term contracts and compensation in Major League Baseball: Estimates from panel data." *The Review of Economics and Statistics* (1993): 157-164.

Lehn, Kenneth (1984) 'Information Asymmetries in Baseball's Free Agent Market', Economic Inquiry, 22, 37–44.

Lewis, Michael. *Moneyball: The art of winning an unfair game*. WW Norton, 2004.

Rosen, Sherwin. "Hedonic prices and implicit markets: product differentiation in pure competition." *The journal of political economy* 82.1 (1974): 34-55.

Scully, Gerald W. *The business of major league baseball*. Chicago: University of Chicago Press, 1989.

Shanks, Bill. *Scout's honor: The bravest way to build a winning team*. Sterling & Ross Pub Incorporated, 2005.

Smith, Sean. "Position Player WAR Calculations and Details." *Baseball-Reference.com*. N.p., 2010. Web. 14 Apr. 2013.

Smyth, David. "W% Estimators." Weblog post. *W% Estimators*. N.p., 1990. Web. 14 Apr. 2013.

Tango, Tom M., Mitchel G. Lichtman, and Andrew E. Dolphin. *The book: Playing the percentages in baseball*. Potomac Books, Inc., 2007.

Tango, Tom. "WAR Updated on Baseball-Reference." ht*tp://www.insidethebook.com/*. N.p., 04 May 2012. Web. 14 Apr. 2013.Smyth, David. "W% Estimators." Weblog post. *W% Estimators*. N.p., 1990. Web. 14 Apr. 2013.

Winston, Wayne L. *Mathletics: How Gamblers, Managers, and Sports Enthusiasts Use Mathematics in Baseball, Basketball, and Football (New in Paper)*. Princeton University Press, 2012.