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ANALYZING MAJOR LEAGUE BASEBALL PLAYER'S PERFORMANCE BASED ON AGE AND EXPERIENCE

Análisis del rendimiento de los jugadores de la Major League Baseball según la edad y la experiencia

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ABSTRACT: This study models player performance as a function of age, experience, and talent. The unbalanced panel includes 5,754 seasons spread among 562 batters and 4,767 seasons spread among 489 pitchers. Peak physical age for hitters and pitchers are 26.6 years and 24.5 years, respectively, when holding experience constant. With increased experience, batters peak near age 29, while pitchers peak near age 28. Also, batters encounter greater fluctuations in performance over their careers than pitchers. This model is designed for use by MLB teams to predict future performance based on a player's first six years of statistics.

KEY WORDS: Aging curves; career fluctuations; career trajectories; MLB

RESUMEN: Este estudio modela el rendimiento del jugador en función de su edad, experiencia y talento. El panel desequilibrado incluye 5.754 temporadas repartidas entre 562 bateadores y 4.767 temporadas repartidas entre 489 lanzadores. La edad pico para los bateadores y lanzadores es 26,6 años y 24,5 años, respectivamente, manteniendo constante la experiencia. Con una mayor experiencia, el pico de los bateadores está cerca de los 29 años, mientras que el pico de los lanzadores esta cerca de los 28 años. Además, los bateadores encuentran mayores fluctuaciones en el rendimiento en sus carreras que los lanzadores. Este modelo está diseñado para ser utilizado por equipos de MLB para predecir el rendimiento futuro basado en los primeros seis años de estadísticas de un jugador.

PALABRAS CLAVE: Curvas de envejecimiento; Fluctuaciones de la carrera profesional; Trayectorias de la carrera profesional; MLB

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1. Introduction

Major League Baseball (MLB) is a $36 billion industry with over $3.7 billion in player salaries (Ozanian, 2015) and an average salary of $4.25 million (Petchesky, 2015). Every major league team uses advanced statistical measures and econometric models to measure player value in order to identify labor market inefficiencies and acquire undervalued players. MLB contracts are guaranteed and must be paid in full, even if the player is released prior to the expiration of the agreement. Therefore, estimating a contract's optimal value and duration is critical to team profitability. While these contracts affect players and teams directly, they indirectly affect fans through ticket pricing. Hence, effective contracts can maximize a team's performance, provide entertainment to fans, and keep tickets at affordable levels. Alternatively, ineffective deals expend limited resources, prevent the acquisition of other talent, and may negatively impact a team for years. Thus, teams must be able to project a player's future performance based on a variety of factors, including previous performance, age, and experience.

This study analyzes players' performances as a function of age, experience, and demonstrated talent. Unlike previous models discussed in the literature, this study utilizes Wins Above Replacement (WAR) as its dependent variable. WAR is an advanced statistic that calculates the number of additional wins each player contributes to a team over the number of wins a replacement minor league player would offer. Since baseball is a team sport, measuring a player's average contribution to each win is preferable to standard statistics, such as batting average. WAR also provides a more consistent and objective measure of performance because it includes, but is not limited to, hits, stolen bases, earned run average, strikeouts, walks and fielding performance. In addition, the sum of the league's WAR is one-thousand for each year, so players may be compared between different eras. For example, a home run in the early 1900's (nicknamed the "Dead-ball Era") would contribute more wins to a team than a home run today, because fewer runs were scored during that period. Finally, since WAR is a function of opportunity, this study assumes that teams play their best players. Since any statistic, including rate statistics, is dependent on playing time, WAR remains a more consistent proxy for performance. Baumer, Jensen, and Matthews (2015) provide a comprehensive overview of WAR and its limitations, which include its lack of uncertainty estimation and difficulty to reproduce. Baumer et al. (2015) provide a statistic openWAR that may be used in the future as a more reliable and transparent statistic, though it has yet to be widely accepted. Thus, the paper utilizes WAR from Baseball-Reference.com, as WAR is currently more commonly used. A detailed explanation of WAR for hitters and pitchers is included in Appendix A.

This study also employs a novel functional form for the experience term in the WAR regression models. Unlike prior studies, the experience term in this study will be calculated using the square root rather than the square of the number of playing years. In the previous studies, researchers expected the squared experience term to be negative.

Hence, at a certain point, these other models suggest that experience leads to diminishing skills. Since this does not match the theoretical expectation that extra experience results in better performance but diminishing marginal returns, the square root function better captures the phenomenon, as it is a strictly increasing function.

Finally, this model utilizes EViews' Period Seemingly Unrelated Regression (SUR) techniques, as well as a proxy for player-specific talent in place of fixed effects. The SUR model will minimize heteroscedasticity and correct for cross-equation residual correlation. The talent proxy is calculated using a weighted average of a player's prior performance. Using these econometric techniques and adjustments, this study provides a unique estimation framework to predict individual player value.

2. Literature Review

Schulz, Musa, Staszewski, and Siegler (1994) studied player performance as a function of age and found players peak between ages 27 and 30 for various standard metrics, including Earned Run Average (ERA) and Batting Average. Elite players experienced longer peaks and slower decays in skill. Schultz et al. (1994) suggested age effects are a function of physical aging attributes, which rise to a peak before declining, and experience which is always increasing, but with diminishing returns. While Schultz et al. (1994) did not separate these effects in the study, it provided a foundation for future research.

Bradbury (2009) conducted a comprehensive study of peak athletic performances and found that male peak physiological function occurs at ages 29 and 30 when strength, speed, and endurance reach a maximum. These attributes correlate with high strikeout rates for pitchers and more extra-base hits for batters (Bradbury, 2009). In comparison, low stress activities, such as high on-base percentages and high walk rates, climax later, at ages closer to 32 (Bradbury, 2009).

Despite a thorough investigation, Bradbury (2009) did not analyze the effect of experience on a player's performance. While years of experience in the minor leagues may help players develop, MLB is the only environment where players face top-level competition and thus reach their peak performance. In addition, Bradbury (2009) only used standard baseball statistics such as batting average, which exhibit significant fluctuations largely attributed to luck ("BABIP," 2015). For example, the same ball hit against two different teams may generate different results. Against a poor fielding team, the batter may earn a hit; however, against a great fielding team, the batter may record an out with no RBI. Thus, batting average may be unreliable. Despite these concerns, Bradbury (2009) still offered a valuable model of player aging.

Krohn (1983) conducted an investigation of baseball players' batting averages as a function of age. Krohn (1983) found that hitters peak at age 28, with the rise and fall from the peak occurring at the same rate. The estimated coefficients on each of the variables matched theoretical expectations and were significant at the 10% level. However, Krohn (1983) used a fixed effects model, which estimates a y-intercept for each player. Unfortunately, he did not provide a method to find this y-intercept value early enough in a player's career to calculate predicted values. Regardless, Krohn's (1983) study provided a comprehensive econometric analysis of the change in a batter's performance, which addressed important estimation errors including autocorrelation of the error term.

Fair (2008), analyzed the rate of increase and decline in performance of baseball players due to aging. Fair (2008) found that the peak ages for On-Base Plus Slugging Percentage (OPS), On-Base Percentage (OBP), and ERA are 27.6, 28.3, and 26.5 years old, respectively. Also, pitchers declined faster from their peak year performances than batters. For example, between peak age and age 37, pitchers face a 9% increase in ERA, while batters only experience a 3.1% decline in OBP and a 5.6% decline in OPS (Fair, 2008). Finally, the model suggested that the improvement rate to a player's peak performance was greater than the subsequent decline rate.

Using these results, teams should offer maximum value contracts to batters at age 28 and pitchers between the ages of 26 and 27. In addition, following the peak, batters slowly lose value, so a long-term contract that compensates players based on the expectation that the hitters will slowly regress would maximize efficiency. However, since pitchers decline more rapidly, long-term contracts based on a pitcher's peak performance are relatively more risky. Therefore, Fair's (2009) results suggest that teams should offer longer contracts to peak-age batters and shorter contracts to peak-age pitchers.

Despite the advantages of this study, it does not include a sufficiently diverse sample of players. For example, relief pitchers are excluded from Fair's (2009) data set. In addition, the data failed to account for changes in rules throughout the sample. For instance, the pitching mound was lowered in 1969, while the designated hitter was added to the American League in 1973. Although Fair (2009) recognized the availability of advanced metrics, he continued to use standard statistics because the newer measures were more subjective. In fact, the WAR statistic underwent many refinements during this period and did not have a consistent definition. Recently, however, all major data sources have created a universal WAR statistic. Regardless, it would be valuable to test Fair's (2009) specification using WAR as the dependent variable.

In fact, WAR has become widely used to study player performance. Furnald (2012) used WAR as the dependent variable to analyze the impact of aging on players during the Steroid Era. The article used the Steroid Era and rule change dummy variables interacting with age and the square of age terms to determine that players peaked later, around age 29, during the Steroid Era compared to approximately age 27.7 in other years. Unfortunately, Furnald (2012) lacked an experience term and did not separate effects on hitting and pitching. Nonetheless, Furnald (2012) provided an early application of WAR for a study on baseball player aging.

Similarly, Sims and Addona (2016) used WAR, along with OPS, to find that players who were younger when drafted had a higher probability of making MLB; however, the relative age of players had no effect on MLB. Though Sims and Addona (2016) have a slightly different focus, the article provides another example of WAR's growing prevalence.

Other studies have provided different variables to consider. Demiralp, Colburn, and Koch (2010) analyzed baseball player performance as a function of age, experience, and managerial talent. Demiralp et al. (2010) determined that batting, base running, and pitching peak at ages 30, 27, and 34, respectively. Also, experience only marginally increased a player's performance, while managerial talent had a small impact on pitching, but a negligible influence otherwise. Hence, this model may help teams maximize yields from multi-year contracts. In sum, age and experience impacted players' performances significantly, while managers' experience only affected pitchers.

While Demiralp et al. (2010) provided a comprehensive analysis of age, experience, and managerial influence on player performance, the analysis may have suffered from multicollinearity. For example, YEARS IN THE LEAGUE and CUMULATIVE GAMES PLAYED variables may be directly related, as players' years played would be expected to increase with games played. Hence, the statistical insignificance and wrong expected sign of the YEARS IN THE LEAGUE variables may be the result of multicollinearity. Despite these concerns, Demiralp et al. (2010) added an experience variable to better predict player performance.

Similarly, Kahn (1993) found that managers significantly impacted individual player performances when accounting for several variables, including player age and experience thresholds. Despite the impact of managers on performance, the current study does not incorporate managerial performance, as players of all ages are naturally randomized on every team. Thus, estimating the causal effect of managerial performance would add extra, unnecessary variance to the estimates.

Similar studies have been conducted in related fields, such as Mangine, Hoffman, Fragala, Vazquez, Krause, Gillett, and Pichardo (2013), which studied the changes in various physical fitness tests in MLB players among different age cohorts. These tests included vertical jump, speed, and handgrip assessments and found that lower-body power peaks between 29 and 31, while other factors are maintained past 35. However, this study only analyzes a subset of important physical attributes, excluding many attributes, such as reaction time. Regardless, Mangine et al. (2013) provides an additional alternative to analyze age's effect on players.

Other articles provide different perspectives on contract negotiations. Krautmann and Oppenheimer (2002) discuss the tradeoff between contract length and value. Similarly, Krautmann and Solow (2009) use Adjusted OPS to find that shirking commonly occurs among players with long-term, guaranteed contracts, especially when the contract is the player's last one. In addition, Scully (1974) explains monopsonistic exploitation occurs during contract negotiations, proposes a model for salary calculation based on standard statistics, and estimates that each point change in win-loss percentage yields about $10,330 extra in revenue (in 1969). Sulloway and Zweigenhaft (2010) note differences in risk-taking behaviors between older and younger siblings in MLB. Sulloway and Zweigenhaft (2010) find that younger brothers are more likely to engage in riskier baseball tasks, such as stealing bases or getting hit by pitches. While the current study does not analyze these factors, it could be used in conjunction with these articles when determining optimal contracts.

3. Empirical Specification

This study will generate ex post forecasts of player performance for previous MLB seasons based upon a player's age, experience, and past statistics. The sample includes all players from 1995 to 2014 who played in at least seven seasons and had careers that commenced after the strike-shortened 1994 season (as the shortened season would deflate WAR values). Requiring all players to have played at least seven years eliminates those players with too few data points to permit useful analyses of their careers. Specifically, a seven-year threshold captures players who enter free agency after their sixth year of play. Thus, it was possible to create a player-specific proxy of talent based on a weighted average of their first six years of play. Finally, all pitchers' hitting statistics were removed from the sample, as the model is only designed to measure position players' batting performances and pitchers' pitching performances. These restrictions limited the sample to 5,754 batter seasons between 562 batters and 4,767 pitching seasons between 489 pitchers. Based on the sample, the descriptive statistics are displayed in Table 1.

Table 1. Descriptive statistics.

Hitting Descriptive Statistics

	WAR	**AGE**	**AGE^2**	**@SQRT(YEAR_PRO)**	**TALENT**
Mean	1.282795	28.33142	818.1721	2.329177	1.571031
Std. Dev.	2.053556	3.937677	228.4722	0.767992	1.567492
Maximum	17.40000	43.00000	1849.000	4.472136	8.085714
Minimum	-4.000000	19.00000	361.0000	1.000000	-0.938095
Observations	5754	5754	5754	5754	5754

Pitching Descriptive Statistics

	WAR	**AGE**	**AGE^2**	**@SQRT(YEAR_PRO)**	**TALENT**
Mean	0.974323	28.26809	815.2977	2.272284	0.367416
Std. Dev.	1.658215	4.026907	235.0763	0.738836	0.925512
Maximum	10.40000	43.00000	1849.000	4.472136	4.557143
Minimum	-2.900000	19.00000	361.0000	1.000000	-1.519048
Observations	4767	4767	4767	4767	4767

Using this data, the model will take the following functional form, which will be applied to batters and pitchers separately:

$$WAR_{it} = f\,[AGE_{it}, AGE_{it}^2, \sqrt{YEAR\_PRO}_{it}, TALENT_i] \quad [1]$$

The dependent variable, Wins Above Replacement (WAR_{it}) is a measure of the number of additional wins that the i^{th} player contributes to a team in comparison to a replacement level player in year t (where a team of replacement level players would win 46.6667 games per season). For the independent variables, AGE_{it} is the i^{th} player's age on July 1 of the t^{th} year, while AGE_{it}^2 is the square of that value. $\sqrt{YEAR\_PRO}_{it}$ is the square root of the number of seasons the i^{th} player has played at least one game in the major leagues up to the t^{th} year. $TALENT_i$ is a calculated weighted average of the WAR of the i^{th} player during his first six years. Specifically, it is calculated by the following equation:

$$\sum_{n=1}^{6}(n * WAR_n) \quad [2]$$

Since players do not enter free agency until after their sixth year, they typically do not receive large contracts until their seventh year. Therefore, the model captures player talent prior to entering free agency, so it may be used to predict a player's WAR to guide contract negotiations after the sixth year. More recent statistics were more heavily weighted as the most current data is the most reflective of future performance. More recent data often results from permanent adjustments each player makes due to experience or injury. In comparison, older data offers less information, though it still provides useful data on inherent talent. All data was obtained from Baseball-Reference.com.

The coefficient on AGE has been shown to be positive, while the coefficient on AGE^2 is predicted to be negative. As younger players mature, their performances should improve, whereas older players experience diminishing athletic performances as they age (Bradbury, 2009). Mathematically, at young ages, AGE^2 takes on relatively small values, so its negative coefficient will only slow improvement up to peak-age performance. At older ages, AGE^2 becomes large and its expected negative coefficient should capture declining performance. Moreover, the coefficient on $\sqrt{YEAR\_PRO}$ is expected to be positive. Greater experience and practice encourages stronger performance; however, each year of additional experience becomes less valuable, so the square root function slows gains from extra experience. The coefficient on TALENT is expected to be positive, as players who are inherently more talented should perform better. Table 2 summarizes the hypothesis tests.

Table 2: Hypothesis Tests

Variable	**Null Hypothesis (H_o)**	**Alternative Hypothesis (H_A)**
AGE	$\beta_{AGE} \leq 0$	$\beta_{AGE} > 0$
AGE^2	$\beta_{AGE^2} \geq 0$	$\beta_{AGE^2} < 0$
$\sqrt{YEAR\_PRO}$	$\beta\,\sqrt{YEAR\_PRO} \leq 0$	$\beta\,\sqrt{YEAR\_PRO} > 0$
TALENT	$\beta_{TALENT} \leq 0$	$\beta_{TALENT} > 0$

4. Multicollinearity Considerations

Simple correlation coefficient calculations and variance inflation factors may be found in Table 3. For both hitting and pitching, TALENT is not collinear with any of the other variables. However, the other three independent variables are highly correlated, as the simple correlation coefficients for AGE, AGE^2, and @SQRT(YEAR_PRO) are above 0.5 and their variance inflation factors are higher than 5, except for pitching @SQRT(YEAR_PRO). Since AGE has a linear and square term, there cannot be a constant linear relationship between them. However, the linearity between @SQRT(YEAR_PRO) and AGE is somewhat problematic. Despite this high relationship, the model was not changed, as experience and age are separate determinants of player performance. For example, a player may play his first season at 21 before returning to the minor leagues and playing his second major league season at 25. Thus, AGE captures both positive and negative changes in physical attributes due to maturing and declining skills; YEAR_PRO isolates performance gains associated with greater experience. Even a limited term in MLB offers young players valuable experience, as they learn from the best coaches and players in the organization. Similarly, the square term for AGE is necessary, as aging eventually results in declining performance. Finally, the Talent variable is robust to the removal of either AGE or the YEAR_PRO variables, so multicollinearity is not biasing its estimation.

Table 3. Multicollinearity considerations

Hitting Simple Correlation Coefficient Table

	AGE	AGE^2	@SQRT(YEAR_PRO)	TALENT
AGE	1.000000	0.996440	0.867342	-0.003804
AGE^2	0.996440	1.000000	0.860682	0.003181
@SQRT(YEAR_PRO)	0.867342	0.860682	1.000000	0.117598
TALENT	-0.003804	0.003181	0.117598	1.000000

Pitching Simple Correlation Coefficient Table

	AGE	AGE^2	@SQRT(YEAR_PRO)	TALENT
AGE	1.000000	0.996257	0.832503	0.019736
AGE^2	0.996257	1.000000	0.819924	0.027017
@SQRT(YEAR_PRO)	0.832503	0.819924	1.000000	0.090191
TALENT	0.019736	0.027017	0.090191	1.000000

Hitting Variance Inflation Factors

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	17.38547	103921.7	NA
AGE	0.005419	26304.27	303.4437
AGE^2	1.01E-06	4222.374	189.7146
@SQRT(YEAR_PRO)	0.012792	448.6829	33.85805
TALENT	6.540996	96502.26	1.002230

Pitching Variance Inflation Factors

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	0.832704	1925.546	NA
AGE	0.004033	7602.479	151.1789
AGE^2	1.10E-06	1838.978	141.1221
@SQRT(YEAR_PRO)	0.002751	36.32144	3.472204
TALENT	0.000521	1.194697	1.032018

5. Model Estimates

Three models were estimated for both pitchers and hitters. The "Hitting OLS" and "Pitching OLS" models used TALENT as a substitute for the EViews' fixed effect specification, while the "Hitting EGLS (Cross-Sectional Weighting)" and "Pitching EGLS (Cross-Sectional Weighting)" utilized extended generalized least squares (GLS) with cross-sectional weighting to minimize heteroscedasticity and provide a unique y-intercept for each player. Unfortunately, fixed effects with period SUR could not be simultaneously employed. Hence, the final models, "Hitting Period SUR" and "Pitching Period SUR," used the TALENT variable as a proxy for fixed effects, while employing panel GLS and period SUR to minimize heteroscedasticity and correct for cross-equation residual correlation. The results are displayed in Table 4.

Table 4. Model estimates

	Hitting *			Pitching*		
	OLS	EGLS Cross-Sectional Weighting	Period SUR	OLS	EGLS Cross-Sectional Weighting	Period SUR
C	-14.63 *t* = -15.24	-4.02 *t* = -3.64	-13.27 *t* = -16.22	-3.29 *t* = -3.61	-3.66 *t* = -3.60	-4.07 *t* = -4.69
AGE	1.06 *t* = 15.87	0.44 *t* = 5.98	0.94 *t* = 15.93	0.30 *t* =4.76	0.37 *t* = 5.39	0.35 *t* = 5.81
AGE^2	-0.02 *t* = -18.17	-0.01 *t* = -11.87	-0.02 *t* = -16.18	-0.006 *t* = -6.16	-0.008 *t* = -8.54	-0.007 *t* = -6.95
$\sqrt{YEAR\_PRO}$	0.60 *t* = 10.39	1.107026 *t* = 9.787	0.477237 *t* = 10.766	0.301632 *t* = 5.751	0.359086 *t* = 3.404	0.26 *t* = 5.03
Talent	0.73 *t* = 51.74	N/A	0.81 *t* =105.93	0.86 *t* = 37.67	N/A	0.99 *t* = 44.41
F-Statistic	872.66	8.32	3203.17	398.75	4.93	546.43
Adjusted R^2	0.38	0.42	0.69	0.25	0.29	0.31
Players	562	562	562	489	489	489
Observations	5754	5754	5754	4767	4767	4767

* All estimates are significant to the 1% level.

For each of the models, the signs of the estimated coefficients match theoretical expectations and are statistically significant at the 1% level. Specifically, AGE is positive, while AGE^2 is negative, as players mature to a peak age before experiencing declining performance. $\sqrt{YEAR\_PRO}$ is positive, as a player improves performance as he gains more experience. TALENT is positive because more talented players with higher WAR statistics in the past are expected to perform to higher levels in the future.

In each of the models, the AGE and AGE^2 terms have the largest impact on the dependent variable (WAR). This large impact results from the high mean value of AGE and AGE^2 and matches the findings of Demiralp et al. (2010). However, as players progress through their careers, AGE, AGE^2, and $\sqrt{YEAR\_PRO}$ all have similar marginal impacts on WAR, while TALENT has the largest influence between years. This large influence by TALENT is expected as player performances vary more between players at a given age than between the same player in consecutive years.

In addition, this model demonstrates the value of using the first six years of a player's performance to predict future results. Since the coefficient on TALENT is significant, a weighted average of the first six years of performance is a valuable predictor of future performance. While this finding clearly matches expectations, it is valuable to observe the significance of past performance in predicting future performance in a model.

Due to the use of panel data, the R-squared and adjusted R-squared statistics are inflated by the fixed effects and TALENT variables. Hence, the R-squared values fluctuate significantly between models and do not provide an accurate measure of overall fit. However, in general, the models have significant variables that account for player performance.

After estimating all six regressions, the period SUR models were used because they provided a proxy for fixed effects, minimized heteroscedasticity, and corrected for cross-equation residual correlation. The "Hitting Period SUR" model produced the following regression:

$$WAR = -13.268 + 0.943*AGE - 0.018*AGE^2 + 0.477*\sqrt{YEAR\_PRO} + 0.814*TALENT \quad [3]$$

The "Pitching Period SUR" model produced the following regression:

$$WAR = -4.072 + 0.354*AGE - 0.007*AGE^2 + 0.256*\sqrt{YEAR\_PRO} + 0.987*TALENT \quad [4]$$

The peak ages were calculated by finding the vertex of equation 5. To find this vertex, equation 3 and equation 4 were rewritten in the form of equation 5 where C collects all the variables except AGE. Equation 5 was differentiated and its derivative was set equal to zero. Hence, the peak age is found using equation 6.

$$f(AGE) = \beta_1 AGE^2 + \beta_2 AGE + C \quad [5]$$

$$\frac{d}{dx}[f(AGE)] = 2*\beta_1 AGE + \beta_2$$

$$\text{Peak Age} = \frac{\beta 2}{-2*(\beta 1)} \quad [6]$$

Using this vertex and holding other variables constant, the peak age for hitters in this study is 26.6 years-old, while the peak age for pitchers is 24.5 years-old. According to these results, batters peak at later ages than pitchers prior to facing declining performance. These ages occur much earlier than the ages in other studies. However, this peak age does not account for contributions from additional experience. Whereas the peak age demonstrates top physical athletic performance, other gains from experience, such as knowledge, continue to contribute positively for several additional years depending on the age of the player when he reached the major leagues. Hence, the actual peak performance age that includes experience gains occurs later than the estimated peak athletic age.

In fact, assuming that a particular player does not miss a year in MLB, this model can calculate the peak performance age of a player based on his first year of experience. While AGE and YEAR_PRO should not be collinear, as players often miss years and each player begins at different ages, they are perfectly collinear for those players who do not miss any future years. Thus, given a player's starting age, *S*, YEAR_PRO may be rewritten in equations 7 and 8 as (1+AGE–S), as their first year playing (age S) would be their first year pro and each additional year of age would mark an additional year pro. With this adjustment, the "Hitting Period SUR" model becomes:

$$WAR = -13.268 + 0.943*AGE - 0.018*AGE^2 + 0.477*\sqrt{1 + AGE - S} + 0.814*TALENT$$

While the "Pitching Period SUR" model becomes:

$$WAR = -4.072 + 0.354*AGE - 0.007*AGE^2 + 0.256*\sqrt{1 + AGE - S} + 0.987*TALENT$$

Differentiating the models with respect to AGE, the following equations are obtained for hitting and pitching, respectively:

$$\frac{\partial WAR}{\partial AGE} = 0.943 - 0.035*AGE + 0.239*(1+AGE-S)^{-1/2} \quad [7]$$

$$\frac{\partial WAR}{\partial AGE} = 0.354 - 0.0145*AGE + 0.128*(1+AGE-S)^{-1/2} \quad [8]$$

Unfortunately, these equations cannot be algebraically solved for AGE; however, a chart of starting ages and peak performances may be calculated numerically. For example, by substituting starting age values of players, between 19 and 33, a graphing calculator can compute the roots of both equation 7 and equation 8. These roots occur when the slope equals zero, which is the peak performance in the curved model opening downward. This table is located in Appendix B. The starting ages range from age 19 to 33 because only one player, Takashi Saito, was a rookie in the sample at an age outside of the range. Also, according to the models, peak ages for rookies older than 33 years occur prior to their first seasons.

Based on the sample, batters had a mean rookie age of 23.31 years, while pitchers had a mean rookie age of 23.37. Based on these rookie ages, Appendix B shows that batters tend to peak at their 29 year-old seasons, while pitchers peak closer to their 28 year-old seasons (assuming they do not take years off due to injury or a trip to the minor leagues). Therefore, with experience gains included, hitters peak slightly later than pitchers.

Referring back to equation 3, as the $\sqrt{\text{YEAR\_PRO}}$ increases by one unit, holding other variables constant, hitters increased their WAR by 0.477, while pitchers' WAR rose by 0.256. In other words, holding AGE and TALENT constant, a batter's WAR increases by 0.477 between the player's first and fourth years; fourth and ninth years; and ninth and sixteenth years because $\sqrt{4} - \sqrt{1} = 1$, the $\sqrt{9} - \sqrt{4} = 1$, and $\sqrt{16} - \sqrt{9} = 1$, respectively. In addition, TALENT has a larger impact on pitchers than batters, as each unit increase in TALENT for pitchers results in a 0.987 rise in future WAR, while each unit increase for batters results in a 0.814 rise in future WAR.

Moreover, the coefficients of all of the hitting variables are higher than those of their pitching counterparts, except for TALENT. This finding suggests that batters experience a larger career arc with very different peak and minimum performance levels, whereas pitchers rely more on inherent talent and undergo smaller WAR changes throughout their careers. In fact, the larger coefficients for batters suggest more rapid increases in performance due to age. Hence, talented free agent pitchers are important to acquire, as lower quality pitchers are less likely to improve as much as lower quality hitters. In addition, the decline in performance due to age and experience would be slower for hitters, as the larger $\sqrt{\text{YEAR\_PRO}}$ coefficient would slow losses. Thus, the model also suggests the importance of acquiring young, talented pitching over young, talented hitting, because older pitchers experience sharper declines than older hitters. In general, it is more valuable to spend extra money on a talented pitcher and a relatively less gifted hitter compared to acquiring a more talented hitter and a less gifted pitcher.

Moreover, similar to the findings in Fair (2008), this study demonstrates the rise to peak performance occurs more rapidly than the decline from it. Although the combination of linear and quadratic age terms suggests equal increase and decrease rates from peak performance, the positive $\sqrt{\text{YEAR\_PRO}}$ term slows the decline after the peak. Therefore, player performance does not follow a perfectly parabolic arc, as experience mitigates losses from athletic declines.

6. Predicting Individual Player Performance

Since this model is designed to predict player performance, it is important to compare actual and predicted values for specific players. The actual and predicted performances of two hitters, Derek Jeter and Derrek Lee, as well as two pitchers, LaTroy Hawkins and Andy Pettitte, are graphically compared in Appendix C. Starting with their seventh season, the root mean square errors for Jeter, Lee, Hawkins, and Pettitte are 2.074, 2.411, 1.300, and 1.550, respectively. The root mean square errors begin at season seven because the model is designed to predict performance for season seven and beyond based on the first six years. Prior to the sixth year, the TALENT variable may not be computed. The model accurately estimates the long-term performance trends of the players after their sixth year. The model overestimated Derek Jeter's performance, but closely modeled Andy Pettitte's and Derrek Lee's end of career statistics. It also provided a relatively steady projection of LaTroy Hawkins' late career performance.

Using this model, MLB teams can predict players' performances based on their age, years of experience, and inherent talent. A MLB team could estimate the average value of the player over the rest of his career. While the model clearly cannot predict every fluctuation in player performance, it does provide an expected value of each player's future performance. Hence, teams could utilize this regression model to negotiate salaries and contract lengths. A team would be wise to calculate the expected WAR of a given player and offer him a contract with a base salary equal to Expected WAR * Salary/WAR. The Salary per WAR can be easily calculated by dividing the total MLB payroll for a particular year by 1,000, which is the WAR in MLB in any given year. Specifically, in 2015, dividing the total payroll, $3.658 billion, by 1,000 WAR suggests that each WAR should cost about $3,658,000 ("Baseball Payrolls History," 2015). This calculation was repeated for each year with each negative value replaced by the annual minimum salary. The average cost per WAR and suggested salaries for the six aforementioned players are included in Appendix D.

7. Conclusion

The econometric evidence presented in this study suggests that, holding experience constant, the peak age for hitters is 26.6 years, while the peak age for pitchers is 24.5 years. In addition, batters experience greater fluctuations in performance over a career than pitchers.

These estimates show hitters and pitchers reach peak gains from age earlier in their careers compared to prior studies. Due to the change in functional form of the experience term, peak performance may occur later than the maximum gains from age. Although the AGE terms contribute negatively to WAR past peak physical age (due to a decline in physical skills) the experience term will contribute positively at a diminishing rate as experience increases. Hence, the peak age performance actually occurs at later ages. Specifically, hitters tend to peak at about age 29, while pitchers peak at age 28. However, the predicted peak ages also depend upon service time in the league and player age.

Using this model, baseball general managers can better predict player performances. In particular, they can project peak performance ages based on experience, as well as forecast the expected performance of a player for the rest of his career. This expected value can guide player evaluation to ensure the base salaries of contracts match expected performance. Given average player salaries of $4.25 million in 2015, this model can help minimize negative effects from significant mismatches between compensation and expected productivity.

With advances in medicine and nutrition, player aging patterns may change the model's parameters. Thus, this study may be improved upon in the future by including new data. In addition, it would be valuable to analyze player motivation in relation to age and experience by including dummy variables for "contract years," or the final years on each player's contract. Perhaps, players would perform better during "contract years" due to increased incentives, as a strong contract year would result in higher base salaries for the contract negotiated in the subsequent year. During other years, the player would already have his salary guaranteed, so he would be less motivated to maximize his potential. In general, there is still a significant amount of future research to be conducted regarding the determinants of peak-age player performance.

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APPENDIX A: WAR CALCULATION

WAR is a cumulative statistic that increases by one unit for roughly every 10 runs a player contributes to a team. Each action contributes a part of a run based on the expected value of runs scored as a result of a specific play. For example, a single, a stolen base, and advancing extra bases during a hit each contribute fractions of a run. Alternatively, a batter striking out contributes negative fractions of a run. These values change each year, as players make different contributions relative to the mean between years. In addition, as fielders or pitchers make mistakes, they allow additional runs, whereas if they make great plays, they allow fewer runs. The number of runs contributed minus the number of runs allowed equals the number of runs added. This value minus the number of runs per player on a team with a 0.2942386 win percentage is the player's Runs Above Replacement statistic. Dividing the Runs Above Replacement by the annual constant for runs per win determines the WAR of a player. The annual constant for runs per win is about 10 based on historical data (Smith, 2013).

The 0.2942386 win percentage permits 1,000 WAR to be distributed throughout the league. The 1,000 WAR results from the total number of wins per season, as each team plays 162 games, so a team wins 81 games per season on average. The following calculations show how the 1000 WAR is calculated.

81 Wins/Season * 30 Teams = 2,430 Total Wins/Season

With a 0.2942386 win percentage, each team wins about 47.666 games per season.

47.6667 Wins/Season*30 Teams = 1,430 Replacement Level Wins/ Season

Hence, the difference between the total wins and replacement level wins is:

2,430 Win/Season – 1,430 Replacement Level Wins/Season = 1,000 WAR/Season

APPENDIX B: PEAK AGES OF PLAYERS WITH CONTINUOUS CAREERS*

Starting Age	Peak Hitting Age **	Peak Pitching Age **
19	28.6	27.4
20	28.7	27.5
21	28.8	27.7
22	29.0	27.9
23	29.1	28.1
24	29.3	28.3
25	29.5	28.6
26	29.7	29.0
27	30.0	29.4
28	30.3	29.8
29	30.7	30.3
30	31.2	30.9
31	31.7	31.6
32	32.4	32.3
33	33.1	33.1

Peak Hitting Age is based on the derivative of the "Hitting Period SUR":

$$\frac{\partial WAR}{\partial AGE} = 0.943 - 0.035*AGE + 0.239*(1+AGE-S)^{-1/2}$$

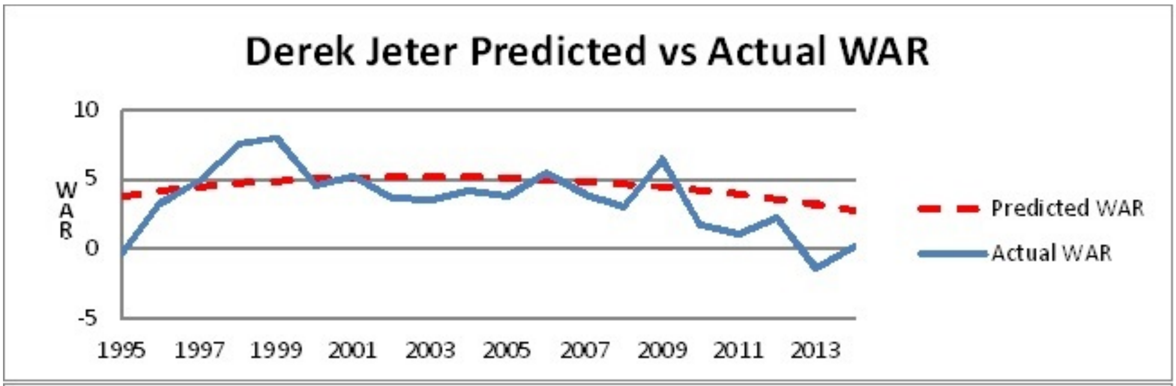
Peak Pitching Age is based on derivative of the "Pitching Period SUR":

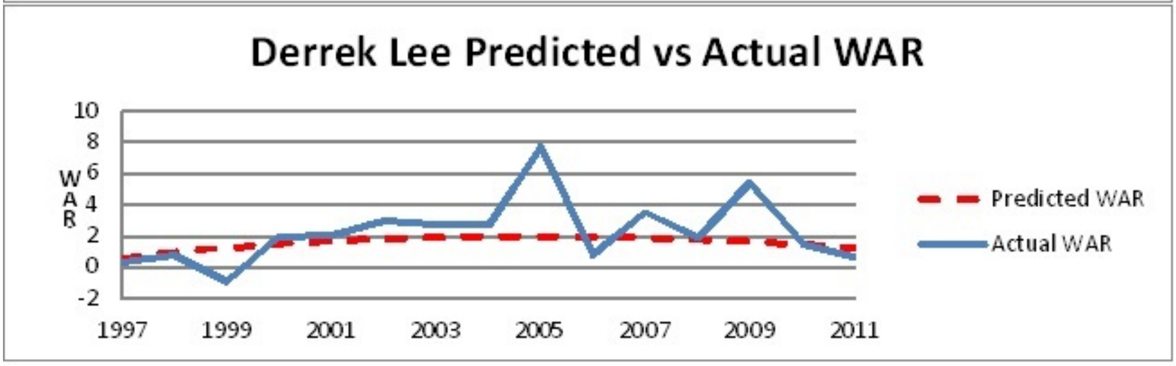
$$\frac{\partial WAR}{\partial AGE} = 0.354 - 0.0145*AGE + 0.128*(1+AGE-S)^{-1/2}$$

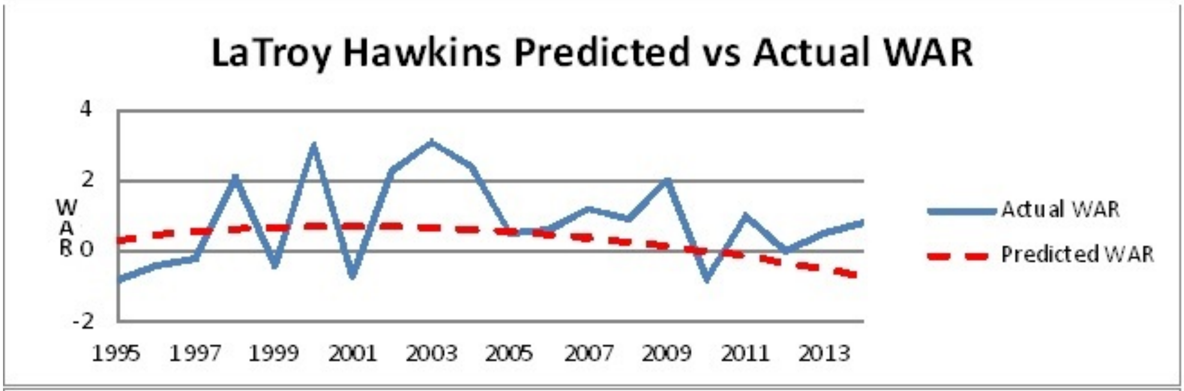
* Players with continuous career records are 423 hitters and 307 pitchers representing 75.3% and 62.8% of total batters and pitchers in the sample, respectively.

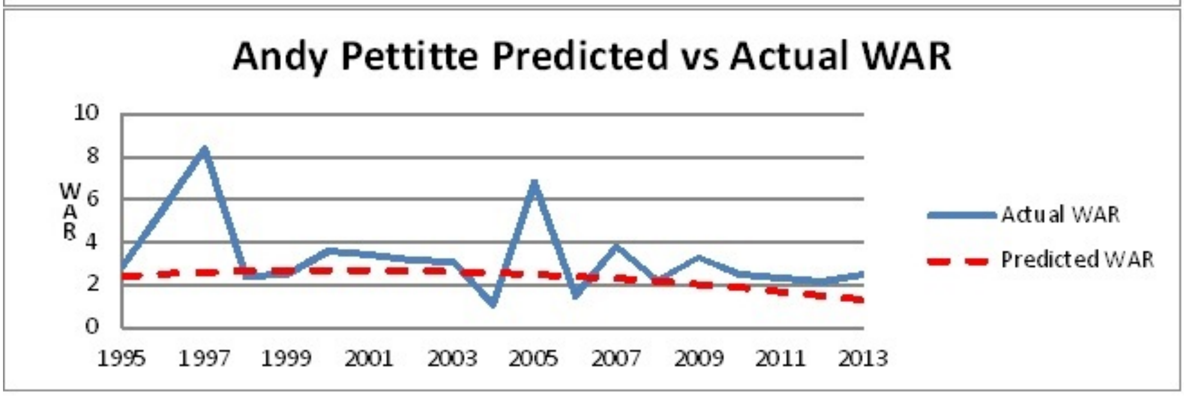
** Peak Age is defined as the top performing age of the player, assuming a continuous career record.

APPENDIX C: MODEL APPLICATION









Derek Jeter

Year	Age	Year Pro	Talent	Predicted WAR	Actual WAR	Residual Squared
2001	27	7	5.647619	5.131234533	5.2	0.004729
2002	28	8	5.647619	5.18603519	3.7	2.208301
2003	29	9	5.647619	5.200057114	3.5	2.890194
2004	30	10	5.647619	5.174163018	4.2	0.948994
2005	31	11	5.647619	5.109004179	3.8	1.713492
2006	32	12	5.647619	5.005086577	5.5	0.244939
2007	33	13	5.647619	4.862812588	3.9	0.927008
2008	34	14	5.647619	4.682508461	3	2.830835
2009	35	15	5.647619	4.464443067	6.5	4.143492
2010	36	16	5.647619	4.208841114	1.7	6.294284
2011	37	17	5.647619	3.915892674	1.1	7.929252
2012	38	18	5.647619	3.585760228	2.2	1.920331
2013	39	19	5.647619	3.218583969	-1.4	21.33132
2014	40	20	5.647619	2.8144485861	0.2	6.835536

Root Mean Square Error (Starting with Year 7): 2.074Wins

Derrek Lee

Year	Age	Year Pro	Talent	Predicted WAR	Actual WAR	Residual Squared
2003	27	7	1.7	1.915981718	2.8	0.781488
2004	28	8	1.7	1.970782376	2.7	0.531758
2005	29	9	1.7	1.9848043	7.7	32.66346
2006	30	10	1.7	1.958910204	0.8	1.343073
2007	31	11	1.7	1.893751365	3.5	2.580035
2008	32	12	1.7	1.789833763	1.9	0.012137
2009	33	13	1.7	1.647559774	5.4	14.08081
2010	34	14	1.7	1.467255646	1.5	0.001072
2011	35	15	1.7	1.249190253	0.7	0.30161

Root Mean Square Error (Starting with Year 7): 2.411 Wins

LaTroy Hawkins

Year	Age	Year Pro	Talent	Predicted WAR	Actual WAR	Residual Squared
2001	28	7	-0.1619	0.701975529	-0.7	1.965535
2002	29	8	-0.1619	0.691180972	2.3	2.588299
2003	30	9	-0.1619	0.663091495	3.1	5.938523
2004	31	10	-0.1619	0.618169642	2.4	3.174919
2005	32	11	-0.1619	0.556764597	0.5	0.003222
2006	33	12	-0.1619	0.47914764	0.6	0.014605
2007	34	13	-0.1619	0.385534506	1.2	0.663354
2008	35	14	-0.1619	0.276100112	0.9	0.389251
2009	36	15	-0.1619	0.150988617	2	3.418843
2010	37	16	-0.1619	0.010320495	-0.8	0.656619
2011	38	17	-0.1619	-0.145802345	1	1.312863
2012	39	18	-0.1619	-0.31729279	0	0.100675
2013	40	19	-0.1619	-0.504075673	0.5	1.008168
2014	41	20	-0.1619	-0.706085606	0.8	2.268294

Root Mean Square Error (Starting with Year 7): 1.300 Wins

Andy Pettitte

Year	Age	Year Pro	Talent	Predicted WAR	Actual WAR	Residual Squared
2001	29	7	1.914286	2.693928119	3.4	0.498538
2002	30	8	1.914286	2.668679563	3.2	0.282301
2003	31	9	1.914286	2.626136086	3.1	0.224547
2004	32	10	1.914286	2.566760233	1.1	2.151386
2005	33	11	1.914286	2.490901187	6.8	18.56833
2006	34	12	1.914286	2.39883023	1.5	0.807896
2007	35	13	1.914286	2.290763096	3.8	2.277796
2008	36	14	1.914286	2.166874703	2.2	0.001097
2009	37	15	1.914286	2.027309207	3.3	1.619742
2010	38	16	1.914286	1.872187086	2.5	0.394149
2012	40	17	1.914286	1.485080245	2.2	0.51111
2013	41	18	1.914286	1.284681801	2.5	1.476998

Root Mean Square Error (Starting with Year 7): 1.550 Wins

APPENDIX D: PROJECTED SALARIES

Historical Cost Per Win

	1995	1996	1997	1998	1999	2000	2001
MLB Payroll (Millions of Dollars)	927.3944	943.967	1121.71	1267.7	1463.83	1699.57	1962.85
Cost Per WAR (Millions of Dollars)	0.927394	0.943967	1.12171	1.2677	1.46383	1.69957	1.96285

	2002	2003	2004	2005	2006	2007	2008
MLB Payroll (Millions of Dollars)	2024.68	2127.88	2071.28	2191.9	2326.7	2476.69	2686.45
Cost Per WAR (Millions of Dollars)	2.02468	2.12788	2.07128	2.1919	2.3267	2.47669	2.68645

	2009	2010	2011	2012	2013	2014	2015
MLB Payroll (Millions of Dollars)	2655.4	2730.6	2786.17	2940.65	3187.59	3453.95	3658.27
Cost Per WAR (Millions of Dollars)	2.6554	2.7306	2.78617	2.94065	3.18759	3.45395	3.65827

Data Collected from Mondout (2005), Baseball Payrolls History, and Minimum Salary (2014)

Suggested Salaries*

Derrek Lee

Year	Predicted WAR	Annual Cost Per Win (Millions of Dollars)	Suggested Salary (Millions of Dollars)	Actual Salary	% Difference
2003	1.915981718	2.12788	4.076979179	$4,250,000	-4.07%
2004	1.970782376	2.07128	4.082042119	$6,166,667	-33.80%
2005	1.9848043	2.1919	4.350492545	$7,666,667	-43.25%
2006	1.958910204	2.3267	4.557796371	$9,416,667	-51.60%
2007	1.893751365	2.47669	4.690235068	$13,250,000	-64.60%
2008	1.789833763	2.68645	4.808298911	$13,250,000	-63.71%
2009	1.647559774	2.6554	4.374930224	$13,250,000	-66.98%
2010	1.467255646	2.7306	4.006488268	$13,250,000	-69.76%
2011	1.249190253	2.78617	3.480456408	$7,250,000	-51.99%

Derek Jeter

Year	Predicted WAR	Annual Cost Per Win (Millions of Dollars)	Suggested Salary (Millions of Dollars)	Actual Salary	% Difference
2001	5.131234533	1.96285	10.0718437	$12,600,000	-20.06%
2002	5.18603519	2.02468	10.50006173	$14,600,000	-28.08%
2003	5.200057114	2.12788	11.06509753	$15,600,000	-29.07%
2004	5.174163018	2.07128	10.71714038	$18,600,000	-42.38%
2005	5.109004179	2.1919	11.19842626	$19,600,000	-42.87%
2006	5.005086577	2.3267	11.64533494	$20,600,000	-43.47%
2007	4.862812588	2.47669	12.04367931	$21,600,000	-44.24%
2008	4.682508461	2.68645	12.57932485	$21,600,000	-41.76%
2009	4.464443067	2.6554	11.85488212	$21,600,000	-45.12%
2010	4.208841114	2.7306	11.49266155	$22,600,000	-49.15%
2011	3.915892674	2.78617	10.91034269	$14,729,364	-25.93%
2012	3.585760228	2.94065	10.54446581	$16,000,000	-34.10%
2013	3.218583969	3.18759	10.25952608	$17,000,000	-39.65%
2014	2.814485861	3.45395	9.72109344	$12,000,000	-18.99%

LaTroy Hawkins

Year	Predicted WAR	Annual Cost Per Win (Millions of Dollars)	Suggested Salary (Millions of Dollars)	Actual Salary	% Difference
2001	0.701975529	1.96285	1.377872667	$2,750,000	49.90%
2002	0.691180972	2.02468	1.399420291	$3,000,000	53.35%
2003	0.663091495	2.12788	1.410979131	$3,000,000	52.97%
2004	0.618169642	2.07128	1.280402417	$4,500,000	71.55%
2005	0.556764597	2.1919	1.22037232	$4,400,000	72.26%
2006	0.47914764	2.3267	1.114832813	$3,250,000	65.70%
2007	0.385534506	2.47669	0.954849455	$3,750,000	74.54%
2008	0.276100112	2.68645	0.741729147	$3,500,000	78.81%
2009	0.150988617	2.6554	0.400935174	$3,250,000	87.66%
2010	0.010320495	2.7306	0.028181144	$4,250,000	99.34%
2011	-0.145802345	2.78617	**0.400**	$3,000,000	86.67%
2012	-0.31729279	2.94065	**0.414**	$1,000,000	58.60%
2013	-0.504075673	3.18759	**0.480**	$2,250,000	78.67%
2014	-0.706085606	3.45395	**0.480**	$2,250,000	78.67%

Andy Pettitte

Year	Predicted WAR	Annual Cost Per Win (Millions of Dollars)	Suggested Salary (Millions of Dollars)	Actual Salary	% Difference
2001	2.693928119	1.96285	5.287776809	$7,000,000	24.46%
2002	2.668679563	2.02468	5.403222137	$9,500,000	43.12%
2003	2.626136086	2.12788	5.588102454	$11,500,000	51.41%
2004	2.566760233	2.07128	5.316479135	$5,500,000	3.34%
2005	2.490901187	2.1919	5.459806313	$8,500,000	35.77%
2006	2.39883023	2.3267	5.581358296	$16,428,416	66.03%
2007	2.290763096	2.47669	5.673510053	$16,000,000	64.54%
2008	2.166874703	2.68645	5.821200546	$16,000,000	63.62%
2009	2.027309207	2.6554	5.38331687	$5,500,000	2.12%
2010	1.872187086	2.7306	5.112194056	$11,750,000	56.49%
2012	1.485080245	2.94065	4.367101223	$2,500,000	-74.68%
2013	1.284681801	3.18759	4.095038862	$12,000,000	65.87%

* Bolded cells are years in which a player is expected to produce less value than the minimum salary
Salary data collected from Society for American Baseball Research (2016).