Fullerton, Jr. T. M. & Peach, J. T. (2017). Slingshots, Leather, Lumber, and the 2016 Season in Major League Baseball. *Journal of Sports Economics & Management*, 7(3), 130-142.

SLINGSHOTS, LEATHER, LUMBER, AND THE 2016 SEASON IN MAJOR LEAGUE BASEBALL

Hondas, cuero, madera y la temporada 2016 en las Grandes Ligas de Béisbol

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ABSTRACT: An econometric analysis of the 2016 Major League Baseball season is conducted with respect to regular season victories. Results obtained confirm many results documented in prior studies, albeit with parameter heterogeneity. The importance of solid team pitching, defense, and offense is corroborated. Salary disparities are found to be inversely correlated with wins, as are injuries. Surprisingly, league affiliation is not found to favor American League teams in 2016 inter-league contests. History provides good insights to what occurs on the field, but the patterns of previous seasons are not always duplicated. Indeed, parameter heterogeneity argues against pooling sample data from multiple seasons.

KEY WORDS: Major League Baseball; Team Performance

RESUMEN: *Este estudio analiza las cantidades de victorias por equipo durante la temporada regular de 2016 en las Grandes Ligas de Béisbol. Los resultados empíricos confirman algunas conclusiones de estudios anteriores con alguna heterogeneidad paramétrica. Se corrobora la importancia del picheo, el fildeo, y el bateo. Existe correlación inversa de victorias con respecto a la disparidad de sueldos y con respecto a las lesiones de jugadores. A diferencia con temporadas anteriores, la afiliación con la Liga Americana no genera ventajas para los juegos inter-liga en el 2016. La historia deportiva ofrece buena información con respecto a los acontecimientos del campo de juego, pero los patrones de años anteriores no siempre son dúplicas. Efectivamente, la heterogeneidad paramétrica indica que no se deben agrupar datos de temporadas distintas.*

PALABRAS CLAVE: Béisbol profesional en EEUU; Desempeño de equipos

Acknowledgements: Financial support for this study has been provided for Fullerton by El Paso Water, City of El Paso Office of Management & Budget, UTEP Center for the Study of Western Hemispheric Trade, and UTEP Hunt Institute for Global Competitiveness. Helpful comments and suggestions were provided by Anthony Krautmann and participants at the 92nd Annual Western Economic Association International Conference in San Diego. Econometric research assistance was provided by Omar Solís, Ernesto Duarte, Andrés Arvizo, and Opeyemi Olantunji.

Recibido/received: 15-11-2017 Aceptado/accepted: 26-03-2018

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Introduction

The 2016 Major League Baseball (MLB) season was a memorable one. The Chicago Cubs won 103 games. At the other end of the spectrum, the Minnesota Twins lost 103 games. In popular culture, Cubs-Cardinals post-game fan interactions and joking on public transportation, colloquially known the "L," showed up in an episode of a Fox network television series called "The Exorcist." The latter simply reflects the mainstream popularity of this multi-billion dollar spectator sport.

How does the 2016 season compare to prior years? If recent seasons are any guide, 2016 shares much in common with MLB historical generalities. It also probably stands econometrically apart from other seasons (Fullerton et al., 2014; Peach et al., 2016). This study examines what influenced regular season wins in 2016 and attempts to quantify the importance of various factors that influence MLB team success.

The material is organized as follows. Section two provides a brief overview of related efforts. MLB is enjoyed on a global scale, but there are relatively few formal studies that directly examine what influences regular season victories (Keener, 2014). Section three describes data and methodology. One new variable representing team defense is introduced to the sample data utilized for this effort. Section four summarizes estimation outcomes and relative contributions of each variable to team wins. Final observations are offered in the concluding section.

Previous Studies

Most studies confirm the importance of pitching, defense, and offense for attaining regular season success (Hakes & Sauer, 2006). Many different facets of conventional wisdom about the game have been tested, with special attention often given to offense (Deli, 2013). Pitching, of course, has had entire books devoted to how it influences the game (Passan, 2016).

A variety of analyses examine how payrolls affect team success (Depken, 2000; Keener, 2014). Because higher performing players command higher contracts, team salary disbursements are generally correlated with more victories both domestically and internationally (Jewell & Molina, 2004; San & Jane, 2008). However, payroll dispersion can also reduce roster cohesion and lead to fewer wins than would otherwise be expected (Breunig et al., 2014).

A series of recent studies have attempted to quantify how various factors impact on field success (Fullerton & Peach, 2016; Small et al., 2008). Empirical results for successive years, while broadly similar, provide evidence of substantial parameter heterogeneity. Is each MLB season a time capsule unto itself? When front offices address roster deficiencies, tighter distributions and smaller standard deviations appear to sometimes erode winning comparative advantages from prior years. This research effort attempts to clarify if that occurred in 2016, also.

Data and Empirical Analysis

Data employed in the study are listed in Table 1. All of the variables are for the 2016 MLB regular season. WINS16, the number of regular season victories each team achieved in 2016 is the variable of interest. The three on-field performance ratios included in the sample are team earned run averages (ERA16), team defensive efficiency (DER16), and team on-base plus slugging percentage (OPS16). Those explanatory variables are used to reflect the effectiveness of team pitching, fielding, and hitting.

Table 1. Variables, Descriptions, and Units

Variable	**Description and units**
WINS16	Number of regular season victories attained in 2016.
ERA16	Regular season team earned run average in 2016.
DER16	Regular season team defensive efficiency ratio in 2016.
OPS16	Regular season team on-base plus slugging percentage in 2016.
TPR16	2016 total team payroll expressed in millions of dollars.
TPRSQ16	2016 total team payroll squared in millions of dollars.
PSD16	2016 team payroll standard deviation in millions of dollars.
DL16	Number of times a team had players on a multi-day disabled (injury) list.
NL	Binary variable for league affiliation; AL = 0; NL = 1.

Teams need to score more runs than opponents in order to win games. To score runs, teams need batters to get on base and that requires avoiding outs. Pitchers attempt to get batters out by preventing them from hitting the ball very well. The biblical story of David bringing down Goliath with a slingshot is an apt metaphor for how good pitching can overcome good hitting and why teams are willing to invest substantial resources in good pitching arms. For team pitching assessment, earned run averages (ERAs) provide a good summary of staff effectiveness. Historically, lower ERAs are associated with higher WIN totals and this appears to have held true in 2016 (Figure 1).

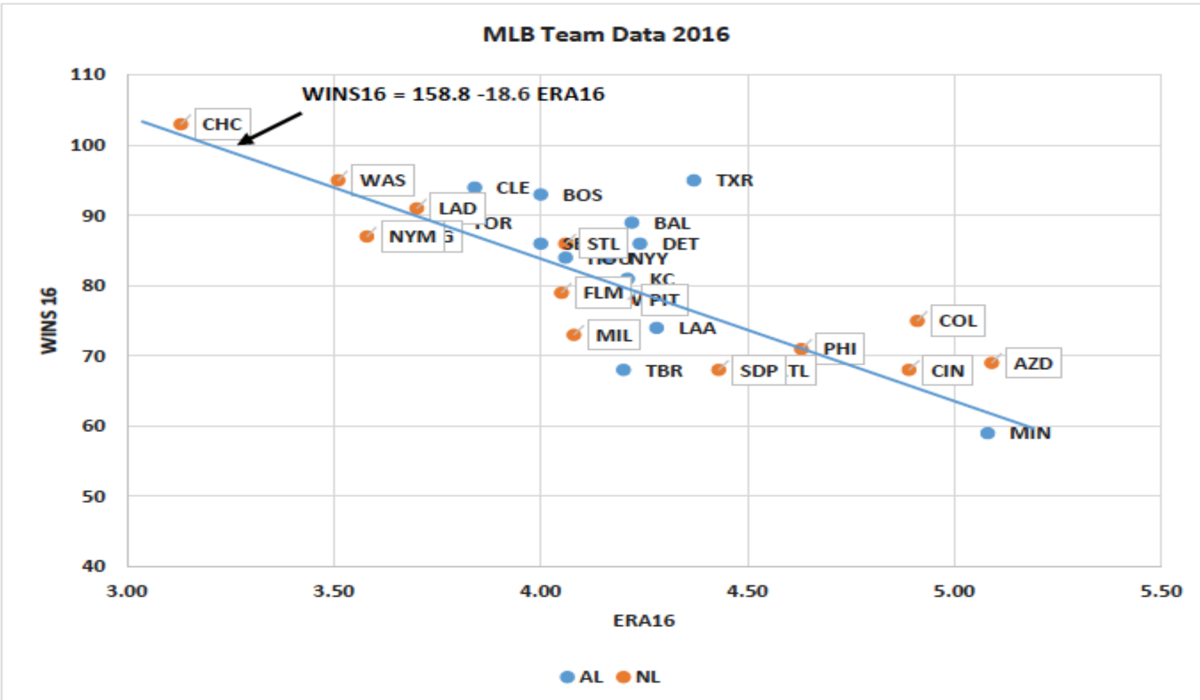

Figure 1. Slingshots, 2016 MLB WINS vs. ERA (Team Pitching Earned Run Averages)

As in many professional sports, MLB defensive prowess is often underappreciated, but critically important to overall team success. The primary MLB defensive tools are leather gloves of various shapes and sizes. DER16, team defensive efficiency ratio, is calculated by taking the ratio of the number of non-homerun hits to the number of defensive opportunities in the field. If a batted ball is caught before it touches the ground, or a runner is thrown out after a batted ball bounces, a team DER will increase. Not surprisingly, the relationship between victories and defense is a positive one (Figure 2).

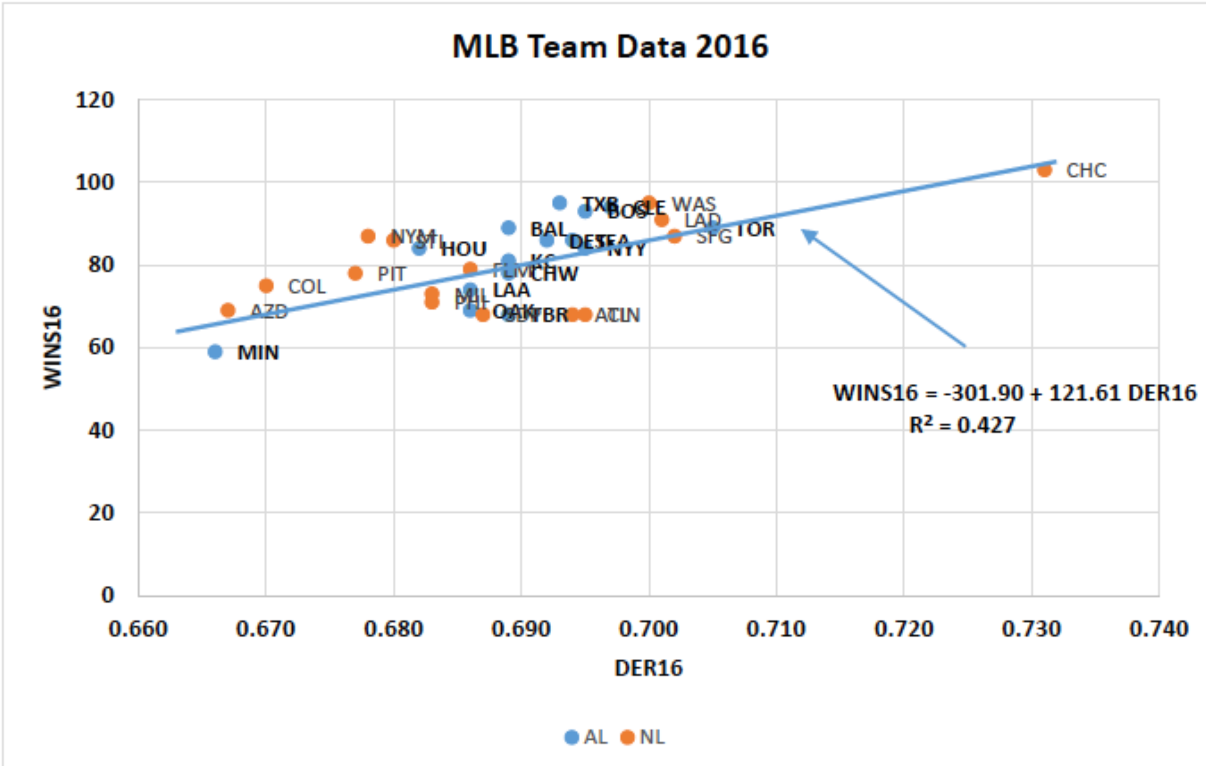

Figure 2. Leather, 2016 MLB WINS vs. DER (Team Defensive Efficiency Ratios)

Good offenses are required to advance base runners and score runs. A reliable gauge of team offense is provided by adding team on-base and slugging percentages (OPS). On-base percentages measure the frequency with which team batters successfully reach base relative to the number of at-bats, or chances to hit, the team has had. Wooden bats, lumber, are used by batters to hit balls thrown by opposing team pitchers. To score a run, a player who reaches base must successfully advance to all four bases. Slugging percentages measure how many bases teams advance, on average, per at-bat. OPS combines both of those measures into a single variable. Teams with higher OPS statistics tend be more successful at scoring runs and the correlation between WIN16 and OPS16 is also positive (Figure 3).

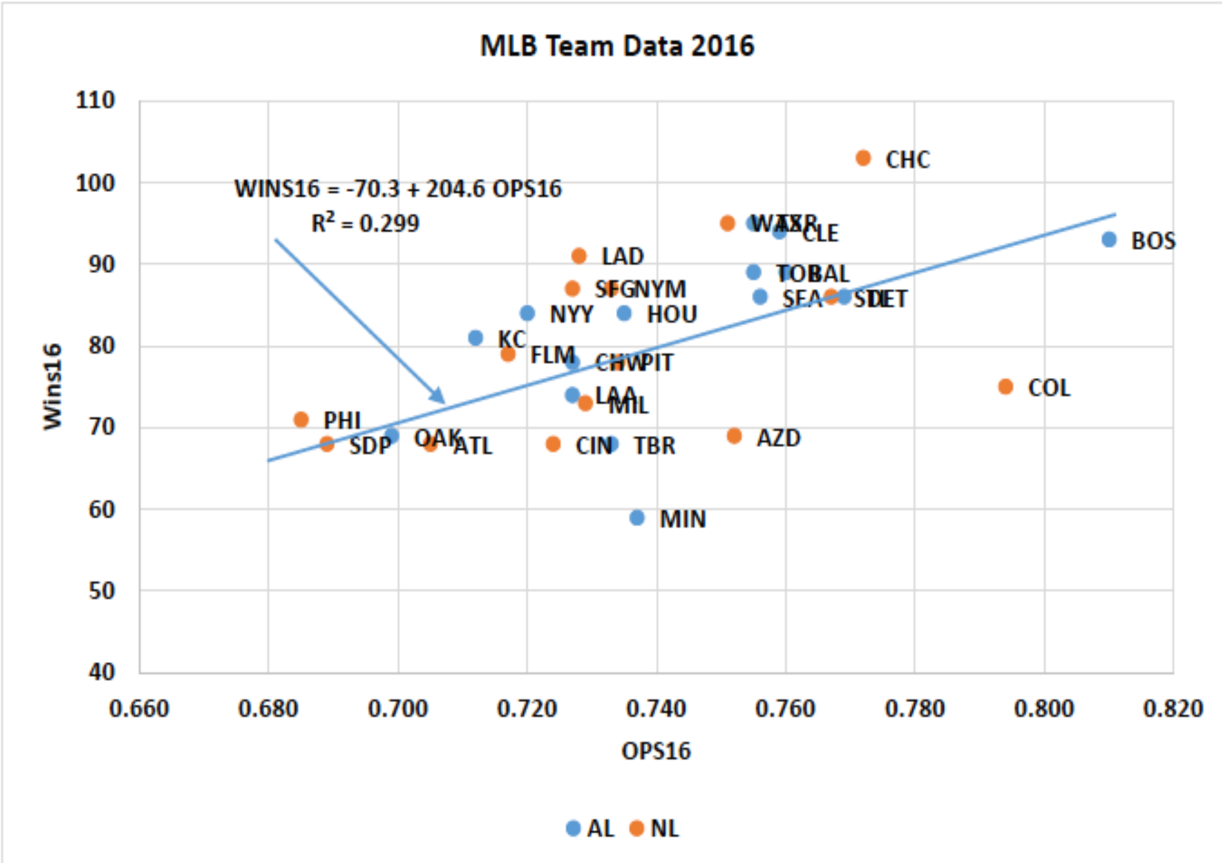

Figure 3. Lumber, 2016 MLB WINS vs. OPS (Team Offense, On-Base plus Slugging Percentages)

Aggregate salaries for each roster, TPR16, is included as a measure of human capital for each organization (Jane et al., 2010; Macdonald & Reynolds, 1994). From a human capital perspective, higher payrolls should be correlated with greater win totals (Figure 4). To allow for potential negative returns, the square of total payrolls (TPRSQ16) is also included in the sample. To measure payroll dispersion, the sample also contains the standard deviations of the roster salaries for each team (PSD16).

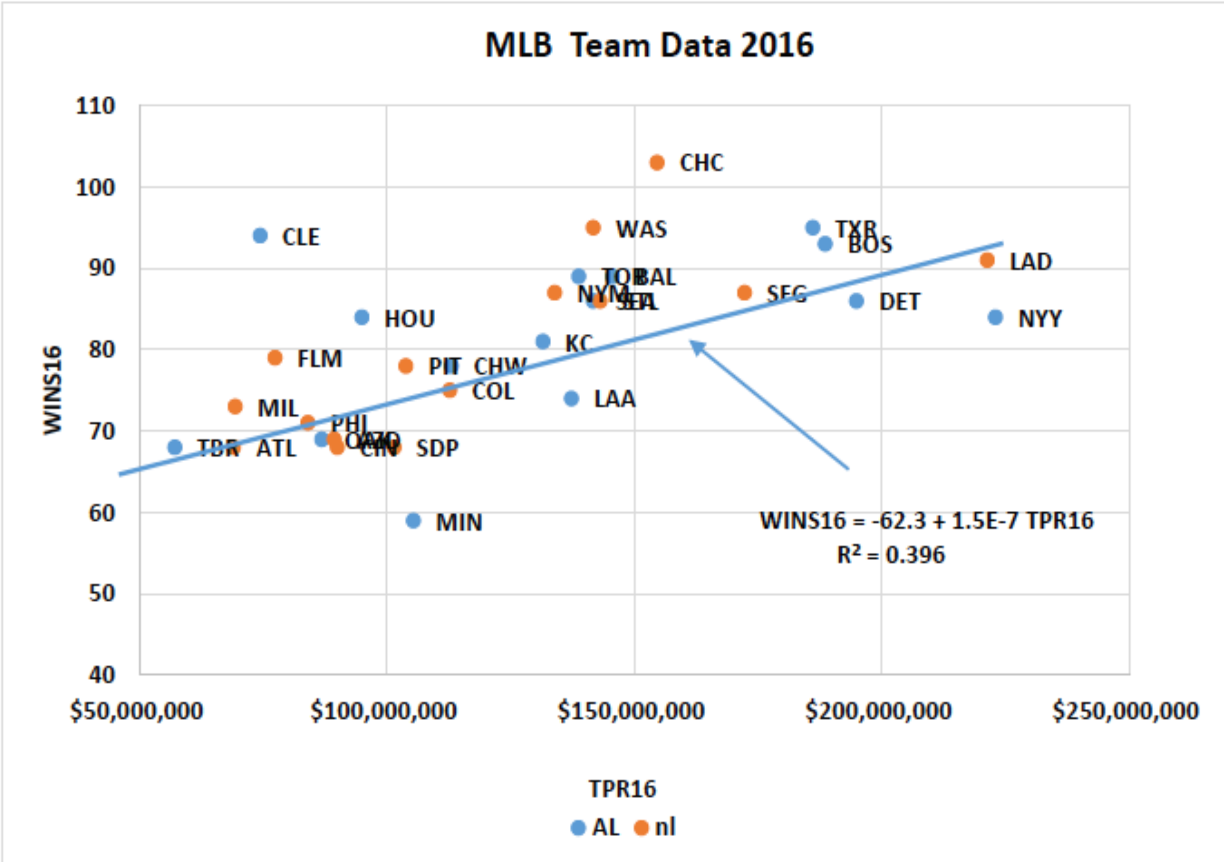

Figure 4. Payrolls, 2016 MLB WINS vs. TPR (Team Total Payrolls, Aggregate Player Salaries)

DL16 represents the number of times an organization was forced to place players on one of the multi-day disabled lists. By affecting player availability, injuries generally hamper team performances (Figure 5). The final variable included in the sample is a dummy variable for league affiliation. It is employed to account for the offensive advantage that American League teams generally enjoy as a consequence of the designated hitter rule that allows replacing pitchers with better hitters.

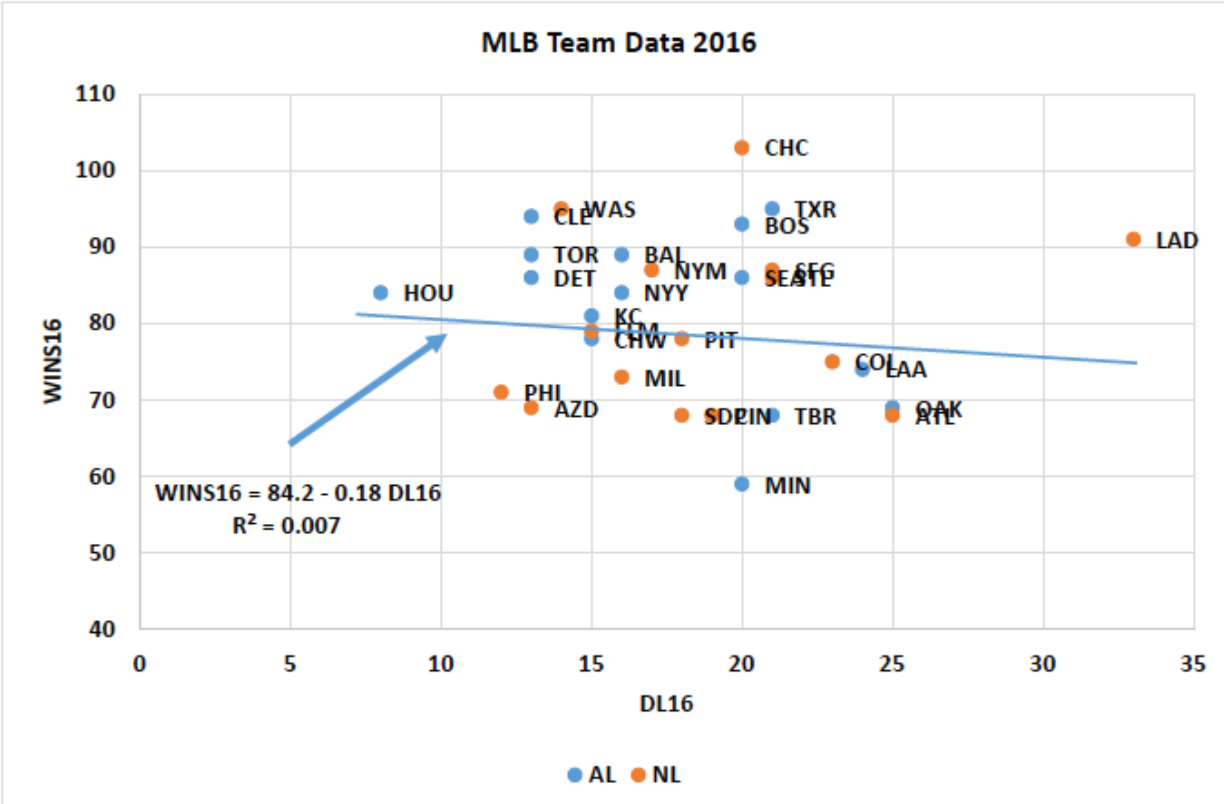

Figure 5. Injuries, 2016 MLB WINS vs. DL (Games Lost to Disabled List Designations)

Equation 1 shows how the model is specified. Arithmetic signs below each regressor indicate the hypothesized effect of each independent variable on WINS16. The parameters represent the marginal effects of the explanatory variables toward achieving victories. U is a stochastic disturbance term and the subscript i = 1, 2, 3, ... , 29, 30 is the numerical designation for each MLB organization.

$$\begin{aligned} WINS16_i = b_0 &+ \underset{(-)}{b_1 \, ERA16_i} + \underset{(+)}{b_2 \, DER16_i} + \underset{(+)}{b_3 \, OPS16_i} + \underset{(+)}{b_4 \, TPR16_i} + \underset{(-)}{b_5 \, TPRSQ16_i} \\ &+ \underset{(-)}{b_6 \, PSD16_i} + \underset{(-)}{b_7 \, DL16_i} + \underset{(-)}{b_8 \, NL_i} + U_i \qquad (1) \end{aligned}$$

Summary statistics for each of the continuous variables in the sample are reported in Table 2. The distribution of WINS16 is both symmetric and somewhat platykurtic. The ERA16 across all teams is 4.18, with the Cubs posting the lowest mark of slingshot effectiveness at 3.13, while the pitchers of the Twins and Diamondbacks both allowed more than 5.07 earned runs per game. The distribution of DER16 is leptokurtic and skews to the right, partially as a consequence of a Cubs fielding (leather) proficiency that is more than 3 standard deviations above the MLB mean for the season under review. In terms of offensive (lumber) dominance, the Red Sox and the Rockies lead their respective leagues in this sample, and OPS16 skews to the right due at least in part to hitter friendly parks such as Fenway Park and Coors Field.

Table 2. Summary Statistics for Continuous Variables

Variable	**Mean**	**Std. Dev.**	**Max.**	**Min.**	**Skew.**	**Kurt.**
WINS16	80.9	10.7	103	59	-0.03	2.18
ERA16	4.18	0.46	5.09	3.13	0.12	3.02
DER16	0.69	0.01	0.73	0.67	0.81	5.56
OPS16	0.74	0.03	0.81	0.69	0.35	3.13
TPR16	$126.06	$45.60	$223.00	$57.10	0.54	2.43
PSD16	$5.51	$1.81	$8.63	$2.42	-0.02	2.03
DL16	18.2	5.0	33	8	0.64	3.99

Source: usatoday.com and mlb.com
TPR16 and PSD16 are reported in millions of dollars

The average team payroll (TPR16) in the sample is just over $126 million. Aggregate salaries for the big-market Dodgers and Yankees both exceed $220 million, while players for the Tampa Bay Rays collectively scrape by on just over $57 million. Individual club payroll standard deviations, PSD16, average $5.5 million in 2016, with the biggest values posted for the Yankees and the Dodgers. The Indians and the Rays exhibit the smallest salary dispersion measures and are the only clubs with payroll standard deviations below $3 million. The salary dispersion estimates are highly symmetric and slightly platykurtic.

The mean number of disabled list placements (DL16) for 2016 is 18.2. The Dodgers were afflicted in 2016 with more casualties than any other team with 33. The Diamondbacks had the healthiest roster with only 8 disabled list injuries over the course of the season. The misfortunes of the Dodgers are one reason why INJURIES is positively skewed. Most of the teams are clustered between 12.5 and 22.5 for this metric, causing it to be leptokurtic.

Estimation results for Equation 1 are summarized in Table 3. All of the slope coefficients exhibit the hypothesized signs, but not all of them satisfy the standard 5-percent significance criterion. The parameter estimate for ERA16 indicates that every one run decline in earned runs allowed translated into nearly 10 additional victories. That impact is similar in magnitude to what is documented for the 2015 MLB season (Fullerton & Peach, 2016), but lower than what was reported for 2014 (Peach et al., 2016).

Table 3. Estimation Results

Variable	Coefficient	Std. Errors	t-Statistic	Probability
Constant	-79.50535	47.39610	-1.68	0.108
ERA16	-9.761032	2.064315	-4.73	0.000
DER16	154.1757	55.28662	2.79	0.011
OPS16	122.5717	23.32534	5.26	0.000
TPR16	0.189044	0.111387	1.70	0.104
TPRSQ16	-0.000193	0.000354	-0.55	0.591
PSD16	-1.660783	0.559572	-2.97	0.007
DL16	-0.420019	0.136204	-3.08	0.006
NL	1.628772	1.459649	1.12	0.277

R-Squared	0.90	Adjusted R-Squared	0.86
Std. Error of Regression	4.04	Sum of Squared Residuals	342.85
Log Likelihood	-79.11	2016 Observations	30
F-Statistic	22.65	F-Statistic Probability	0.000
Wald Breakpoint Statistic*	50.89	Wald Chi-Squared Probability	0.004

Notes: * Indicates that parameter estimate satisfies 5-percent statistical significance criterion.
120 observations are employed for the Wald breakpoint test using 2013-2016 regular season data.

To gauge fielding competence, team defensive efficiency ratios (DER16) are employed. DER16 measures the percentage of fair balls that each team converted in to outs (only batted balls that stay in field of play are counted). The slope coefficient for this regressor suggests that a 20-point increase in DER16 is associated with a 3 game gain in the win column during the 2016 season. Offensive output is represented in the sample data with team on-base plus slugging percentages (OPS16). The coefficient for this independent variable implies that a 40-point increase in OPS16 generates nearly 5 additional victories.

The TPR16 parameter estimate indicates that each $10 million increment to team payrolls led to slightly less than 2 more victories in 2016. While negative as hypothesized, the TPRSQ16 coefficient is not significant. Its magnitude may be economically plausible since it suggests that team payrolls can rise to almost $490 million before negative returns will be observed. Even if that figure is too large, it also indicates that the Dodger and Yankee payrolls may be more plausible than often assumed by many fans.

As was the case in 2015 (Fullerton & Peach, 2016), large payroll dispersion seems to damage roster unity. The coefficient for PSD16 indicates that a $1.2 million increase in the standard deviation of a team payroll precipitated 2 fewer wins. Losing players to injuries exercises a statistically reliable damaging effect on team wins. The parameter estimate for DL16 implies that roughly 4 losses occur for every ten disabled list designations. NL teams fared better against junior circuit teams in 2015. Contrary to the hypothesis stated above, the parameter estimate for the NL binary variable is positive, although it does not surpass the standard significance threshold.

Parameter estimation can also be carried out using a pooled data sample. Using data for four separate seasons, 2013-2016, such a step was completed. Results from a test allowing for breakpoints between each season indicate that pooling across seasons should not be conducted due to coefficient instability (Andrews, 1993; Chow, 1960). The Wald statistic for that step is reported at the bottom of Table 3. The result confirms numerical evidence reported in prior studies as well as this effort (Fullerton & Peach, 2016; Peach et al., 2015).

To examine the effects of potential outliers, a separate equation was estimated for a sample that excluded the Cubs and the Twins. Those organizations were excluded because they were the 2016 regular season wins and loss leaders. The most notable difference in the estimation results using the reduced 28 team sample is that the NL coefficient drops from approximately 1.629 in Table 3 to 1.072. The senior circuit success in 2016 does not appear to be an accidental consequence of the best team in the National League or the worst team in the American League outlier effects, so the full sample results are reported in Table 3.

Alternative specifications featuring interaction terms for the three on-field performance variables do not result in superior estimation diagnostics. Relatively severe multicollinearity results when interaction terms are included, obscuring the contributions of the individual regressors toward explaining the variation in the dependent variable about its mean. Given that, only the results in Table 3 are reported and those parameter estimates are employed for the standardized coefficient and elasticity calculations shown in Table 4.

To help clarify the relative importance of the various regressors included in the sample, standardized regression coefficients and elasticities are displayed in Table 4 for all of the continuous variables in the sample. Human capital, as approximated by TPR16, exercised the biggest influence over WINS16 last season and has a standardized regression coefficient of 0.81. Large team payrolls tend to be associated with on-field effectiveness. In absolute terms, the next largest standardized coefficient is that for ERA16, -0.42. Not surprisingly, OPS16 follows at 0.33. Team chemistry is important. The standardized parameter for PSD16 is -0.28.

Only two of the elasticities in Table 4 exceed unity. The largest elasticity is that for DER16. That helps clarify why teams like the Cardinals scored so many runs, committed relatively few errors, but fell short in the standings. Good defense yields victories like no other regressor in the sample. Former players like Bill Mazeroski and Ozzie Smith have pointed this out for years and Table 4 confirms, at least for 2016, the wisdom of those observations. An elastic response is also tallied for OPS16. While inelastic, the next most prominent sensitivity is associated with ERA16 at -0.51.

Table 4. Elasticities

Variable	Regression Coeff.	Standardized Coeff.	Elasticity at Means
ERA16	-9.76	-0.42	-0.51
DER16	154.18	0.18	1.31
OPS16	122.57	0.33	1.12
TPR16	0.19	0.81	0.30
TPRSQ16	-0.00	-0.23	-0.04
PSD16	-1.66	-0.28	-0.11
DL16	-0.42	-0.20	-0.09

Conclusion

The 2016 MLB season will be remembered by fans and analyzed by sabermetricians and others for years to come. The unique feature of the 2016 season for fans was, of course, the fact that the Chicago Cubs won the World Series for the first time in 108 years. Reflective of that, senior circuit teams overcame the designated hitter offensive imbalance favoring junior circuit teams and prevailed in more games than not in inter-league play.

While the analysis above documents parameter instability between seasons, on-field performance measures still matter as documented in other recent studies. The estimated coefficients for ERA16, DER16, and OPS16 all exhibit the expected signs and satisfy the 5-percent significance criterion. Among the human capital variables, the coefficients of both TP16 and TPR16SQ also display the predicted signs, but both have relatively large standard errors. Team payroll dispersion continued to represent a risk for roster unity and is inversely correlated with wins.

The econometric results presented here illustrate how the 2016 MLB season shares both similarities and differences with prior seasons. Ongoing parameter heterogeneity suggests that there is little reason to pool the data from earlier years. It also suggests that future seasons may be characterized by unanticipated outcomes. The surprise factor, no doubt, contributes to fan interest and the success of MLB as a spectator sport.

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