The Impact of Pitch Counts and Days of Rest on Performance among Major-League Baseball Pitchers

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Abstract

Background: Though the belief that overuse can harm pitchers is widespread, there exists little evidence that the number of pitches thrown and days of rest affect future performance and injury at the major-league level.

Hypotheses: Pitches thrown are negatively correlated with performance. Days of rest are positively correlated with performance.

Study Design: Cross-Sectional Study.

Methods: Examined performances of starting major-league baseball pitchers from 1988 through 2009. Employed factional polynomial multiple regression to estimate the immediate and cumulative impact of pitches thrown and days of rest on performance (measured by ERA, strikeouts, home runs, and walks) while controlling for other factors that affect pitcher effectiveness.

Results: Each pitch thrown in the preceding game increased ERA by 0.007 in the following game. Each pitch averaged in the preceding five and ten games increased ERA by 0.014 and 0.022, respectively. More pitches thrown were associated with fewer strikeouts, more home runs, and fewer walks (the latter result is counterintuitive). Older pitchers were more sensitive to cumulative pitching loads than younger pitchers, but were less affected by pitches thrown in the preceding game. Each rest day between starts decreased ERA by 0.015; however, the estimate was not statistically significant.

Conclusion: There is a negative relationship between past pitches thrown and future performance that is virtually linear. The impact of the cumulative pitching load is larger than the impact of a single game. Rest days do not appear to have a large impact on performance. However, given that few pitchers in the sample pitched after less than three days of rest, the results should not be extrapolated to shorter rest periods.

Relevance: This study supports the popular notion that high pitching loads can dampen future performance; however, because the effect is small, pitch-count benchmarks have limited use for maintaining performance and possibly preventing injury.

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Introduction

In an effort to prevent fatigue and injury among pitchers, many baseball talent overseers (e.g., managers, coaches, trainers, etc.) have suggested limiting the number of pitches that pitchers are allowed to throw. For example, during the 2010 season the Washington Nationals put top-prospect rookie pitcher Stephen Strasburg on a 100-pitch-count limit per game and limited him to 160 total innings pitched for the year in an attempt to protect his future health and effectiveness [7]. This regimen proved unsuccessful as Strasburg would require elbow ulnar collateral ligament replacement after pitching a total of 123.33 innings between the major and minor leagues. The handling of Strasburg was not an isolated case. Figure 1 maps the maximum pitches per game thrown by season since 1988, showing a clear downward trend in the number of pitches that managers allowed their starting pitcher to throw. The maximum pitches thrown in a game declined from highs in the 160s and 170s in the 1980s and 1990s to highs in the 130s in the 2000s. In 2010, Arizona pitcher Edwin Jackson threw 149 pitches in a no-hit game, which was only the third time in the 2000s that a pitcher had thrown that many pitches. In the 1990s, that load was met or surpassed at least 49 times.

Though the maximum number of pitches per game had a declining trend, the average number of pitches per game thrown by starters did not change. Figure 2 shows that median pitches per game remained stable from 1988 through 2009. However, over this same period the lower bound of pitches per game increased. Though managers reduced the maximum number of pitches they allowed their pitchers to throw per game, they also increased the minimum number of pitches thrown.

Despite the recent growth in the popularity of using pitch-count limits to protect pitchers, there has been scant study of the effectiveness of setting pitch limits to regulate effectiveness and prevent injuries among major-league pitchers. While it is intuitive that limiting use ought to prevent fatigue that can dampen future performance and result in injury, it is also possible that heavier pitching loads may enhance durability, which might improve stamina and performance. Furthermore, simple counting may be too simple a metric to account for the differing stress levels placed on pitchers given the unique nature of game situations faced. No matter the direction of the effect, it is important to quantify the impact of pitchers' workloads to assess the usefulness of popular objective benchmarks for protecting the health of pitchers.

Nearly all of the past analysis of pitches thrown on injuries has focused on adolescent pitchers. Several studies [6, 8, 9, 12, 13] have found evidence that pitches thrown and overuse is associated with injuries and pain, and limiting pitches thrown can reduce injuries among youth pitchers. However, given the rapid development among this age cohort, the results may not translate to adult major-league pitchers.

Escamilla et al [5] examined the change in pitching mechanics over the course of simulated games using a sample of collegiate baseball pitches–a cohort with the maturity approaching major-league pitchers. The researchers found that the pitching mechanics of pitchers who threw between 105 and 135 pitches for seven to nine innings were "remarkably similar," and the results did not support the idea that shoulder and elbow forces and torques increased with muscular fatigue. Anz et al [1] found that elbow and shoulder torque have been shown to be positively correlated with injury; thus, pitches thrown, within the high end of the typical range of pitches thrown, were not correlated with factors known to cause injuries among pitchers.

Murray et al [11] compared the performances of major-league baseball pitchers in their first and last innings of play in a game and identified kinematic and kinetic changes that were consistent with fatigue; though, alternative explanations for the changes could not be ruled out. The study did not examine pitches thrown as an explanatory factor, and it did not examine performance in games that followed. Woolner and Jazayerli [16] (unpublished data) reported that pitching loads dampened future pitching performances at an increasing rate among major-league pitchers.

Though the main subject of analysis in this study is pitch counts, we also estimated the impact of rest days on performance. The empirical estimation procedure holds rest days constant while estimating the impact of pitches thrown, and vice versa, in order to separate the impact of each factor on the other. This control is necessary, because additional rest days may possibly dampen the impact of past pitches thrown on performance. Potteiger et al [14] used markers of skeletal muscle fiber damage to measure the recovery of baseball pitchers over three simulated games with periods of four and two days of rest. After 72 hours, markers of muscle damage had returned to baseline levels, and that pitchers pitched with slightly less velocity with two days of rest compared to four days; however, the difference was not statistically significant.

To our knowledge, there have been no peer-reviewed studies of pitches thrown and days of rest on the performance of major-league baseball pitchers. This is due largely to the fact that previously such data was not widely available. Using newly available pitch-count data, we quantified the impact of past pitches thrown and days of rest on future performance among major-league baseball pitchers. We did not study injuries directly, because publicly available baseball injury data is sparse. However, poor performance is often a consequence of a developing injury; therefore, we examined performance data to examine hypothesized injury markers in the hope of identifying the usefulness of these markers for preventing injuries.

Methods

We used game-level performances of starting pitchers from 1988 through 2009 who had less than 15 days of rest. Data were from Baseball-Reference.com and we included all available data from games during the time period, with some data not available in the 1990s. The rest-days cutoff was chosen for two reasons. First, pitching rotations typically include five pitchers who receive between four or five rest days between starts. When off-days permit, weak or tired pitchers often have their turn skipped to give them eight to ten rest days between starts. Pitchers who have more-than-normal rest are typically inferior pitchers who switch between starting and relieving roles or bounce between the minor- and major-league levels. Second, injured pitchers are placed on the disabled list which requires them to spend a minimum of 15 days without playing before returning to the lineup. Including pitchers with less than 15 rest days excludes inferior and recently-injured pitchers who may perform poorly for reasons other than days of rests. Furthermore, the greater the distance between starts, the less relevant past pitching loads ought to be to present performances.

Equation 1 was estimated using Stata 10 statistical software. In order to measure potential non-linear impacts of marginal pitches thrown–each pitch beyond a certain threshold may have a greater or lesser effect than preceding pitches–and the multitude of factors that affect pitching performance, we employed multiple-variable fractional polynomial regression estimation. This estimation technique does not impose a pre-determined functional form on the relationship between variables and permits controlling for other factors that ought to affect pitcher performance. The fractional polynomial estimation procedure uses an iterative processe to select a transformation of the explanatory variables and a coefficient (β) to generate a functional approximation of the relationship. Royston and Alston [15] demonstrated that fractional polynomial is good at measuring curved relationships concisely and accurately.

P is the performance of the pitcher in game *g* using one of several measures of performance: earned run average (more commonly referred to as ERA), strikeout rate, home run rate, and walk rate (all measured per nine innings pitched). ERA is a cumulative measure of performance. The other metrics are components of pitching performance that do not require the help of fielders, which McCracken [10] (unpublished data) and Bradbury [3] demonstrated may measure pitching ability better than ERA.

PT is the number of pitches thrown in the preceding game (*g-1*), the average number of pitches thrown in the previous five games (*g-5*), or the average number of pitches thrown in the previous 10 games (*g-10*). The measures proxy the immediate and cumulative effects of pitches thrown on performance, estimated in separate equations. DR is the number of rest days the pitcher had before game *g*. Performance P in the year of analysis *t* is included to serve as a proxy to control for the ability of the pitcher, which should positively impact performance. Age is the age of the pitcher as of game day measured continuously in years, which is included to capture any effects of durability due to aging. To further capture aging effects, separate estimations by age cohorts were conducted. **Y** is a vector of year indicator variables that equal one for games played in the year of analysis and zero for all other games. The indicators control for factors unique to individual seasons (e.g., run environment, rule changes, etc.) that impact performance in games played in each season. α is a constant term, and ε is a standard error term. Table 1 reports the summary statistics for the included variables.

Results

Table 2 reports the regression results using the game, five games, and ten games preceding the present game on ERA performance. Tables 3, 4, and 5 report the results for strikeouts, home runs, and walks, respectively. The reported coefficients are estimated according to the fit with variables transformed in order to measure non-linear impacts. The transformations that modify the variables are listed in the bottom portion of the tables. Figure 3 graphically depicts the estimated relationships between pitches per game and performance for each performance metric. The graphs are easier to interpret than the raw regression estimates of the transformed variables.

For ERA, each pitch in the preceding game raised a pitcher's ERA by approximately 0.007 in the following game. Though the relationship is non-linear, the graph reveals that the curvature of the function is so slight that a linear approximation is appropriate for practical purposes. Each pitch averaged in the previous five games increased a pitcher's ERA by 0.014, and each pitch averaged in the preceding ten games increased a pitcher's ERA by 0.022.

For strikeouts, each pitch in the preceding game decreased a pitcher's strikeout rate by 0.0008. Each one-pitch increase in the five- and ten-game averages lowered the strikeout rate by 0.0011 and 0.0027, respectively. The estimates are linear, small, and only the ten-game average approaches a standard level of statistical significance. At the average strikeout rate for the sample of 6.1 strikeouts per nine innings pitched, a one-pitch increase in the preceding game, five-game average, and ten-game average lowered the strikeout rate by 0.13 percent, 0.18 percent, and 0.44 percent, respectively.

For home runs, a one-pitch increase in the preceding game was associated with a 0.0013 increase in home runs allowed (a one-percent change at the average). A one-pitch increase in the five-game and ten-game averages raised the home run rate by 0.002 (1.6 percent, estimated at the 101^{st} pitch) and 0.0025 (two percent), respectively.

For walks, the estimated impact of pitches thrown on future performance was non-linear and the opposite of the expected effect. Each pitch in the preceding game decreased the walk rate by 0.0024 (0.66 percent) at the 101^{st} pitch. The 101^{st} pitch for the preceding five-game and ten-game average pitches thrown lowered the walk rate by 0.0038 (one percent) and 0.006 (1.67 percent).

Table 6 reports the impact of previous pitches thrown on ERA overall and by three age cohorts: 25 to 34 (10 years centered on the estimated peak age for pitchers as estimated by Bradbury

[4]), under 25, and over 34. The top half of the table lists the marginal impact of pitches thrown, and the bottom half lists the number of pitches needed to raise a pitcher's ERA by 0.25. Younger pitchers were no more sensitive to high-pitch performances than the middle age-cohort. Older pitchers suffered much less than younger pitchers from pitches thrown in the previous game; however, older pitchers suffered more from increased cumulative pitching loads than their younger counterparts.

The estimated impact of days of rest on ERA was small and insignificant, with each rest day associated with an improvement of 0.015. Based on this estimate, skipping a pitcher in a five-man rotation—giving him four additional days of rest—lowers his ERA by 0.06. Also, rest days were not strongly correlated with performance components. The relationship with strikeouts was not statistically significant. The estimated impact of rest days on walks was to increase the walk rate by 0.032, approximately 0.08 percent at the average walk rate. As with pitches thrown, the estimated effect is counterintuitive. Rest days lowered the home run rate by 0.012 (0.98 percent), and the estimate was statistically significant in two of the three models.

Discussion

The finding that pitches thrown were negatively correlated with future performance should be interpreted with caution. Though the estimated effect was statistically significant, it was small. Escamilla et al [5] found few differences between pitches thrown and biomechanical changes as pitchers reached between 105 and 135 pitches. The range is within the upper range of pitches thrown that modern pitchers are typically allowed. The ERA difference in a game following 105 pitches versus 135 pitches is approximately 0.19—a small effect of 0.33 percent at the average sample ERA that is consistent with Escamilla's finding.

On potential problem with the estimated model is that managers may be more patient with pitchers when they are preventing runs; therefore, if a pitcher pitched well (poorly) in preceding contests, he is more likely or have thrown more (less) pitches. After controlling for the pitcher's ERA for the season, the ERA in the following game may rise (decline) as performance regresses to the mean. To address this potential bias, we estimated alternate models that included ERA performance in the previous game, five games, and ten games as a control. The results are presented in Table 7, and the estimated function of pitches thrown and ERA in the following game is presented graphically in Figure 4. The estimates for the five- and ten-game averages of pitches thrown were statistically significant at better than the one-percent level, while the p-value for the previous game estimate was 0.097. The non-linear shape of the relationships for the five- and ten-game averages make the raw coefficients difficult to interpret, but the graphs demonstrate that the impact over the range of pitches normally thrown in a game was positive. Similar to the estimates reported in Table 2 and Figure 3, the impact of pitches thrown in the previous ten games was greater than the impact of the previous game; in contrast, the five-game impact was less than the previous-game and ten-game impacts over most of the typical range of pitches thrown. The disadvantage of this correction is that immediate performance is likely to be highly correlated with present performance; thus, it is difficult for the estimation algorithm to disentangle the impact of pitches thrown, seasonal ERA, and in-season fluctuations in ERA that deviate from the season mean. The important finding of the alternate estimates is that the positive relationship between pitches thrown and future ERA persisted, and the size of the effect continued to be small.

One interesting finding of the study is that despite using an empirical technique designed for estimating subtle non-linearities in relationships, the estimated relationship between pitches thrown and performance was virtually linear for overall performance, strikeouts, and home runs. Even in cases were non-linear estimates were found, the curvature was small. Therefore, simple rules of thumb (e.g., each pitch thrown in a game raise ERA in the following game by 0.007) can be used to estimate damage to pitchers from pitches thrown in a game. Also, managers can quickly weight the strategic risk of leaving a pitcher in a game versus taking him out. For example, in a close game in which a pitcher is performing well, knowing that additional pitches likely inflict little future harm, a manager may choose to leave a pitcher in the game.

Though there is a clear relationship between pitches thrown and overall performance, the relationship between pitches thrown and the performance components differs. The strongest effect occurred with home runs—each pitch increased the home run rate between one and two percent—and the weakest effect occurred with strikeouts—each pitch decreased the strikeout rate between 0.13 and 0.44 percent, and the estimates were not statistically significant. The counterintuitive relationship between pitches thrown and walks is difficult to explain. It may be that pitchers who threw many pitches were cognizant of past high pitch counts, and thus tried to be more efficient with pitches and throw more pitches in the strike zone, thereby reducing walk rates.

As a regressor, age was not associated with changes in performance after controlling for the other factors in the regression equations. However, when the sample was separated into age-cohorts there was a clear difference in responses to pitches thrown among age groups. It is not surprising that older pitchers were more sensitive to cumulative pitches thrown than younger pitchers; however, that older pitchers were less sensitive to pitches thrown in the preceding game is interesting. This response is consistent with experience providing an advantage over less-experienced pitchers. Veterans are likely more-familiar with their bodies than younger pitchers and know when to ask out of games as they tire and can credibly communicate to their managers whether or not they are capable to continue pitching. They may also be able to exploit their knowledge of the game to pitch effectively as their physical stamina decreases. Baker et al [2] found evidence of golfers using experience to substitute for deteriorating physical ability. Among baseball players, Bradbury [4] identified differences in aging functions across skills that were consistent with players using experience to compensate for diminished physical capacity.

Though days of rest did not appear to affect the performance of pitchers, it is likely that rest days are important for maintaining performance. Otherwise, teams would not give pitchers any rest days. Less than 0.5 percent of the pitchers in the sample pitched with less than three days of rest; therefore, it would be unwise to extrapolate the estimates to predict the impact of rest days below that threshold. This finding is consistent with Potteiger [14], which found that after three days of rest, markers of muscle damage returned to baseline levels. The results of this study indicate that additional days of rest beyond the normal do not appear to have a strong impact on performance.

Conclusion

This study quantified the impact of pitches thrown and days of rest on future performance using a cross section of major-league pitcher-games from 1988 through 2009. The results indicate that pitches thrown negatively impact future performance at a linear rate; but, though the effect is real, it is small. Also, days of rest beyond the minimal standard of three days does not significantly affect performance. While this study did not study did not examine the direct impact of pitches thrown and days of rest on injuries, it is likely that injuries from overuse would initially manifest in diminished performance. The results indicate pitch counts may measure fatigue that leads to diminished performance and possibly injury. Because the magnitude of the effect is small, it takes a rather large change in pitches thrown to have even a modest effect on performance; therefore, the guidance offered by raw pitch counts may be limited. Pitchers and coaches should be mindful of potential overuse, but occasional high or low pitch games likely have only a minor effect on future performance. The longer the high- or low-pitch counts are maintained, the greater the dampening or improvement will be. Furthermore, marginal days of rest beyond the ordinary appear to have little effect on performance.

It is our hope that future researchers will quantify the usefulness of pitch counts as a predictor of performance and injury more precisely than we have identified here. Researchers should draw upon the vast amounts of sports data that are becoming increasingly available to researchers to examine factors relating to performance and injury. In addition, future studies that examine the direct impact of pitching loads on injury are necessary.

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Table 1. Summary Statistics

Variable	Mean	Median	Std. Dev.
ERA	5.64	3.86	8.32
Strikeouts per 9 Innings	6.10	5.87	3.35
Home Runs per 9 Innings	1.22	0.00	2.02
Walks per 9 Innings	3.59	3.00	3.97
Pitches per Game	97.17	99.00	19.16
Days of Rest	4.57	4.00	1.17
Age	28.69	28.15	4.51

Table 2. Impact on ERA

Variable		Previous Game	Previous 5 Games	Previous 10 Games
Pitches	1	0.0836982	0.0135269	0.0219639
		0.002	*0.000*	*0.000*
	2	1.486948		
		0.000		
Days Rest	1	-0.0180876	-0.0092031	-0.0176906
		0.473	*0.746*	*0.592*
ERA_t	1	5.833797	11.11848	0.1184051
		0.000	*0.000*	*0.000*
	2	35.95548	7.128779	-0.0464524
		0.000	*0.000*	*0.000*
Age	1	-0.0073185	-0.0058643	-0.0011849
		0.261	*0.416*	*0.889*
R^2		0.047	0.043	0.041
Obs.		77,131	59,784	42,919

Transformations of Independent Variables

Previous Game	Previous 5 Games	Previous 10 Games
Pitches 1 = X^-1-1.023314091	Pitches 1 = Pitches-97.0906731	Pitches 1 = Pitches-97.60557562
Pitches 2 = X^.5-.9885429036 (where: X = (Pitches+1)/100)	Days Rest = DR-4.562575271	Days Rest 1 = DR-4.56459843
Days Rest 1 = DR-4.569057837	ERA_t 1 = X-.4253092926	ERA_t 1 = ERA^3-73.87130632
ERA_t 1 = X^-.5-1.521863228	ERA_t 2 = X^2-.1808879944 (where: X = ERA/10)	ERA_t 2 = ERA^3*ln(ERA)-105.9394431
ERA_t 2 = X^.5-.6570892714 (where: X = ERA/10)	Age 1 = Age-28.81099803	Age 1 = Age-28.95326417
Age 1 = Age-28.68537899		

P-values in italics below coefficients. Constant and year effects not reported.

Table 3. Impact on Strikeouts

Variable	Previous Game	Previous 5 Games	Previous 10 Games
Pitches 1	-0.0007793	-0.0011328	-0.0027152
	0.153	*0.277*	*0.071*
Days Rest 1	-0.0023223	-0.0077685	-0.0046793
	0.799	*0.459*	*0.704*
Strikeouts$_t$ 1	0.9994239	0.9969871	1.002649
	0.000	*0.000*	*0.000*
Age 1	0.0007883	-0.0007189	-0.0013729
	0.738	*0.788*	*0.665*
R^2	0.23	0.22	0.22
Obs.	77,131	59,784	42,919
	Transformations of Independent Variables		
	Pitches 1 = Pitches-96.72170723	Pitches 1 = Pitches-97.0906731	Pitches 1 = Pitches-97.60557562
	Days Rest 1 = DR-4.569057837	Days Rest 1 = DR-4.562575271	Days Rest 1 - DR-4.56459843
	Strikeouts$_t$ 1 = Strikeouts$_t$-6.086449989	Strikeouts$_t$ 1 = Strikeouts$_t$-6.121764796	Strikeouts$_t$ 1 = Strikeouts$_t$-6.163530502
	Age 1 = Age=-28.68537899	Age 1 = Age-28.81099803	Age 1 = Age-28.95326417

P-values in italics below coefficients. Constant and year effects not reported.

Table 4. Impact on Home Runs

Variable		Previous Game	Previous 5 Games	Previous 10 Games
Pitches	1	0.0013493	-0.4162523	0.0024815
		0.000	*0.000*	*0.008*
Days Rest	1	-0.0145247	-0.0140708	-0.0074324
		0.017	*0.043*	*0.353*
Home Runs$_t$	1	1.013665	1.233847	1.679031
		0.000	*0.000*	*0.000*
	2	0.135506	0.3459446	0.1395627
		0.000	*0.000*	*0.000*
Age	1	-0.0020901	-0.0020337	-0.0015729
		0.183	*0.250*	*0.444*
R^2		0.06	0.06	0.05
Obs.		77,131	59,784	42,919
		Transformations of Independent Variables		
		Pitches 1 = Pitches-96.72170723	Pitches 1 = X^-.5-1.014871938 (where: X = Pitches/100)	Pitches 1 = Pitches-96.72170723
		Days Rest 1 =DR-4.569057837	Days Rest 1 =DR-4.562575271	Days Rest 1 =DR-4.56459843
		Home Runs$_t$ 1 = X-1.020392569	Home Runs$_t$ 1 = X^.5-1.005027458	Home Runs$_t$ 1 = HR$_t$^.5-.999828865
		Home Runs$_t$ 2 = X^2-1.041200995	Home Runs$_t$ 2 = X^2-1.020261991	Home Runs$_t$ 2 = HR$_t$^3-.9989736349
		(where: X = (HR$_t$+2.98023223877e-08))	(where: X = (HR$_t$+2.98023223877e-08))	
		Age 1 = Age-28.68537899	Age 1 = Age-28.81099803	Age 1 = Age-28.95326417

P-values in italics below coefficients. Constant and year effects not reported.

Table 5. Impact on Walks

Variable		Previous Game	Previous 5 Games	Previous 10 Games
Pitches	1	0.0008739	-0.1252327	-0.5877361
		0.000	*0.006*	*0.004*
	2	-0.0801233		-2.352229
		0.002		0.000
Days Rest	1	0.0326065	0.0319805	0.0321523
		0.005	*0.013*	*0.032*
$Walks_t$	1	12.4122	9.570991	2.155183
		0.000	*0.000*	*0.000*
	2	2.3396	3.788982	0.0909253
		0.000	*0.000*	*0.000*
Age	1	-0.0046243	-0.0033327	-0.0012424
		0.132	*0.319*	*0.750*
R^2		0.10	0.10	0.09
Obs.		77,131	59,784	42,919

Transformations of Independent Variables

Previous Game	Previous 5 Games	Previous 10 Games
Pitches 1 = X^-2-1.047171729	Pitches 1 = (Pitches/100)^3-.9152348227	Pitches 1 = ln(X)+.0242355669
Pitches 2 = X^3-.9331965764		Pitches 2 = ln(X)^2-.0005873627
(where: X = (pitches_1+1)/100)		(where: X = Pitches/100)
Days Rest = DR-4.569057837	Days Rest = DR-4.562575271	Days Rest = -4.56459843
$Walks_t$ 1 = X-.3140493231	$Walks_t$ 1 = (BBt/10)-.3092638758	$Walks_t$ 1 = BBt^.5-1.746483948
$Walks_t$ 2 = X*ln(X)+.3637335671	$Walks_t$ 2 = (BBt/10)^2-.0956441448	$Walks_t$ 2 = BBt^2-9.303757745
(where: X = (BBt+1.19209289551e-07)/10)		
Age 1 = Age-28.68537899	Age 1 = Age-28.81099803	Age 1 = Age-28.95326417

P-values in italics below coefficients. Constant and year effects not reported.

Table 6. Impact of Pitches Thrown on ERA by Age Cohort

	Previous Game	5-Game Mean	10-Game Mean
		Marginal Impact to ERA	
All	0.0066*	0.0135	0.0220
Under 25	0.0076	0.0132	0.0212
25 to 34	0.0076	0.0134	0.0214
Over 34	0.0043	0.0154	0.0225
		Pitches needed to raise ERA by 0.25	
All	38	19	11
Under 25	33	19	12
25 to 34	33	19	12
Over 34	58	16	11

*Non-linear estimate, estimated impact at 100 pitches.

Table 7. Impact on ERA, Controlling for Recent Performance

Variable		Previous Game	Previous 5 Games	Previous 10 Games
Pitches	1	0.0026853	-0.1433443	-0.4419834
		0.097	*0.009*	*0.001*
Days Rest	1	-0.0166921	-0.0102605	-0.0106451
		0.509	*0.719*	*0.749*
ERA_t	1	5.654914	13.38017	2.244064
		0.000	*0.000*	*0.000*
	2	35.92875	6.098284	
		0.000	*0.000*	
$ERA_{(g-1)}$	1	-1.668305	-1.853004	-1.507632
		0.000	*0.000*	*0.000*
Age	1	-0.007573	-0.0072052	-0.0044885
		0.245	*0.318*	*0.597*
R^2		0.047	0.045	0.046
Obs.		77,054	59,481	42,511

Transformations of Independent Variables

Previous Game	Previous 5 Games	Previous 10 Games
Pitches 1 = Pitches-96.804345	Pitches 1 = (Pitches/100)^-2-1.058057469	Pitches 1 = (Pitches/100)^-1.046425437
Days Rest 1 = DR-4.569055468	Days Rest = DR-4.561473412	Days Rest 1 = DR-4.563501211
ERA_t 1 = X^-.5--1.521937514	ERA_t 1 = X-.4250685391	ERA_t 1 = ERA^4.192038497
ERA_t 2 = (ERA/10)^.5-.6570571991	ERA_t 2 = X^2-.1806832629	ERA(g-1) = ln(ERA/10)+.637125272
ERA(g-1) = X^.5-.2316560384	(where: X = ERA/10)	Age 1 = Age-28.95375987
(where: X = (ERA+9.53674316406e-07)/10)	ERA(g-1) = X^.5-.731771742	
Age 1 = Age-28.68569016	(where: X = (ERA+5.96046447754e-08)/10)	
	Age 1 = Age-28.81091935	

P-values in italics below coefficients. Constant and year effects not reported.

Figure 1. Maximum Pitches per Game (1988–2009)

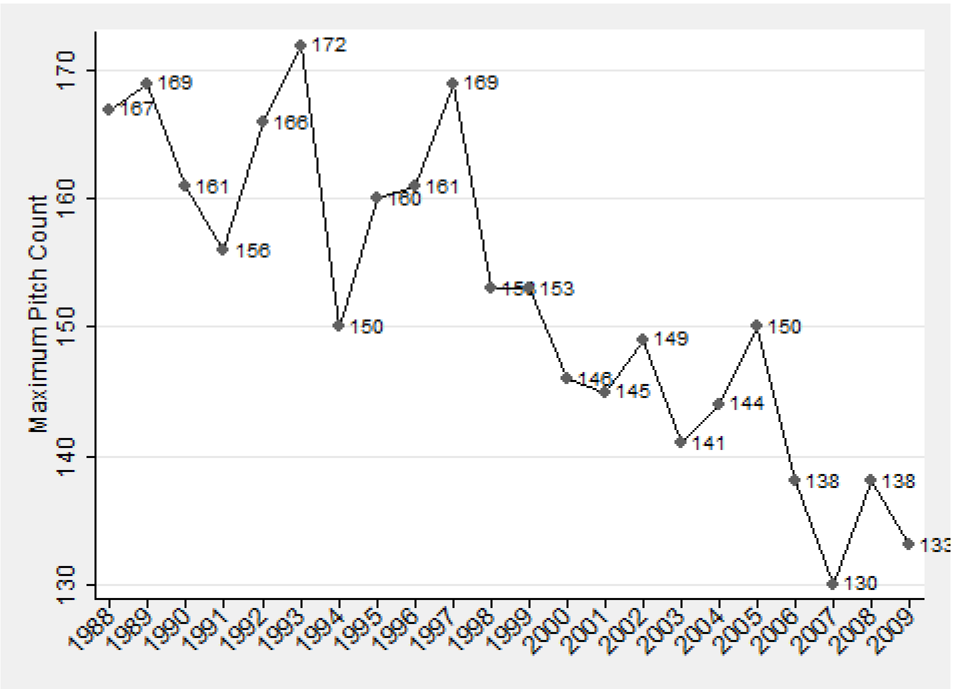
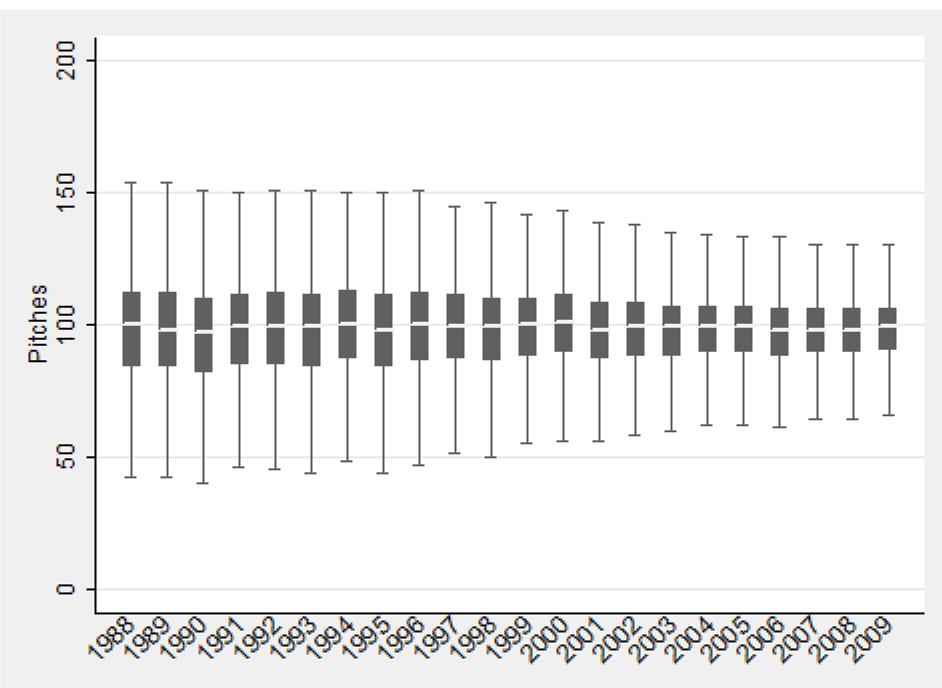


Figure 2. Box Plot of Pitches per Game (1988–2009)



The shaded box ranges from the 25th to the 75th percentile of observations, and the horizontal line within the box marks the median. The whiskers range from 5th to the 95th percentiles.

Figure 3. Impact of Previous Pitches Thrown on Performance

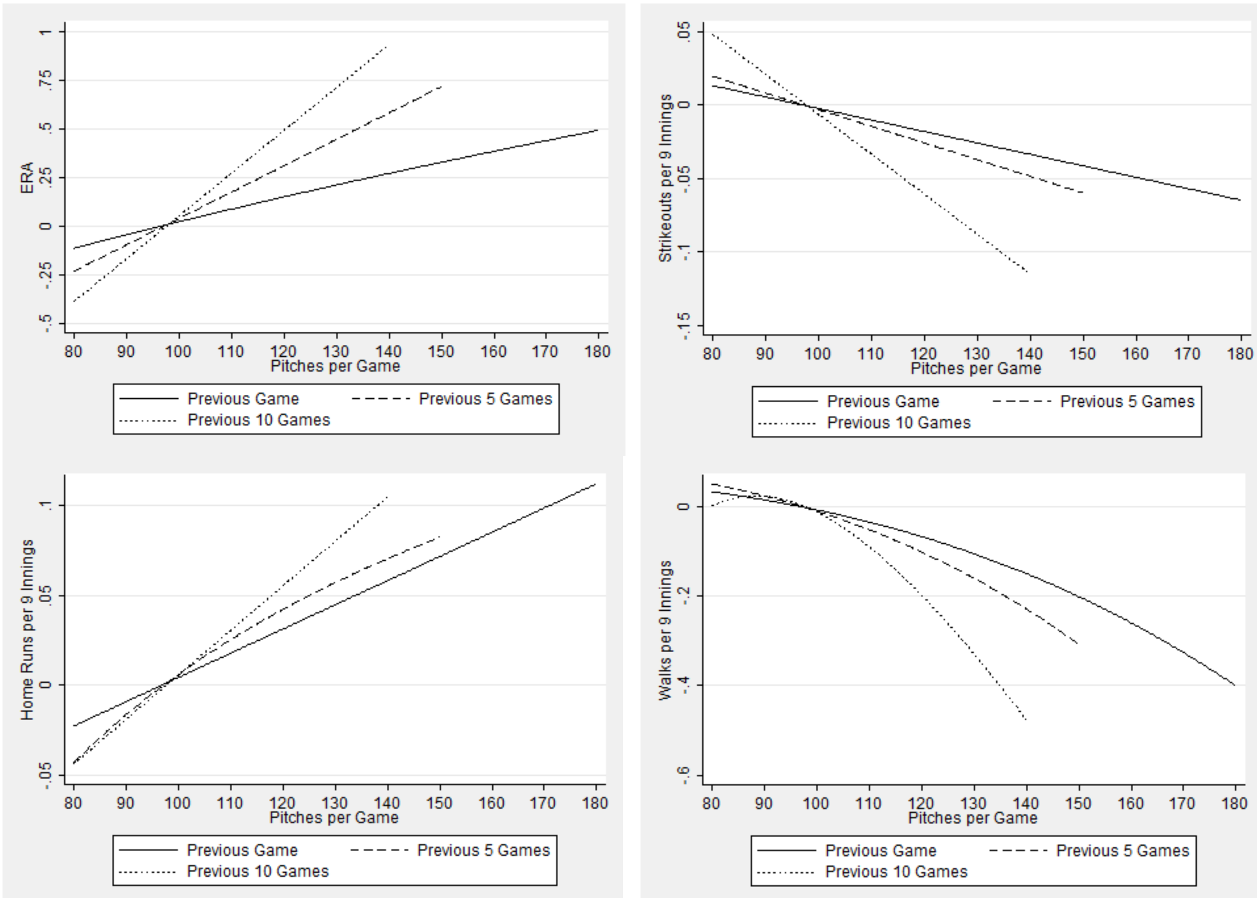


Figure 4. Impact of Previous Pitches Thrown on ERA, Controlling for Recent Performance