“We want a Pitcher, not a Belly-itcher!”
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Introduction

Motivation of the Case Study

Seasoned veterans, Chuck Finley, Doug Drabek, and Tim Belcher have proven to be reliable, successful Major League Baseball pitchers throughout their careers. Their combined, average Earned-Run-Average for the 1997 season, however, was an exorbitant 5.00 earned runs per nine innings; yet, they did not disappoint their teams by combining for a 0.575 winning percentage (WinPct). Despite resembling belly-itchers rather than reliable starters for the season, they bettered the league averages for regular starters\(^1\) in 1997, which were 4.30 and .518 for the ERA and WinPct, respectively. Such examples often lead brash spectators and commentators to complain that a pitcher’s success doesn’t stem from his\(^2\) pitching ability, but rather from some other luck factor, such as the pitcher’s team’s offense. In order to gauge the validity of these comments, this study examines the relationship between a starting pitcher’s abilities and his success during a particular season.

Simplifying Assumptions

- For this case study, I am defining a pitcher’s success as his impact on his team. Thus, I have chosen a pitcher’s WinPct as the estimator for his success.
- Two types of factors contribute to a pitcher’s success.
  1. The first includes factors that relate directly to his abilities. I have chosen the amount of hits, walks, and strikeouts per inning (hit/ip, bb/ip, and so/ip, respectively) as an indicator of a pitcher’s abilities. (Note that I am not studying the attributes, such as height, weight, and types of pitches, that make a good pitcher, but rather how a pitcher can use these attributes.)
  2. The second type of factors includes ones that are largely out of a pitcher’s direct control. These factors include the offensive production of his team. I have chosen run support as an indicator of offensive support\(^3\).
- Apart from offensive support, a pitcher will also receive defensive support from his team that can affect his success. I could not find compiled statistics measuring the defensive backup a pitcher receives while on the mound.
- Note that though a pitcher’s earned-run-average (ERA) will be more correlated to his winning percentage, it does not depict his pitching abilities as well as the other indicators I have chosen. An ERA will depend more upon a pitcher’s defensive support compared to the amount bases on balls or hits he allows. Furthermore, hit/ip, bb/ip, and so/ip are highly correlated with ERA. Using all three

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\(^1\) Regular starters are defined in the Source Materials and Selected Data
\(^2\) Throughout the case study, I use “his” as a possessive personal pronoun when describing a pitcher’s attribute. My choice reflects the fact that virtually all Major League Baseball players are male and was not meant to slight female pitchers.
\(^3\) Note that in the NL, pitchers are required to bat. Thus, they do have an impact on their run support, but the magnitude of the impact is minimal because NL pitchers lack hitting abilities.
will give a better indication of the specific factors that contribute to his success. *Had this study concentrated on predicting winning percentages, I would have included ERA. But, the case study investigates the relative importance of a pitcher’s ability versus “luck” in explaining his success.*

**Source Materials and Selected Data**

- The data for this case study was compiled from the following online sources:

Most of the data was gathered from the first source. Park factor data was gathered from the second, and run support was gathered from ESPN’s web page.

- I was afraid that pitchers with minimal starts would not provide an accurate reflection of a starting pitcher’s ability on his success. Thus, I used data from the 1997 season for 132 starting pitchers who had greater than 16 starts. The choice of 16 was somewhat arbitrary, but guided by the fact that most MLB teams have 5 starting pitchers in their rotation, meaning that each one starts 162 games / 5 pitchers = 32 games / pitcher per season. I chose pitchers who had been starters for at least half a season.

**Summary of Findings**

Belly-itching on the mound while waiting for run support proved an ineffective method for achieving success. I found that when regressing starting pitchers’ WinPet’s against their walks per inning allowed, hits per inning allowed, and run support, the factors that define a pitcher’s abilities explain more of his success than the run support that assists him. Specifically, a key component to winning involves reducing the number of hits a starting pitcher allows. However, run support was also significant factor in explaining a pitcher’s WinPet. This fact can help explain the “luck” that Tim Belcher, Doug Drabek, and Chuck Finley received as well as its outcome on their WinPet. No reliable conclusions could be drawn on the relative importance of strikeouts per inning pitched or bases on balls per inning pitched, besides the fact that they were less significant than hits per inning pitched and run support per nine innings.
Analysis

The Distribution of the Winning Percentage

As can be seen below, the distribution of WinPct is quite normal (see normal quantile plot with 95% confidence bands), with a mean of 0.519 and a std dev of 0.133. As I mentioned in the introduction, not all starting pitchers were included in this analysis. Only ones with a significant amount of starts (≥16) were included. However, usually, better pitchers get more starts; so, a selection bias may exist. In fact, the mean is greater than 0.500, which should be the league average for all MLB pitchers, considering someone’s win is another’s loss. The 95% confidence interval of (.4958, 0.5416) provides an approximate measurement of the true mean. So, is a WinPct 0.5187 statistically significant?

Exhibit 1

<table>
<thead>
<tr>
<th>WinPct</th>
<th>Quantiles</th>
<th>Moments</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Median 50.0%</td>
<td>0.5100</td>
</tr>
</tbody>
</table>

When using a one-sided hypothesis testing framework developed in Chapter 8 of the SYS 302 bulk pack and a α-level of 0.05, the null hypothesis can be rejected if the sample mean is greater than 0.5191. The null hypothesis holds; however, a α-level of 0.0545 (instead of 0.05) would have lead to a rejection of the null hypothesis. In fact, a slight positive skew can be seen in the histogram.

But in the spirit of compromise, the 132 starting selection provides a satisfactory balance between a selection bias by choosing too few pitchers and inaccuracies caused by choosing too many² (a low cut-off for the number of starts).

² See Source Materials and Selected Data in the Introduction for a greater of discussion of why pitchers with a minimal number of starts would skew data.
Studying the “Independent” Drivers of Winning Percentage

Table 1 – Summarizing the Linear Fits (Exhibits 2 – 5)

<table>
<thead>
<tr>
<th>Driver</th>
<th>t-value of $\beta_1$ coeff</th>
<th>Type I error</th>
<th>$R^2$</th>
<th>Residual Dist &amp; Fit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hit/ip</td>
<td>-7.21</td>
<td>&gt; 0.001</td>
<td>0.285723</td>
<td>Normal and linear</td>
</tr>
<tr>
<td>Bb/ip</td>
<td>-4.40</td>
<td>&gt; 0.001</td>
<td>0.129828</td>
<td>Normal and linear</td>
</tr>
<tr>
<td>Rs</td>
<td>3.87</td>
<td>0.002</td>
<td>0.103352</td>
<td>Normal and linear</td>
</tr>
<tr>
<td>So/ip</td>
<td>3.61</td>
<td>0.004</td>
<td>0.084121</td>
<td>Normal and linear</td>
</tr>
</tbody>
</table>

As one can judge from the Residual Distributions and Plots for each of the linear fits (see Exhibits 2 – 5), the residuals seem normally distributed with fairly constant variance. Note that the hit/ip and so/ip fit seem somewhat heteroscedastic for small values from the Residual Plots, but the taper in variance is due to outliers rather than an underlying nonlinear distribution. (I tried a logarithmic fit for hit/ip and a square root fit for so/ip to no avail. The $R^2$ was reduced in both.) Thus, the Gauss-Markov assumptions apply and we can proceed safely with linear fits (single and multiple-regressions):

$$\text{WinPet} = \beta_0 + \sum \beta_n x_n.$$  
- $x_n = \{ \text{so/ip, bb/ip, hit/ip, and rs} \}$
- $n = 1$ for a single regression, and $n = 2,3$, or 4 for multiple regressions.

The table, specifically the t-values and P-values, corroborates my hypothesis that hits per inning pitched (hit/ip), bases on balls per inning pitched (bb/ip), run support per nine innings pitched (rs), and strikeouts/ip are significant drivers of WinPet. Based on the single regressions, it seems as though a pitcher’s ability seems to be more important for the most part than the offense’s run support. However, we cannot draw valid conclusions, yet, without a multiple-regression. Individually, none of the drivers’ $R^2$ values can explain more than 30% of the variance between actual and predicted values. Since the selected drivers all seem to be significant explainers of a pitcher’s WinPet, we can proceed to a multiple regression.

(Please see Exhibits 2 - 5 for greater detail.)

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5 A logarithmic fit for rs seems to be better. This fit makes more sense due to the of a diminishing return to WinPet of additional run support when run support is high. By fitting WinPet by ln(rs), I increased the $R^2$ to 0.114, but the change in $R^2$ was not significant enough to warrant abandoning my simplifying, linearity assumption and to investigate the tapering effect.
**Hits Per Innings Pitched**

**Exhibit 2**

**WinPct By hit/p**

Linear Fit
WinPct = 1.03292 + 0.50705 hit/p

**Residual Plot**

**Residual Distribution**

**Summary of Fit**

| Parameter       | Estimate | Std Error | t Ratio | Prob>|t| |
|-----------------|----------|-----------|---------|-----|
| Intercept       | 1.0329246| 0.071982  | 14.35   | <.0001 |
| hit/p           | -0.50705 | 0.070314  | -7.21   | <.0001 |
Bases on Balls Per Innings Pitched

Exhibit 3

WinPct By bb/ip

Residual Plot

Residual Distribution

Linear Fit
WinPct = 0.69725 0.49206 bb/ip

Summary of Fit
Rsquare 0.129828
Rsquare Adj 0.123134
Mean of Response 0.518695
Observations (or Sum Wgts) 132

Parameter Estimates
| Term   | Estimate | Std Error | t Ratio | Prob>|t|
|--------|----------|-----------|---------|-------|
| Intercept   | 0.6972534| 0.041968  | 16.61   | <.0001|
| bb/ip      | -0.492061| 0.111729  | -4.40   | <.0001|
### Strikeouts Per Innings Pitched

**Exhibit 4**

**WinPct By so/ip**

**Linear Fit**

WinPct = 0.35192 + 0.23519 so/ip

**Residual Plot**

**Residual Distribution**

![Graph of WinPct by so/ip, Linear Fit equation, Residual Plot, and Residual Distribution](image)

**Summary of Fit**

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rsquare</td>
<td>0.09112</td>
</tr>
<tr>
<td>Rsquare Adj</td>
<td>0.084121</td>
</tr>
<tr>
<td>Root Mean Square Error</td>
<td>0.12726</td>
</tr>
<tr>
<td>Mean of Response</td>
<td>0.518695</td>
</tr>
<tr>
<td>Observations (or Sum Wgts)</td>
<td>132</td>
</tr>
</tbody>
</table>

**Parameter Estimates**

| Term     | Estimate | Std Error | t Ratio | Prob>|t| |
|----------|----------|-----------|---------|-----|---|
| Intercept| 0.3519195| 0.047508  | 7.41    | <.0001|
| so/ip    | 0.2351865| 0.065149  | 3.61    | 0.0004|
Exhibit 5

Run Support per 9 Innings Pitched

WinPct = 0.2738 + 0.04798 rs

Summary of Fit

| Term          | Estimate | Std Error | t Ratio | Prob>|t| |
|---------------|----------|-----------|---------|------|---|
| Intercept     | 0.2738011| 0.064214  | 4.26    | <.0001| |
| rs            | 0.0479828| 0.012396  | 3.87    | 0.0002| |
Teasing out the Multicolinearities

The Diagnosis

Before proceeding to a multiple regression, one should ask, of course, if multicolinearities will exist, reducing the significance of dependent explanatory drivers. Forecasting multicolinearities is quite simple if you look at dependencies between explanatory variables, but removing them is much more difficult.

Table 2 - Response: WinPct

| Term    | Estimate | Std. Error | t Ratio | Prob>|t| | Lower 95% | Upper 95% |
|---------|----------|------------|---------|-------|----------------|-------------|
| Intercept | 0.89374340.096954 | 9.22 | <.0001 | 0.7018875 | 1.0855994 |
| hit/p   | -0.6156760.063858 | -9.64 | <.0001 | -0.742039 | -0.489312 |
| bb/p    | -0.446070.072927 | -6.12 | <.0001 | -0.590382 | -0.301759 |
| so/i/p  | 0.01872610.051215 | 9.38 | <.0001 | 0.0615135 | 0.0944236 |
| rs      | 0.07796680.008316 | 9.38 | <.0001 | 0.0615135 | 0.0944236 |

The multiple regression’s results look quite good. The regression accounts for roughly 63% (see R²) of the variance in the data. But one obvious inconsistency is the t-value (0.37) of the β₁ coefficient of so/i/p. The single regression of WinPct by so/i/p clearly showed a significant relation with a t-value of 3.61. The drop in significance relies primarily on the significant correlation between hit/p and so/i/p. The negative relationship implies that the more strikeouts per inning a pitcher can achieve, the less hit/p he will allow (see Exhibit 6). The relationship proves quite believable, intuitively, and the P-value of <0.0001 on the β₁ coefficient’s t-value of -8.21 supports our hypothesis of the codependence.
The other apparent and explainable dependency exists between hit/ip and rs. In fact, a regression of these two factors (see Exhibit 7) has a positive relation with a t-value for the $\beta_1$ coefficient of 3.45 and P-value of just 0.0007.

The Remedy

The dependency between run support and hits per inning pitched should be apparent to baseball aficionados. 2 significant factors cause these dependencies: the differences between the NL and the AL, as well as park factors. So, two questions remain. The first asks if the dependence between rs and hit/ip will have an effect on my regression model. The answer is no because $\beta_1$ coefficients of both run support and hit/ip are already significant with t-values of 9.38 and -9.64, respectively. The mild multicollinearities have not skewed the significance of either. The second question asks if the two factors listed above, the league differences and PF, cause the dependence between so/ip and hit/ip. Again the answer is "no". The hypothesis is that pitchers who strikeout more batters per inning allow less hits.

Thus, our plan of action for the multiple regression model is two-fold. The first is to ignore the mild correlation between run support and hit/ip. The second is to run two separate regression models. One

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6 To see an explanation of these factors, as well as a detailed analysis of their impact, please see the Appendix. The explanation detracts from the purpose of this section, but is still interesting.
regression model will include hit/ip, bb/ip, and rs as explanatory variables; whereas, the second will regress WinPct against so/ip, bb/ip, and rs. The separate regressions will allow us not only to avoid the multicolinearities, but also to gauge the relative importance of a pitcher’s abilities versus the run support he gets, as well as between the individual variables defining a pitcher’s abilities.

The Multiple Regression Analysis

The Regressions

Both Exhibit 8 and 9 show that rs, hit/ip, bb/ip, and so/ip are significant explanatory variables with convincing $\beta_1$ values, judging from the P-values of $< 0.0001$ for all. Unexpected, high correlations have not arisen. The low $R^2$ for the second regression model does cause one to hesitate because of the large amount of variance not explained, but the similarity of $\beta_1$ coefficients for rs and bb/ip does quell some anxiety. I will assume that the $R^2$ remains large enough to proceed with the analysis.

Now, the difficulty lies in estimating the relative importance of the explanatory variables compared to the others, particularly when comparing run support against the factors that rate a pitcher’s abilities. To address this issue, I introduce the Percentage Change Model.

Exhibit 8 – Multiple Regression 1: WinPct Against hit/ip, bb/ip, and rs

<table>
<thead>
<tr>
<th>Summary of Fit</th>
</tr>
</thead>
<tbody>
<tr>
<td>WinPct = 0.920824 – 0.628754 * (hit/ip) – 0.44543 * (bb/ip) + 0.0778176 * (rs)</td>
</tr>
<tr>
<td>Rsquare</td>
</tr>
<tr>
<td>Rsquare Adj</td>
</tr>
<tr>
<td>Root Mean Square Error</td>
</tr>
<tr>
<td>Mean of Response</td>
</tr>
<tr>
<td>Observations (or Sum Wgts)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parameter Estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Term</td>
</tr>
<tr>
<td>intercept</td>
</tr>
<tr>
<td>hit/ip</td>
</tr>
<tr>
<td>bb/ip</td>
</tr>
<tr>
<td>rs</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Correlation of Estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corr</td>
</tr>
<tr>
<td>Intercept</td>
</tr>
<tr>
<td>hit/ip</td>
</tr>
<tr>
<td>bb/ip</td>
</tr>
<tr>
<td>rs</td>
</tr>
</tbody>
</table>
Exhibit 9 – Multiple Regression 2: WinPct Against so/ip, bb/ip, and rs

| Term | Estimate | Std Error | t Ratio | Prob>|t| | Lower 95% | Upper 95% |
|------|----------|-----------|--------|------|----------|-----------|
| Intercept | 0.1771063 | 0.081064 | 2.17 | 0.0318 | 0.0156371 | 0.3385755 |
| bb/ip | -0.494024 | 0.956377 | -5.18 | <0.001 | -0.682744 | -0.305304 |
| rs | 0.061023 | 0.010654 | 5.73 | <0.001 | 0.0399412 | 0.0821047 |
| so/ip | 0.2953111 | 0.055617 | 5.31 | <0.001 | 0.1852624 | 0.4053598 |

The Percentage Change Model

The Percentage Change Model takes the mean values of rs, hit/ip, bb/ip, and so/ip, institutes a 5% favorable increase or decrease on one of the mean values, holding the rest constant, and then predicts the change in the WinPct based on the regression model, WinPct = β0 + β1*(rs) + β... This step is repeated for all explanatory variables. The model also uses the percentage-changed means with the 95% confidence intervals’ (CI) endpoints for the β1 coefficients to produce lower and upper bounds for the predicted WinPct. The larger the effect of a percentage change in an explanatory variable on WinPct, the more influential the explanatory variable will be considered. The following table summarizes the results of the Percentage Change model on the first regression.

Table 4 – The Percentage Change Model for Multiple Regression 1 (Exhibit 8)

<table>
<thead>
<tr>
<th>% Increase / Decrease of Explanatory Variables</th>
<th>Numerical Change in Explanatory Variable</th>
<th>Predicted Increase in WinPct</th>
<th>Lower Bound for Increase in WinPct</th>
<th>Upper Bound for Increase in WinPct</th>
</tr>
</thead>
<tbody>
<tr>
<td>5% decrease in hit/ip</td>
<td>-0.05071</td>
<td>0.03188</td>
<td>0.02659</td>
<td>0.03717</td>
</tr>
<tr>
<td>5% increase in rs</td>
<td>0.25519</td>
<td>0.01986</td>
<td>0.01568</td>
<td>0.02404</td>
</tr>
<tr>
<td>5% decrease in bb/ip</td>
<td>-0.01814</td>
<td>0.00808</td>
<td>0.00547</td>
<td>0.01069</td>
</tr>
</tbody>
</table>

The results overwhelmingly favor hit/ip as the most influential factor in determining a pitcher’s success. Run support appears more than twice as influential as bb/ip, though. But if the contributions from the individual percentage changes were summed, then the total Predicted Increase in WinPct would be 0.05982. If the individual percentage increases effects on WinPct were then taken as a fraction of the total, then hit/ip would account for 53.3%. Rs would account for 33.2%, and bb/ip would account for remaining 13.5%. Categorized differently, a pitcher’s ability would account for 53.3% + 13.5% = 66.8%, a majority.

1 Note that I “borrowed” this concept from a past case-study by Rob Armitage.
of the total increase.

<table>
<thead>
<tr>
<th>% Increase / Decrease of Explanatory Variables</th>
<th>Numerical Change in Explanatory Variable</th>
<th>Predicted Increase in WinPet</th>
<th>Lower Bound for Increase in WinPet</th>
<th>Upper Bound for Increase in WinPet</th>
</tr>
</thead>
<tbody>
<tr>
<td>5% increase in rs</td>
<td>0.25519</td>
<td>0.01557</td>
<td>0.01019</td>
<td>0.02095</td>
</tr>
<tr>
<td>5% increase in so/ip</td>
<td>0.035455</td>
<td>0.01047</td>
<td>0.00657</td>
<td>0.01437</td>
</tr>
<tr>
<td>5 % decrease in bb/ip</td>
<td>-0.01814</td>
<td>0.00896</td>
<td>0.00558</td>
<td>0.01234</td>
</tr>
</tbody>
</table>

Table 5’s results aren’t as clear as Table 4’s. Though the predicted increase in WinPet is the highest for rs, one cannot conclude that it is the most influential because of the overlap of bounds for the predicted values. Similar to the Multiple Regression 1’s analysis, run support is more influential than bb/ip. The obscurity of this table compared to the first can perhaps be attributed to the high variance in this regression. In fact, the standard errors, relative to the parameter estimates, are greater in the second regression, causing relatively larger confidence intervals.

Based on the results from Table 5 and 6 and after performing a relative ranking of the influence of a 5% favorable change on the change in WinPet, I can safely conclude that pitching abilities as a whole contribute more to a pitcher’s success than the run support he receives. Furthermore, ranking the explanatory variables in their influential power on WinPet, i.e. a starting pitcher’s success results in the following standings:

1) hits per inning pitched
2) run support per nine innings
4) strikeouts per inning
4) bases-on-balls per inning

**Defending the Percentage Change Model**

The values for the parameters, run support, bb/ip, hit/ip, and so/ip, were chosen to be the mean because they best represent MLB starting pitchers on average. The findings would not hold as well for data with outrageously large values for run support and with small values of the hit/ip, so/ip, and bb/ip. The change in WinPet for a percentage change in run support would be much greater simply because of its large initial value. Such data for the most part is not representative of the Major Leagues.

Also, the choice of 5% was quite arbitrary. The results would have held regardless of the percentage change used because of the “linear-in-parameters” model. A proportional change in the explanatory variable causes a proportional change in WinPet due to the linearity assumptions.
Conclusion

Analyzing the performances of 1997 starting pitchers, this case study reassures us that a pitcher’s ability significantly contributes to his success. Brash comments by spectators and commentators based on the observation of a few individual starting pitchers exaggerate the importance of run support. Though run support proved to be a significant factor in determining a pitcher’s success rate, hit/ip could be stated conclusively to have a greater effect on his WinPct than the amount of offense the pitcher’s team provides. In fact, I found that when regressing starting pitchers’ WinPct’s against their walks per inning allowed, hits per inning allowed, and run support, the factors that define a pitcher’s abilities account for a majority of the explanation of a pitcher’s WinPct. No reliable conclusions could be drawn on the relative importance of strikeouts per inning pitched or bases on balls per inning pitched, besides the fact that they were less significant than hits per inning pitched and run support per nine innings.

Using single regressions, I began the analysis by ascertaining that the explanatory variables I had chosen did in fact explain a starting pitcher’s WinPct. The single regressions helped to discover multicolinearities when performing a multiple regression. The dependencies between run support and hit/ip were ignored due to the significance of the β coefficients, meaning that the mild multicolinearities did not compromise the significance of these parameters. Multicolinearities between strikeouts per inning pitched as well as walks per inning pitched did devalue the significance of the so/ip parameters. Thus, two separate multiple regressions had to be performed in order to avoid the reduction in significance. The first regressed WinPct against hit/ip, bb/ip, and rs. The second replaced hit/ip with so/ip. The two regressions had the following predicting equations:

1) \[ \text{WinPct} = 0.920824 - 0.628754 \times \text{hit/ip} - 0.44543 \times \text{bb/ip} + 0.0778176 \times \text{rs} \]
2) \[ \text{WinPct} = 0.1771063 + 0.2953111 \times \text{so/ip} - 0.494024 \times \text{bb/ip} + 0.061023 \times \text{rs} \]

Using the Percentage Change Model on the first regression, we could state conclusively that bb/ip and hit/ip combined to explain 66.8% of the increase in WinPct; whereas, a pitcher’s luck, or his run support accounted for only a third. Thus, a pitcher’s abilities were more important than his run support in explaining WinPct. When analyzed with the same Percentage Change Model, the second multiple regression provided inconclusive results, but affirmed that rs was in fact more important than bb/ip.

Belly-itching on the mound while waiting for run support proved an ineffective method for achieving success. One can safely conclude that a pitcher has control over his success. Furthermore, luck, or run support, does not determine his fate, but rather his ability to pitch well.

*The tied ranking is due to inconclusiveness of Table 6’s findings. Though I could venture to assign a rank by their predicted increases in WinPct from Table 6 or the fact that rs was definitely greater than bb/ip, but not so/ip, I hesitate to pass a judgement due to the low R^2 of the second multiple regression.
Appendix

Factors that cause dependencies between rs and hit/ip:

1) The fact that the American League (AL) is more productive offensively on average than the National League (NL). Thus, when regressing rs against hit/ip, the data will consist of two pools, one for more productive, statistically higher AL and one for the less productive NL. A positive relation will appear when trying to "connect" these two pools.

2) Park Factors. Some parks are built or located in such a way to give batters an advantage. Thus, runs and hits are scored much easier in these parks than others. If a pitcher's home park, where he starts a majority of his games, is such a park, than not only will he give up more hits and runs on average, but he will also get more run support. Thus, the park factor causes a dependency between run support and hit/ip.

Table 7 – NL vs. AL

<table>
<thead>
<tr>
<th></th>
<th>National League – hit/ip</th>
<th>American League – hit/ip</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Moments</td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>0.97399</td>
<td>5.39969</td>
</tr>
<tr>
<td>Std Dev</td>
<td>0.12930</td>
<td>0.89418</td>
</tr>
<tr>
<td>Std Error Mean</td>
<td>0.01580</td>
<td>0.11091</td>
</tr>
<tr>
<td>Upper 95% Mean</td>
<td>1.00553</td>
<td>5.62126</td>
</tr>
<tr>
<td>Lower 95% Mean</td>
<td>0.94245</td>
<td>5.17812</td>
</tr>
<tr>
<td>N</td>
<td>67.00000</td>
<td>65.00000</td>
</tr>
<tr>
<td>Sum Weights</td>
<td>67.00000</td>
<td>65.00000</td>
</tr>
</tbody>
</table>

|                   | National League – rs     | American League – rs      |
|                   | Moments                  |                            |
| Mean              | 4.81672                  | 1.05556                   |
| Std Dev           | 0.79390                  | 0.13983                   |
| Std Error Mean    | 0.09699                  | 0.01734                   |
| Upper 95% Mean    | 5.01037                  | 1.09021                   |
| Lower 95% Mean    | 4.62307                  | 1.02092                   |
| N                 | 67.00000                 | 65.00000                  |
| Sum Weights       | 67.00000                 | 65.00000                  |

To check if the American League averages were actually higher for hit/ip and rs, I used a two sample hypothesis testing framework discussed in the SYS 302 bulk pack on page 9-2 and assumed normality (the distributions are quite normal and well-behaved according to the normal quantile plots) because the sample sizes were both greater than 30. The Z-value for hit/ip is 3.477 with a P-value of 0.0003, and the Z-value for rs is 3.967 with a P-value of <0.0001. Thus, it is safe to conclude that the American League is more productive.

To remove the majority of the dependencies caused by the above factors, one can regress the National and American Leagues separately. As can be seen from Exhibit 10, the positive relationship has been practically erased, leaving t-values of just 1.88 and 1.66 for the National and American Leagues, respectively.
Exhibit 10 – Rs against hit/ip for the National and American Leagues

National League
Rs by hit/ip

American League
Rs by hit/ip

Linear Fit
Rs = 3.45699 + 1.39604 hit/ip
Summary of Fit
Rsquare = 0.051699
Rsquare Adj = 0.03711

Parameter Estimates
Term Estimate Std. Error t Ratio Prob>|t|
Intercept 3.4569881 0.728559 4.74 <.0001
hit/ip 1.3960383 0.741604 1.88 0.0643

Linear Fit
Rs = 4.02105 + 1.30608 hit/ip
Summary of Fit
Rsquare = 0.041712
Rsquare Adj = 0.026501

Parameter Estimates
Term Estimate Std. Error t Ratio Prob>|t|
Intercept 4.0210465 0.839695 4.79 <.0001
hit/ip 1.3060754 0.78871 1.66 0.1027

As stated in the analysis, dividing the leagues does not change the strong negative relationship between so/ip and hit/ip, meaning that league differences are not contributing to the dependency. In fact, the t-values for the β₁ are quite large with P-values <0.0001 for both. This fact solidifies my intuitive hypothesis that pitchers who strike out more batters per inning allow less hits/ip as well.
Exhibit 11 – AL vs. NL (so and hit/ip)

**American League**

hit/p By so/ip

**Summary of Fit**

<table>
<thead>
<tr>
<th>Parameter Estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Term</td>
</tr>
<tr>
<td>Intercept</td>
</tr>
<tr>
<td>so/ip</td>
</tr>
</tbody>
</table>

**National League**

hit/p By so/ip

**Summary of Fit**

<table>
<thead>
<tr>
<th>Parameter Estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Term</td>
</tr>
<tr>
<td>Intercept</td>
</tr>
<tr>
<td>so/ip</td>
</tr>
</tbody>
</table>
# Glossary

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>American League</td>
</tr>
<tr>
<td>bb/ip</td>
<td>Bases-on-balls per inning pitched (or walks per inning pitched)</td>
</tr>
<tr>
<td>bs</td>
<td>Blown saves</td>
</tr>
<tr>
<td>c</td>
<td>Complete games</td>
</tr>
<tr>
<td>er</td>
<td>Earned runs allowed</td>
</tr>
<tr>
<td>ERA</td>
<td>Earned Run Average = (Runs allowed per 9 innings pitched)</td>
</tr>
<tr>
<td>g</td>
<td>Games played in</td>
</tr>
<tr>
<td>hit</td>
<td>Hits allowed</td>
</tr>
<tr>
<td>hit/ip</td>
<td>Hits per inning pitched</td>
</tr>
<tr>
<td>ip</td>
<td>Innings pitched</td>
</tr>
<tr>
<td>lost</td>
<td>Losses</td>
</tr>
<tr>
<td>MLB</td>
<td>Major League Baseball</td>
</tr>
<tr>
<td>N</td>
<td>National League</td>
</tr>
<tr>
<td>PF</td>
<td>Park Factor</td>
</tr>
<tr>
<td>Rs</td>
<td>Run Support (Runs produced by pitcher’s team’s offense per 9 innings)</td>
</tr>
<tr>
<td>run</td>
<td>Runs allowed</td>
</tr>
<tr>
<td>sa</td>
<td>Saves</td>
</tr>
<tr>
<td>sho</td>
<td>Shutouts</td>
</tr>
<tr>
<td>so</td>
<td>Strikeouts</td>
</tr>
<tr>
<td>so/ip</td>
<td>Strikeouts per inning pitched</td>
</tr>
<tr>
<td>st</td>
<td>Games started</td>
</tr>
<tr>
<td>WHIP</td>
<td>Walks and hits per inning pitched</td>
</tr>
<tr>
<td>WinPct</td>
<td>Winning Percentage = Wins / (Wins + Losses)</td>
</tr>
<tr>
<td>won</td>
<td>Wins</td>
</tr>
</tbody>
</table>