University Avenue Undergraduate Journal of Economics

Volume 3 | Issue 1 Article 8

1999

Free Agents, Fire Sales, and Fungoes: An Econometric Examination of Team Success in Major League Baseball

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University Avenue
UNDERGRADUATE JOURNAL OF ECONOMICS

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INTRODUCTION

Major League Baseball is an industry. It has been and will continue to be run as one. Much to the chagrin of those who plea for the game to be truer to its boyish essence, the Major Leagues are driven by businessmen who want their corporations to be successful. Major League Baseball teams are in business to produce wins. Other authors have explored the relationship between a team's success and its revenue.[1] It is logical and fair to say that teams that win more often than they lose will draw more fans, and thus make more money, than those who lose more often than they win. With that in mind, I have explored what good organizational strategies teams use to put themselves into the first group, and conversely, what poor strategies cause teams to fall into the latter.

It seems almost too obvious a statement that teams with more productive players tend to win. In my study, I attempted to control for players' ability and focus on some finer, more disputed aspects of the game. Specifically, I looked at starter turnover rates, player acquisition techniques, managerial expertise, and the efficiency wage hypothesis as applied to Major League Baseball. In addition to players' talent, I controlled for other aspects of teams' success such as average player age, average player experience, percentage of games played by the starters, and the effect of being a non-expansion team in an expansion year.

Because I developed a model to study several different phenomena, it seemed only logical to break down my discussion into distinct categories, so each topic could be given individual attention. Therefore, I offer my four-part hypothesis of organizational strategies and team success in Major League Baseball:

1) Major League Baseball teams will tend to win more often when the amount of change in their starting line-up and pitching staff is minimized from one year to the next;

[1] Zimbalist, 1992.

2) Teams that sign a higher percentage of their players from the free-agency market are not necessarily more productive;
3) Managerial expertise has a positive and significant effect on a team's success;
4) The individual impact of team payroll on winning percentage, and thus the efficiency wage hypothesis, is often overstated in the case of Major League Baseball, and is not significant.

Baseball is an attractive subject to study for a couple of reasons. First, both the outputs and the inputs are definable and quantifiable. An extraordinary abundance of data has been collected on the subject. Inputs (such as team payroll) are much more attainable in baseball than in virtually any other industry.

Secondly, the baseball model can be applied to other issues in labor economics. For example, in my model, a compensation variable tested whether people produce more by being paid a higher salary – independent of other effects. This subject, the efficiency wage hypothesis, is a current topic of discussion in labor economics. The age and experience variables could be very telling for a hiring firm – which is more important, the energy of youth or the knowledge and experience of older workers? The hiring practice variables could help firms decide between training their own workers or hiring workers that have been trained by other companies to do similar things. The cohesiveness variables could also offer useful economic information, such as the effect on productivity of people working with the same group over a period of time and the value of hiring workers to long-term contracts (to encourage unit cohesiveness). The managerial expertise variables attempted to measure the direct effect of a manager's ability on the production of the company.

Although the baseball industry is parallel in many ways to the rest of the business world, it also has some fairly major differences. These include the monopsonistic nature of the labor market and the fact that teams may not all be driven by exactly the same motives (some have stronger financial constraints and concerns, for instance). However, I believe that the results

obtained from my study are relevant to the larger business community despite some peculiarities of this industry.

In the next section, the Methodology, I will outline my analytical technique and further explore the variables of my model. I will also introduce and explain my four "Effects," to isolate the different issues of my hypotheses within my econometric model. In the Results section, I will outline how I made model specification changes during the regression-running process. I will then report the results of the regressions and interpret those results. In my Conclusion, I will reflect on my original hypotheses in light of the findings of my study and close with a short discussion of areas for possible future research.

METHODOLOGY

In developing my theoretical model, I did extensive research of studies that attempted to answer similar questions. Although no study has looked at the effects of as many different aspects of team success as I did here, some tested somewhat similar models. Many authors looked at small components of my model, and the results of their research contributed to the development of this study.[2]

My first hypothesis, the inverse relationship of player turnover and team winning percentage, was included because I believe that continuity and familiarity translates into success in baseball. The more comfortable players are with their teammates, coaches, city, etc., the more relaxed the players will be, and ready to perform at optimum levels.

The second hypothesis, an insignificant relationship between percentage of starters obtained through free agency and winning percentage, was included to dispel a commonly held belief. I believe that development of talent through the minor leagues has been vastly under-

appreciated, and that the success of teams that rely on the free agency market has been exaggerated. Minor league baseball is a training program for aspiring major leaguers. In the minors, players are taught the baseball-specific philosophy of their organization, become acquainted with many of their future big-league teammates, and become acclimated to the world of professional athletics. Teams set up their affiliation hierarchies to gradually let the players become accustomed to the team-specific Major League environments.[3] Without this socialization, I believe that teams would have a difficult time realizing the full production potential of their players.

The third hypothesis, that managers who have won in the past will win in the future, is fairly straightforward. I believe that managers possess specific human-capital and that the addition of a good manager will help a team, and conversely, that a poor manager will hinder the team's performance.

The final hypothesis, the lack of significance in the relationship between team payroll and winning percentage, is a response to the efficiency wage hypothesis. This theory will be explored later in this section. In brief, it assumes a positive relationship between salary and performance. I contend that in competitive sports the desire to produce for the sake of the team winning is more important than the desire to produce because the player has a large contract. Contrarily, it may be the case that players shirk their competitive desire, and thus their performance suffers, as they begin to think of themselves as a commodity rather than a baseball player (an observation not limited to, but certainly more present in, higher-paid athletes).

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[2] A comprehensive literature review is not included here because of spacial constraints although it was a section of the original thesis. For more information about obtaining the original paper, contact the Lewis & Clark College economics departmant.

[3] This can include cultural (the Boston Red Sox's AAA team is located in New England – Pawtucket, RI; the Seattle Mariners' is in northwest Washington, Tacoma, minutes away from Seattle), altitude-specific (the "mile-high" Colorado Rockies have their AAA ball club in the Rocky Mountains -- Colorado Springs), and climatic concerns (the Los Angeles Dodgers' AAA team is in sunny Albuquerque, NM; the Houston Astros' is in sizzling Tucson, AZ).

The Analytical Technique

I tested my four-part hypothesis through econometric modeling and regression analysis, using the OLS framework. I specified a production function, with the dependant variable being team winning percentage[4] in a single year and the independent variables being those directly related to my hypothesis as well as several controls. I chose a production function because I believed the primary responsibility of baseball teams is to produce victories, and a team may include more or less of certain inputs to increase their organization's relative output (to win more games). This specification was supported by my literature research.

However, my model did not fall into the Cobb-Douglas mold[5] (not all of the exogenous variables are logarithmically related to a logarithmic endogenous variable), and it therefore lacks some of the valuable interpretive characteristics of that specification. I hoped that my model would successfully isolate the phenomena discussed in my hypothesis. Success was judged by how well the model fit the data (through the adjusted R^2 statistic) and the overall explanatory power of the model (with the F-statistic), with attention to variable-specific significance (through t-statistics), and an eye toward multicollinearity issues (through pair-wise correlation matrices and auxiliary regressions). Other violations of the OLS assumptions were then evaluated and dealt with as they arose.

The observations in my model were every Major League Baseball team from 1989 through 1996 (216 in all).[6] I looked at both cross-sectional and time-series data, but each team's winning percentage and make-up were treated as individual, unrelated observations. To test for

[4] Team winning percentages from *Total Baseball* and *The Baseball Encyclopedia.*
[5] The Cobb-Douglas model was specified as $Q=AK^{\alpha}L^{\beta}$ (or $\ln Q=\alpha \ln K + \beta \ln L$).
[6] Originally I intended my data set to include all teams from 1985 through 1996, but I learned that owners had been found guilty of collusion (not signing free agents) from 1985 through 1988. This seemed to be an unnatural force on the free movement of players from team to team, and for fear that it would skew the acquisition data I decided to exclude observations from 1985, 1986, 1987, and 1988. For studies on collusion in Major League Baseball, see Bruggink and Rose (1990) and Durland and Sommers (1991).

any underlying organization-specific factors of team success, I included dummy variables for every team (except the Toronto Blue Jays who were excluded to avoid perfect multicollinearity).

One issue that arose was that the relationships of some of the controls to one another and the dependant variable were a little unclear (multicollinearity may have muddied the results). Thus, the exact specification of the model had to be slightly altered from its original form. To avoid fitting the model to the specific set of data ("data mining"), I divided the data sample randomly into two halves and ran regressions on one half. I then tried to find the best fitting specification on the basis of the aforementioned tests and apply the altered model to the other, untainted half.[7]

The remainder of the methodology section explores the independent variables I used in my model. For clarity, they are separated according to which of the four parts of my hypothesis they attempted to capture. I also include a fifth section to discuss the various controls I incorporated into my model.

The Variables

1) *The Cohesion Effect*

The starter turnover variables (PS1, PS3, PS5) were defined as the percentage of starters that were starters on the same team 1, 3, and 5 years before.[8] A "starter" was defined as the single player who played the most games at a given position in a given year for a given team. For this variable, the top 4 pitchers in the rotation (top 4 in "games started") and the relief pitcher (team leader in "saves") were included and given equal weight as each of the "position player" starters. In the American League (AL), the position player starters are the catcher, first baseman, second

[7] This process was accomplished by using the Random Number Generator function in Microsoft Excel to assign a random number (between 0 and 1) to each observation, then using the Filter function to isolate the top 50%.

[8] While I would have preferred to study the entire roster of teams and have the player statistics weighted based on games played or at-bats, logistical problems prevented that. With just the starters, approximately 3000 players' data was studied.

baseman, shortstop, third baseman, left fielder, center fielder, right fielder, and designated hitter. In the National League (NL), the starters are the same, with the exclusion of the designated hitter. Each starter for a team was given a value of 1 or 0 for this variable, 1 if they were a starter on the team in year t-1 and 0 if they were not (for PS1). The values for the team were then averaged, and this became the variable PS1.[9]

The theory behind this variable is that it is important that the players are comfortable and familiar with their surroundings and their teammates for the team to be successful. I refer to this as the "Cohesion Effect." It is not uncommon to hear baseball analysts talk of teams trying to "buy a pennant" by signing expensive free agents and trading away young prospects for players who can help them immediately. I argue that players do not perform as well, and thus their teams don't produce wins as often, when they are unsettled and uncertain of their future, as is often the case with players who were not starters on the team in the previous year. Therefore, it might make more sense for teams not to trade away a starter for one with a little more ability (other things being equal), as the Cohesion Effect would negate a small improvement in talent. Therefore, the expected sign for this variable was positive. However, I suspected that the positive benefits of the cohesion effect tend to decline with time, and the significance of PS3 and PS5 to be less than that of PS1.

2) *The Acquisition Effect*

The acquisition variables (PFA, PML, PTR, and PMT) were defined as the percentage of starters (see Cohesion Effect) that were acquired through free agency, through minor league development, through trade, and through minor league trade.[10] A player acquired in a minor

[9] The yearly team data on games by position, games started, and saves were found in the 1997 *Total Baseball* encyclopedia.

[10] Acquisition information from various years of *The Sporting News' Baseball Almanac*

league trade is a player who was predominantly a minor league player at the time of the trade, with little or no major league experience.[11]

Obviously, not all four variables could be included at the same time in a regression because of the problem of perfect multicollinearity. Therefore, in one regression, I included three of the techniques (excluding PTR); in another I combined PML and PMT to a new variable, PMA, and once again excluded PTR; and in a third I included only PML and PFA. I also included squared values of the variables, as I suspect that the relationships may be quadratic.[12]

This set of variables was introduced to this model to test what I believe is a common misconception: that teams must sign many high-priced free agents to compete in the Major Leagues today. I believe that teams are no less productive when they have a higher percentage of players developed in their own organization.[13] I refer to this as the "Acquisition Effect." Recently, many of the wealthier organizations have been condemned for buying pennants, and small-market franchises have cried for revenue sharing, saying they cannot compete without signing the big-name, big-salary free agents. However, impartial observation show that most big-market teams developed their "core" of players in their own minor league system.[14] This is at least partially true because each organization grooms their players to fit into their particular

[11] This fourth category is included because the player will receive some of the positive benefits of having been in the team's minor league system, but not as much as one who had been in the same system his entire career.

[12] I specify these relationships as quadratic, because I believe that the best acquisition technique is probably a combination of the possible inputs. Therefore, for any single input, the productivity level (winning percentage) will increase to a certain point, beyond which it will decline.

[13] Although as expressed earlier, I do not believe this to be a purely linear relationship – at some point a mix of outside players is probably healthy to bring in foreign teachings and techniques.

[14] For a few examples: The Braves' most important players in 1996 were arguably Chipper Jones, Javy Lopez, Tom Glavine, John Smoltz, Jeff Blauser, Mark Lemke, and Mark Wohlers, all "home-grown" players. The Marlins' heroes in the 1997 World Series were Charles Johnson, Livan Hernandez, and Edgar Renteria – all developed in their young minor league system. The Yankees' stars in 1996 were Bernie Williams, Derek Jeter, Andy Pettite, and Mariano Rivera – all Yankees from day one.

philosophy.[15] Familiarity with the system and style of baseball that an organization practices logically makes its players and thus the team more successful. I argue that teams should invest more money in scouting and player development and less in free agents and high-priced veterans. I hoped for this variable to capture differences in teams based solely on their hiring practices. If the means of acquisition does, in fact, lead to a difference in performance, this variable should be positive and significant.

3) *The McCarthy Effect*

The variables to measure managerial expertise (MGM, MGW, MGT) are the number of games the manager has managed in Major League Baseball, the manager's career winning percentage, and the number of games the manager had been the manager of the given team.[16] All of the statistics were recorded for the manager for his career prior to the given season. To deal with teams for whom mid-season managerial changes occurred, each manager's statistics were weighted by percentage of the team's games he managed.

Another issue that arose was that career winning percentages became fairly meaningless when the manager managed few or no games (if a manager has never managed, it was not necessarily the case that he had no managerial talent). To deal with this effect, all managers who had less than 20 games managed were thrown into a pool – their success with their new team (that season) was recorded and averaged with the rest of the "rookie managers." From that data, a winning percentage was found and assigned to all rookie managers.[17] While individuals obviously vary immensely in their managerial ability, I believed this to be a fairly accurate way of predicting the success of an inexperienced manager in Major League Baseball.

[15] The St. Louis Cardinals, for instance, are more likely to develop players to fit into an aggressive, pressure oriented game, while the Seattle Mariners are probably more likely to develop players to fit into a line-up that tends to play for the three-run home run.
[16] Managerial data from *The Baseball Encyclopedia.*
[17] Incidentally, the winning percentage turned out to be .483, not too surprising considering that most above average teams would be reluctant to take a chance and hire an inexperienced rookie manager.

The theory behind this variable is that, holding everything else constant, the experience and talent of the manager affects the success of the team. I refer to this as the "McCarthy Effect."[18] While this seems to be a fairly logical conclusion, it is not undisputed. Scully (1974) basically dismissed the impact of the manager and coaches because the high R^2 statistics he found without its inclusion. I believe that since he looked at the player performance for the year in question and not the talent the players had displayed before being coached by their specific manager, some of the effect of the above-average managers was captured in his player talent statistics (overstating the contribution of the players). Scully's article is an academic representative of the prevailing school of thought that underappreciates good managers and overrates mediocre players.

My model includes the games managed with the given team in addition to games managed in the major leagues. The reasoning for this is that as a coach comes to know his players and their specific abilities better, he is more likely to make more successful decisions. However, I feared a high degree of multicollinearity between the two, and that one may need to be excluded from the final model.

I expected the McCarthy Effect and the corresponding variables to be positively correlated with the teams' winning percentages. The MGW variable was specified as linear, but MGT and MGM was logarithmic, as I believed them to be relationships with diminishing returns.[19]

4) *The Steinbrenner Effect*

The fourth part of my hypothesis is the effect of team payroll on success, other things held constant. This concept was captured in the variable LNPSAL, defined as the natural log of

[18] I have named this theory after Joe McCarthy, the manager with the highest career winning percentage in the modern era (.615).
[19] A manager with 10,000 games managed will probably not be twice as successful as one with 5,000.

the team payroll[20] divided by the average team payroll for the given year.[21] Team payroll was used instead of average starter salary for two reasons. To begin with, it was much easier to deal with 217 data points than almost 3000. More importantly, however, is that the focus of the study is team performance. While in some other variables starter data were used out of logistical necessity, it is more accurate to include the data for the entire team when available.

This variable was included to test another popularly accepted belief – that teams with bigger payrolls are more successful. That belief is referred to as the "Steinbrenner Effect."[22] In labor economics, this is part of the efficiency wage hypothesis. The theory is that people who are paid more than their worth are compelled to behave less selfishly than those paid less than their worth. As defined by Akerlof and Yellen (1986), "The efficiency wage hypothesis [states that] labor productivity depends on the real wage paid by the firm . . . [The theory identifies] four benefits of higher wage payments: reduced shirking of work by employees due to higher cost of job loss, lower turnover, improvement in the average quality of job applicants, and improved morale."

I question the notion that a huge payroll means a successful ball club. I argue that, given the enormous and escalating nature of players' salaries, a big contract for a player has little effect on either the job security or lifestyle of the player.[23] The superstars have begun to see the enormous, multi-million dollar contracts as status symbols rather than a means of sustenance. Therefore, when a player such as Gary Sheffield receives a record contract, his period of

[20] Team payroll data from *USA Today*, various issues.
[21] The payrolls are adjusted by year because of the tremendous increase in average team payroll in the time period being studied. In 1989, the average Major League team had a payroll of just over $14,000,000. By 1996, that figure more than doubled, to almost $32,000,000.
[22] I have named this effect after George Steinbrenner, the extremely active owner of the New York Yankees who has become a symbol of the high-spending strategy of player compensation. The Yankees perennially have the highest team payroll.

[23] Alternatively, some have argued that a big salary makes a player more likely to be terminated or traded, as teams are reluctant to sign or want high priced mediocre talent when comparable players can be found at much more affordable prices.

unselfishness is short-lived. As soon as another player (read: Albert Belle) receives a bigger contract, Sheffield is motivated to post statistics that will put him in a position to sign another record contract. As has often been demonstrated, big individual seasons do not directly equate to championship seasons for teams.[24]

Even those who support the significance of this variable do not claim it to be linearly related to winning percentage. Therefore, it was specified as logarithmic. If my hypothesis held, however, it would have been insignificant. If the Steinbrenner Effect was a real phenomenon, LNPSAL would have been positive and significant.

5) *The Controls*

The controls were the parts of regression that were mostly likely to be altered one way or another from the beginning model to the final product. I hoped to control for player talent, age, and experience, as well as the percentage of games played by the starters and expansion-related effects.

The player talent controls were by far the most complex and time-consuming of the variables. With that in mind, several alternative controls were offered, with the ones used determined through regression analysis. There were different kinds of controls for position players, for starting pitchers, and for relief pitchers.

For the position player controls I used a combination of Total Player Rating (TPR), batting average (AVG), slugging average (SLG), Production (PRO), and weighted fielding average (WFA).[25] The most important aspect of these controls to note is that they were an attempt to measure the abilities of the players independent of the other factors. For that reason, statistical

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[24] For example, Andre Dawson won the Most Valuable Player award in 1987 while leading the National League in home runs and RBIs. His team, the Chicago Cubs, finished in last place. In 1996, Pat Hentgen won the American League Cy Young Award, while winning 20 games with a 3.22 ERA. His team, the Toronto Blue Jays, only managed to edge out the lowly Detroit Tigers to avoid last place in the AL East.

data for the year in question were not used, but rather career statistics prior to the season. This was a key difference from other authors and a reason to expect my R^2 statistics to not be as high.

The weighting system for the fielding statistics was based on the percentage of attempts for each position as they occurred in a single year. 1995 was used because it was the only season for which I had complete team-by-team positional fielding statistics. There was no apparent reason why 1995 should not be representative of every season in terms of percentage of chances by position. One problem with fielding statistics, however, is that they are notoriously poor evaluators of fielding ability. The fielding average, from which the WFA was derived, is the number of accepted chances divided by the number of total chances. This statistic rewards players with "good hands," rather than those with great mobility. Unfortunately, I was forced to use the WFA statistic for lack of a better alternative.

The Total Player Rating (TPR) recorded was the sum of the teams' players in year (t-1). Since TPR was a cumulative statistic, I did not use career totals because of multicollinearity problems with experience. The other offensive statistics (AVG, SLG, PRO) were team averages of the players' career totals prior to the given year.

Similar to rookie managers, players with few or no at-bats in the Major Leagues would have skewed the data set, so they were thrown into a pool. For the cut-off for inclusion in this pool, I decided to use the same amount of at-bats that the Baseball Writers Association of America uses as the guidelines for consideration for the Rookie of the Year Award (130 at-bats). Instead of throwing all players into the same pool, however, I chose to distinguish between the average performance of different positions. One would not expect a rookie second baseman to produce the same kind of statistics as a rookie first baseman or center fielder. As with the

[25] For the statistical definitions of the terms, consult Appendix A, which can be found after the conclusion.

managers, though, rookies (by position) were assigned an average level at which they were expected to produce.

For the pitcher control statistics, I used the same ones for starting and relief pitching, although they were separated as different variables. The variables I used for pitchers was a combination of Total Pitcher Index (TPI), earned run average (ERA), strikeout to walk ratio (SOB), walks plus hits per nine innings (BBH), and strikeouts per nine innings (SO9). Since the AL pitchers were forced to face an extra hitter in the lineup (the DH), their statistics were typically worse than those in the NL. Considering the structural difference between the leagues and the fact that AL pitchers did not directly compete against NL pitchers (until 1997), it seemed fair to consider pitching talent for each league separately. Therefore, all pitching statistics, except TPI (which is already deflated), were related to the yearly league-specific average.

TPI was treated the same way as TPR was for the hitters, and with the exception of the yearly averages, the rest of the pitching controls were treated the same way as the offensive hitter statistics. Rookie pitchers[26] were dealt with slightly differently than their hitting counterparts, however. For the reason stated above, rookie pitchers were separated by league. Additionally, it is consistently argued that expansion causes a "thinning of the pitching talent," meaning that pitchers that may otherwise be developing in the minor leagues or working in the bullpen are forced into starting roles. A simple comparison of rookie pitcher performance before and after expansion supported this argument.[27] In light of this, I decided to distinguish between pre-expansion and post-expansion rookies.

Two other important controls included in my model were intended to capture the effects of age and experience on team performance. This area has been studied fairly well, and previous

[26] Rookie pitchers are defined by the BBWAA as those with less than 50 innings pitched.
[27] ERAs, for example: NL pre-EXP = 3.86, post-EXP = 4.09; AL pre-EXP = 4.07, AL post-EXP = 5.14

authors agreed that talent peaks at about age 27.[28] The experience factor (number of games played in Major League Baseball) was expected to be logarithmic, while the age factor (average player age at opening day, to the nearest half-year) was quadratic. The age and experience variables should account for the fact that younger players' career statistics tend to understate their talent, and older players' career statistics may speak of talent that has lessened.

Another important control was that of percentage of games played by the position players (HGA) and percentage of games started by the top 4 in the pitching rotation (PGA). This was key because it accounts for injuries that may keep a very talented team from having its best players on the field in any given game. The final control was for non-expansion teams in an expansion year (EXP). This was expected to be positive, as expansion teams are generally not at the same competitive level in their first year of play.

As noted earlier, the variety of controls offered a large degree of flexibility in the specification of the model. The final set of variables was not determined until after regressions and tests were run. It was with this in mind that the data sample was halved to avoid data mining.

THE RESULTS

With my data set halved, I began running a series of regressions to find the best-fitting model (with judgement based on adjusted R^2 statistics, t-statistics, and F-statistics). I ran the regressions in five stages. First, I included all of the independent variables in the model and tested each control (i.e. hitter performance statistics) until I found the best-fitting combination. After that, I experimented with the specification of a variable group I was unsure of. Next, I looked at the coefficients of the variables, taking special note of their signs, and compared them to what I expected. If variables had unexpected signs, I tried to determine if the reason for that outcome

[28] See Krohn, 1983 and Schultz, Musa, and Staszewski, 1994.

was a real-world phenomenon or a function of the model specification. To address issues of multicollinearity, I ran auxiliary regressions (and compared their adjusted R^2 results to that of the overall model) and interpreted the pair-wise correlation matrix. When problems arose, I re-evaluated my model and made changes where necessary. Finally, I applied my model to the other half of the data sample and examined those results. [29]

The results on the untainted half were, as could be expected, not as strong as on the first half. However, the results of this regression were very telling about the nature of team organization and success in Major League Baseball. In addition to the ordinary least squares estimation, I ran auxiliary R^2 regressions and a pair-wise correlation matrix. The results of this final regression and the auxiliary regressions are shown in figure 1.0.

Figure 1.0

OVERALL MODEL:

Adjusted R^2	F-Statistic	P-Value	n
0.4547	5.958	0.000	108

BY VARIABLE:

Variable Group	F-Test (p-value)	Variable	Coefficient	t-statistic	P-value	Aux R^2
Cohesion Effect	1.993 (0.142)					
		PS1	0.0551	1.537	0.128	0.372
		PS5	-0.0841	-1.357	0.178	0.443
Acquisition Effect	0.657 (0.684)					
		PFA	0.0073	0.061	0.952	0.907
		PML	0.0335	0.236	0.814	0.944
		PMT	-0.1300	-0.794	0.429	0.903
		PFA2	0.0244	0.103	0.918	0.906
		PML2	-0.1143	-0.635	0.527	0.943
		PMT2	0.4853	0.873	0.385	0.898
McCarthy Effect	0.044 (0.834)					
		MGW	0.0270	0.210	0.834	0.327
Steinbrenner Effect	1.646 (0.203)					

[29] Again, a much more thorough discussion of the manipulation of the model was included in the original thesis.

Controls	lnPSAL	0.0278	1.283	0.203	0.588
	TPI	0.0030	2.143	0.035	0.357
	RSO9	0.0007	0.202	0.841	0.224
	TPR	0.0036	3.363	0.001	0.272
	WFA	-0.0275	-0.296	0.768	0.075
	EXP	-0.0192	-0.974	0.332	0.092
	GML	-0.0000	-1.247	0.216	0.659
	HGA	0.2617	2.487	0.015	0.204
	PGA	0.8896	3.332	0.001	0.248

Obviously, some variables acted more like I had expected than others. The player salary and player turnover statistics (LNPSAL, PS1 and PS5) behaved very much like I had anticipated. The experience variable, GML, reflected the same pattern that was shown on regressions of the first half of the data sample. HGA, PGA, TPR and TPI also reflected earlier trends. The other variables, however, were not quite as close to the expected results.

The acquisition variables (PFA, PML, PMT), all became extremely insignificant. The MGW variable was the sign I had originally anticipated, but was no longer of any real significance. For an unexplainable reason, the relief pitchers' talent statistic, RSO9, also became extremely insignificant. Finally, the EXP and WFA variables also presented questionable results.

The overall explanatory power of the model was less than the preliminary regressions, but the F-statistic was strong enough to reject the null that the model was equal to zero beyond the 99.9% level. Serious issues of multicollinearity seemed to have been dealt with for the most part, as the auxiliary regressions and pair-wise correlation matrix showed no extremely significant relationships.

To look at what the results of the regression say about my hypotheses, I will address each variable group and their corresponding effects.

The Cohesion Effect

In my model, the Cohesion Effect, or the phenomena that Major League teams win more often with less change in their starting players from one year to the next, was captured by the variables PS1 and PS5. PS1 and PS5 were defined as the percentage of starters (position players and pitchers) who were starters on the same team in the previous year and five years prior to the current year (respectively). The hypothesized sign was positive, because of the Cohesion Effect. The results of the regression showed that PS1 was indeed positive, and fairly significant (at an 88% level). The PS5 statistic yielded interesting results, however, as its coefficient was *negative* and significant. This could be indicate that *not enough* turnover for a team over a five year period means no influx of new, younger talent – and the team is not as successful.

According to the results, all else constant, a one-percent increase in the number of starters kept in the line-up or rotation from one year to the next will lead to a .0005 increase in a team's winning percentage. In terms more relevant to the subject matter, one additional player being retained in the starting line-up from one year to the next will, on average, lead to a increase of .004 on the teams' rate of success. While this effect may seem relatively minor, maintaining an entire line-up and pitching rotation as opposed to completely changing them makes an average of a .056 change in the team's performance (nine games). That amount is large enough to alter the outcome of most of the pennant races in the evaluated time period. The Cohesion Effect, at least in the short-term, appeared to be a very real phenomenon.

The Acquisition Effect

The Acquisition Effect was an examination of the recent trend to hire players through the free agency market, as opposed to developing them through a team's own minor league system. This effect was represented in my model by the variables PFA, PML, PMT, PMT2, PML2, and PFA2. PFA, PML, and PMT are defined as the percentage of starters that were acquired through the free agency market, minor league system, and minor league trade, respectively. PMT2,

PML2, and PFA2 are the squares of PMT, PML, and PFA, respectively. The squared terms were included in the model, with support from the first data sample, to illustrate the quadratic nature of this relationship.

However, as the analysis of the second data set illustrated and as Krautman (1994) found, there was extremely little relationship between the way the players were acquired and the teams' winning percentages. This runs contrary to the popular current belief in the Major Leagues that has made smaller market teams feel they cannot compete without the ability to sign expensive free agents.

The McCarthy Effect

The McCarthy Effect is the hypothesis that the individual talents of managers affected the performance of their teams. In my model, it was represented by MGW, the managers' winning percentages going into the season in question. I expected it would be positive, as I thought that the managers' ability levels would have significant effect on teams' performances. However, the results did not support this hypothesis.

While I did, in fact, see a positive relationship (unlike prior regressions), the results could not reject the null of the relationship being equal to zero with any level of certainty. This could have occurred for a couple of reasons. The first possibility is that managers do not, in fact, perform a very significant function in Major League Baseball. Since the players are called upon to perform, and the manager just puts the best players in the line-up as often as possible, the success of the team does not rely on the ability of the manager.

The other possibility, and the one I am more inclined to believe, is that the talent of managers was not captured nor isolated enough in my model. The managers' past winning percentages are a very simple measure of the managers' abilities and dependent on the talent of the players they had coached before. Also, if the player talent control statistics are not excellent

measures of the true talents of the players (which I suspect), the managerial effect would not be very well isolated.

The lack of isolation of the managers' talents may have also been due to the fact that the talent statistics used were the player ratings from the previous year. Considering that most baseball players do not change teams from one year to the next, and most managers stay with a team for more than one year, the players' previous year statistics were already affected by the ability of the manager. My variable would only look at how much *better* the manager made a player perform than he had made the same player in the *previous year* – not an entirely fair evaluation of coaching ability.

For these reasons and with a lack of statistical evidence, I withhold judgement on the McCarthy Effect. More research may shed more light on the contribution of managers.

The Steinbrenner Effect

The last of my four-part hypothesis was the Steinbrenner Effect, or as labor economists refer to it, the efficiency wage hypothesis. This states that, controlling for everything else, players that are paid more will be more productive. In my model, I attempted to capture this phenomenon with the variable LNPSAL, defined as the natural log of the teams' payrolls relative to other teams in the same year. While defining the variable this way was necessary because of inflating salaries, it made the variable lose some of its interpretive ability.

LNPSAL was found to be positive and significant in my regressions (at the 80% level). This could have occurred for two reasons. The first explanation is that my model captured the effect I was hoping it would explain. This would mean that teams with more money would possess a competitive advantage, because to get more out of their players they would need only to pay them more. However, I suspect that a second explanation is more likely. Considering that the primary determinants of player salary (and thus team payroll) are experience and talent, I would

need to control for those two factors to fully isolate the Steinbrenner Effect. I fear that my controls did not account for as much as I had hoped, and thus some of the player talent was captured in the LNPSAL variable. This would make the variable seem more positive and significant than it may be in reality.

Regardless of the explanation, the results did show a positive and fairly significant relationship here, and the inclusion of the variable seemed necessary. This supports small market claims that it is difficult for teams with smaller payrolls to compete with those without as much financial constraints. The Steinbrenner Effect appears to be a real phenomenon.

Controls

The most important controls came out almost exactly as I had expected. HGA, PGA, TPR, and TPI were all extremely significant and positive (all were significant at the 97% level). The results of the other controls, while less significant, were somewhat surprising.

I had expected that as the average amount of experience increased for a team, the team would be more successful. However, the results of the regressions show that GML, the average number of games in the major leagues, was significant and negative. This means that all else being equal, a less experienced (and probably younger) team will be more successful. This could in part be due to the nature of the baseball season. The baseball season is extraordinarily long, and mostly takes place in the hottest times of the summer. It is not uncommon for the performance of talented players to fade as the season progresses for no other reason than physical and mental exhaustion. Younger, more vibrant players are probably better able to handle the grueling summer and to help their teams win more. So, if two teams of identical talent, make-up, payroll, etc are competing against each other, the less experienced (and more importantly younger) players will win more often.

The variable used to capture relief pitchers' contributions produced a much less explainable result. RSO9, the relief pitchers' strikeouts per nine innings pitched, was expected to be positive, and it was. However, in the untainted data set the variable lost most of its significance. The only possible explanation that I can offer is that the variable did not capture what I had hoped. In future studies, a different variable to reflect the contribution of relief pitchers should be used.

The EXP variable, positive and significant in preliminary regressions, also changed signs and lost significance. This suggested that all else being equal, teams are less successful when they are a non-expansion team in an expansion year. The surprising outcome of this regression may in part be due to the strength of other independent variables. If the other exogenous factors accurately captured the reason why expansion teams are typically bad performers, than this variable would not be of very much significance.

The final control variable, weighted fielding average (WFA) was also insignificant and of the wrong sign. The weakness of fielding measures was addressed earlier, and the lack of solid results for this variable are probably a reflection of that.

CONCLUSION

The testing of my hypotheses produced mixed results, but the outcomes were for the most part as expected. The Cohesion Effect (that Major League Baseball teams will tend to win more often when the amount of change in their starting line-up and pitching staff is minimized from one year to the next) appeared to be a real phenomenon, as the PS1 variable was both positive and significant. The insignificance of the free agency variables helped support the Acquisition Effect (that teams that sign a higher percentage of their players from the free-agency market are not necessarily more productive). The McCarthy Effect (that managerial expertise has a positive and

significant effect on a team's success) was not supported by the data, but that may have been due to the weakness of the managerial talent variable, MGW. The Steinbrenner Effect (that, other things equal, teams with bigger payrolls will be more successful) and thus the efficiency wage hypothesis was somewhat supported – contrary to my original hypothesis.

These results shed some light on issues that have been disputed by the popular press and baseball personnel recently. I believe this study has contributed two significant findings to the current baseball discussion. Firstly, teams should no longer complain about the necessity and unaffordability of signing free agents to compete in the big leagues. The results show that they are not vital to a team's success. Secondly, teams should focus on keeping their line-up as intact from one year to the next as they can, as cohesion breeds victories.[30]

Successful organizational strategies are more complex than simply buying talent. Teams like the Montreal Expos have shown that it is not impossible for small market clubs to compete with their more wealthy peers. I hope that the current owners and general managers of baseball will operate based on the realities of their industry and not on the flawed conventional wisdom that has victimized the industry of late.

Professional baseball offers a wealth of information on an amazingly diverse variety of subjects. I hope that shortcomings in my model are explored and developed further in future research. More explanatory controls would have been extremely helpful, and current statistical experimentation is starting to offer alternatives. Better measures of managerial talent and fielding ability would have made my model much stronger. It may be very interesting for a researcher to apply my model, or one similar to it, to the data for entire teams – not just the starters. The direct impact of specific general managers may even be an interesting study. The baseball industry has not suffered from a lack of scholarly interest. New statistical and analytical techniques make the

explanatory power of models much stronger and their specifications more complex. With each study, we learn a little bit more about the intricacies of our national pastime.

[30] Unfortunately, for teams to keep their line-up intact from year to year they are often forced to pay higher salaries to their players to deter them from entering the free agent market. This is yet another explanation (from the wage efficiency theory) of why teams with higher payrolls may be more successful.

APPENDIX A -- VARIABLE REFERENCE SHEET

ABBH: Average League Adjusted career walks plus hits per 9 innings for starting pitchers

AERA: Average League Adjusted career Earned Run Average for starting pitchers

AGE: Average Age of all players

ASO9: Average League Adjusted career strikeouts per 9 innings for starting pitchers

ASOB: Average League Adjusted career strikeout to walk ratio for starting pitchers

AVG: Average career Batting Average for non-pitchers

EXP: Dummy for being a non-expansion team in an expansion year

GML: Average games played in MLB for non-pitchers

HGA: Average % of games in year (t) played by non-pitcher starters

IPML: Average innings pitched in MLB by pitchers

MGM: Number of games managed in MLB by manager

MGT: Number of games managed with given team by manager

MGW: Manager's career winning percentage

PFA: % of players acquired through free agency

PGA: Average % of games in year (t) started by starting pitchers

PMI: % of player acquired via the minor leagues or through minor league trade

PML: % of players acquired through the minor leagues

PMT: % of players acquired through minor league trade

PRO: Average career Production for non-pitchers

PS1: % of players that started on the same team 1 year before

PS3: % of players that started on the same team 3 years before

PS5: % of players that started on the same team 5 years before

PSAL: Team payroll divided by yearly average team payroll

PTR: % of players acquired through major league trade

RBBH: Career walks plus hits per 9 innings for relief pitchers

RERA: Career Earned Run Average for relief pitchers

RSO9: Career Strikeouts Per 9 innings for relief pitchers

RSOB: Career strikeout to walk ratio for relief pitchers

SLG: Average career Slugging Average for non-pitchers

TPI: Sum of Total Pitcher Indexes in year (t-1) for starting pitchers

TPR: Sum of Total Player Ratings in year (t-1) for non-pitchers

WFA: Career Weighted Fielding Average for non-pitchers

WIN: Team winning percentage in year t

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