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The *Moneyball* Anomaly and Payroll Efficiency: A Further Investigation

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Abstract

In our 2006 paper, we examined the implications of Michael Lewis' book for the labor market in Major League Baseball. Our tests provided econometric support for Lewis' claim of mis-pricing in the baseball labor market's valuation of batting skills. We also found suggestive evidence that the dispersion of statistical knowledge throughout baseball organizations was associated with a sharp attenuation of the mis-pricing. This paper takes a closer look at the economic issues raised by Lewis for the baseball labor market. We extend the sample both backward and forward in time, seeking to determine how long the pricing anomaly existed, and whether the recent attenuation in the anomaly is robust to new observations. In addition, we refine the measures of skill used in our tests to more closely match the narrative account in Lewis' book. Using both our earlier and refined measures, we find that the pricing anomaly extends well before the period described in *Moneyball*, and that with some important caveats, the market correction in the post-*Moneyball* period persists. Finally, improvements in personnel management associated with a closer link between pay and performance may be responsible for the sharply increased correlation between winning percentage and payroll in recent years.

Keywords: market dynamics and equilibrium, baseball salaries, pay and productivity, managerial cost-effectiveness

Introduction

Michael Lewis' *Moneyball* was an illuminating account of an innovative and successful sports organization. The book touched a nerve among people in a variety of business professions, the collection of papers in this volume providing ample evidence of that. But the content of the book poses challenges, too, particularly to the academic discipline of economics.

At the heart of the *Moneyball* story is the claim that, for the five-year period 1999-2003, the Oakland A's successfully exploited mis-pricing of skill in the labor market for baseball players. The book makes a compelling narrative case to support this claim. As social scientists, however, we recognize that the proposition of mis-priced skills in the labor market can be cast in a framework that can be formally tested. Our recent paper, *An Economic Evaluation of* *the Moneyball Hypothesis*, conducted these tests. We found that the *Moneyball* hypothesis withstood close scrutiny. Specifically, in the period covered by Lewis' book, one element of batting skill—the ability to get on base, and thus avoid making an out—was under-priced in the baseball labor market. Intriguingly, however, we found evidence that the mis-pricing vanished in the final year of the period for which we had data (2004). A tentative conclusion based on this analysis is, that the value in the A's strategy, like many innovations, depended on there being no (or few) imitators. Once the value of reaching base is revealed, then price adjustment would nullify the effectiveness of a strategy based on under-priced skill.

On its own terms then, the *Moneyball* hypothesis is consistent with the data from the period described in the book. But two questions remain: First, was the adjustment in returns to skill observed at the end of the period in our earlier paper robust? Are subsequent seasons consistent with mis-pricing or efficient pricing? Second, while Lewis focuses his argument on the seasons around the turn of the century, how far back did the alleged mis-pricing extend?

In this paper we extend the sample period backwards and forwards in time to address the question of the extent of the mis-pricing, and the robustness of the claim that knowledge of the value of getting on base erased the anomaly beginning in 2004. In addition, rather than focusing on the stat du jour ("OPS") we break down batting skills further into components that more directly address the strategies used by the A's in fashioning their remarkable run of success. This refinement allows the data to clearly demonstrate that the returns to "plate discipline" (i.e., the ability to avoid swinging at bad pitches) were persistently under-valued long before the period discussed in Lewis' book.

An Extension of the Basic Test of the *Moneyball* Hypothesis

In a baseball game, scoring takes place in discrete sequences of play called innings. Scoring runs can be accomplished in a variety of ways, but opportunities to score in an inning cease immediately once three outs are made. Each out is thus a precious item to an offense (i.e., the team "at bat") to be preserved. Careless outs are costly in that they sharply truncate the probability distribution of runs scored in an inning. Lewis argued in *Moneyball* that the Oakland A's organization was unique among baseball clubs in that it employed statistical knowledge of this characteristic of the game, and built a financial and competitive strategy around it. Specifically, other clubs' relative ignorance of this issue left an important batting skill under-priced: the simple ability to get on base and avoid making an out.

Although other skills impact the game, two statistics explain the bulk of the variance in winning percentage across teams: the team's on-base percentage and its slugging percentage, relative to the same percentages it allows for its opponents. In the 1999-2004 period spanned by our 2006 paper and Lewis' book, the marginal impact of on-base percentage is about twice that of slugging percentage.

We explore a much longer period in this paper, from 1986-2006. Our basic model estimates the productivity of wins resulting from each of the skill components of a team. When the skill components of a team's offense are measured with on-base and slugging, a team's defense can be thought of as the reduction of those quantities for one's opponent. An equation for a team's winning percentage (WinPct) can be estimated with the following regression:

$$WinPct = a1 + b1(OBP) + b2(Slug) - b1'(OBP\_opp) - b2'(Slug\_opp) + e \quad (1)$$

where e is a random error term, and OBP and Slug are its on-base and slugging percentage. OBP_opp and Slug_opp are the on-base and slugging percentage that a team allows its opponents (i.e., a measure of its inability to prevent the other team from scoring). In all cases we estimated unrestricted versions of equation (1) along with the restricted version in which b1 = b1' and b2 = b2'. This restriction imposes the reflexive property that a team's ability to score and its inability to prevent its opponent from scoring are equally important. The hypothesis (b1 = b1', b2=b2') is not rejected by the data for all models and periods estimated in this paper. Hence, parsimony and simplicity leads us to concentrate on results obtained from the restricted version.

While on-base and slugging are the standard measurements of avoiding outs and hitting for power, they also pose an empirical and a theoretical problem. Because hits help increase both statistics, there is a strong built-in correlation between the two.[1] As singles (one-base hits) have a very similar impact on both statistics, there is a classic multicollinearity problem where productivity of singles might falsely be attributed to the "wrong" category or otherwise mismeasured.

This empirical problem can be addressed by considering the ability to make contact, or hit for average, as a separate hitting skill. Following this line of thought, we use three sabermetric statistics to measure independent components of hitting. First, while it's not quite true that "a walk is as good as a hit," by displaying patience at the plate, the player can get on base through walks or hit-by-pitches, both avoiding an out and helping the team's scoring chances without swinging the bat. This component, which closely matches Lewis's idea of the skill the A's were seeking as an undervalued input, can be measured with (BB+HBP)/PA, where BB is bases on balls, HBP is hit-by-pitches, and PA is the total number of plate appearances.[2]

In addition to refraining from swinging at bad pitches, the second theoretical component of hitting is, in Wee Willie Keeler's words, to "hit 'em where they ain't." We isolate this component with the traditional batting average, hits over at bats.[3]

The third component of hitting recognizes that extra-base hits are better than singles. Rather than using slugging percentage, which includes outs in the denominator and thus biases the statistic to correlate with batting average, we adopt a variant of the sabermetric statistic of isolated power. This simply measures the average number of bases per hit.[4]

This framework, in addition to coinciding nicely with the traditional categories of "tools" sought by baseball scouts, uses statistics that greatly reduce the empirical problems created by the high correlation between on-base and slugging.[5] When applied to our team productivity model, the resulting regression is:

$$\text{WinPct} = a2 + b3(\text{Eye}) + b4(\text{Bat}) + b5(\text{Power}) - b3'(\text{Eye\_opp}) - b4'(\text{Bat\_opp}) - b5'(\text{Power\_opp}) + e$$
$$\text{s.t.: } b3 = b3';\ b4 = b4';\ b5 = b5' \quad (2)$$

The sample used in our analysis covers the 1986 through 2006 seasons, with the starting year coinciding

Table 1. Average Values of Team Offensive Statistics, by Time Period

	All years	1988-1993	1994-1997	1998-2003	2004-2006
On-Base Percentage	0.332	0.324	0.338	0.337	0.334
	(0.0006)	(0.0008)	(0.0013)	(0.0011)	(0.0012)
Slugging Percentage	0.412	0.389	0.422	0.426	0.426
	(0.0012)	(0.0017)	(0.0025)	(0.0020)	(0.0023)
Power	1.562	1.507	1.572	1.600	1.598
	(0.0031)	(0.0044)	(0.0057)	(0.0045)	(0.0064)
Eye	0.096	0.093	0.099	0.099	0.094
	(0.0004)	(0.0007)	(0.0009)	(0.0008)	(0.0012)
Batting Average	0.264	0.258	0.268	0.266	0.267
	(0.0005)	(0.0007)	(0.0010)	(0.0009)	(0.0009)
Observations	587	205	112	180	90

Notes: Standard error of means in parentheses. On-base percentage is the ratio of times on base by hit, walk or hit by pitch over total plate appearances. Slugging percentage is the ratio of total bases over at bats. Power measures total bases per hit. Eye is ratio of walks and hit by pitch over plate appearances. Batting average is hits per at bat.

Data Source: Retrosheet Game Logs, www.retrosheet.org. The data were obtained free of charge from, and are copyrighted by Retrosheet, 20 Sunset Rd., Newark, DE 19711.

with the earliest reliable salary data available. The most likely potential sources of structural changes during this period would be the league expansion—from 26 to 28 teams in 1993, and then to 30 teams in 1998—and the introduction of a third level of divisional playoff games in 1994. As the proximity of the 1993 and 1994 changes would leave a subsample of only one year, we make only one structural break, coinciding with the latter because the strategic effects from doubling of the number of play-off teams would likely influence team decisions more than the thinned talent pool from franchise expansion. Also anticipating the salary regressions to come, we look

Table 2. Productivity Estimates

Panel A – The Impact of On-Base and Slugging Percentages on Winning					
	All years	1986-1993	1994-1997	1998-2003	2004-2006
Constant	0.500	0.500	0.500	0.500	0.500
	(0.001)	(0.002)	(0.003)	(0.002)	(0.003)
On-Base	2.156	2.264	1.805	2.103	2.367
	(0.102)	(0.187)	(0.240)	(0.171)	(0.234)
Slugging	0.820	0.931	0.766	0.855	0.766
	(0.060)	(0.118)	(0.132)	(0.098)	(0.145)
β(OBP)/β(Slg)	2.63	2.43	2.36	2.46	3.09
Observations	587	205	112	180	90
R^2	0.818	0.767	0.792	0.879	0.822

Panel B – The Impact of Separable Hitting Skills on Winning					
	All years	1986-1993	1994-1997	1998-2003	2004-2006
Constant	0.500	0.500	0.500	0.500	0.500
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
Eye	1.751	1.792	1.880	1.529	1.974
	(0.090)	(0.170)	(0.229)	(0.152)	(0.188)
Bat	2.986	3.288	2.357	3.217	2.904
	(0.085)	(0.165)	(0.175)	(0.136)	(0.221)
Power	0.255	0.269	0.275	0.230	0.278
	(0.018)	(0.038)	(0.038)	(0.029)	(0.045)
β(Eye)/β(Bat)	0.59	0.55	0.80	0.48	0.68
β(Eye)/β(Power)	6.9	6.7	6.8	6.6	7.1
Observations	587	205	112	180	90
R^2	0.824	0.769	0.814	0.880	0.839

Notes: Data are aggregate statistics for all team-seasons from 1986-2006. Coefficient estimates obtained using OLS. Standard errors are in parentheses. Each model also included opposing team value of each variable; the coefficient was restricted to equal its counterpart in the regression.

F-statistic for Chow test hypothesis that pooling of time periods is appropriate in Panel A is 0.89. F-statistic for Chow test hypothesis that pooling of time periods is appropriate in Panel B is 0.98.

Data Source: See Table 1.

for a structural break caused by the *Moneyball* correction noted in the 2006 paper, which would occur after the 2003 season. These breakpoints combine to create four time periods within our larger sample: 1986 to 1993; 1994 to 1997; 1998 to 2003; and 2004 to 2006.

Table 1 reports the average values of the offensive statistics used in equations (1) and (2) for the team-seasons in our sample and within each time period. We report the standard errors of these means to show that the level of offense during the 1988-1993 period was somewhat lower than in later years. There is also an upward trend in extra-base hitting noticeable in both the reported slugging percentages and the isolated power means. These differences are statistically significant, but they are of small magnitude and do not adversely affect the regression analysis.

The regressions of team productivity are displayed in Table 2, with Panels A and B reporting the results from equations (1) and (2), respectively. The Panel A results constitute an extension of the analysis in the 2006 paper, where we estimated the coefficient for on-base at 2.032 and the coefficient for slugging at 0.900 for the years 1999 through 2003. All of the estimated coefficients are statistically different from zero at the 99% confidence level. While there is some variation in the magnitude of each coefficient across the four periods, the ratio of the relative productivities is relatively stable, ranging from 2.4/1 to 3.1/1. A Chow test for structural stability fails to reject the null hypothesis that the coefficients on the variables remain constant across time periods. Even so, the increase in the ratio of the productivity of on-base to slugging in the years 2004-2006 from 2.46 to 3.09 should be noted, as that might explain at least some of the recent increase in attention (and payroll) devoted to plate discipline.

The use of the less correlated hitting skills to estimate production of wins in Panel B results in a very slightly improved overall goodness of fit, but more interesting details concerning the relationships between inputs. The relationship between plate discipline and power is very stable throughout the sample in the 6.6 to 7.1 range, but the ratio of the coefficients for plate discipline (Eye) and batting average (Bat) fluctuates more widely (in terms of coefficient of variation), as the ratio ranges from 0.48 to 0.80. These variations, however, do not follow a systematic time pattern and the Chow test fails to reject the null hypothesis of structural stability. As in the previous models, all coefficients are statistically significant at the 99% confidence level.

Labor Market Returns to Skill

The regression estimates discussed in the previous section show the relative contribution of OBP to winning is about twice that of Slugging, for the sample as a whole, and in every sub-period as well. They also estimate the relative value of hitting for average, hitting for power, and drawing walks. and confirm that each is a significant input to winning games. The crucial economic question is whether the returns to skill in the labor market reflect the relative productivity of these skills in producing wins for the team.

Our labor market model estimates position player salaries as a function of hitting ability, defensive skills as roughly indicated by their position on the field, playing time, freedom to contract, and changes in the level of player salaries. More specifically, we will estimate the regression:

$$\ln(\text{salary}) = \alpha + \beta'\text{Hitting} + \gamma'\text{Pos} + \delta'\text{PA} + \zeta'\text{Contract} + \eta'\text{Year} + \varepsilon \quad (3)$$

The dependent variable is the natural logarithm of salary, Pos represents indicator variables for infielders (here meaning second base, third base, or shortstop) and catchers, PA is plate appearances, Contract represents indicators for free agents and arbitration-eligible players, and Year is a set of indicators to control for annual fixed effects due to changes in overall player demand, and other season-specific phenomena. As in our productivity models, we have two sets of Hitting variables. The first model will measure the salary returns to on-base and slugging, while the second will measure returns to batting average, isolated power, and the "Eye" measure of plate discipline. Our use of the log form means that the coefficients will measure returns to skill as a percent of salary for a representative player. In an efficient labor market these returns should match the impact of the skill on winning games.

The unit of observation for the labor market models estimated with equation (3) is the player-season. For a player-season to be included, a position player's salary in year t had to be coupled with hitting statistics in year $t-1$ covering at least 130 at bats.[6]

Panel A of Table 3 shows the results of estimating equation (3) using on-base and slugging as the measures of hitting skill. We report only these coefficients as the control variables are not the focus of our analysis. Unlike the productivity models, where the productivity of on-base and slugging were both clearly estimated as significantly positive, the coefficient for on-base percentage in the early years is not statistically different from zero. While the returns to slugging are relatively stable over the length of our sample, the returns to on-base percentage increase dramatically over time, with the coefficient more than doubling between the 1986-1993 and 1994-1997 periods, and more than doubling again between 1998-2003 and 2004-2006. Expressed as a ratio to the slugging coefficient, the effect of a one-point change in on-base percentage increases from a salary impact 0.27 times as much as a point of slugging percentage in the early time period to 1.37 times as much in the most recent time period.

Although Panel A of Table 3 shows that returns to on-base percentage have increased, the aggregation of walks and hits (and hit-by-pitches) in on-base percentage makes it difficult to conclude whether the market is valuing the avoidance of outs in general, or walks more specifically. The regression results in Panel B of Table 3 show that *all three* components of hitting are more valued in 2004-2006 than they were in 1986-1993, and all three coefficients increased sharply in magnitude from 1986-1993 to 1994-1997. Even so, the time trends in market valuation of the skills differ. The traditional scouting "tools" of hitting for average (Bat) and hitting for power

Table 3. Estimated Labor Market Valuations of Skills

Panel A – On-Base and Slugging Percentage	All Years	1986-1993	1994-1997	1998-2003	2004-2006
On-Base	1.29	0.49	1.14	1.39	3.36
p, if not <.005		(0.137)	(0.059)	(0.006)	
Slugging	2.37	1.84	2.60	2.42	2.44
R^2	0.75	0.77	0.71	0.73	0.65
Observations	6761	2402	1254	2087	1018

Panel B – Separable Hitting Skills	All Years	1986-1993	1994-1997	1998-2003	2004-2006
Eye	1.83	0.82	1.38	1.98	4.00
		(0.007)	(0.011)		
Bat	3.92	2.76	4.52	4.09	4.82
Power	0.662	0.490	0.715	0.705	0.746
R^2	0.75	0.77	0.71	0.73	0.65
Observations	6761	2402	1254	2087	1018

Notes: The dependent variable is ln(Salary) for year t, and performance variables are from year $t-1$. Each model includes control variables for plate appearances, free agent eligibility, and arbitration eligibility, plus indicator variables for infielders and catchers, and fixed effects for year. The samples include all players with at least 130 plate appearances during the relevant seasons. P-values shown in parentheses when greater than 0.005.

Data Source: Lahman database, version 5.4.

(Power) have had relatively constant market returns since the beginning of the wildcard period in 1994. Returns to plate discipline (Eye), by contrast, increased significantly each period and overall increased nearly five-fold, whereas the returns to a one-point increase of Bat and Power jumped by "only" about 75% and 52%, respectively.

The relative increase in returns to patience can more easily be seen by calculating ratios of the coefficients in Panel B of Table 3. While the relative returns to Bat and Power were roughly constant throughout the sample, the ratio of the coefficients of Eye over Power more than tripled, from 1.67 in 1986-1993 to 5.36 in 2004-2006. Similarly, the ratio of the coefficients of Eye over Bat increased 177% between the earliest and latest period, from 0.30 in 1986-1993 to 0.83 in 2004-2006. This supports the *Moneyball* hypothesis that it was *walks* in partic-

Table 4. MLB Labor Market Valuation of On-Base and Slugging Percentage

Panel A – Mean and Standard Deviation of Salary and Skills	All Years	1986-1993	1994-1997	1998-2003	2004-2006
Salary ($m),	2.02	0.89	1.75	2.76	3.53
arith. mean	(2.76)	(0.93)	(1.87)	(3.13)	(4.22)
ln(salary)	13.77	13.21	13.73	14.15	14.35
	(1.25)	(1.01)	(1.20)	(1.25)	(1.25)
Salary ($m),	0.96	0.55	0.92	1.40	1.71
geo. mean					
On-Base Pct.	0.336	0.328	0.341	0.341	0.338
	(0.040)	(0.038)	(0.041)	(0.041)	(0.038)
Slugging Pct.	0.418	0.395	0.425	0.433	0.433
	(0.079)	(0.070)	(0.081)	(0.083)	(0.074)
Power	1.561	1.514	1.561	1.594	1.604
	(0.220)	(0.212)	(0.223)	(0.220)	(0.213)
Eye	0.096	0.093	0.098	0.100	0.096
	(0.035)	(0.034)	(0.036)	(0.036)	(0.035)
Batting Avg.	0.268	0.261	0.272	0.271	0.270
	(0.032)	(0.031)	(0.033)	(0.032)	(0.029)

Panel B – Expected Salary Increase From a One Standard Deviation Increase in Hitting Skills, as Percent of Geometric Mean Salary Value of std dev increase (%)	All Years	1986-1993	1994-1997	1998-2003	2004-2006
On-Base	5.2	1.9	4.7	5.7	12.8
Slugging	18.7	12.9	21.1	20.1	18.1
Power	13.7	9.3	14.8	14.8	16.0
Eye	6.4	2.8	5.0	7.1	14.0
Bat	12.5	8.6	14.9	13.1	14.0

Notes: The samples include all players with at least 130 at bats during the relevant seasons. Standard errors are in parentheses in Panel A.

Data Source: Lahman database, version 5.4.

ular that the Oakland A's could purchase relatively cheaply during the earlier periods in the player market. The growing returns to on-base percentage, and to walks in particular, are sufficiently large that the Chow tests reject the null hypothesis of structural stability in the hitting skill coefficients in both models, with F-ratios of 23.1 in Panel A and 16.8 in Panel B.

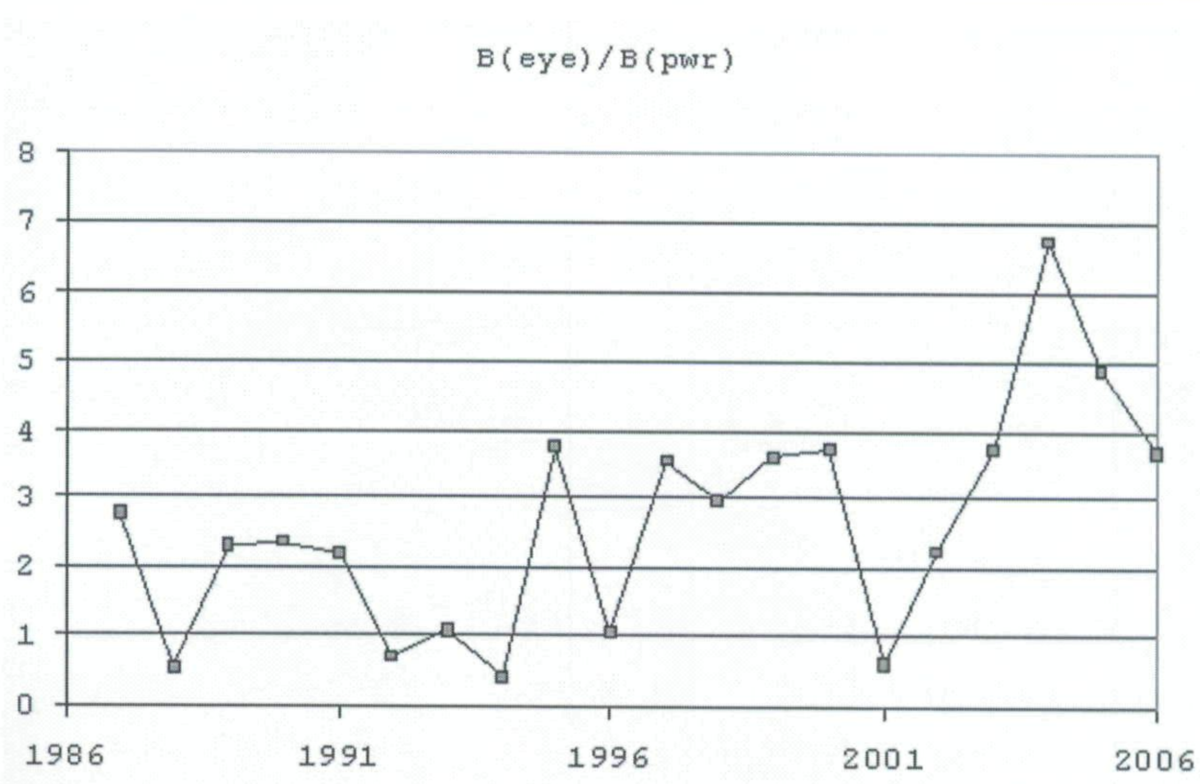
Although it is clear that the returns to plate discipline are far greater now than in past years, the salary coefficient ratios in Table 3 in all instances remain smaller than the corresponding productivity ratios in Table 2. However, this is not necessarily evidence of persistently inadequate compensation for players who draw more walks. The salary regression coefficients are measured as returns to a one-point increase in a statistic. Yet one point of on-base percentage may represent a larger skill improvement than a point of slugging percentage.

An alternative calculation is based on the increased salary from a one-standard deviation improvement in each hitting skill. Table 4 reports the mean values of salaries and hitting skills for the overall sample of player-seasons, and those within each of the four sub-sample time periods. The top three rows of statistics in Panel A of Table 4 characterize the upward trend in salaries over time, while the lower five rows show patterns in hitting statistics that mimic the results in Table 1. The standard deviation of each statistic is reported underneath the corresponding mean.

In Panel B of Table 4, the slope coefficient estimates from Table 3 are used to calculate a salary increase for an otherwise representative player from a one-standard deviation increase in one hitting statistic. The estimates are reported as premiums above the geometric mean salary, to correspond with our use of ln(salary) as the dependent variable. While the trends match those in Table 3, it is interesting to note that in the period after the publication of *Moneyball*, the salary premiums for one-standard deviation improvements in each skill are nearly equalized at 14-16% of mean salary.

The intuition here is that while Table 1 shows the demand for labor inputs of hitting skills in terms of the

Figure 1. Salary Returns to Plate Discipline Relative to Power Hitting



Notes: Each data point represents the ratio of the coefficient of Eye to the coefficient of Power for the seasons 1986-2006, as reported in Table 5.

Table 5. Trends in the Salary Valuation of Plate Discipline, by Season

Year	β(On-Base)	β(Slugging)	β(Eye)	β(Bat)	β(Power)
1986	0.80	1.03*	0.69	2.26**	0.22*
1987	1.41	1.82**	1.27	3.87**	0.46**
1988	0.34	1.51**	0.20	2.76**	0.37**
1989	1.36	1.99**	1.15	4.04**	0.50**
1990	-0.14	2.15**	1.48*	1.75*	0.63**
1991	-0.36	1.76**	1.13	1.20	0.52**
1992	-0.99	2.13**	0.40	2.76**	0.57**
1993	0.87	2.54**	0.71	4.42**	0.65**
1994	0.21	3.12**	0.36	4.78**	0.86**
1995	2.63*	2.45**	2.86*	5.33**	0.76**
1996	-0.66	2.58**	0.78	1.85	0.73**
1997	2.52*	2.17**	1.84*	5.80**	0.52**
1998	1.81*	2.40**	2.21*	4.23**	0.74**
1999	1.75*	2.42**	2.77**	3.81**	0.77**
2000	2.53*	2.49**	2.72**	5.30**	0.73**
2001	0.12	3.29**	0.53	5.28**	0.84**
2002	0.81	2.31**	1.52	3.64**	0.68**
2003	1.43	1.94*	2.12	3.07*	0.57**
2004	4.11**	2.32**	5.26**	4.14**	0.78**
2005	3.64**	2.72**	4.19**	5.38**	0.86**
2006	2.09	2.14**	2.14	4.66**	0.58**

Notes: Numbers in table are coefficients from two separate estimations of Equation (3) (see text for details), where On-Base and Slugging were included in one model, and Eye, Bat, and Power in the other. * - significant at 95% level, one-tailed test; ** - significant at 99% level, one-tailed test

marginal product,[7] the increases calculated in Panel B of Table 4 incorporate a supply-side effect. For our purposes, the nature-nurture question is irrelevant; the supply effect can arise either from players working to develop skills to earn salary increases, or alternatively from scouts seeking young players with outstanding latent skills in particular dimensions, or from any combination of the two.

From the results shown in Tables 3 and 4, one can easily get the impression that, rather than a sudden revolution, the increased appreciation of batting patience is the result of a steady convergence over time. This notion is at odds with our conceptions of efficiency and equilibrium, where market prices adjust rapidly once information becomes known. Indeed, the reliability of event studies in financial economics and in gambling markets depends upon rapid corrections of temporary disequilibria.

To examine the possibility that the aggregation of several years of labor market data in each of our four time periods is concealing a more distinct correction, such as that we reported in our 2006 paper, Table 5 presents the coefficients measuring returns to each hitting skill for contracts from each annual labor market.[8] The second and third columns of Table 5 are the coefficients for on-base and slugging from a model corresponding to Panel A of Table 3, while the rightmost three columns of Table 5 correspond to Panel B of Table 3 and measure returns to Eye, Bat, and Power. The asterisks represent significance of the coefficient estimates at the 95 and 99% confidence levels.

Table 6. Effectiveness of Team Payroll Spending on Win Percentage

Time period	beta(index)	s.e.(beta)	R^2	n
1986-2006 (all years)	0.078	0.008	0.146	587
1986-1993	0.035	0.016	0.022	205
1994-1997	0.095	0.019	0.182	112
1998-2003	0.095	0.014	0.209	180
2004-2006	0.082	0.014	0.271	90

Notes: Indexed payroll is ratio of team payroll to league average payroll in that season. Beta(index) is the slope coefficient in a regression of win percentage on indexed payroll for all team-seasons in that time period. The rightmost three columns report the standard error of the estimated slope, the coefficient of determination, and the sample size for each model.

Data source: Payrolls for Lahman database, version 5.4. Win percentage from Retrosheet game logs (see Table 1).

Looking across the 21 sets of annual labor market regressions in Table 5, it is clear that hitting for power has consistently been rewarded in salaries, and at more or less the same "price." Even hitting for average (Batting) has traditionally influenced salaries, allowing for a couple of tiny hiccups. Plate discipline (Eye), however, and on-base percentage as a whole were typically ignored prior to 1995. Then, after a hesitant flirtation in the late 1990s, returns to On-Base and Eye dropped sharply in 2001 and remained statistically insignificant until the sudden two-year burst in 2004-2005. The magnitudes of the coefficients are still reasonably high in 2006, but they are not statistically significant. The spike in the salary returns to Eye relative to Power can be seen more clearly in Figure 1. The plot point for the ratio in 2006 corresponds to the regression results in that it is still among the higher historical values, but a marked decline from its 2004 maximum. It is too soon to tell if this is itself a hiccup, or if the market reflects a determination that teams were overpaying for plate discipline.

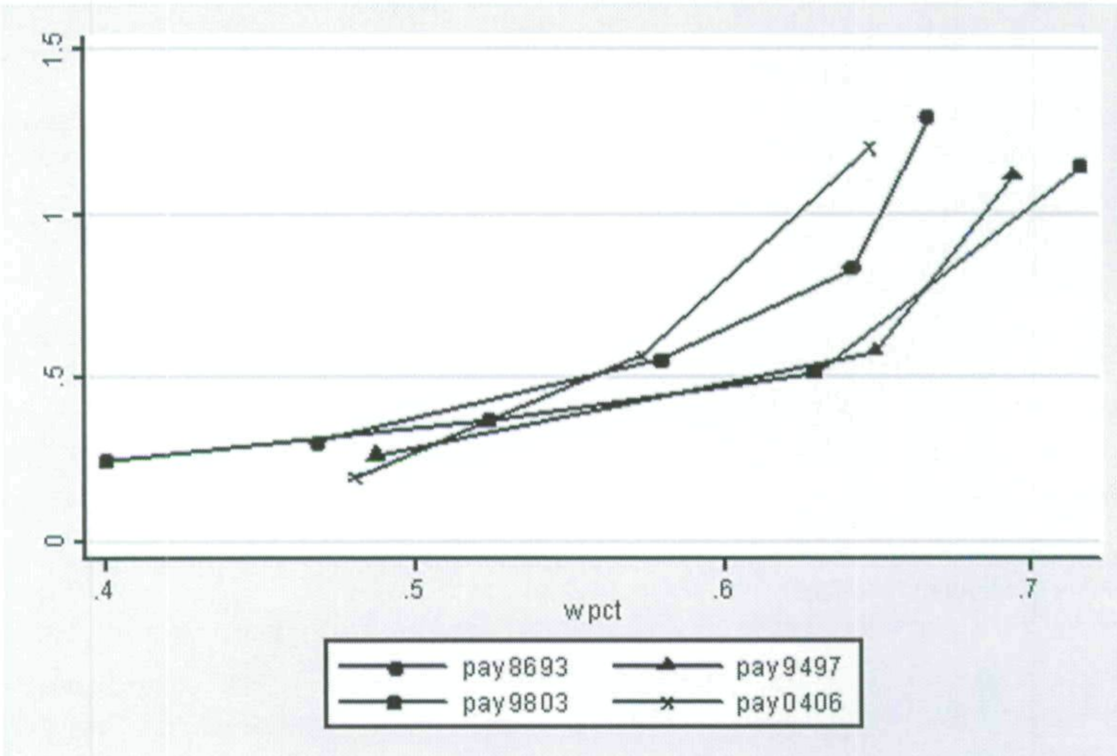
Returns to Skill and Payroll Efficiency over Time

If teams are more efficient at identifying player contributions to team productivity and reward those contributions with higher salaries, to the extent that teams can accurately forecast future productivity, it follows that team payrolls should more closely match team performance. Convergence in the returns to skill across teams—that is, a movement towards pricing consistent with a competitive equilibrium, where all teams purchase inputs at the same set of prices—implies that the ability to predict output from team expenditures would increase, whatever the market prices happen to be.

We examine this implication using regressions of team winning percentage on team payroll for the various time periods in our sample. Table 6 presents the slope coefficients of winning percentage on team payroll. To control for real and nominal salary increases over time, we measure team payroll relative to the average MLB payroll in a given year. As one win in a 162-game season represents a 0.0062 increase in winning percentage, the reported coefficient for the entire sample of 0.078 means that a 10% increase in team salary at the mean corresponds with an expected increase of about 1.25 victories.

Most relevant to our discussion are the sub-sample results in Table 6. There are three notable findings. First, the expected returns from payroll increases at the margin have been relatively stable since 1994, and are much larger in the eight-team playoff era than in the 1986-1993 seasons, when only the (then) four division champions made the playoffs. Second, the explanatory power of team payroll in predicting winning percentage has improved over time. In 1986-1993, team payroll explained 2.2% of the variation in winning percentage.

Figure 2. Changes in the Payroll Efficiency Frontier over Time



Notes: The vertical axis represents indexed payroll. The horizontal axis represents team winning percentage. The points represent the convex set of trade-offs between payroll and winning percentage.

This percentage has increased by an order of magnitude, to 27.1% in the 2004-2006 seasons. Third, it should be noted that despite the stronger correlation between these variables, nearly three-quarters of the variation in winning percentages is *not* predicted by team payrolls. In other words, although fewer teams appear to "throw their money away", there may still be room for innovation.[9]

To be sure, the idea that variation in spending explains 100% of the variation in team success calls into question the idea of a sporting contest itself. There are many sources of slippage between the acquisition of talent in the labor market and outcomes on the field of play. A partial list includes

(a) effects of injuries and illness;

(b) effects of off-field distractions such as legal troubles or family issues;

(c) stochastic variation in player performance after controlling for known and measurable determinants (age, physical conditioning, practice, etc.);

(d) a failure of teams to measure all relevant dimensions of performance; and

(e) failure to efficiently convert player performances into victories (setting team rosters and lineups; on-field game strategy).

Improvements in team strategies and financial management fall into categories (d) and (e), and—in an equilibrium where all teams are similarly endowed in these skills—can account for an increase in the predictive power of payroll on team performance. The stochastic nature of items (a) through (c) imply (among other factors) that the upper bound R^2 in this regression is less than 1.0, even when all teams are equally adept at strategy and financial management.

In our 2006 paper, we presented a scatter plot of indexed payrolls versus winning percentage in order to illustrate the "frontier" of cost-effective expenditures. Figure 2 shows how this frontier has changed over time as a result of the diffusion of innovations, of which the improved compensation of hitting skills may be but one example. Figure 2 includes only the points representing cost-effective combinations of winning percentage and payroll in each time period, and connects those points to illustrate the frontier. Using the curve for the 1986-1993 seasons as a reference, the ability of innovating teams to exploit undervalued inputs such as plate discipline pushed the frontier downward and to the right during the 1994-1997 and 1998-2003 periods. The expansion of the frontier was most noticeable at winning percentages between .575 and .625, which is the range where the likelihood of making the playoffs increases rapidly. Whereas building a contending team in 1986-1993 would require a payroll of about 60-80% of league average, the *Moneyball* hypothesis contends the innovators learned how to build a contending team for less. In Figure 2, we see the teams on the frontier fielding playoff quality teams in 1994-2003 for about 50% of league average payroll.

Competitive dynamics imply that following a breakthrough, imitators copy the methods used by innovators. In the *Moneyball* case, copycats could mimic the strategy of purchasing undervalued inputs, but this adds to demand, raising their prices. Under complete information, the process concludes only when the prices of those inputs are bid up to the efficient level. While we cannot show that the price signals are now efficient, Figure 2 displays evidence that wins became much more expensive in 2004-2006 than in the previous periods. The frontier has retreated to the left, beyond the benchmark 1986-1993 levels, with the changes most notable in the increased steepness at the right end of each curve. The payroll increase necessary to "buy" wins between the .575 and .625 levels became much higher, and teams were no longer able to field a playoff quality team for half the league average salary.

Concluding Comments

By expanding our period of inquiry, we have verified that the alleged mis-pricing at the core of Lewis' *Moneyball* has persisted for many years. By breaking down batting skills into factors that are more independent than those typically studied, we observe that the returns to skill have increasingly—albeit with aberrations in 2001 and 2002—matched the impact of skills on winning percentage. Moreover, this improved correspondence is focused on the ability of a batter to take a base-on-balls (Eye), as opposed to getting on base via hitting a single.[10]

We find several pieces of corroborating evidence of increased team ability to spend wisely. Over time, the relative expected salary increase from one-standard deviation improvements in hitting skills have equalized. Team payroll is a stronger predictor of winning percentage in 2004-2006 than in previous seasons, and especially so compared to the pre-strike years before 1994. The "frontier" that describes the most cost-effective combinations of payroll and wins contracted sharply in 2004 as other teams began to compete for inputs, ending a period of years when Oakland was able to push out the frontier by purchasing wins cheaply in the form of walks.

Although the pricing anomaly described by Lewis has been exposed and appears to have been corrected, two caveats remain. First, the sharp increase in the relative valuation of on-base percentage in 2004 was followed by declines in each of the two subsequent years. It is unclear whether these declines merely represent stochastic variation, or constitute evidence of a backlash among baseball general managers who believe that on-base percentage had become *over*valued in 2004. Secondly, while the correlation between team payroll and wins has increased greatly over the past two decades, the coefficient of determination remains below 30%. Opportunities surely remain for future innovation in the production of wins. In baseball, currency is not yet destiny.

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Endnotes

[1] For individual player-seasons, the correlation coefficient between on-base and slugging is 0.656. For team-seasons, the correlation coefficient is 0.787.

[2] Plate appearances is the sum of official at-bats, bases on balls, hit-by-pitches, and sacrifice flies. Sacrifice bunts do not count as a plate appearance. Hit-by-pitches are relatively infrequent, but are included here for theoretical completeness and because some players, such as Don Baylor and Craig Biggio, appear to have had a conscious knack for "taking one for the team."

[3] Since walks and hit-by-pitches are separated out, at bats makes a more appropriate denominator than plate appearances in this instance. The idea is to find the percentage of attempts to swing for a hit that successfully resulted in a hit.

[4] Branch Rickey and Allan Roth originally defined isolated power as *extra* bases per at bat, which still results in correlation with batting average, as the better hitter for average among two equally powerful hitters will have more extra-base hits. The statistic defined by TB/H, where TB is total bases and H is hits, resolves this problem.

[5] In our player-season data, the correlation coefficient between power and batting average is 0.04. The correlation between plate discipline ("eye") and batting average is 0.10. The correlation between "eye" and power is 0.31, with the correlation here likely inflated by pitchers who choose to "pitch around" home run threats in certain situations.

[6] The choice of 130 at bats is somewhat arbitrary, but is the threshold used by MLB to distinguish rookie position players from non-rookies. Both salary and player performance data are drawn from version 5.4 of Sean Lahman's database (available at http://www.baseball1.com).

[7] In this case the marginal product is physical (wins), not revenue (MRP). The possibility that wins from walk-off home runs generate more revenue than wins from walks and singles is perhaps best captured in the MLB TV ad from the late 1990s where pitchers Greg Maddux and Tom Glavine commiserate about their perceived lack of adoration, eventually concluding that "chicks dig the long ball."

[8] The changes in coefficients from year to year will be biased downward due to the presence of multi-year contracts. Regrettably, a reliable and comprehensive source of historical contract data (as opposed to salary data) extending back more than one or two seasons is not available in the public domain.

[9] Undoubtedly, one very large source of unexplained variation is the rents collected by teams from players who still have limited freedom to contract for salaries. When a team is able to sign and develop a player through its minor league "farm" system, it benefits from significant monopsony power during the player's first six major league seasons. Teams can set salaries more or less unilaterally in seasons one through three, and players are allowed the recourse of final-offer arbitration in seasons four through six. Unpredictable injuries and stochastic error in pitching output are other large sources of variation.

[10] Intriguingly, the emergence of an increase in the value of patience at the plate in the late 1990s corresponds with Lewis's description (pp. 58-59) of the Damascene conversion of Oakland general manager Sandy Alderson in 1995 following his reading of a pamphlet by Eric Walker.

Author's Note

We are grateful to Frank Stephenson for helpful comments.