Economics Bulletin

Volume 44, Issue 2

Moneyball revisited: Some counter-evidence

Koji Yashiki
Tohoku University

Yoshiyuki Nakazono
Yokohama City University

Abstract

This study revisited the Moneyball hypothesis to address the potential bias that should have been addressed in previous studies. Basic economic theory suggests an exact corre- spondence between pay and productivity when markets are competitive and information- rich, while it is difficult for researchers to provide empirical evidence on the correspondence between pay and productivity in the real labour market. By measuring the productivity of professional baseball players more closely, we found that after the publication of Moneyball, slugging average, which is widely accepted as one of the most common measures of batting skill, had the dominant effect on winning relative to the factors that Moneyball considered important. After Moneyball was published, slugging average was undervalued in determin- ing payrolls. The evidence against Moneyball suggests that payrolls may have become less efficient than they were before Moneyball.

We thank the discussant, Masaru Sasaki, for invaluable input, and also thank the participants in the Japanese Joint Statistical Meeting and the Autumn meeting of the Japanese Economic Association. In addition, we thank Akira Hibiki, Rui Ota, Qing-Yuan Suin, and Michio Suzuki for their helpful comments and suggestions. Nakazono acknowledges the financial support from JSPS KAKENHI (Grant Numbers 21H04397, 22K01438, and 23K17553), the Institute of Social and Economic Research, Osaka University, and Strategic Research Promotion of Yokohama City University

Citation: Koji Yashiki and Yoshiyuki Nakazono, (2024) "Moneyball revisited: Some counter-evidence", *Economics Bulletin*, Volume 44, Issue 2, pages 620-634
Contact: Koji Yashiki - yashiki.koji.t6@dc.tohoku.ac.jp, Yoshiyuki Nakazono - nakazono@yokohama-cu.ac.jp.
Submitted: March 07, 2024. **Published:** June 30, 2024.

1 Introduction

We revisited the *Moneyball* hypothesis and presented evidence against it. *Moneyball* is a hypothesis that accounts for the discrepancy between the payroll for professional athletes and their contribution to winning in sports. For example, Hakes and Sauer (2006), studying the labor maket for baseball players, argue that the essence of the Moneyball hypothesis is that the ability to get on base was undervalued in the baseball labor market. The hypothesis is widely known because of Michael Lewis, who is the author of *Moneyball: The Art of Winning an Unfair Game*. The book describes Billy Beane, the general manager of Oakland Athletics. As described in Lewis (2003), the general manager acquired undervalued players and led the team to victory with a small budget. Before the publication of *Moneyball*, it was believed that the contributors to winning were the powerful sluggers who smashed home runs or long hits. Lewis (2003) claimed that this was a myth. Lewis (2003) and Hakes and Sauer (2006) suggested that a batter's skill in avoiding being out contributed more to winning than smashing a long hit. The argument by Billy Beane was supported by Oakland Athletics, and it adopted the new hypothesis and shifted its strategy for winning. Athletics reorganized the team by acquiring those who were, on average, likely to reach base. As a result, they won the American League West with the lowest player payroll in the league. The achievement of Athletics defied a common fundamental belief and had a major influence on strategy in major league baseball (MLB). Thus, *Moneyball* is now regarded as a standard theory in professional labor markets.[1]

A growing number of studies of professional labour markets have revealed the discrepancy between workers' pay and performance.[2] For example, Brown et al. (2017) and Kahn (2000) used data on professional athletes to test whether monopsony explains the distorted relationship between wages and productivity. We combined payroll data for MLB professionals with detailed data on each player's performance to re-evaluate the hypothesis.

To verify the story in *Moneyball*, we re-examined the results, as shown in Hakes and Sauer (2006), to address the potential bias that should have been addressed in previous studies.[3] Previous studies on *Moneyball* evaluated the hypothesis based on a naïve comparison between on-base percentage (OBP) and slugging percentage (SLG). By regressing wages on OBP and SLG and comparing the coefficients, the literature concluded that OBP was more important in run production than SLG. However, a simple comparison requires the assumption that OBP and SLG are drawn from a similar distribution. We choose to use standardized variables in unites of standard deviations for comparability. There are two reasons. First, we think that absolute changes in the

[1] Based on the *Moneyball* hypothesis, Weimer and Daniel (2017) examined the labor market in German professional soccer, and Pinheiro and Szymanski (2022) studied the market for racehorses.

[2] In sports economics, the literature helps to test efficiency and rationality in the economic sense, because performance (or productivity) and rewards are measurable. See for example Berri (2018), Berri et al. (2007), Berri et al. (2011) and Harris and Berri (2015).

[3] Duquette et al. (2019) also investigate the validity of the analytics in Moneyball and provide the supportive evidence for the original story in *Moneyball*.

productivity measures matter for winning and salaries. Second, a simple comparison requires the assumption that OBP and SLG are drawn from a similar distribution. Howerver, Deli (2013) showed that this assumption is false.[4] Deli (2013) suggested that naïve comparison of the coefficients introduces a bias in the evaluation of the *Moneyball* hypothesis. Third, productivity measures can sometimes be zero or even negative. For example, all the measures we use, such as OBP, SLG, Eye, Power, ERA, can potentially be zero. Another example is Wins Above Replacement (WAR), which measures a player's value in all facets of the game by deciphering how many more wins he's worth than a replacement-level player at his position. The measure can be negative when a player's productivity is low. Because not a few variables take zero or negative values and we cannot take the logarithm of these values, we use standardized measures.

We provide evidence against the standard theory. We show that after the publication of *Moneyball*, slugging average, which is widely accepted as one of the most common measures of batting skill, dominates the effect on winning relative to OBP, which *Moneyball* considered most important. We also found that in MLB, slugging average is probably undervalued by *Moneyball*, even though our first step showed that it is the factor that contributes most to winning. The evidence we found suggests that payrolls do not efficiently reflect the productivity of individual players. In other words, the skills that contribute most to winning are less predictive of payroll than they were before *Moneyball* was published. This is the striking evidence against *Moneyball*: the payroll may have become less *efficient* than it was before *Moneyball*.[5]

The structure of our paper is as follows: Section 2 explains our approach to verify the *Moneyball* hypothesis and describes our data. Section 3 identifies what contributes to winning and Section 4 shows what explains annual salary. Section 5 concludes the paper.

2 Estimation Strategy

2.1 What contributes to winning?

This study estimates two equations to test whether the labour market pays based on productivity, using panel data with performance measures and MLB payrolls from 1989 to 2018.[6] First, we

[4] Deli (2013) showed that even after the publication of *Moneyball*, SLG was still more important than OBP as a factor contributing to winning. Pinheiro and Szymanski (2022) assess the role of run value on the compensation, relying on a structural approach.

[5] Our conclusion is consistent with Berri (2018) and Holmes et al. (2018) in the sense that both argue that the *Moneyball* hypothesis is wrong. However, the story is different; Berri (2018) and Holmes et al. (2018) provide evidence that the baseball labour market is efficient and has not changed both before and after the publication of Lewis (2003). However, the approach in Berri (2018) and Holmes et al. (2018) is different from that of this study. To retest the *Moneyball* hypothesis, we did not compare partial regression coefficients. Rather, we standardised the variables in the estimating equations and obtained parameters. Section 2 explains why.

[6] The information on performance, position and salary comes from the Larman database (http://www.seanlahman.com/ before 2016) and spotrac (https://www.spotrac.com/ after 2016). The original salary data was

followed Hakes and Sauer (2006) in examining what factors contribute to winning, using data on the winning records of each team.[7] Second, we re-examined the indices that explain payroll, based on data relating each player's performance indices to their payroll level.[8] More specifically, the first analysis regressed winning percentage on team performance indices to identify the index that contributed most to winning. Our focus was on whether the "new" measures to capture players' batting skills, such as on-base percentage (OBP) as proposed by "*Moneyball*", were superior to slugging percentage (SLG). By superior, we mean that the new measures would have more predictive power for team wins compared to the predictive power of the traditional measures. Based on the results of the first estimation, we measured the impact of batting skill indicators on payroll and examined whether factors that contribute to winning, which may reflect productivity, explain annual salaries.

To retest the *Moneyball* hypothesis, we standardised the variables in the estimating equations and obtained parameters. While studies such as Hakes and Sauer (2006) compared partial regression coefficients, we used standardised regression coefficients. Partial regression coefficients indicate the effect of a one-unit change in explanatory variables on an outcome, holding all other explanatory variables constant. Without standardising the variables in the estimating equation, the variances fluctuate and we could not interpret the size of the partial regression coefficients. On the other hand, we could interpret the sizes of the standardised partial regression coefficients as the contributions of the explanatory variables to the outcome because the variances of the variables were normalised to one.

We have estimated the following equation:

$$WP_{j,t} = c + \alpha_1 \times OBP_{j,t} + \alpha_2 \times SLG_{j,t} + \mathbf{X}\beta + \epsilon_{j,t}, \tag{1}$$

where $WP_{j,t}$ and $\mathbf{X}$ are denoted as the winning percentage of team j at time t and a vector of control variables including earned run average (ERA) and the cross term between OBP and SLG, respectively.[9] We have performed pooling estimation in both equation (1) in this subsection and equation (2) in the next subsection. This is because we assume that salary and probability of winning are fully explained by the variables we use. Even if some variables were omitted from the model, the fixed effects would still hide most of the variation in the regressors (Hakes and Sauer, 2006). We benefited from pooling estimation in identifying which factor determines winning percentage and payroll. Here we focused on the size of α_1 and α_2 in the pooled estimation. We compared the estimated αs using standardised independent and dependent variables.

provided by Doug Pappas. The data we have used is exactly the same as that used by Hakes and Sauer (2006). All salaries have been converted into real terms using the Consumer Price Index.

[7]The basic statistics of the data are shown in panel (A) of Table I.

[8]Panel (B) in Table I shows the descriptive statistics.

[9]ERA represents average earned runs per game; this is an index used to measure overall defensive skills (Hakes and Sauer, 2006).

Table I: Descriptive statistics and correlation matrix of batting indicators

Panel (A): descriptive statistics in MLB: team averages in each regular season

	OBP	SLG	Eye	Power	ERA	WP
Mean	0.329	0.411	0.094	0.150	4.236	0.500
Median	0.328	0.409	0.093	0.150	4.200	0.500
Maximum	0.374	0.491	0.131	0.206	6.380	0.716
Minimum	0.292	0.327	0.068	0.088	2.940	0.265
Std. Dev.	0.015	0.029	0.011	0.021	0.555	0.069
Observations	874	874	874	874	874	874

OBP: on-base percentage is defined as the fraction of plate appearances in which the player reached base successfully through either a hit or a walk.
SLG: slugging percentage is total bases divided by at-bats, so that doubles count twice as much as singles, and home runs twice as much as doubles.
Eye: eye is calculated by dividing the sum of bases-on-balls and hit-by-a-pitch by plate appearances.
Power: power is calculated by subtracting batting average from SLG.
ERA: earned run average represents average earned runs per game.
WP: winning percentage.

Panel (B): descriptive statistics of batters in MLB

	OBP	SLG	Eye	Power	Salary (USD)	Plate Appearance
Mean	0.340	0.422	0.102	0.155	3,313,839	447
Median	0.338	0.417	0.097	0.149	1,350,000	458
Std. Dev.	0.041	0.079	0.037	0.062	4,529,835	175.172
Observations	8,349	8,349	8,349	8,349	8,351	8,349

Panel (C): correlation matrix of batting indicators

	OBP	SLG	Eye	Power
OBP	1.000			
	–			
SLG	0.743*	1.000		
	(0.000)	–		
Eye	0.698*	0.397*	1.000	
	(0.000)	(0.000)	–	
Power	0.501*	0.917*	0.401*	1.000
	(0.000)	(0.000)	(0.000)	–

Notes: Standard error is indicated in parentheses. Significance at the 1% level is indicated by *.

2.2 What explains annual salary?

The next step was to examine whether there was a structural shift in the determinants of annual salaries in MLB. Hakes and Sauer (2006), Hakes and Sauer (2007), and Baumer (2014) pointed out that compared to the skill of hitting the ball, the skill of avoiding being thrown out had more predictive power for annual salary after 2004, when the *Moneyball* hypothesis was introduced by Lewis (2003), than it did before 2004. However, the findings in these studies were based on a comparison of partial regression coefficients rather than standardised partial regression coefficients. Our paper used standardised partial regression coefficients to re-examine whether there was a structural shift in the MLB labour data after the publication of *Moneyball*.

Specifically, we regressed players' annual salaries at time t on indices reflecting players' hitting ability calculated at time $t-1$. To deflate players' annual salaries, we used the consumer price index for each city. Thus, $Salary_{i,t}$ is not nominal but real wages. The estimation equation is as follows

$$Salary_{i,t} = c + \gamma_1 \times OBP_{i,t-1} + \gamma_2 \times SLG_{i,t-1} + \mathbf{X}\beta + \epsilon_{i,t}, \tag{2}$$

where X and β are vectors of control variables and coefficients, respectively. We also performed pooling estimation in equation (2) for the same reason as in equation (1).

Following Hakes and Sauer (2006), the sample we used includes players with at least 130 plate appearances in the relevant seasons. As the annual salary is based on the previous season's performance, we regressed the salary at time t on the performance indices at time $t-1$. Following Hakes and Sauer (2006) and Brown et al. (2017), we included free agency, arbitration eligibility, and defensive and offensive productivity as control variables.[10]

[10] $free\ agency$ is a dummy variable that takes one for players with more than six years since their debut year, otherwise zero. $arbitration\ eligble$ is a dummy variable which takes one for players with between 3 and 6 years of experience, otherwise zero. Salary is defined as annual income based on data provided by the Lahman database (http://www.seanlahman.com/) before 2016 and the Spotrac database (https://www.spotrac.com/) after 2016.

Table II: The impact of batting skill on winning percentage in MLB

Panel (A): Entire sample

	Partial regression coefficient		Standardised partial regression coefficient	
	(1)	(2)	(3)	(4)
α_1: OBP	1.700^*		0.359^*	
	(0.119)		(0.021)	
α_2: SLG	1.083^*		0.440^*	
	(0.062)		(0.021)	
α_3: Eye		1.156^*		0.178^*
		(0.143)		(0.022)
α_4: Power		1.690^*		0.515^*
		(0.080)		(0.024)
γ: ERA	-0.101^*	-0.099^*	-0.808^*	-0.787^*
	(0.002)	(0.003)	(0.014)	(0.022)
Adjusted R^2	0.834	0.711	0.834	0.711
Observation	874	874	874	874
Wald Test				
H_0: $\alpha_1 = \alpha_2$	0.613^*		0.081^*	
H_0: $\alpha_3 = \alpha_4$		0.534^*		0.337^*

Panel (B): Before and after the publication of *Moneyball*

	Standardised partial regression coefficient			
	Before the publication of *Moneyball*: 1989 to 2003		After the publication of *Moneyball*: 2004 to 2018	
	(1)	(2)	(3)	(4)
α_1: OBP	0.419^*		0.267^*	
	(0.033)		(0.033)	
α_2: SLG	0.436^*		0.431^*	
	(0.037)		(0.031)	
α_3: Eye		0.237^*		0.098^*
		(0.028)		(0.301)
α_4: Power		0.575^*		0.452^*
		$(0.0.35)$		(0.030)
γ: ERA	-0.824^*	-0.800^*	-0.783^*	-0.782^*
	(0.023)	(0.030)	(0.022)	(0.029)
Adjusted R^2	0.827	0.715	0.838	0.721
Observation	424	424	450	450
Wald Test				
H_0: $\alpha_1 = \alpha_2$	0.017		0.164^*	
H_0: $\alpha_3 = \alpha_4$		0.338^*		0.354^*

Notes: Robust standard errors in parentheses are clustered at team levels. Significance at the 1% level is indicated by *. We conduct a Wald test and report the (absolute value of) differences between the relevant coefficients.

3 Determinants of winning

3.1 Replication of Hakes and Sauer (2006)

To identify the determinants of winning, we first estimated equation (1). Panel (A) in Table II shows which factors of batting skill contribute to winning, using the full sample. The first column shows the partial regression coefficients, while the fourth column shows the standardised partial regression coefficients. The partial regression coefficients for OBP and SLG in the first column are significantly positive and the Wald test shows a significant difference between them. The partial regression coefficient of OBP (α_1) is larger than that of SLG (α_2) and almost equal to that of Hakes and Sauer (2006). This result shows that our dataset successfully replicates Hakes and Sauer (2006).

3.2 Results using the normalised sample

We also show results using the standardised sample in the fourth column of the Table II; these are in sharp contrast to the results in the first column. The fourth column of the Table shows that the standardised α_2 significantly exceeds α_1. Moreover, the difference is significant. This suggests that SLG contributes more to winning than OBP.[11] This result contradicts the *Moneyball* hypothesis and Hakes and Sauer (2006), which argue that the skill of avoiding being out is more important to winning than the skill of hitting the ball. As a robustness check, we regressed winning percentage on Eye and $Power$ to mitigate multicollinearity between OBP and SLG.[12] Eye and $Power$ are also indices that measure the ability to avoid being out and the ability to hit the ball, respectively.[13] As an index, Eye is similar to OBP: the correlation between them is 0.698. As an index, $Power$ is similar to SLG: the correlation between them is 0.917. The fifth column in panel (A) of Table II shows that the standardised partial regression coefficient of $Power$ (α_4) is significantly higher than that of Eye (α_3). Furthermore, the difference between them is significant. This confirms that our benchmark result is robust: the indices related to the ability to hit the ball, such as SLG and $Power$, can explain winning percentage better than those related to the ability to avoid being out, such as OBP and Eye.

We split the full sample into subsamples before and after the publication of *Moneyball* in 2003. Panel (B) in Table II shows the pre- and post-publication estimation results using the stan-

[11] The sixth column in panel (A) of Table II shows that the standardised partial regression coefficient of SLG (α_2) significantly exceeds that of OBP (α_1), even when the model allows for an interaction term between OBP and SLG.

[12] Hakes and Sauer (2007) and Holmes et al. (2018) discussed the issue of multicollinearity between OBP and SLG.

[13] Eye and $Power$ are calculated by dividing the sum of bases-on-balls and hit-by-a-pitch by plate appearances and by subtracting batting average from SLG, respectively. Panel (C) in Table I presents the correlation matrix and shows that the correlation between OBP and SLG is high (0.746), while the correlation between Eye and $Power$ is relatively low (0.401). Following Hakes and Sauer (2007), we used Eye and $Power$ as well as OBP and SLG to address the issue of multicollinearity.

dardised data. The results suggest that SLG is a more stable contributor to wins than OBP over the entire sample. The first column shows that α_2 exceeds α_1 before the publication. The fourth column shows that α_2 is still significantly larger than α_1 after the release. The second and fifth columns show that the above results are similar when we use Eye and $Power$.[14] Furthermore, the difference between α_1 (α_3) and α_2 (α_4) is greater after publication. These results suggest that the skill of hitting the ball contributes more to winning than the skill of avoiding being out, and the discrepancy increases after 2004.

4 Determinants of annual salary

The second step was to identify what determines annual pay. Our focus is on whether productivity can explain pay.

4.1 Replication of Hakes and Sauer (2006)

First, we replicated the results of Hakes and Sauer (2006) using the full sample from 1989 to 2018. Hakes and Sauer (2006) showed that before the publication of *Moneyball*, SLG was more predictive of annual salary than OBP, while after the publication OBP was more important. Our estimation results replicate their findings when the data are not normalised. Table III shows the estimation results from equation (2) and reports the partial regression coefficients. The third and fifth columns show the results using the 1989 to 2003 and 2004 to 2018 subsamples, respectively. The coefficient of SLG (γ_2) is significantly larger than that of OBP (γ_1) before the publication of *Moneyball*, while after the publication the coefficient of SLG (γ_2) becomes smaller than that of OBP (γ_1). This reversal was also found when we used the other indicators, namely Eye and $Power$. The fourth and sixth columns show that the coefficient of $Power$ (γ_4) is significantly larger than that of Eye (γ_3) before publication, while the coefficient of $Power$ (γ_4) becomes smaller than that of Eye (γ_3) after publication. These results are in line with those of Hakes and Sauer (2006).

4.2 Results using the normalized sample

However, the situation changes when we use the normalised data. Panel (A) of table IV shows the estimation results from equation (2) and reports the standardised partial regression coefficients. The third and fifth columns show the results using the sub-samples from 1989 to 2003 and from 2004 to 2018, respectively. In panel (A), the coefficient of SLG (γ_2) is significantly larger

[14] The sixth column in panel (B) of Table II shows that the standardised partial regression coefficient of $Power$ (α_4) significantly exceeds that of Eye (α_3), even when the model allows for an interaction term between Eye and $Power$.

than that of OBP (γ_1) before the publication of *Moneyball*, while the difference between them becomes almost zero (0.02) after the publication.

This is the case when we use the log of salary as the dependent variable and the normalised variables as the independent variables. In panel (B), the coefficient of SLG (γ_2) is significantly larger than that of OBP (γ_1) before the release of *Moneyball*, while the difference between them becomes 0.02 after the release. This was robust to using Eye and $Power$ instead of OBP and SLG. The fourth and sixth columns show that the difference between γ_3 and γ_4 becomes smaller after the release of *Moneyball*. These results suggest that prior to the publication of *Moneyball*, metrics such as SLG and $Power$, which measure the skill of hitting the ball, were superior to metrics such as OBP and Eye, which measure the skill of avoiding being out, in determining annual salaries. However, there is no significant difference between them after the release of *Moneyball*. This may indicate a change in salary determinants: the skill of hitting the ball is undervalued after the publication of *Moneyball*, even though SLG and $Power$ contribute more to winning than OBP and Eye, as shown in Table II.

We also checked whether the determinants of pay changed over time. In order to identify any shift in salary determinants, we ran a rolling regression using equation (2). We estimated equation (2) on a single year basis. The top panel of Figure 1 shows the standardised regression coefficients of OBP (γ_1) and SLG (γ_2). The figure suggests that there is a structural break in the determinants of salary. It shows that the red line (γ_2) is higher than the blue line (γ_1) until 2003 and that the discrepancy between them disappears thereafter. This is the case when we look at the standardised regression coefficients of the eye (γ_3) and the power (γ_4). The bottom panel of Figure 1 shows that the red line (γ_4) is larger than the blue one (γ_3) until 2003 and that the discrepancy between them becomes small thereafter. The figure suggests that the determinants of salary changed after the publication of *Moneyball*.

Table III: What factors determine wages?: partial regression coefficients

	All year		Before the publication of *Moneyball*: 1989-–2003		After the publication of *Moneyball*: 2004–2018	
	(1)	(2)	(4)	(5)	(7)	(8)
Dependent variable: Logarithm of salary						
γ_1: OBP	1.740*		1.129*		2.597*	
	(0.278)		(0.365)		(0.419)	
γ_2: SLG	2.086*		2.433*		1.663*	
	(0.149)		(0.199)		(0.223)	
γ_3: Eye		2.025*		1.382*		2.965*
		(0.244)		(0.322)		(0.369)
γ_4: Power		2.570*		2.917*		2.130*
		(0.155)		(0.209)		(0.228)
Plate Appearance	0.003*	0.003*	0.003*	0.003*	0.003*	0.003*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Free Agent	1.803*	1.790*	1.675*	1.674*	1.917*	1.893*
	(0.024)	(0.025)	(0.035)	(0.035)	(0.034)	(0.034)
Arbitration Eligible	0.691*	0.679*	0.719*	0.719*	0.648*	0.624*
	(0.026)	(0.026)	(0.037)	(0.037)	(0.036)	(0.036)
Catcher Dummy	0.070*	0.055†	0.129*	0.118*	0.015	−0.006
	(0.025)	(0.025)	(0.035)	(0.035)	(0.036)	(0.036)
Infielder Dummy	−0.018	−0.004	−0.004	−0.004	−0.022	0.008
	(0.019)	(0.019)	(0.026)	(0.026)	(0.027)	(0.027)
Adjusted R^2	0.671	0.670	0.674	0.672	0.658	0.658
Observation	8,351	8,351	4,144	4,144	4,207	4,207
Wald Test						
H_0: $\gamma_1 = \gamma_2$	0.345		1.304*		0.934	
H_0: $\gamma_3 = \gamma_4$		0.545		1.535*		0.835

Notes: Robust standard errors in parentheses are clustered at player levels. Significance at the 1% level is indicated by *. The last two lines indicate the difference between the two coefficients as absolute values. The dependent variable is the logarithm of salary (deflated) for year t, and the performance variable is from $t-1$. Dummy variables for each year are included in each regression. The sample includes all players with at least 130 plate appearances during the relevant seasons. We conduct a Wald test and report the (absolute value of) differences between the relevant coefficients.

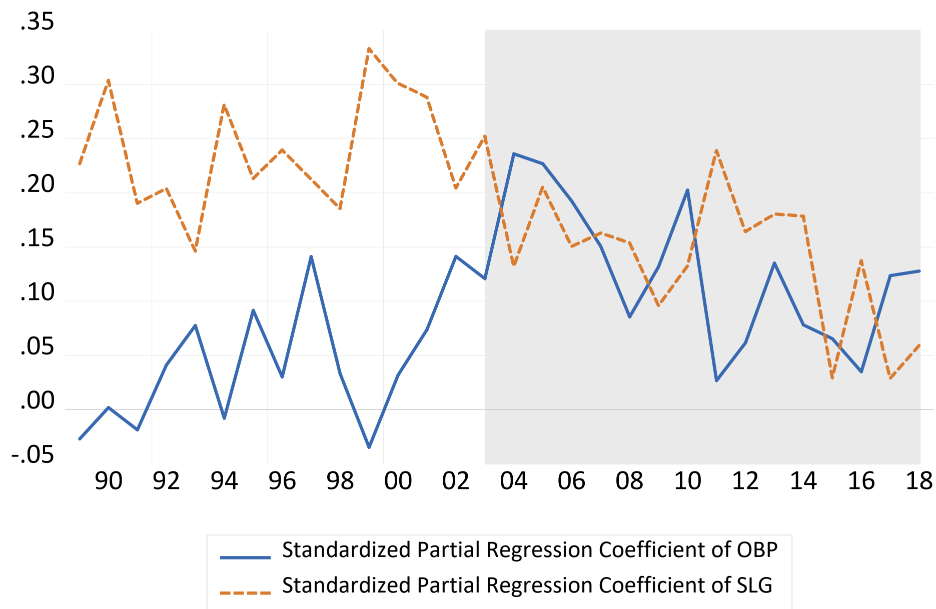
Table IV: What factors determine wages?: standardised partial regression coefficient

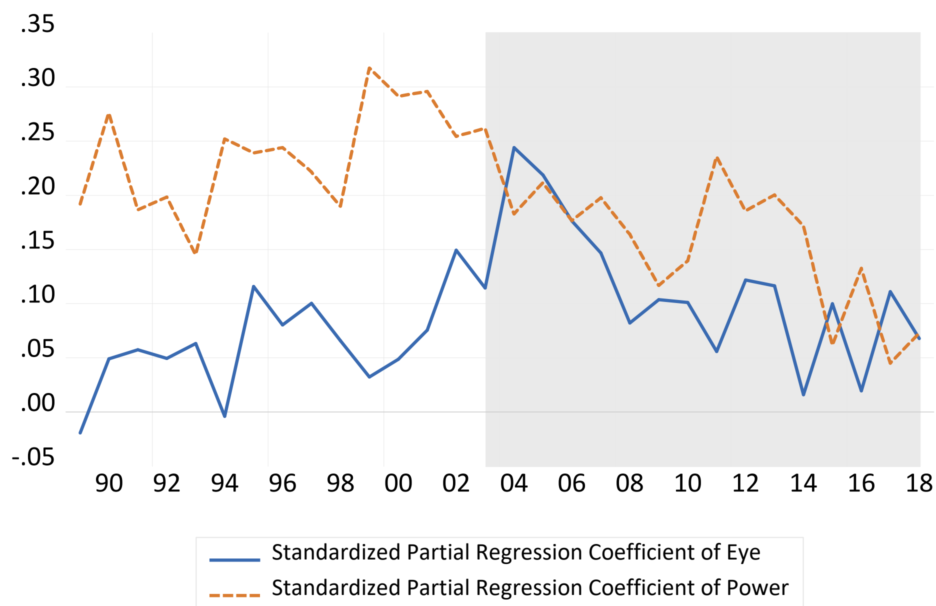
	Standardised partial regression coefficient					
	All year		From 1989 to 2003		From 2004 to 2018	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel (A): dependent variable: standardised salary (in the real term)						
γ_1: OBP	0.093^*		0.056^*		0.135^*	
	(0.011)		(0.015)		(0.015)	
γ_2: SLG	0.152^*		0.251^*		0.114^*	
	(0.011)		(0.016)		(0.016)	
γ_3: Eye		0.111^*		0.093^*		0.142^*
		(0.009)		(0.012)		(0.012)
γ_4: Power		0.156^*		0.242^*		0.124^*
		(0.009)		(0.013)		(0.013)
Wald Test						
H_0: $\gamma_1 = \gamma_2$	0.059^*		0.194^*		0.021	
H_0: $\gamma_3 = \gamma_4$		0.046^*		0.149^*		0.018
Adjusted R^2	0.483	0.487	0.535	0.540	0.492	0.495
Observation	8,351	8,351	4,144	4,144	4,207	4,207

	(1)	(2)	(3)	(4)	(5)	(6)
Panel (B): dependent variable: logarithm of salary (in the real term)						
γ_1: OBP	0.072^*		0.049^*		0.102^*	
	(0.011)		(0.016)		(0.016)	
γ_2: SLG	0.164^*		0.201^*		0.123^*	
	(0.012)		(0.016)		(0.017)	
γ_3: Eye		0.075^*		0.053^*		0.106^*
		(0.009)		(0.012)		(0.013)
γ_4: Power		0.161^*		0.189^*		0.127^*
		(0.010)		(0.014)		(0.014)
Wald Test						
H_0: $\gamma_1 = \gamma_2$	0.092^*		0.153^*		0.021	
H_0: $\gamma_3 = \gamma_4$		0.085^*		0.136^*		0.021
Adjusted R^2	0.671	0.670	0.674	0.672	0.658	0.658
Observation	8,351	8,351	4,144	4,144	4,207	4,207

Notes: Robust standard errors in parentheses are clustered at player levels. Significance at the 1% level is indicated by *. The dependent variables in Panel (A) and (B) are standardised (deflated) salary and the logarithm of (deflated) salary for year t, and the performance variable is from $t-1$. Dummy variables for each year are included in each regression. The sample includes all players with at least 130 plate appearances during the relevant seasons. We conduct a Wald test and report the (absolute value of) differences between the relevant coefficients. We do not report the estimated coefficients of the control variables to save space.

Figure 1: Development of standardised partial regression coefficients





5 Conclusion

In our paper, we re-examined the *Moneyball* hypothesis. We combined payroll data for MLB professionals with detailed data on each player's performance to reevaluate the hypothesis. We provided counter-evidence to the standard theory by showing that after the publication of *Moneyball*, slugging average, which is widely accepted as one of the most common measures of batting skill, dominated the effect on winning relative to the factor that *Moneyball* considered important. We also found that, in MLB in particular, slugging average is *undervalued* as a determinant of wages, probably as a result of *Moneyball*, even though it was identified in the first step as the factor that most contributes to winning. This evidence suggests that payrolls do not efficiently reflect the productivity of each player. In other words, the skill that most contributes to winning had less predictive power for the payroll after the publication of *Moneyball*. This is the striking evidence against *Moneyball*: the MLB payroll may have become less *efficient* after *Moneyball*.

References

Baumer, B., and Zimbalist, A. (2014) "Quantifying Market Inefficiencies in the Baseball Players' Market," *Eastern Economic Journal* 40(4), 488–498.

Berri, D. J. (2018) *Sports Economics* Worth Publishers/Macmillan Education (New York, New York).

Berri, D. J., Brook, S. L., and Fenn, A., (2011) "From College to the Pros: Predicting the NBA Amateur Player Draft." *Journal of Productivity Analysis* 35(1), 25–35.

Berri, D. J., Brook, S. L., and Schmidt,M. B., (2007) "Does One Simply Need to Score to Score?" *International Journal of Sport Finance* 2, 190–205.

Brown, D., Link, C., and Rubin, S. (2017) "Moneyball After 10 Years: How Have Major League Baseball Salaries Adjusted?" *Journal of Sports Economics* 8, 771–786.

Deli, D. (2013) "Assessing the Relative Importance of Inputs to a Production Function: Getting on Base Versus Hitting for Power," *Journal of Sports Economics* 14, 203–217.

Duquette, M., Cebula, R., and Mixon, F. (2019) "Major League Baseball's Moneyball at Age 15: A Reappraisal," *Applied Economics* 51(52), 5694–5700.

Hakes, J., and Sauer, R. (2006) "An Economic Evaluation of the Moneyball Hypothesis," *Journal of Economic Perspectives* 20(3), 173–186.

Hakes, J., and Sauer, R. (2007) "The Moneyball Anomaly and Payroll Efficiency: A Further Investigation," *International Journal of Sport Finance* 2(4), 177–189.

Harris, J., and Berri, D. J. (2015) "Predicting the WNBA Draft: What Matters Most from College Performance?" *International Journal of Sport Finance* 10, 299–309.

Holmes, P. M., Simmons, R., and Berri, D. J. (2018) "*Moneyball* and the Baseball Players' Labor Market," *International Journal of Sport Finance* 13(2), 141–155.

Kahn, L. (2000) "The Sports Business as a Labor Market Laboratory," *Journal of Economic Perspectives* 14(3), 75–94.

Lewis, M. (2003) *Moneyball: The Art of Winning an Unfair Game*, Norton: New York.

Pinheiro, R., and Szymanski, S. (2022) "All Runs Are Created Equal: Labor Market Efficiency in Major League Baseball," *Journal of Sports Economics* 23, 1046–1075.

Weimar, D., and Wicker, P. (2017) "Moneyball Revisited: Effort and Team Performance in Professional Soccer," *Journal of Sports Economics* 18(2), 140–161.