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Moneyball Revisited: Some Counter-Evidence

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Abstract

This paper replicates Hakes and Sauer (2006) and reconsiders the *Moneyball* hypothesis to address the potential bias that should have been dealt with in past studies. Basic economic theory suggests an exact correspondence between pay and productivity when markets are competitive and rich in information, while it is hard for researchers to provide empirical evidence on the correspondence between pay and productivity in the real labor market. By measuring more precisely the productivity of professional baseball players, we find that after the publication of *Moneyball*, the slugging average, which is widely accepted as one of the most common measures of batting skill, has the dominant effect on winning when compared to the factor that *Moneyball* considered important. After publication, the slugging average becomes *undervalued* in determining the payroll, probably because of *Moneyball*. The counter-evidence against *Moneyball* suggests that the payroll may have become less *efficient* than before *Moneyball*.

JEL Classification: J31; J44; Z20; Z21

Keywords: baseball statistics; labor market; measureing productivity; Moneyball; wage inefficiency

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1 Introduction

Moneyball is a hypothesis that accounts for the discrepancy between the payroll for professional athletes and their contribution to winning in sports. 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]

After Lewis (2003), the literature verifying *Moneyball* has generally supported the grand theory. A growing number of studies on professional labor markets have revealed the discrepancy between workers' wages and performance. For example, Brown (2017) and Kahn (2000) examined whether monopsony explains the distorted relationship between wage and productivity using data on professional athletes. Depken (2000) investigated the nexus between the pay gap and team productivity in MLB. Gould and Winter (2009) used data from professional baseball to show that workers can affect the productivity of their coworkers

[1]Based on the *Moneyball* hypothesis, Weimer and Daniel (2017) examined the labor market in German professional soccer, and Plant and Stowe (2019) studied the market for racehorses.

based on income maximization considerations. Kahane et al. (2013) considered the potential gains to firms from employing culturally diverse work teams, using data from the National Hockey League (NHL). As for *Moneyball*, Hakes and Sauer (2006) was the first study, and it indicated not only resource misallocation in the MLB labor market but also a structural shift from excessive dependence on power hitters to the new "winning strategy" proposed by *Moneyball*. Subsequent studies such as Hakes and Sauer (2007), Baumer (2014), and Duquette (2019) also provided supportive evidence for *Moneyball* that the undervaluation of the skill of avoiding being out was drastically corrected after *Moneyball*. These studies have improved the reputation of *Moneyball* as a standard theory over the last 15 years.

This paper reconsiders the *Moneyball* hypothesis and shows counter-evidence against it by measuring more precisely the productivity of professional baseball players. We combine data on the payroll for MLB professionals with detailed data on each player's performance to reevaluate the hypothesis. To verify the story in *Moneyball*, we replicate the results, as shown in Hakes and Sauer (2006), to address the potential bias that should have been dealt with in past studies. More specifically, past studies on *Moneyball* assessed 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 was SLG. However, a simple comparison requires the assumption that OBP and SLG are drawn from a similar distribution. Deli (2013) showed that this assumption is wrong.[2] This suggests that the naïve comparison of the coefficients yields a bias in assessing the *Moneyball* hypothesis. In this paper, controlling for these differences, we first identify the factors that contribute to winning in the professional league. Second, we examine whether factors we identified in the first step more precisely explain the payroll compared to factors in past studies.

[2] Deli (2013) showed that SLG was more impartant as the factor that contributes to winning than OBP even after the publication of *Moneyball*.

Providing counter-evidence against the standard theory, we show that after the publication of *Moneyball*, the slugging average, which is widely accepted as one of the most common measures of batting skill, dominates the effect on winning compared to OBP that *Moneyball* considered most important. We also find that in MLB, the slugging average becomes *undervalued* probably due to *Moneyball*, even though our first step showed that it is the factor that most contributes to winning. The evidence suggests that the payroll fails to efficiently reflect each player's productivity. In other words, the skills that most contribute to winning have less predictive power for the payroll than they did before the publication of *Moneyball*. This is the striking evidence against *Moneyball*: the payroll may have become less *efficient* than it was before *Moneyball*.

Our findings have a potentially important implication for the real labor market. Basic economic theory suggests an exact correspondence between pay and productivity when markets are competitive and rich in information, as would seem to be the case in baseball. While it is hard for researchers to provide empirical evidence on the correspondence between pay and productivity in the real labor market, the data on the performance of professional athletes and their payroll allow us to test the theoretical prediction of the relationship between pay and productivity. In this sense, the evidence we provide is relevant to any other labor market in the economy.

The structure of this paper is as follows. Section 2 explains our approach to verify the *Moneyball* hypothesis and describes our data. Section 3 shows the results. Section 4 discusses our findings and Section 5 concludes the paper.

2 Estimation Strategy

2.1 What contributes to winning?

This study estimates two equations to verify whether labor markets pay based on productivity, using panel data with performance indicators and the MLB payroll from 1989 to 2018.[3] First, we follow Hakes and Sauer (2006) to review what factors contribute to winning, using data on the winning records of each team.[4] Second, we re-examine the indices that explain the payroll based on data that matches the performance indices of each player to their payroll level.[5] More specifically, the first analysis regresses the winning percentage on the team's performance indices to identify the index that most contributes to winning. Our focus is on whether the "new" measures to capture player batting skills, such as on-base percentage (OBP) as proposed by the "*Moneyball*," are 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 traditional measures. Based on the results from the first estimation, we measure the impact of batting skill indicators on the payroll and examine whether factors that contribute to winning, which can reflect productivity, explain annual salaries.

To retest the *Moneyball* hypothesis, we standardize variables in estimating equations and obtain parameters. While studies such as Hakes and Sauer (2006) compared partial regression coefficients, we use standardized regression coefficients. Partial regression coefficients indicate the impact of a one-unit change in explanatory variables on an outcome when all other explanatory variables are constant. Without standardization of variables in the estimating equation, the variances fluctuate, and we cannot interpret the size of the partial regression coefficients. On the other hand, we can interpret the sizes of the standardized

[3]The information about performance, position, and salary is from the Larman database <http://www.seanlahman.com/>

[4]The basic statistics of the data are shown in Panel (A) in Table 1.

[5]Panel (B) in Table 1 shows the descriptive statistics.

partial regression coefficients as the contributions of the explanatory variables to the outcome because the variances of the variables are normalized to one.

We estimate the following equation:

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

where $WP_{T,t}$ and $\mathbf{X}$ are denoted as the winning percentage of team j at time t and a vector of control variables such as the earned run average (ERA), respectively.[6] Our focus is on the size of α_1 and α_2. We compare the estimated αs using standardized independent and dependent variables.

2.2 What explains annual salary?

In the next step, we examine whether there is any 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 out had more predictive power for annual salary after as opposed to before 2004, when the *Moneyball* hypothesis was introduced by Lewis (2003). However, the findings in these studies were based on a comparison of partial regression coefficients rather than of standardized partial regression coefficients. This paper uses standardized partial regression coefficients to reexamine whether any structural shift occurs in the MLB labor data after the publication of *Moneyball*.

More specifically, we regress players' annual salaries at time t on indices that reflect players' batting skill, calculated at time $t-1$. The estimation equation is the following:

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

[6] ERA represents the average earned runs per game; this is an index used to measure comprehensive skills in defense (Hakes and Sauer, 2006).

where X and β are vectors of the control variables and coefficients, respectively.

Following Hakes and Sauer (2006), the sample we use covers players with at least 130 plate appearances during the relevant seasons. Because the annual salary is evaluated based on performance in the previous season, we regress the salary at time t on the performance indices at time $t-1$. Following Hakes and Sauer (2006) and Brown (2017), we include working hours, bargaining power, and defensive productivity as well as offensive productivity as control variables.

3 Results

3.1 Determinants of winning

To identify the determinants of winning, we first estimate Equation (1). Panel (A) in Table 2 shows what factors of batting skills contribute to winning using full sample. The first column shows the partial regression coefficients, while the third column shows the standardized 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 the same as that of Hakes and Sauer (2006). This result shows that our dataset successfully replicates Hakes and Sauer (2006).

We also show results using the standardized sample in the third column; these are in sharp contrast with the first column results. The third column shows that the standardized α_2 significantly exceeds α_1. Furthermore, the difference is significant. This suggests that SLG contributes more to winning than OBP does. This result contradicts the *Moneyball* hypothesis and Hakes and Sauer (2006), which argued that the skill of avoiding being out is more important to winning than the skill of hitting the ball. As a robustness check, we regress the winning percentage on eye and power to mitigate multicollinearity between OBP and SLG.[7] Eye and power are also indices to measure skill at avoiding being out and that of hitting the ball, respectively.[8] Thus, 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 fourth column in Panel (A) in Table 2 shows that the standardized partial regression coefficient of power (α_4) significantly exceeds that of the eye (α_3). Furthermore, the difference between them is significant. This supports that our benchmark result is robust: the indices related to the skill of hitting the ball, such as SLG and power, can better explain the winning percentage than those related to the skill of avoiding 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 2 shows the estimation results before and after the publication using the standardized data. The results suggest that over the entire sample, SLG more stably contributes to winning than does OBP. The first column shows that α_2 exceeds α_1 before the publication. The third column shows that, even after the publication, α_2 is significantly larger than α_1. The second and fourth columns show that the above results are similar when we use eye and power. Furthermore, the difference between α_1 (α_3) and α_2 (α_4) is larger after the publication. These findings suggest that the skill of hitting the ball contributes more to winning than the skill of avoiding being out, and the discrepancy becomes wider after 2004.

3.2 Determinants of annual salary

In the second step, we identify what determines the annual salary. Our focus is on whether productivity can explain the payroll.

[7] Hakes and Sauer (2007) discussed the multicollinearity issue between OBP and SLG.

[8] Eye and power are calculated by dividing the sum of bases-on-balls and hit-by-a-pitch by plate appearance and by subtracting the batting average from SLG, respectively. Panel (C) in Table 1 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 use eye and power as well as OBP and SLG to address the multicollinearity issue.

First, we replicate the results of Hakes and Sauer (2006) using the entire sample from 1989 to 2018. Hakes and Sauer (2006) showed that before the publication of *Moneyball*, SLG had more predictive power for annual salary than did OBP, while after publication, OBP was more important. Our estimation results replicate their finding when the data are not normalized. Table 3 shows the estimation results from Equation (2) and reports partial regression coefficients. The third and fifth columns show the results using the subsamples from 1989 to 2003 and from 2004 to 2018, respectively. The coefficient of SLG (γ_2) is significantly larger than that of OBP (γ_1) before the publication of *Moneyball*, while after publication, the coefficient of SLG (γ_2) becomes smaller than that of OBP (γ_1). This reversal is also found when we use the other indicators, that is, 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 the publication, while after publication, the coefficient of power (γ_4) becomes smaller than that of eye (γ_3). These results are consistent with those of Hakes and Sauer (2006).

The situation changes, however, when we use the normalized data. Panel (A) in Table 4 shows the estimation results from Equation (2) and reports the standardized partial regression coefficients. The third and fifth columns show the results using the subsamples from 1989 to 2003 and from 2004 to 2018, respectively. In Panel (A), the coefficient of SLG (γ_2) is significantly larger than that of OBP (γ_1) before the publication of *Moneyball*, while the difference between them becomes almost zero (0.004) after the publication. That is the case when we use the logarithm of salary as the dependent variable and the normalized variables as independent variables. In Panel (B), the coefficient of SLG (γ_2) is significantly larger than that of OBP (γ_1) before the publication of *Moneyball*, while the difference between them becomes 0.04 after the publication. This is robust when we use 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 publication of *Moneyball*. These results suggest that before the publication of *Moneyball* indices such as SLG and power, which measure the skill of hitting the ball, were superior to those such as OBP and eye, which measure the skill of avoiding being out, in terms of determining annual salaries. However, there is no significant difference between them after the publication of *Moneyball*.This may indicate that the salary determinants change: the skill of hitting the ball becomes undervalued after the publication of *Moneyball*, even though SLG and power contribute more to winning than do OBP and eye, as shown in Table 2.

To identify any shift in the salary determinants, we conduct a rolling regression using Equation (2). We estimate Equation (2) on a single-year basis. The top panel in Figure 1 shows the standardized regression coefficients of OBP (γ_1) and SLG (γ_2), respectively. The figure suggests that there is a structural break in the determinants of salary. It shows that the red line (γ_2) is larger than the blue one (γ_1) until 2003 and that the discrepancy between them disappears after that. This is the case when you observe the standardized regression coefficients of eye (γ_3) and power (γ_4), respectively. The bottom panel in 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 after that. The figure suggests that the determinants of salary change after the publication of *Moneyball*.

4 Discussion

Our first estimation using Equation (1) shows that after the publication of *Moneyball*, over the entire sample, SLG dominates the effect on winning. In our second estimation, after the publication of *Moneyball*, SLG becomes *undervalued* as the determinant of wages probably as a result of the publication, even though in the first step, it was identified as the factor that most contributes to winning. This implies that *Moneyball* had a negative effect on the payroll. As shown by Figure 1, before 2003, SLG had more predictive power for the payroll than OBP did. This suggests an *efficient* market in the sense that the payroll seemed to reflect players' productivities. However, after the publication of *Moneyball*, the efficiency deteriorated, and annual salaries rewarded underproductive skills. This is not consistent with the claim that the appearance of *Moneyball* improved efficiency in the labor market. Thus, our finding suggests that the prevalence of the *Moneyball* hypothesis may have caused labor market efficiency to deteriorate.

5 Conclusion

This paper reconsiders the *Moneyball* hypothesis. We combine payroll data for professionals in MLB with detailed data on each player's performance to reevaluate the hypothesis. In order to verify the story in *Moneyball*, we replicate the results as shown in Hakes and Sauer (2006) but not by a naïve comparison of the coefficients, which yields a bias in assessing the *Moneyball* hypothesis. Controlling for these differences, we first identify the factors that contribute to winning in the professional league. Second, we examine whether the factors we identified in the first step explain the payroll levels more precisely than did the factors in past studies. The more precise way to measure the productivity of employees contributes to avoiding resource misallocation.

We provide counter-evidence against the standard theory by showing that after the publication of *Moneyball*, the slugging average, which is widely accepted as one of the most common measures of batting skill, dominates the effect on winning compared to the factor that *Moneyball* considered important. We also find that in MLB, especially, the slugging average becomes *undervalued* as the determinant of wages probably as a result of *Moneyball*, even though in the first step, it was identified as the factor that most contributes to winning. This evidence suggests that the payroll fails to efficiently reflect each player's productivity. 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.

Brown, D., Link, C., 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* 8, 771–786.

Depken II, Craig A., (2000) "Wage Disparity and Team Productivity: Evidence from Major League Baseball," *Economics Letters* 67(1), 87–92.

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

Gould, E., and Winter, E., (2009) "Interactions between Workers and the Technology of Production: Evidence from Professional Baseball," *Review of Economics and Statistics* 91(1), 188–200.

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

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

Kahane, L., Longley, N., Simmons, R. (2013) "The Effects of Coworker Heterogeneity on Firm-Level Output: Assessing the Impacts of Cultural and Language Diversity in the National Hockey League," *Review of Economics and Statistics* 95(1), 302–314.

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

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

Plant, E., Stowe, C., (2019) "Is Moneyball Relevant on the Racetrack? A New Approach to Evaluating Future Racehorses," *Journal of Sports Economics* 20, 428–447.

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

Table 1: 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

Panel (B): Descriptive statistics of batters in MLB

	OBP	SLG	Eye	Power
Mean	0.340	0.422	0.102	0.155
Median	0.338	0.417	0.097	0.149
Std. Dev.	0.041	0.079	0.037	0.062
Observations	8,349	8,349	8,349	8,349

	Salary (USD)	Plate Appearance	Experience
Mean	3,313,839	447	8
Median	1,350,000	458	7
Std. Dev.	4,529,835	175.172	4.026
Observations	8,351	8,349	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 5% level is indicated by † and at the 1% level by *.

Table 2: The impact of batting skill on winning percentage in MLB

Panel (A): Full sample

	Partial regression coefficient		Standardized 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*

	Standardized partial regression coefficient			
	Before the publication of *Moneyball* From 1989 to 2003		After the publication of *Moneyball* From 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: $\alpha_2 = \alpha_4$	–	0.338∗	–	0.354∗

Notes: Standard error is indicated in parentheses. Significance at the 5% level is indicated by † and at the 1% level by *. We conduct a Wald test and report the (absolute value of) differences between the relevant coefficients.

Table 3: What factors determine wages?: Partial regression coefficients

	Partial regression coefficient					
	All year		Before the publication of *Moneyball* 1989-2003		After the publication of *Moneyball* 2004–2018	
	(1)	(2)	(3)	(4)	(5)	(6)
γ_1: OBP	1.488∗	–	0.745†	–	2.483∗	–
	(0.275)		(0.374)		(0.404)	
γ_2: SLG	2.219∗	–	2.524∗	–	1.844∗	–
	(0.148)		(0.204)		(0.215)	
γ_3: Eye	–	1.793∗	–	1.086∗	–	2.742∗
		(0.243)		(0.330)		(0.357)
γ_4: Power	–	2.691∗	–	2.982∗	–	2.311∗
		(0.153)		(0.213)		(0.220)
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)
Experience	0.479∗	0.476∗	0.453∗	0.452∗	0.498∗	0.493∗
	(0.008)	(0.008)	(0.011)	(0.011)	(0.011)	(0.011)
Experience2	−0.017∗	−0.017∗	−0.016	−0.017∗	−0.176∗	−0.017∗
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Catcher Dummy	0.070∗	0.055†	0.139∗	0.129∗	0.008	−0.014
	(0.025)	(0.025)	(0.036)	(0.035)	(0.035)	(0.035)
Infielder Dummy	0.001	0.013	0.006	0.008	0.002	−0.029
	(0.019)	(0.018)	(0.026)	(0.027)	(0.026)	(0.026)
Adjusted R^2	0.708	0.707	0.685	0.683	0.685	0.683
Observation	8,351	8,351	4,144	4,144	4,207	4,207
Wald Test						
H_0: $\gamma_1 = \gamma_2$	0.732	–	1.779∗	–	0.638	–
H_0: $\gamma_3 = \gamma_4$	–	0.898∗	–	1.896∗	–	0.431

Notes: Standard error is indicated in parentheses. Significance at the 5% level is indicated by † and at the 1% level by *. The last two lines indicate the difference between the two coefficients as absolute values. The dependent variable is ln (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.

Table 4: What factors determine wages?: Standardized partial regression coefficient

	Standardized partial regression coefficient					
	All year		From 1989 to 2003		From 2004 to 2018	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel (A) Dependent variable: Standardized salary						
γ_1: OBP	0.079∗	–	0.053∗	–	0.121∗	–
	(0.011)		(0.015)		(0.015)	
γ_2: SLG	0.132∗	–	0.244∗	–	0.117∗	–
	(0.011)		(0.015)		(0.015)	
γ_3: Eye	–	0.091∗	–	0.092∗	–	0.117∗
		(0.009)		(0.012)		(0.012)
γ_4: Power	–	0.135∗	–	0.235∗	–	0.123∗
		(0.009)		(0.013)		(0.013)
Wald Test						
H_0: $\gamma_1 = \gamma_2$	0.053∗	–	0.191∗	–	0.004	–
H_0: $\gamma_3 = \gamma_4$	–	0.044∗	–	0.143∗	–	0.006
Adjusted R^2	0.482	0.484	0.533	0.538	0.511	0.510
Observation	8351	8,351	4,144	4144	4207	4207
Panel (B) Dependent variable: Logarithm of salary						
γ_1: OBP	0.061∗	–	0.030∗	–	0.098∗	–
	(0.012)		(0.017)		(0.016)	
γ_2: SLG	0.174∗	–	0.209∗	–	0.137∗	–
	(0.012)		(0.018)		(0.016)	
γ_3: Eye	–	0.066∗	–	0.040∗	–	0.098∗
		(0.009)		(0.013)		(0.013)
γ_4: Power	–	0.167∗	–	0.193∗	–	0.138∗
		(0.010)		(0.015)		(0.013)
Wald Test						
H_0: $\gamma_1 = \gamma_2$	0.113∗	–	0.179∗	–	0.039	–
H_0: $\gamma_3 = \gamma_4$	–	0.101∗	–	0.153∗	–	0.040
Adjusted R^2	0.703	0.702	0.661	0.660	0.685	0.684
Observation	8,351	8,351	4,144	4,144	4,207	4,207

Source: The information about performance, position, and salary is from the Larman database <http://www.seanlahman.com/>

Notes: Standard error is indicated in parentheses. Significance at the 5% level is indicated by † and at the 1% level by *. The dependent variable is ln (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 standardized partial regression coefficients