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# What Makes for a Useful Statistic

## Not All Numbers Are Created Equal

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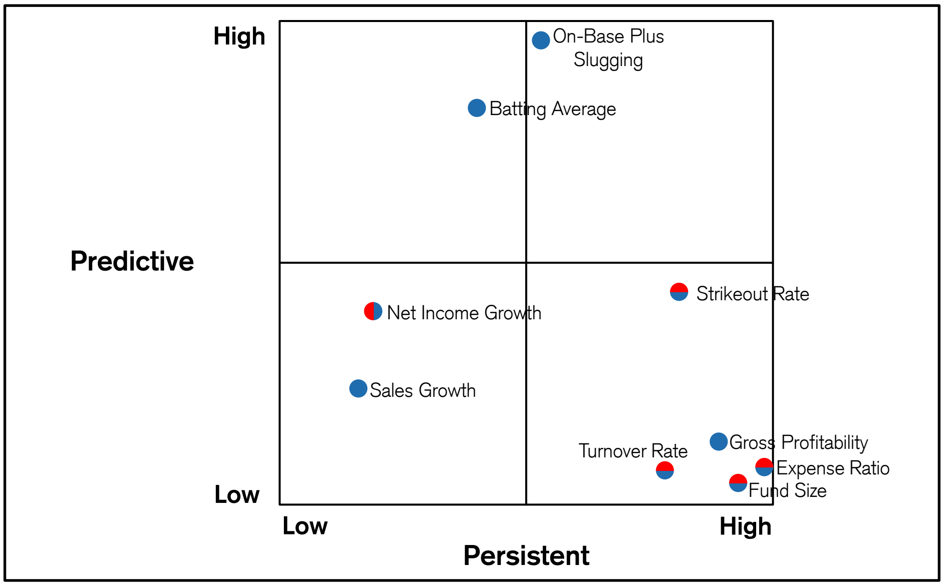
Authors

**Michael J. Mauboussin**
michael.mauboussin@credit-suisse.com

**Dan Callahan, CFA**
daniel.callahan@credit-suisse.com

**Darius Majd**
darius.majd@credit-suisse.com


*Source: Credit Suisse.*

"To our surprise, we discovered that most companies have made little attempt to identify areas of nonfinancial performance that might advance their chosen strategy. Nor have they demonstrated a cause-and-effect link between improvements in those nonfinancial areas and in cash flow, profit, or stock price."

Christopher D. Ittner and David F. Larcker[1]

- The worlds of business, investing, and sports are awash in numbers, yet we rarely pause to consider what makes for a suitable statistic.
- We provide a way to think about the numbers you use and put them in a format that allows you to compare across domains.
- The first quality to seek in a statistic is persistence, which means what happens in the present is similar to what happened in the past.
- The second quality is that the statistic is predictive, or highly correlated with the outcome you are trying to achieve.
- The goal is to find a statistic that offers a robust combination of persistence and predictive value.

## Introduction

In 2009, Robert Jones, a delivery driver, was on the job in the town of Todmorden in West Yorkshire, England. He relied on his BMW's navigation feature, guided by the Global Positioning System (GPS), to lead him to his destination safely. The system led him up a steep and narrow footpath, "insisting the path was a road." The car finally came to a stop at a fence, inches from a cliff with a 100-foot drop. Jones was whisked to safety, but the lesson is clear: slavishly submitting to false signals can lead you astray.[2]

The worlds of business, investing, and sports are awash in numbers. We all know that the numbers are not equally informative, yet we rarely pause to consider what makes for a suitable statistic. Here, we provide a way to think about the numbers you use and put them in a format that allows you to compare across domains.[3]

## Persistent and Predictive

The first quality to seek in a statistic is persistence, which means what happens in the present is similar to what happened in the past. For activities that are largely a matter of skill, persistence tends to be high. For activities that have a lot of luck, persistence is low. Statisticians use the word "reliable" to capture this idea.

True score theory is one of the best ways to think about persistence.[4] It says:

Observed score = true ability (skill) + random error (luck)

When the ratio of true ability to observed score is high, we know the statistic will be persistent. We can measure persistence using the correlation coefficient, a measure of the degree of linear relationship between two variables in a pair of distributions.

The correlation coefficient, $r$, takes a value that ranges from 1.00 to -1.00. When $r$ is 1.00, a plot of each point from both distributions falls on a straight line. Values from each distribution need not be the same, but the differences are identical. If $r$ = -1.00, there is a perfect inverse correlation: an increase in one variable leads to a decrease in the other. When $r$ = 0, results are random.

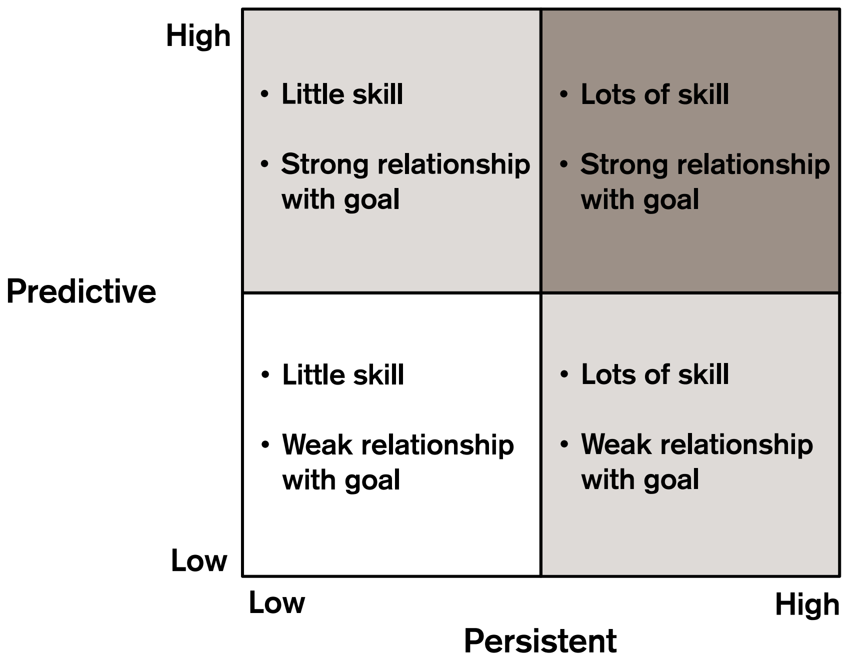
The SAT, a standardized test for admission into U.S. colleges, provides a good example.[5] About half of the students who sit for the SAT take it more than once.[6] The correlation between the score on the first and second test is about 0.90.[7] SAT scores are very persistent, which means the exam accurately captures the skills it tests for.

The second quality you want in a statistic is predictive value, or that it is highly correlated with the outcome you are trying to achieve. Statisticians say a statistic is "valid" if it effectively measures what it is supposed to measure. For the SAT, for instance, you might want to predict cumulative college grade point average (GPA), graduation rate, or income after college. The correlations between SAT scores and these factors, roughly in a range of 0.20 to 0.50, are not as high as those for persistence but are positive.[8]

Note that while the concepts of persistence and predictive value may be related, they are really distinct ideas. You can have a metric that is extremely persistent but tells you very little about what you are trying to achieve. Imagine shooting arrows that consistently land in the same spot far from a bullseye. Alternatively, you can have a statistic that is predictive but not persistent. Here, the arrows are scattered all over the target but the average of all the arrows is a bullseye. The group is accurate but no individual shot is reliable.

The goal is to find a statistic that offers a robust combination of persistence and predictive value. One way to visualize this is to plot the statistics on a simple chart (see Exhibit 1). The horizontal axis uses the correlation coefficient to measure persistence, with zero on the left and one (or negative one) on the right. Referring to the equation for true score theory, results on the left reflect mostly random error, or luck, and those on the right capture true ability, or skill.

**Exhibit 1: The Persistent-Predictive Chart**




*Source: Credit Suisse.*

The vertical axis measures predictive value, also using correlation. Statistics on the bottom of the axis have a low correlation with the objective, while those on the top correlate closely with the goal. The dream statistic is in the upper right corner, and those in the bottom left corner are of little utility.

To illustrate how this works, we can look at SAT results and cumulative college GPA. We noted that when a student takes the SAT twice, the persistence in the scores is 0.90, which is close to the right side of the chart. One study found that the correlation between SAT score and cumulative college GPA is 0.36, so a little more than a third of the way up from the bottom on the vertical axis.[9] If the quadrant in the bottom right corner contained a circular clock face, the point would fall close to two o'clock.

A sensible way to search for a useful statistic is to start with your goal and go backward. You can then observe which statistics are most persistent and predictive of that outcome. You may be waiting for the standard warning about correlation and causation, and here it is: you should consider causation carefully when assessing the predictive value. In many instances of practical utility, correlation and causality go together.

We will examine examples from three fields: business, investing, and sports. In business, for instance, the objective might be to deliver an attractive total shareholder return. Investors seek to anticipate returns, adjusted for risk, that are in excess of an appropriate benchmark. And in baseball the goal on offense is to score runs.

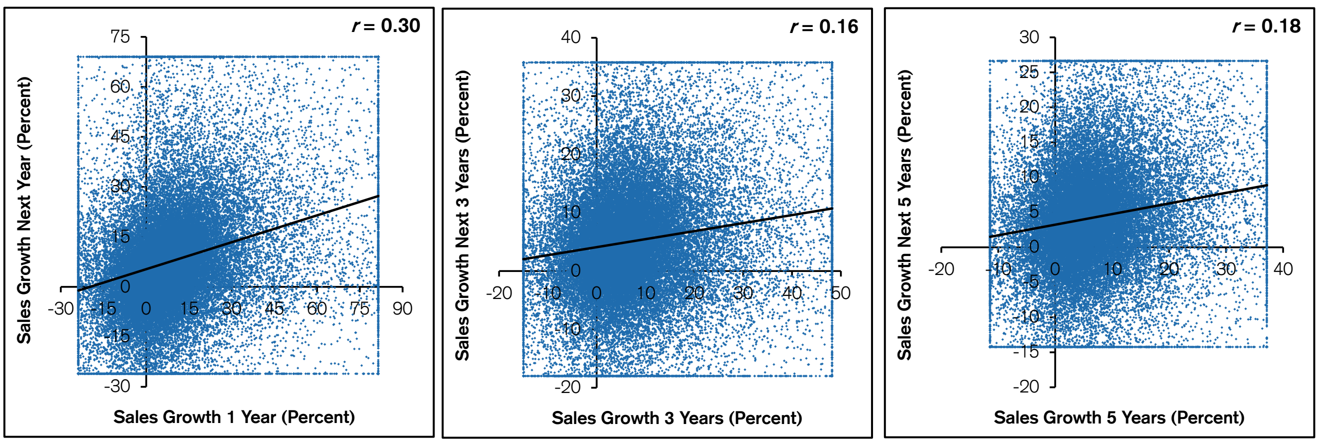
## Statistics for Assessing Business

A strong case can be made that maximizing long-term shareholder value should be a company's governing objective.[10] Indeed, a recent survey of executive compensation for the 250 largest companies in the S&P 500 Index found that total shareholder return (TSR) is the number one metric used in incentive compensation.[11]

Earnings growth and sales growth are the most common statistics that companies and analysts use to anticipate TSR. Nearly 60 percent of the companies in the S&P 500 give guidance for earnings growth and nearly 40 percent do so for revenue growth.[12] Earnings and sales are also the most visible estimates that analysts produce, and the price/earnings multiple is the most popular measure of valuation.[13]

Let's start by examining the persistence and predictive value of sales growth. Exhibit 2 shows the correlation of one-, three-, and five-year sales growth rates for the top 1,000 companies in the world by market capitalization from 1950-2014. For example, the middle figure shows how well the next three years of sales growth correlate with the prior three years. All numbers are adjusted for inflation.

**Exhibit 2: Persistence of Sales Growth Rates (1-, 3-, and 5-Year)**

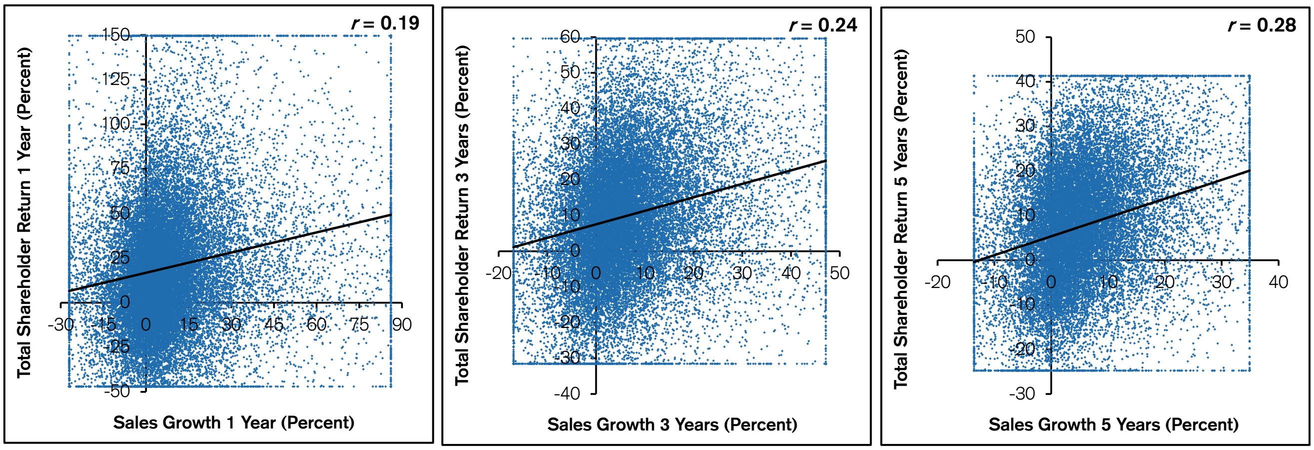



*Source: Credit Suisse HOLT®.*
*Note: Top 1,000 global companies, 1950-2014; Calculations use annual data on a rolling 1-, 3-, and 5-year basis; Winsorized at 2nd and 98th percentiles; Depicted growth rates are annualized.*

The correlation is 0.30 for one year but drops to the high teens for the three- and five-year periods. From a practical point of view, this means that executives and analysts should expect substantial regression toward the mean for multi-year sales growth forecasts.[14]

Exhibit 3 shows the correlation between sales growth and total shareholder return in order to assess the predictive value of sales. For example, the middle figure shows the correlation between the last three years of sales growth and total shareholder return over the same time.

**Exhibit 3: Predictive Value of Sales Growth Rates (1-, 3-, and 5-Year)**

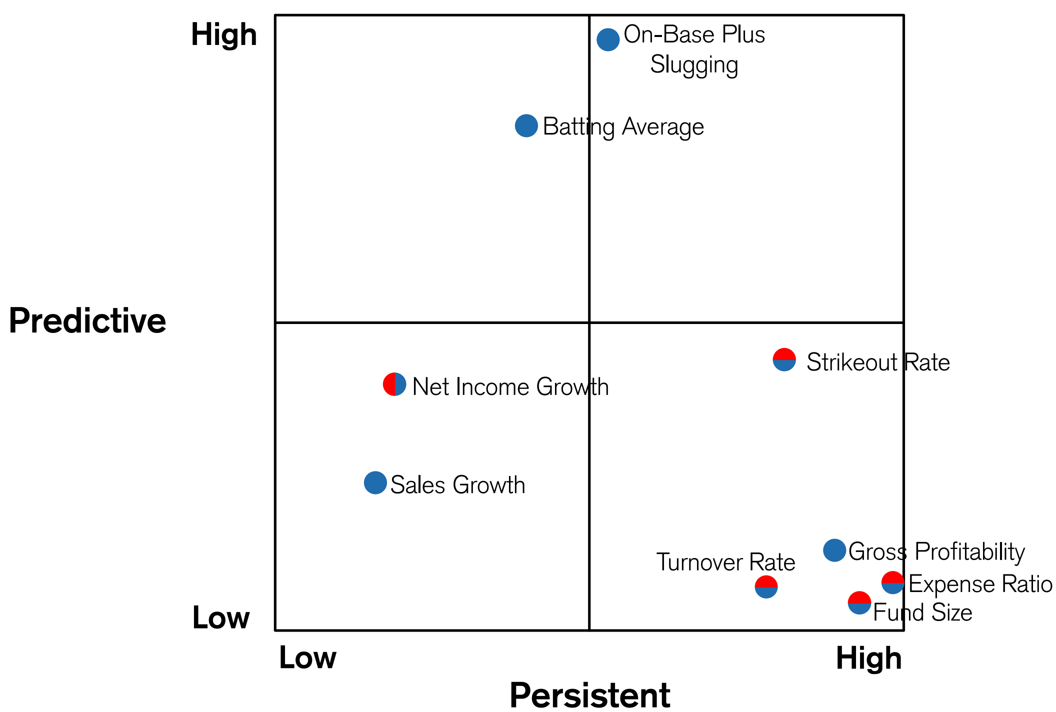



*Source: Credit Suisse HOLT®.*
*Note: Top 1,000 global companies, 1950-2014; Calculations use annual data on a rolling 1-, 3-, and 5-year basis; Winsorized at 2nd and 98th percentiles; Depicted growth rates and TSRs are annualized.*

We see that the correlation is 0.19 for one year but improves to 0.24 for three years and 0.28 for five years. If we look at the numbers for three years for both persistence and predictive value, we see that sales growth is not a strong statistic.

Exhibit 4 places the data point for the three-year persistence and predictive values of sales growth, along with other figures we will discuss, on the persistent-predictive chart. We can see that it falls in the bottom left quadrant, far from the ideal metric in the top right corner.

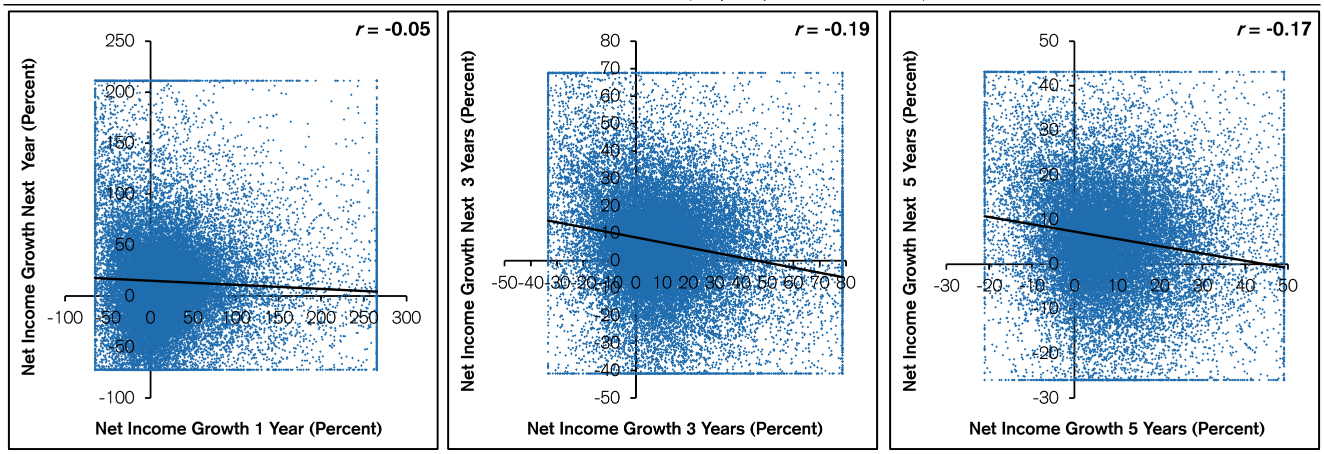
**Exhibit 4: The Persistent-Predictive Chart**




*Source: Credit Suisse.*
*Note: Blue indicates a positive correlation. Red on the left represents a negative correlation in persistence while red at the top shows a negative correlation in predictive value; Calculations reflect 3-year periods for business and investing and 1-season periods for sports.*

We now turn to earnings growth. Exhibit 5 shows the persistence of net income growth over one-, three-, and five-year periods. None of the correlations, in a range from -0.05 to -0.19, are strong, and all of them are negative. That means that growth rates above the average are often followed by growth rates below the average. That's the bad news.

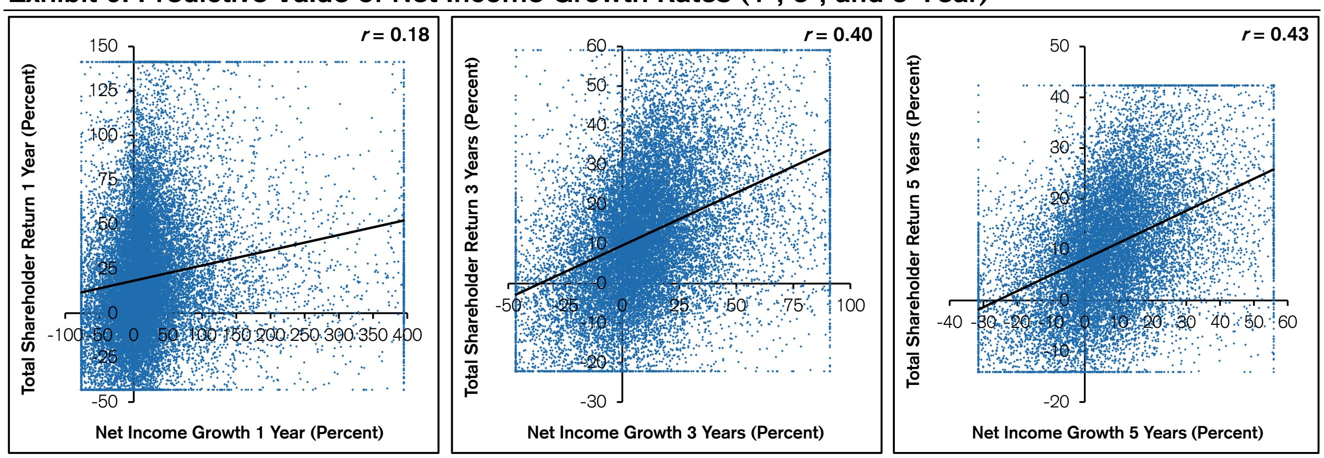
**Exhibit 5: Persistence of Net Income Growth Rates (1-, 3-, and 5-Year)**




*Source: Credit Suisse HOLT®.*
*Note: Top 1,000 global companies, 1950-2014; Calculations use annual data on a rolling 1-, 3-, and 5-year basis; Winsorized at 2nd and 98th percentiles; Depicted growth rates are annualized.*

The good news is that net income growth has a higher correlation with total shareholder return than sales growth does. Exhibit 6 shows that the correlation coefficient is 0.18 for one year but increases to about 0.40 for the three- and five-year assessments.

**Exhibit 6: Predictive Value of Net Income Growth Rates (1-, 3-, and 5-Year)**




*Source: Credit Suisse HOLT®.*
*Note: Top 1,000 global companies, 1950-2014; Calculations use annual data on a rolling 1-, 3-, and 5-year basis; Winsorized at 2nd and 98th percentiles; Depicted growth rates and TSRs are annualized.*

Exhibit 4 shows that net income growth is more predictive of TSR than sales growth. But its persistence is comparable, albeit with a negative correlation. This research corroborates findings by financial economists.[15]

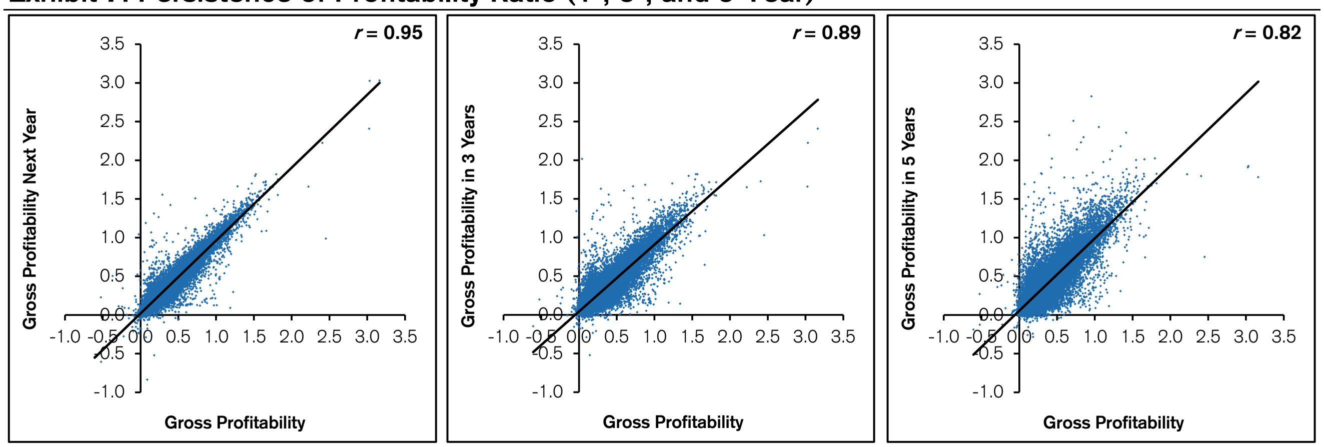
"Profitability" is a business statistic that has gained attention in recent years. Robert Novy-Marx, a professor of finance at the Simon Business School at the University of Rochester, defines profitability as a company's revenues minus cost of goods sold, scaled by assets—or, more simply, as gross profit divided by assets.[16]

Research by Novy-Marx suggests that firms with high profitability outperform those with low profitability even though the high profitability firms generally start with more lofty valuations.

Eugene Fama and Kenneth French, finance professors renowned for their work on asset pricing, include profitability as one of the factors that helps explain changes in asset prices. The others include beta (a measure of the sensitivity of an asset's returns to market returns), size, valuation, and investment.[17] While their definition of profitability differs somewhat from that of Novy-Marx, it captures the same essence.

Exhibit 7 shows that the Novy-Marx definition of profitability is very persistent over one-, three-, and five-year periods. For example, the correlation between profitability in the current year and three years in the future is 0.89. But even the five-year correlation is relatively high at 0.82. This universe includes the top 1,000 firms in the world measured by market capitalization from 1950 to 2014. The sample includes dead companies but excludes firms in the financial services and utilities sectors.

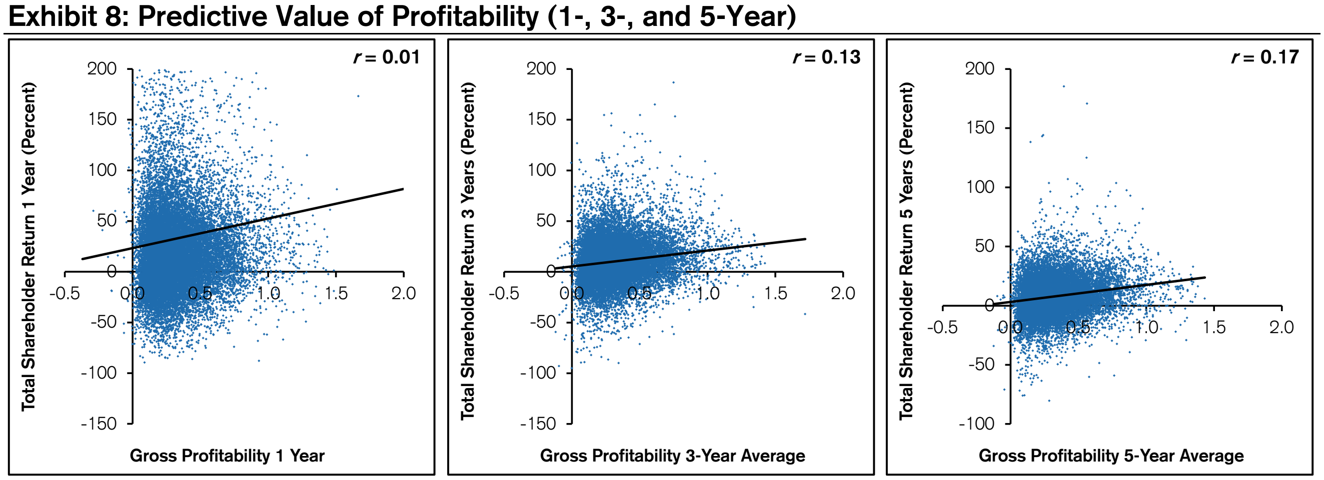
**Exhibit 7: Persistence of Profitability Ratio (1-, 3-, and 5-Year)**




*Source: Credit Suisse HOLT®.*
*Note: Top 1,000 global companies excluding financials and utilities, 1950-2014; Calculations use annual data on a rolling 1-, 3-, and 5-year basis.*

Exhibit 8 shows that the simple correlation between profitability and three-year TSR is low at 0.13. However, neither Novy-Marx nor Fama and French recommend simply using the correlation between the measure and stock returns to explain outcomes.

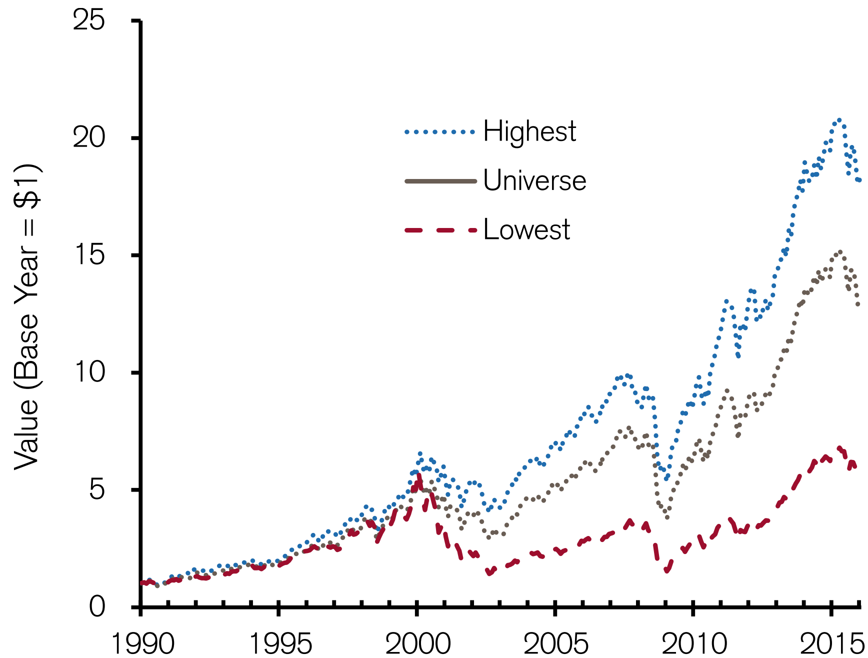
**Exhibit 8: Predictive Value of Profitability (1-, 3-, and 5-Year)**




*Source: Credit Suisse HOLT®.*
*Note: Top 1,000 global companies excluding financials and utilities, 1985-2014; Calculations use annual data on a rolling basis; TSRs are annualized.*

Rather, the most effective way to use the profitability ratio is to rank stocks in quintiles by profitability and build portfolios for each. Exhibit 9 shows the cumulative growth in value of $1 for the quintiles with the highest and lowest profitability, as well as that for the whole universe. The sample includes the largest 1,000 U.S. industrial and service companies from 1990 through January 2016. The portfolios are rebalanced monthly.

**Exhibit 9: Total Return for the Highest and Lowest Quintiles of Profitability (1990-January 2016)**




*Source: Credit Suisse HOLT®.*
*Note: Gross profitability is calculated using the average of the assets at the beginning and the end of the fiscal year.*

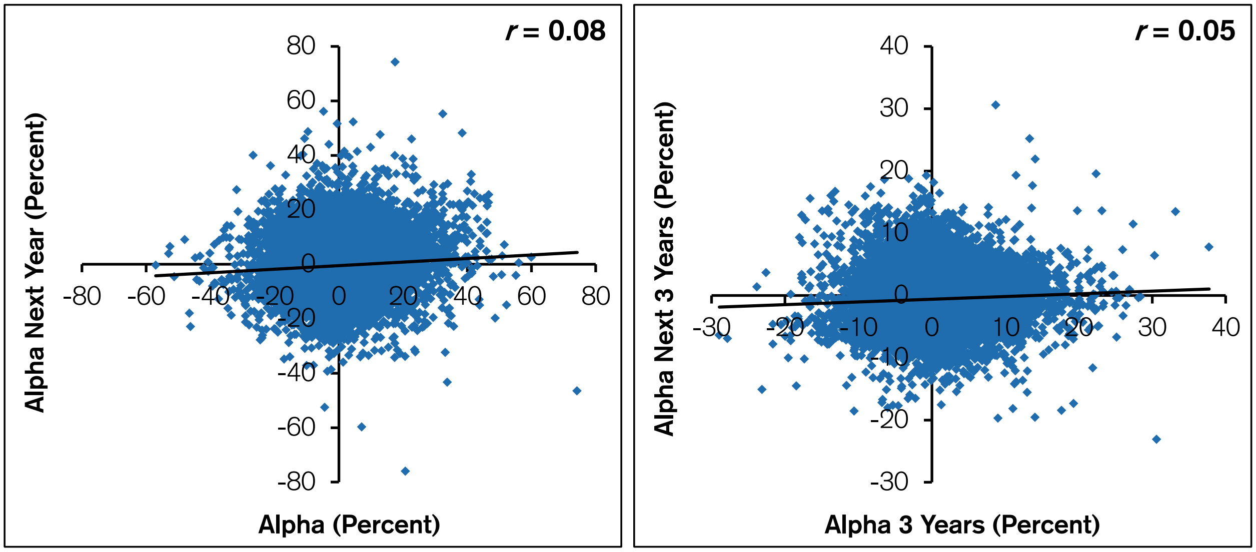
While we have dwelled on financial measures, companies and investors can also examine non-financial measures such as customer satisfaction, safety, and product quality measures in the same way.[18] The exercise of examining statistics for persistence and predictive value allows analysts to model more thoughtfully, places appropriate emphasis on what matters, and reduces the risk of focusing on the wrong metrics.

## Statistics for Assessing Investing

While there may be some debate about the proper corporate objective, investors seek to generate excess returns, adjusted for risk, relative to an appropriate benchmark.[19] In finance, these excess returns are called "alpha." A focus on alpha makes sense because investors can generally buy an index or exchange-traded fund that offers a low-cost alternative to an active manager.

Since alpha is the goal, we can't run it through the persistent and predictive framework. But we can assess the persistence of alpha. The left side of exhibit 10 shows the year-to-year persistence of alpha for U.S. mutual funds that manage stocks of large capitalization companies. The correlation is 0.08, which demonstrates that persistence in alpha is low. The right side shows that the correlation between the next three years of alpha and the prior three years is even lower. Academic work generally supports the view that alpha does not have a great deal of persistence, although some researchers find higher levels of persistence by carefully considering additional factors.[20]

**Exhibit 10: Persistence of Alpha (1- and 3-Year)**



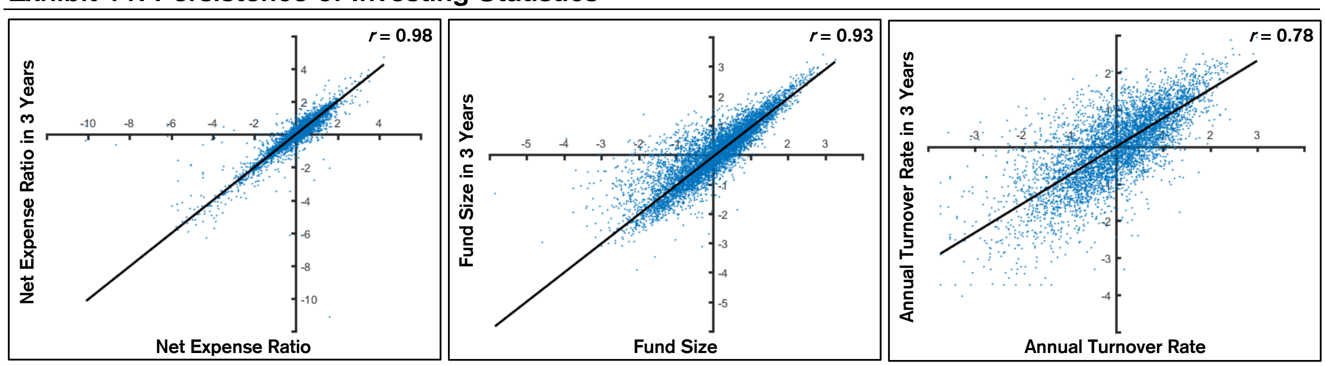

*Source: Markov Processes International, Morningstar, and Credit Suisse.*
*Note: U.S. large cap equity mutual funds, 2000-2015; Calculations use quarterly data on a rolling 1- and 3-year basis.*

Alpha must sum to zero over time because for all of the investors who "win" positive excess returns there must be investors who "lose" an equivalent amount. But alpha is zero only before costs. Alpha for investors is negative in the aggregate after expenses.[21]

Expense ratios for mutual funds are very persistent, with a correlation of 0.98 (left panel of Exhibit 11). This correlation compares the current annual net expense ratio to that three years hence. The predictive value of expense ratios is -0.08, indicating a weak link between fees and alpha for a broad sample of mutual funds (left panel of Exhibit 12).

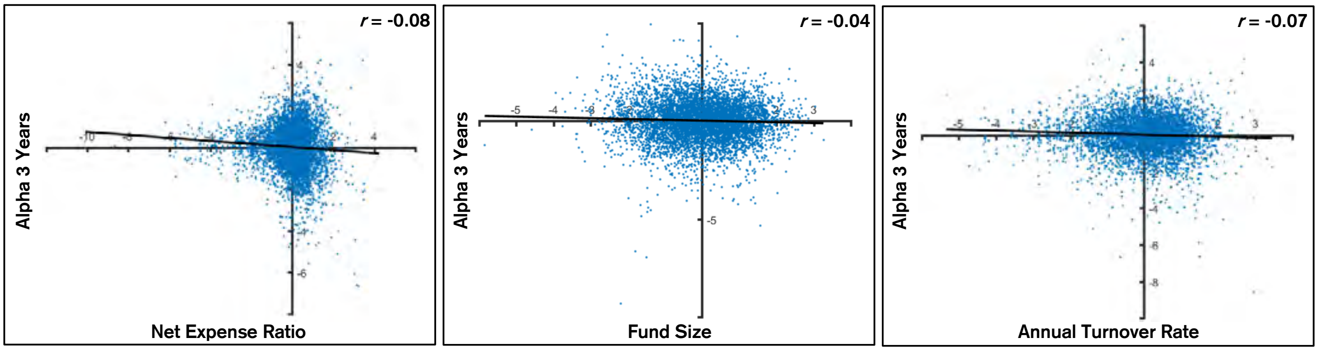
Notwithstanding the weak correlation between fees and returns, it stands to reason that low expenses are better than high expenses over time. Funds in the quintile with the lowest fees generate higher total returns than funds in the quintile with the highest fees. For instance, one study of funds invested in U.S. equities found that funds in the cheapest quintile generated returns that were 125-150 basis points higher than those in the most expensive quintile.[22] Similar to profitability, segregation of the data provides clearer results.

**Exhibit 11: Persistence of Investing Statistics**




*Source: Markov Processes International, Morningstar, and Credit Suisse.*
*Note: U.S. equity mutual funds, 2000-2015; Calculations use monthly data on a rolling 3-year basis, and data is normalized.*

**Exhibit 12: Predictive Value of Investing Statistics**




*Source: Markov Processes International, Morningstar, and Credit Suisse.*
*Note: U.S. equity mutual funds, 2000-2015; Calculations use monthly data on a rolling 3-year basis, and data is normalized.*

Size is among the most useful statistics in assessing a fund. The persistence of fund size is 0.93 (middle panel of Exhibit 11), which suggests the impact that performance and flows have on size is relatively modest. The correlation between fund size and alpha is -0.04 (middle panel of Exhibit 12), which says that the largest funds deliver below-average alpha as a group. This finding, too, is revealed in the academic literature.[23]

Two finance professors, Jonathan Berk and Richard Green, developed a model to explain this result.[24] They suggest a world where there are skillful investment managers and both the managers and investors recognize this skill. The manager's ability to deliver excess returns is limited by assets under management such that each incremental dollar an investor adds reduces the expected return of the portfolio.

In such a world, a skillful manager attains assets through inflows until the expected return of the portfolio falls to a level roughly equal to that of the market. Berk and Green suggest that equilibrium is realized when all managers, irrespective of their level of skill, have identical expected returns. The model doesn't explain the modest negative slope of the correlation, but makes clear that the capacity of a manager to deliver value tends to be constrained by the size of the assets under management.

Investors commonly conflate recent results with skill. As a result, they have a tendency to invest in funds that have done well and to withdraw money from funds that have done poorly. This is true for institutional investors as well as individuals.[25] These flows benefit the fund's results when they are positive and detract from performance when they are negative. One study suggests that one-third of the alpha in the hedge fund industry is the result of fund flows.[26]

There has been a great deal of hand wringing over the topic of short-termism, a tendency to make decisions that appear beneficial in the short term at the expense of decisions that have a higher payoff in the long term.[27] A rise in portfolio turnover for mutual funds is a purported manifestation of this short-termism.[28]

The portfolio turnover rate, which typically reflects results for one year, is the lesser of the total amount of new securities that the fund buys or sells, divided by the average monthly total assets of the fund. For instance, an equity mutual fund that bought $50 million of new stocks with average assets of $100 million had a portfolio turnover rate of 50 percent. You impute the holding period by dividing one by the rate. For instance, a 50 percent turnover rate equals a two-year holding period (1/.50 = 2).

Turnover is higher today than it was in the 1960s, implying shorter holding periods. While higher turnover may simply reflect better information, the rise of institutional investors, lower taxes, and sharply lower transaction costs, there remains a distinct sense that investors today have a shorter time horizon than in the past.[29] One survey suggested a holding period of 2.8 years or more qualified as a long-term investment.[30]

Portfolio turnover is persistent, with a correlation of 0.78, since it is largely within the manager's control (right panel of Exhibit 11). Investment processes vary in their optimal trading activity. Strategies that result in active trading generally incur higher costs, and are less tax efficient, than strategies that trade less frequently. Turnover is not very predictive, with a correlation of -0.07. So while trading costs may make a difference, the overall impact is modest.[31]

Quantitatively assessing the differential skill of money managers is a challenge because it is hard to beat the market. Indeed, the correlations near zero in Exhibit 12 indicate that results include a great deal of luck. This reflects the "paradox of skill": when absolute skill is high and relative skill is narrow in competitive realms, luck plays a big role in outcomes.

But the data suggest we can improve the probability of success by focusing on fair fees, smaller funds, and high active share. Active share is a measure of how different a portfolio is from its benchmark.[32] Further, investors should seek congruence between an investment firm's perceived source of edge and the process to find edge. It is less important to ask how frequently a portfolio manager trades and more important to determine whether the manager's process serves the goal.

## Statistics for Assessing Sports

We relegate the discussion of persistence and predictive value for offense in baseball to the appendix, but we include the results in exhibit 4. The most sophisticated statistics today are much more complex than those we depict, although even these simple measures can explain a great deal.

## Summary

Companies, investors, and sports teams commonly have goals they want to achieve. As a result, each group monitors certain measures to determine whether they are on track. These same measures are commonly used by outsiders to assess and anticipate results.

The main message is that statistics vary in their persistence and predictive value. The ideal statistic is both persistent, indicating the presence of skill, and predictive of the desired outcome. Poor statistics are either unreliable because of a large dose of luck or are unrelated to the end goal.

Exhibit 13 summarizes the statistics we consider in this report. We create a score for each one, in a range from zero to one, that indicates the aggregate strength of the measure.[33] A score of zero says the statistic has no utility at all, and a score of one says the result is perfectly persistent and predictive. Note that the sports statistics we consider are much more useful than those for investing or business.

**Exhibit 13: Scores of Nine Statistics on Persistent-Predictive Chart**

| | Persistent (*r*) | Predictive (*r*) | Score |
|---|---|---|---|
| **Business** | | | |
| Sales Growth | 0.16 | 0.24 | 0.20 |
| Net Income Growth | -0.19 | 0.40 | 0.29 |
| Gross Profitability | 0.89 | 0.13 | 0.38 |
| **Investing** | | | |
| Annual Net Expense Ratio | 0.98 | -0.08 | 0.35 |
| Fund Size | 0.93 | -0.04 | 0.32 |
| Annual Turnover Rate | 0.78 | -0.07 | 0.32 |
| **Sports** | | | |
| Batting Average | 0.40 | 0.82 | 0.56 |
| On-Base Plus Slugging | 0.53 | 0.96 | 0.67 |
| Strikeout Rate | 0.81 | -0.44 | 0.58 |

*Source: Credit Suisse.*

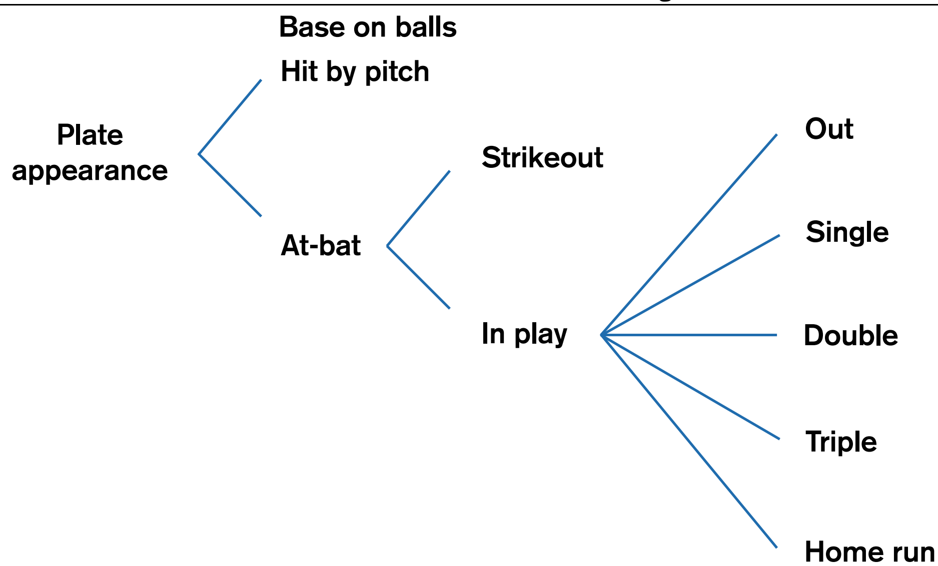
With this simple framework in hand, you can now test some of your favorite metrics. Naturally, you must be careful to gather sufficient sample sizes. But in general it is our experience that many are surprised when they see their favorite statistic plotted on exhibit 4.

## Appendix: Baseball Statistics

The use of statistics has become more widespread in all sports but is particularly popular in baseball. Batting average is the traditional statistic that general managers and fans use to assess offensive players, and earned run average is popular for pitchers. In recent decades, the sabermetrics community and front offices of teams have developed more useful statistics to assess players.[34] We focus on hitting statistics.

Exhibit 14 shows the common outcomes that occur when a player goes up to home plate. Note that an "at-bat" is different than a "plate appearance." A batter records a plate appearance no matter what happens but only records an at-bat if he strikes out or puts the ball in play (leaving aside rare events).

**Exhibit 14: Breakdown of Common Outcomes in Baseball Hitting**




*Source: Based on Jim Albert, "A Batting Average: Does It Represent Ability or Luck?"* Working Paper*, April 17, 2004.*

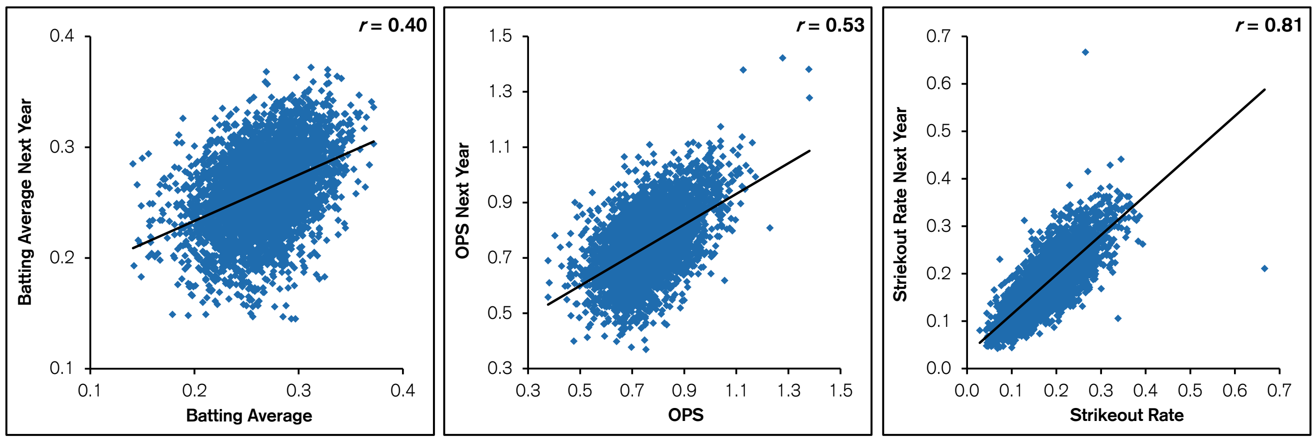
Batting average equals hits (singles, doubles, triples, or home runs) divided by at-bats. Strikeout rate is the number of times a batter strikes out divided by the number of plate appearances. On-base percentage plus slugging percentage (OPS) has become more popular, especially since it was featured in Michael Lewis's book, *Moneyball*.[35] On-base percentage roughly equals the number of hits a batter gets plus the number of times he walks divided by the number of plate appearances. Slugging percentage equals total bases divided by at-bats, with a single worth one base, a double worth two bases, and so on.

Exhibit 15 shows scatter plots for these three statistics using data from Major League Baseball in the 2000 through 2015 seasons. We include all players with 100 or more at-bats, an average sample of 338 players per season.

Both batting average ($r$ = 0.40) and OPS ($r$ = 0.53) have a respectable correlation from year to year. Strikeout rate, the plot on the far right, has a high correlation from year to year ($r$ = 0.81) and thus is a solid indicator of skill.

The difference in correlations is not surprising. There are more variables in determining whether a batted ball becomes a hit than there are in determining whether a batter will strike out. For example, a batted ball can result in either a hit or an out depending on how well the ball was hit, where it was hit, the skill of the defense, the field, and the weather. On the other hand, the strikeout rate largely reflects a one-on-one battle between the pitcher and batter. The only other meaningful variable is the judgment of the umpire.

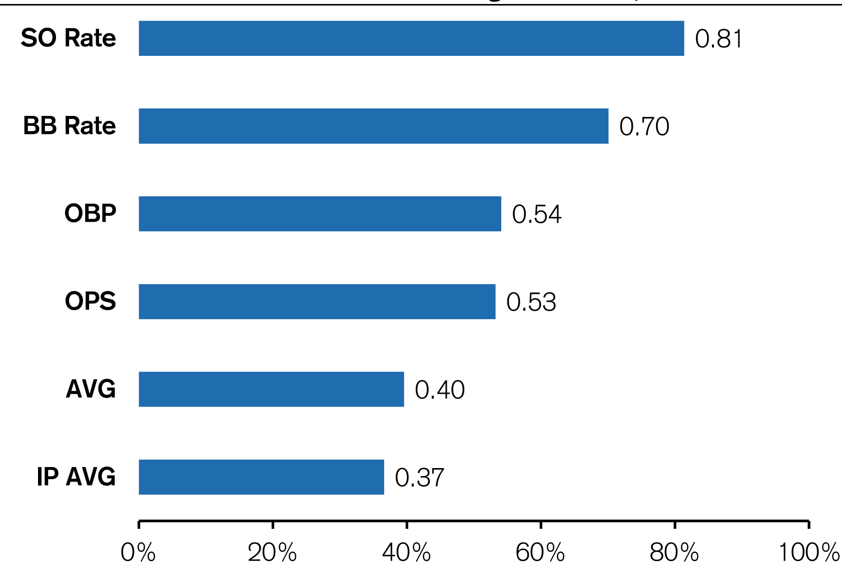
**Exhibit 15: Season-to-Season Persistence of Three Hitting Statistics, 2000-2015**




*Source: Based on Jim Albert, "A Batting Average: Does It Represent Ability or Luck?"* Working Paper*, April 17, 2004; Baseball Prospectus.*
*Note: Minimum of 100 at-bats.*

Exhibit 16 shows the coefficient of correlations for six batting statistics again using data from the 2000 through 2015 seasons. The base-on-ball rate, which measures how frequently a player is walked, is another strong measure of skill. On-base percentage and OPS are in the middle of the ranking, and batting average and in-play average (the percentage of times a batter gets a hit when putting a ball in play) are toward the bottom.

**Exhibit 16: Season-to-Season Persistence of Six Hitting Statistics, 2000-2015**



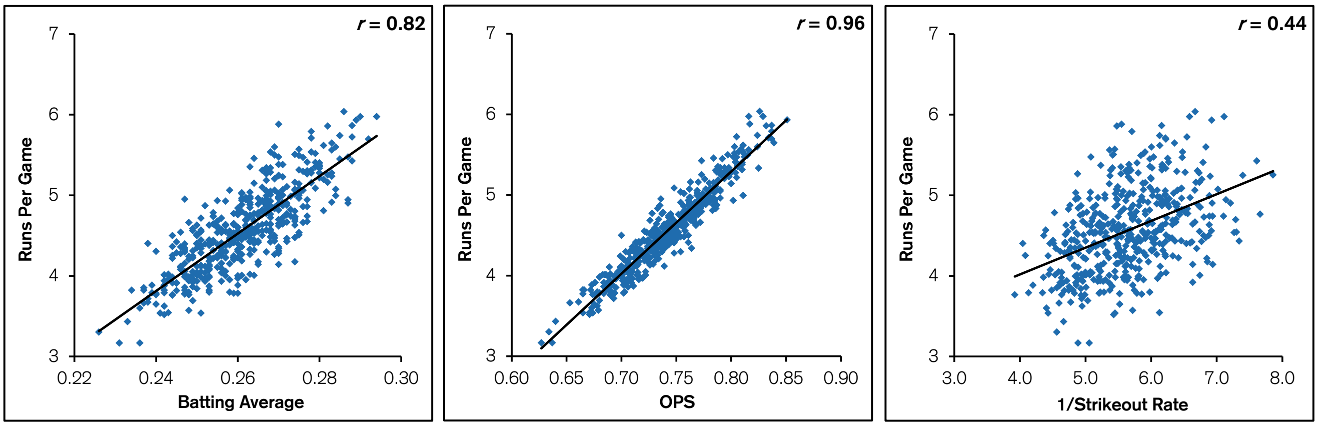

*Source: Based on Jim Albert, "A Batting Average: Does It Represent Ability or Luck?"* Working Paper*, April 17, 2004; Baseball Prospectus.*
*Note: Minimum of 100 at-bats; Definitions: SO rate: Strikeout rate (strikeouts/plate appearances); BB rate: Base on balls rate (base on balls/plate appearances); OBP: On-base percentage ([hits + base on balls + hit by pitch]/[at-bats + base on balls + hit by pitch + sacrifice flies]); OPS: On-base percentage + slugging percentage (slugging percentage = total bases/at-bats); AVG: Batting average (hits/at-bats); IP AVG: In-play average (hits/[at-bats - strikeouts]); IP AVG is a simplified version of Batting average on balls in play (BABIP).*

We now turn to the predictive value of baseball statistics. The ultimate goal of a team is to win games, which requires a team to score more runs than it allows. Since we are focused on offensive statistics, we calculate how the statistics correlate with total runs scored.

Exhibit 17 shows the results for the three statistics in Exhibit 13 (batting average, OPS, and strikeout rate). The plots show only 30 data points for each year because we are using a team's average for each statistic and comparing that to the team's total runs scored.

The coefficient of correlation shows that OPS has an extremely high correlation with run production ($r$ = 0.96). Batting average has a weaker but still fairly strong relationship ($r$ = 0.82). And the inverse of the strikeout rate (a higher number equals fewer strikeouts) has a fairly weak relationship ($r$ = 0.44).

**Exhibit 17: Predictive Value of Three Hitting Statistics, 2000-2015**




*Source: Based on Jim Albert, "A Batting Average: Does It Represent Ability or Luck?"* Working Paper*, April 17, 2004; Baseball Prospectus.*

This analysis makes it clear that OPS is superior to batting average. In terms of persistence, OPS (0.53) is better than batting average (0.40). But it tells an even clearer story in predicting the desired outcome. A team's OPS has a 0.96 correlation with a team's total runs, making batting average (0.82) pale in comparison. The strikeout rate shows very strong persistence but has limited use overall because of its weak relationship to total runs scored.

* * *

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## Endnotes

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