Perspectives

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Mauboussin on Strategy: Untangling Skill and Luck

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advantage. Social imitation, then, is both an important source of randomness and the primary source of inefficiency that a skillful investor must exploit.

Placing activities on the skill-luck continuum

Now that we have an urn model to help guide our intuition and some ideas about what shapes luck, we can turn to actually placing activities along the skill-luck continuum. Where we place an activity is going to be very sensitive to the sample size we consider. In cases where luck is normally distributed, the larger the sample we consider the better we can observe skill. But large sample sizes, which can take years to accrue, have a downside if skill deteriorates. For example, skill tends to decline after an athlete reaches his or her late 20s. Further, in pure luck or near-pure luck activities, some participants will enjoy good outcomes solely as a result of chance.

One very useful method for placing activities is to combine pure skill and pure luck distributions in a proportion that matches the empirical results. Analysis of sports lends itself to this approach, and a natural period of assessment is a season. This analysis starts with three distributions: what would happen if luck determined the outcome of each game (a basic binomial model), what would happen if skill determined each game (a higher-skilled team always beats a lower-skilled team), and what actually did happen. Appendix A goes through this approach in detail based on the work of Brian Burke, the author of the terrific web site, Advanced NFL Stats. Burke concludes that luck's contribution to the win-loss record of NFL teams is in excess of 50 percent.

Tom Tango, a respected sabermetrician, offers a four-step process that gets us to the same answer.[21] The equation he solves is: variance(skill) = variance(observed) - variance(luck). Rather than figuring out what blend of skill and luck best fits the empirical results, he determines skill by removing the role of luck from the outcomes. Here are the steps with data from the recent National Basketball Association (NBA) season.

1. *Take a sufficiently large number of teams* (preferably with the same number of games). We will analyze all 30 teams in the NBA for the 82-game season in 2009-2010.

2. *Figure out each team's winning percentage.* For the 2009-2010 season, the Cleveland Cavaliers had the best regular-season record, winning 74 percent of its games. The most futile team was the New Jersey Nets, which managed to win only 15 percent of its games.

3. *Figure out the standard deviation of the winning percentage.* For the most recent season, the standard deviation of the winning percentage was 0.1630 and has averaged 0.1548 over the past five seasons. So the variance(observed) is 0.027, or 0.1630^2.

4. *Figure out the standard deviation of outcomes determined by luck.* This is the binomial model. The luck standard deviation = $\sqrt{.5 * .5/n}$, where n = the number of games. For the NBA, n equals 82 so the luck standard deviation is 0.0552 and the variance (luck) = 0.003, or 0.0552^2.

Knowing two of the three variables in the equation, we can solve for variance(skill):

Variance(skill) = variance(observed) – variance(luck)
Variance(skill) = 0.027 – 0.003
Variance(skill) = 0.024

Now we can look at the ratio of variance(luck) to variance(observed) to determine the contribution of luck, which equals about 11 percent. Exhibit 5 places sports along the continuum, using the skill/luck ratio based on the averages of the last five seasons for each sport. Appendix B shows the calculation for the NBA. Note that the length of the season is also an important factor: with only 16 games, the NFL has by far the fewest games and the NBA could have a much shorter season and still have a clear sense of which teams are best.

Exhibit 5: Sports on the Skill-Luck Continuum (Average of the Last 5 Seasons)

Source: LMCM analysis.

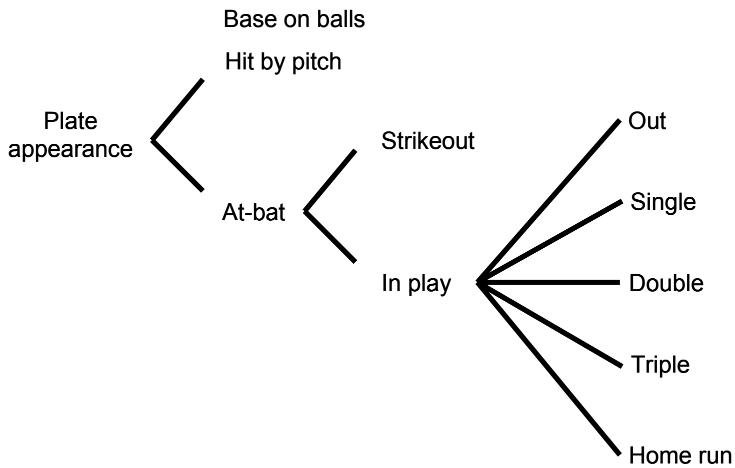
Professional basketball in the U.S. certainly stands out as the sport where skill plays the largest role in shaping results. One intriguing explanation for the NBA's strong skill contribution is the height of the players. In most sports, the most skillful players within a wide range of heights can make it to the pros. But a relatively small percentage of the population is tall enough to play in the NBA. In their book, *The Wages of Wins*, David Berri, Martin Schmidt, and Stacey Brook note that only about 3 percent of the male population in America is 6' 3" or taller, and a tiny percentage is above 6' 10" (about four standard deviations from the average). Yet almost 30 percent of NBA players are at least 6' 10". They conclude that a "short supply of tall people" contribute to the talent disparity and hence the greater relative role of skill. The right tail of the height distribution does not overlap completely with the right tail of the skill distribution. [22]

Decomposing measures to better understand skill

In many activities, we track certain statistics in order to calibrate skill. But there are plenty of cases where those statistics are sufficiently coarse that untangling the contributions of skill and luck is difficult. This section looks at how to decompose statistics to get a better handle on the role of skill.

Jim Albert, a professor of math and statistics, presents an analysis of batting average, the most widespread statistic used to measure hitters in baseball. [23] Albert wanted to determine the usefulness of batting average. He started by decomposing a plate appearance into the possible outcomes (see Exhibit 6). Batting average is the ratio of hits (singles, doubles, triples, or home runs) to at-bats. But naturally there are lots of ways to analyze hitters, including on-base percentage (roughly base on balls + hits divided by plate appearances) and strikeout rate (strikeouts divided by at-bats). Albert wanted to know which statistics were the result of skill and which ones had lots of luck.

Exhibit 6: Breakdown of Plate Appearances for a Baseball Hitter

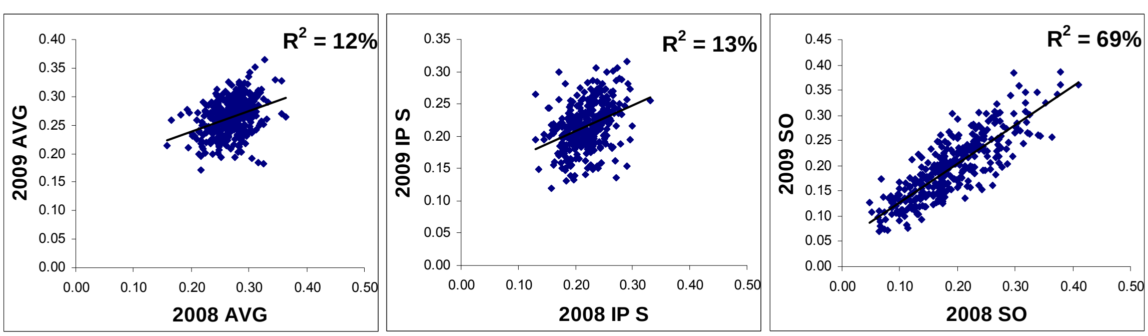


Source: Based on Jim Albert, "A Batting Average: Does It Represent Ability or Luck?" *Working Paper*, April 17, 2004.

He reasoned that a good way to test the skill-luck mix is to compare two years of hitting data. If a statistic accurately measures a player's skill, you would expect the values for the statistic to be similar from one season to the next. On the other hand, if the statistic varies a great deal from year to year you can assume that luck plays a large role in that outcome.

Exhibit 7 shows scatter plots for three hitting statistics: batting average, in play, singles (a hit that lands for a single), and strikeout rate. What is clear is that both batting average and hitting for singles have a low correlation from year to year, with R^2's of less than 15 percent, suggesting that luck plays a large role in those outcomes. [24]

Exhibit 7: Scatter plots of Three Baseball Hitting Statistics (2008-2009 Seasons for Players with 100+ At Bats)

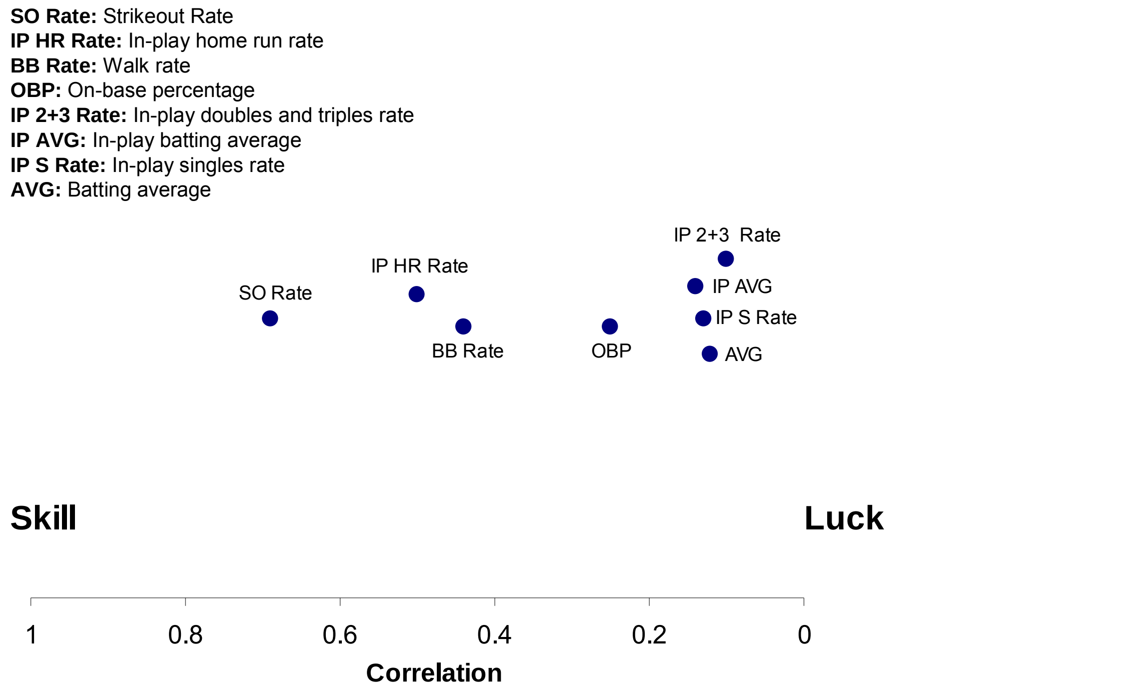


Source: LMCM analysis based on Jim Albert, "A Batting Average: Does It Represent Ability or Luck?" *Working Paper*, April 17, 2004.

By contrast, strikeout rate is highly correlated from year to year and is a good indicator of skill. Here, the R^2 is close to 70 percent. These correlations make intuitive sense. There are many factors that determine whether a ball falls for a hit when a player puts it into play, including the quality of the defense, the field, where he hits it, and the weather. On the other hand, strikeout rates match only pitcher and batter and fewer variables weigh on the outcome.

Exhibit 8 shows the correlations for eight batting statistics using data from the 2008 and 2009 seasons in MLB. We only included players with 100 or more at-bats in the sample. The analysis shows that a few statistics are very strong measures of skill, including strikeout rate, home run rate, and base-on-ball rate (how frequently a player draws a walk). Measures like batting average, singles, and doubles are extremely noisy because of the role of luck.

Exhibit 8: Ranking of Correlations of Hitting Statistics (2008-2009 Seasons for Players with 100+ At Bats)



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

In their latest book, *Stumbling on Wins*, David Berri and Martin Schmidt show similar statistics for football, basketball, and ice hockey. In hockey, for instance, shots on goal per minute correlates at a strong 80 percent from year to year while shooting percentage is less than 40 percent, and plus-minus (measures the goal differential when a specific player is on the ice) is less than 10 percent. [25]

This analysis raises the central question of whether we can decompose measures of performance in other activities in a similar fashion. Vital to this approach is focusing on statistics that have a pair of attributes. First, the statistic should measure something that an individual, or team, actually controls and that is consistent from period to period. Second, the measure should have some direct bearing on outcomes.

The assessment of investment managers may lend itself to this method, and one measure that holds promise is active share. Active share, developed by two professors of finance at Yale University, Martijn Cremers and Antti Petajisto, reflects the fraction of the portfolio that is different from the benchmark index. The measure has a range from 0 percent (the portfolio is identical to the benchmark) to 100 percent (completely different than the benchmark). Active share is persistent, and high active share correlates well with excess returns. [26]

The two-urn framework suggests a pair of methods that we can apply to various activities to better appreciate the role of luck. The first method is to study streaks of success. As Stephen Jay Gould, the famed biologist, summed up, "Long streaks are, and must be, a matter of extraordinary luck imposed on great skill." [27] Using our urns to make the idea more vivid, streaks occur when the right tail of the skill distribution combines with the right tail of the luck distribution. Neither luck nor skill is enough, by itself, to meld a long streak.

This idea comes with a specific prediction: the longest streaks should be held by the most skillful participants. As we will see, this is the case. The idea also implies a large role for luck. Indeed, Gould's quote was in response to a writer who suggested that Joe DiMaggio's 56-game hitting streak in 1941 was hype because five of his hits were "narrow escapes and lucky breaks." Gould responds, "Of course DiMaggio had a little luck during his streak. That's what streaks are all about." He also reinforces the point about skill: "Good players have higher characteristic probabilities, and hence longer streaks."

Another method that the urn model suggests is a study of reversion to the mean. The rapidity of mean reversion gives you some clues about the contributions of skill and luck. Lots of skill makes outcomes stickier because good or bad luck are insufficient to sway results. When skill is absent, the luck distribution takes over and reversion to the mean tends to be rapid.

We will look at one additional approach, the degree of transitivity, which does not come directly from the urn model. The idea is that in activities with a narrow basis of competition and differential skill, transitivity holds (i.e., if A>B and B>C, then A>C). But as the basis of competition expands, transitivity weakens and outcomes become less predictable. The degree of transitivity can give us a sense of success given changing matchups and strategies.

Methods to Sort Skill and Luck Applied to Sports, Business, and Investing

We now apply these methods to gain some insight into the role of skill and luck in sports, business, and investing. When possible, we try to use the same analytical tools in each realm so as to compare them most effectively. Exhibit 9 shows some conclusions from the analysis.

Exhibit 9: Applying Skill-Luck Methods to Three Activities

	Sports	Business	Investing
Streaks	There is strong evidence that streaks in sports combine skill and luck.	Some companies enjoy periods of sustainable excess returns beyond what a null model predicts.	Long streaks in mutual fund results occur more frequently than the null model predicts.
Mean reversion	Solid evidence for mean reversion across team sports. There is less mean reversion in individual sports.	Mean reversion is well documented over time.	Strong mean reversion for results in mutual funds, investing styles, and asset classes.
Transitivity	Matchups often lack transitivity. Increasingly used in strategy as well.	Different strategies work in varying economic situations. Circumstance versus attribute. Disruptive innovation.	Different strategies work in varying economic situations.

Source: LMCM analysis.

While we will see evidence of skill and luck in each of these endeavors, it is worth noting up front that the relative contributions of skill will be different (just as they are within sports). In sports, players or teams compete with one another, and there are a lot of one-on-one interactions that determine outcomes. In business, firms compete against other firms and evidence of good profits invites competition. So success encourages additional competition, which tends to squeeze profits over time. Finally, investors compete with the collective of other investors. As we saw with pari-mutuel betting, being better than the person at a rival firm isn't good enough; you must be better than the crowd. This is extremely difficult to do in practice for psychological and organizational reasons. But, as we will see, some participants clear those hurdles.

Skill has other constraints besides competition. For example, athletes follow a skill arc. At first an individual's skill rises as he or she develops physically and hones ability. But skill then degrades as a consequence of aging. Skill can be much more persistent in cognitive tasks, as experience is additive. In cognitive activities like chess and science, for example, the peak skill occurs in the 30's. More creative experts, including novelists, historians, and philosophers, hit the apex of skill in their 40's or 50's.[28]

Skill can also be diluted by size. For instance, an executive who makes lots of acquisitions for the sake of growth or the investment manager who collects lots of assets under management will find it more difficult to add value as the size of the enterprise swells. Jack Bogle shows how the investable universe of stocks declines sharply as a function of fund size. Assuming that a fund can hold no more than 5 percent of the outstanding shares of any company, Bogle estimates that a fund with $1 billion of assets can choose from over 1,900 stocks while a fund with $20 billion has a universe of about 250 stocks. So it happens that success can sow the seeds of its own failure.[29]

Streaks

A streak is a consecutive series of successes or failures. Streaks are one of the most elegant indicators of skill because if there is any differential capability within the population, the most skillful will hold the records for streaks. Not all skillful performers have streaks, but all long streaks of success are held by skillful performers.

With a large enough starting sample, you should expect some participants to have streaks of success solely due to luck. Teachers often illustrate this point with the example of coin tosses. For example, if you start with 1,000 people and ask them to call coin tosses, you should expect about 3 percent of the group to get five in a row correct. I recently did this exercise with a group of about 400 students, and two students were right for seven consecutive tosses.

So the first obvious point is that in testing for differential capability using streaks, you need to compare the actual results with a null model that reflects randomness. So it's not the existence of streaks that we're interested in—we know that they exist. What we're looking for are streaks that extend beyond what chance dictates, in either frequency or duration. This distinction is at the core of the debate about hot hands—the belief that recent success portends further success. The researchers who debunk the hot hand acknowledge that streaks of fruitfulness or futility exist; they just believe that those streaks are consistent with what probability dictates.

Sports are a convenient place to start the analysis of streaks because there are a lot data and we can easily assess the role of skill. And coming to a quick verdict is not difficult. Streaks of success in sports are held by the most skillful players. For example, the record for consecutive made field goals in basketball is held by Wilt Chamberlin, who drained eighteen consecutive shots in February 1967. Chamberlin made 54 percent of his field goal attempts over his career, placing him among the top twenty-five in shooting percentage in the league's history. (He also set the single-season field goal percentage record by making 72.7 percent of his shots in the 1972-73 season.) Hockey has a similar case: Wayne Gretzky, who is by far the NHL's leader in career goals, assists, and points, holds the record for most consecutive games with a point.

The most famous streak in sports (at least if you're an American) is Joe DiMaggio's 56 consecutive games with a hit, which he achieved almost 70 years ago. First, we can establish that the streak was the result of skill and luck. DiMaggio was clearly a very skilled player. For example, his batting average is in the top 50 all-time, easily in the top 2 percent of all players in history. Luck also played a prominent role, as Michael Seidel's day-to-day chronicle of the feat attests.[30] But was it really "the most extraordinary thing that ever happened in American sports," as Stephen Jay Gould claimed?

Sam Arbesman, a computational biologist, and Steve Strogatz, a mathematician, recently did a fresh analysis of DiMaggio's streak.[31] They wondered what the probability was of *any* player in the history of baseball getting a hit in 56 straight games. Using data from actual results and simulation techniques, they found that there was somewhere between a 20 and 50 percent chance that some player would have a DiMaggio-like streak. As surprising, the simulations suggested that DiMaggio was barely in the top 50 players most likely to achieve the feat. Players including George Sisler, Ty Cobb, and even Ichiro Suzuki (who currently plays for the Seattle Mariners) were much more likely to set the record than DiMaggio was.

Thomas Powell, a professor of strategy at Oxford University, created a useful bridge between sports and business through a novel study of competitive parity.[32] Powell studied more than 20 industries in the U.S. and measured the degree of parity using a Gini coefficient. The coefficient was developed by Corrado Gini, an Italian statistician, to measure income inequality. Zero represents perfect parity and 1.00 reflects maximum disparity. Powell found that the average Gini coefficient for U.S. companies was 0.60, with a standard deviation of 0.24.

Powell then measured the Gini coefficient for non-industrial domains, including many sports (baseball, tennis, hockey, basketball, cricket, golf, football, and lacrosse) as well as other competitive fields (chess, snooker, bridge). He found that the non-industrial domains had an average Gini coefficient of 0.56, nearly identical to that of the companies, with a standard deviation of 0.24, exactly the same as the industrial sample. As he summarizes, "performance distributions in business are statistically indistinguishable from distributions in non-business domains.[33] Since we know that skill plays a meaningful role in the outcomes we see in sports, this research clearly suggests that skill—better known as competitive advantage—is also relevant in shaping business results.

Researchers typically define superior results in business as high and sustainable return on assets (ROA).[34] What is clear is that there is heterogeneity in this measure between companies, as the Gini coefficients suggest. The question relates to the source of those differences. Jerker Denrell, also a professor of strategy at Oxford University, suggests that the differential results may be the result of a random walk process. In other words, even if all firms start off at the same point, some will do a little better or worse than average by chance, allowing for differences in resource accumulation and, ultimately, corporate results.[35] In sociology, this is known as the "Matthew effect," which basically says the rich get richer and the poor get poorer.[36] So the null model must account for the random walks.

A recent paper by Andy Henderson, Michael Raynor, and Mumtaz Ahmed does just that.[37] Raynor and Ahmed are consultants and Henderson is a professor of management at the University of Texas at Austin. They study the results of over 20,000 companies from 1965-2005, amassing over 230,000 firm-years of observations of ROA. The researchers carefully structured the analysis so that it would discern whether the occurrences of sustained superior results were beyond what chance would dictate.

The main finding of the study is that "the results consistently indicate that there are many more sustained superior performers than we would expect through the occurrence of lucky random walks." While this is comforting because it suggests that management's actions—skill—can help shape results, no one has been able to pinpoint what behaviors lead to superior results. So unlike sports where there are some observable measures of skill, all we can really say today is that we cannot explain results by luck alone and that it appears that skill plays a role in shaping outcomes.

The authors also caution that it is easy to confuse superior performance with the results you would expect by chance. Just as probabilities can explain the apparent hot hands in sports, so is the case in much of business. The researchers write, "Our results show that it is easy to be fooled by randomness, and we suspect that a number of the firms that are identified as sustained superior performers based on 5-year or 10-year windows may be random walkers rather than the possessors of exceptional resources." This is a very relevant point for management research. Numerous studies observe superior corporate results, attach attributes to those results (great management, robust culture, etc.), and propose those attributes as a means to success. Such studies are utterly invalid if the apparent superior results are the result of luck, and this is undoubtedly the case. [38]

While their analysis was not focused on streaks, the authors allow that "casual inspection of [the data] indicate[s] that streakiness was often the case." This, as well as the other findings, is what you would expect if you combined skill and luck distributions. The challenge for researchers in competitive strategy is to get to the root causes of sustained superior results.

Streaks in the investment business have not been studied in great detail, and most critics write off streaks as the product of chance. A streak is defined as consecutive years of generating returns after costs in excess of a benchmark. For example, one pundit suggested that there was a roughly 75 percent probability that over the past 40 years *some* fund would generate a streak of 15 years, the duration of the longest known streak by a mutual fund. [39] One needs a complete disregard for the empirical facts to arrive at such an estimate. The only way to get there is to assume a large starting sample (in the thousands) and a coin-toss model. There were, in fact, 170 mutual funds in 1965 (the number didn't exceed 1,000 until 1988), and only about 40 percent of mutual funds have beaten the market annually, on average, with a standard deviation of about 20 percent. [40]

Andrew Mauboussin and Sam Arbesman analyzed mutual fund streaks over the past four decades or so, capturing over 50,000 mutual-fund years. Their null model applied the observed outcomes in each year to the funds in existence, capturing the role of chance. They simulated 10,000 mutual fund worlds and compared the simulated results to the actual record of streaks. Similar to Arbesman and Strogatz, as well as Henderson, Raynor, and Ahmed, they found evidence that some funds generated streaks beyond what chance would dictate. They also observed that the funds that had established the streaks had a much higher "batting average"—the percentage of years that they successfully beat the benchmark—than did the average of all funds. [41] So the analysis of streaks indicates skill across all three activities, although the strength of the signal is by far the highest in sports.

Researchers using alternative approaches have also concluded that there is some skill in investing. [42] But the research also shows that only a small subset of the investing population is skillful, and that the percentage of funds that are skillful is declining. This is consistent with a market that steadily rises in informational efficiency over time. Note that these results take costs into consideration. One analysis suggests that about three-quarters of funds earn gross excess returns in line with the costs that they incur, making them "zero-alpha" funds. Alpha is a risk-adjusted measure of excess returns.

Reversion to the mean

Most people understand reversion to the mean in principle, but few properly reflect it in their decision making. The two-urn model is particularly useful in articulating the challenges and opportunities with reversion to the mean.

One insight the model reveals is that the *rate* of reversion to the mean is a function of the relative contribution of luck. For activities that are pure skill, reversion to the mean plays no role. Only shifting levels of skill will dictate outcomes. For activities that are pure luck, reversion to the mean is powerful. In the case where luck follows a normal distribution with a zero mean, each new draw from the urn has an expected value of zero. So it stands to reason that extreme events will migrate rapidly toward the middle.

You can think of skill as a drag on the reversion process for the activities that combine skill and luck. An above-average shooter in basketball, for example, may go through good or bad stretches of shooting. But she will not revert back to the average over time because of her skill. The same would be true of a below-average player. Luck may help or hinder in the short term, but reversion is limited because of the level of skill.

Humans, as natural pattern seekers, have a very difficult time dealing with reversion to the mean. The main challenge with the concept is that *change within* the system occurs at the same time as *no change to* the system. Change and no change operate side-by-side, causing a lot of confusion.

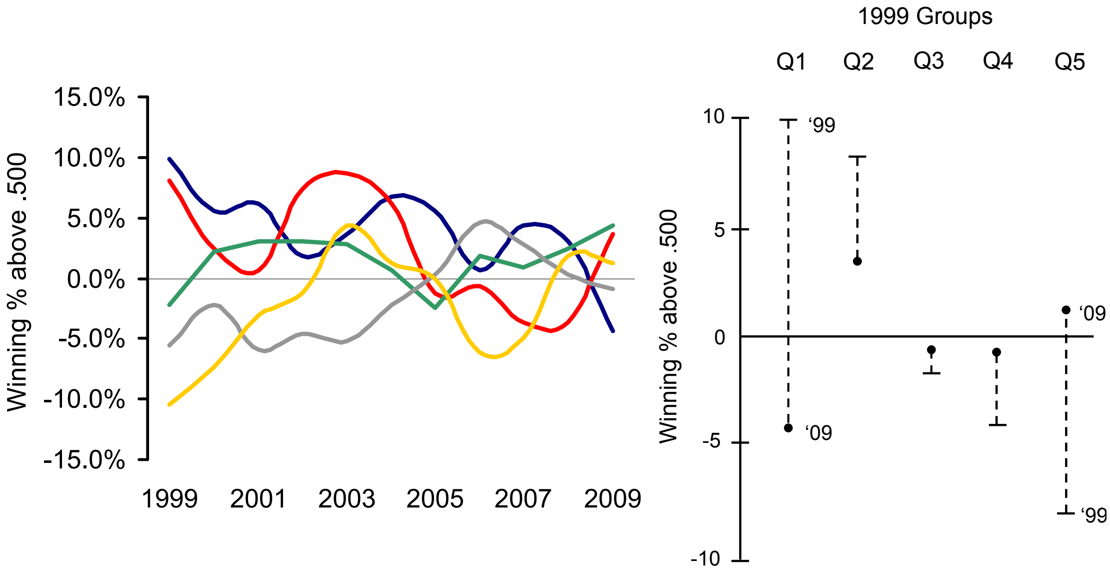
The change part is reversion to the mean. As we will see, the results of the groups that have done really well or poorly in one period tend to move toward the average in future periods. Most people find it hard to internalize reversion to the mean because it is more natural to extrapolate the performance of the recent past. So if a stock, or an asset class, has done well the natural inclination is to assume it will continue to do well and to act accordingly.

An equally common mistake with reversion to the mean is to assume that all results revert to the mean, which effectively means that the standard deviation of outcomes narrows over time. This is not true. For example, say you rank the teams in the NBA in quartiles based on their winning percentage for a season. Check in on the same quartiles in five years, and you will see that the win-loss percentages for each quartile are closer to 0.500. But, at the same time, the variance in the league's win-loss rate will not have changed much. It will be pretty much the same as it was years ago.

What's going on is that luck is reshuffling the teams on the distribution, even as skill is trying to keep them in the same spot. So teams that were lucky in one season may be unlucky in five years, or a team with average luck may enjoy above-average success or failure. Thus, while extreme performers migrate toward the middle, middle performers also migrate to the extremes. The lesson is to always bear in mind the ratio of skill to luck in the activity and to recognize that recent results, especially if they are extremely good or bad, are unlikely to persist.

The world of sports is filled with reversion to the mean. You can readily see it on a team or individual level. The left panel of Exhibit 10 shows reversion to the mean of the win-loss record of Major League Baseball teams from 1999 to 2009. Even though the year-to-year outcomes appear messy, the ultimate outcome is clear: in the decade ended in 2009, the best teams see their median win percentage erode by over 14 percentage points while the teams initially in the cellar see their win percentage improve by almost 12 percentage points (see Exhibit 10, right panel).

Exhibit 10: Mean Reversion in Major League Baseball Team Winning Percentages

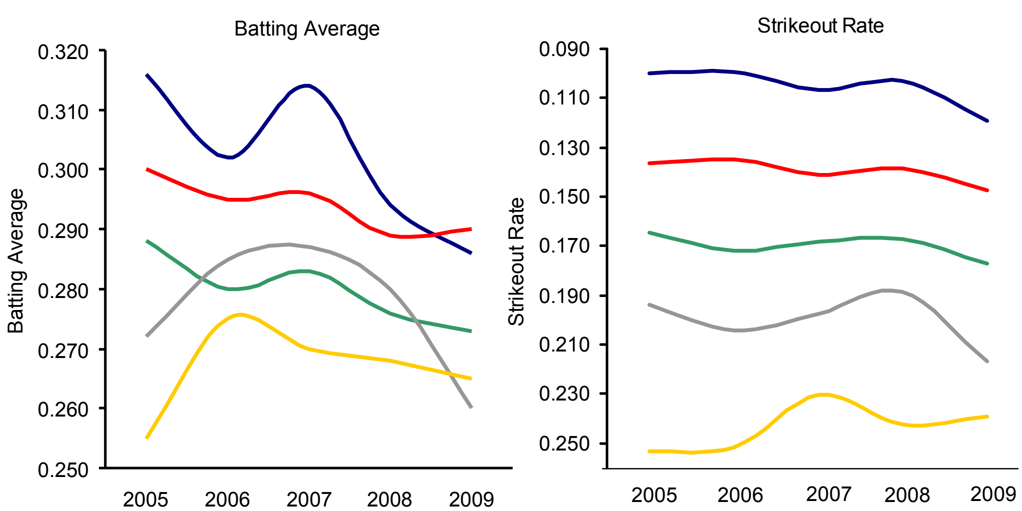


Source: Baseball Prospectus and LMCM analysis.

Consistent with the idea that reversion to the mean accommodates change and no change, the win percentage of the best and worst quintiles moved toward 0.500 while the standard deviation of the distribution of winning percentage for the league held reasonably constant at about 0.07.

We can see how the interplay between luck and skill shapes reversion to the mean by analyzing hitting statistics side by side: one more reliant on luck (batting average) and one more reliant on skill (strikeout rate). Exhibit 11's left panel shows the batting averages of roughly 100 major leaguers who had at least 150 at-bats for the five seasons ended 2009. The 0.60 basis point gap between the best and the worst quintile (0.315 versus 0.255) is cut by two-thirds by the final year (0.285 versus 0.265). This result would occur even without the assumption of any change in skill level.

Exhibit 11: Mean Reversion in Major League Baseball Player Batting Averages



Source: Baseball Prospectus and LMCM analysis.

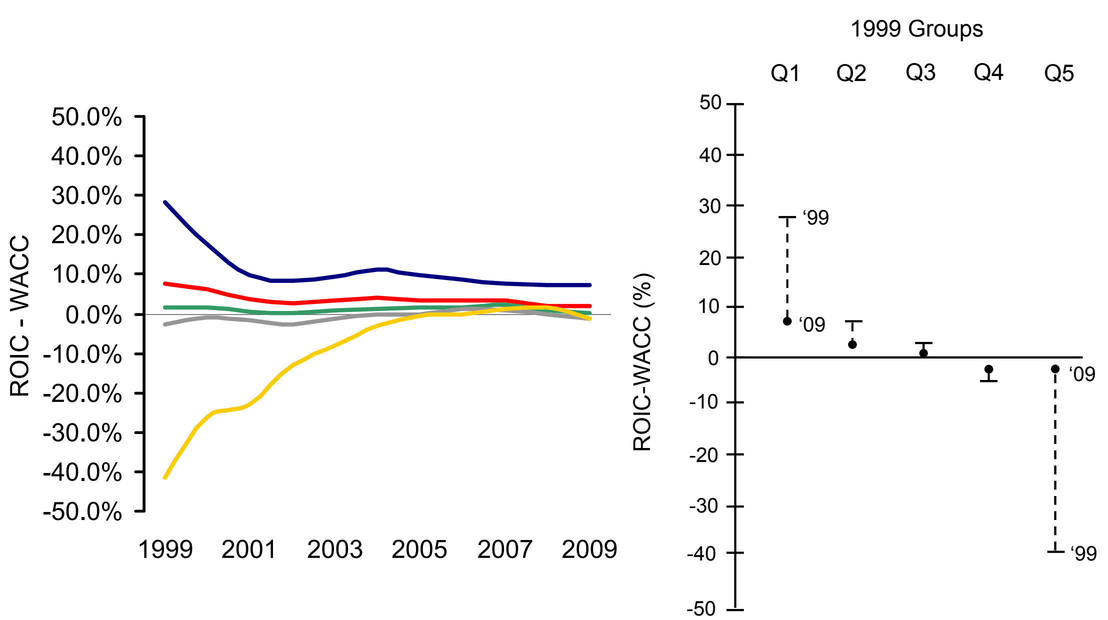
As the right panel of Exhibit 11 shows, the mean reversion is much less pronounced with strikeout rate because skill is more important. While the gap from best to worst does narrow from roughly 0.150 to 0.120, you can see that the outcomes remain relatively persistent.

The persistence of skill and the absence of luck is also the reason that the world's top tennis players dominate the ranking for extended periods of time. For instance, four players—Pete Sampras, Roger Federer, Ivan Lendl, and Jimmy Connors—each held the number one spot for the equivalent of five or more years.

Corporate performance also shows reversion to the mean. This phenomenon has been well documented for decades. [43] For a company, skill is equivalent to competitive advantage, which confers an ability to generate returns on capital in excess of the cost of capital. Companies, like athletes, tend to follow a lifecycle. A company typically sees its skill diminish as the industry matures, as all competitors move toward optimal efficiency, and as prices are set so that they squeeze out excess profits. Competitive advantage is closely linked to barriers to entry. Bruce Greenwald, an economist at Columbia University, is fond of saying, "In the long run, everything is a toaster." He picked the toaster to symbolize a mature, competitive business with no barriers to entry and no excess returns. [44]

Here's what the pattern of performance looks like for companies. The left panel of Exhibit 12 places the non-financial companies in the Russell 3000 that had data throughout the entire period (a sample in excess of 1,800 companies) into quintiles based on the spread between their return on invested capital (ROIC) and the weighted average cost of capital (WACC) in 1999. It then tracks the median returns for those quintiles though 2009.

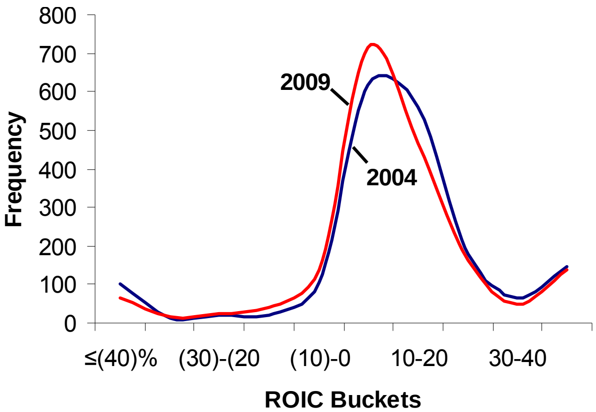
Exhibit 12: Mean Reversion in ROIC – WACC Spreads for the Russell 3000 Non-Financial Firms (1999-2009)



Source: Capital IQ, LMCM analysis.

Specifically, the spread between the highest and lowest quintiles shrinks from 70 percentage points in 1999 to about 10 percentage points in 2009 (see Exhibit 13, right panel). Note that this powerful reversion to the mean accommodates the superior results of some companies, as we discussed in the section on streaks and persistence. Said differently, we would expect the rate of reversion to the mean to be even more rapid absent some companies with competitive advantage. This pattern of reversion to the mean also belies the principle that the distributions do not change. The distribution of ROIC - WACC spreads, in fact, remained similar throughout the measured period. Exhibit 13 lays the 2009 distribution on that of 2004. Even a brief visual inspection confirms the similarity of the two distributions.

Exhibit 13: Change and No Change Co-Exist

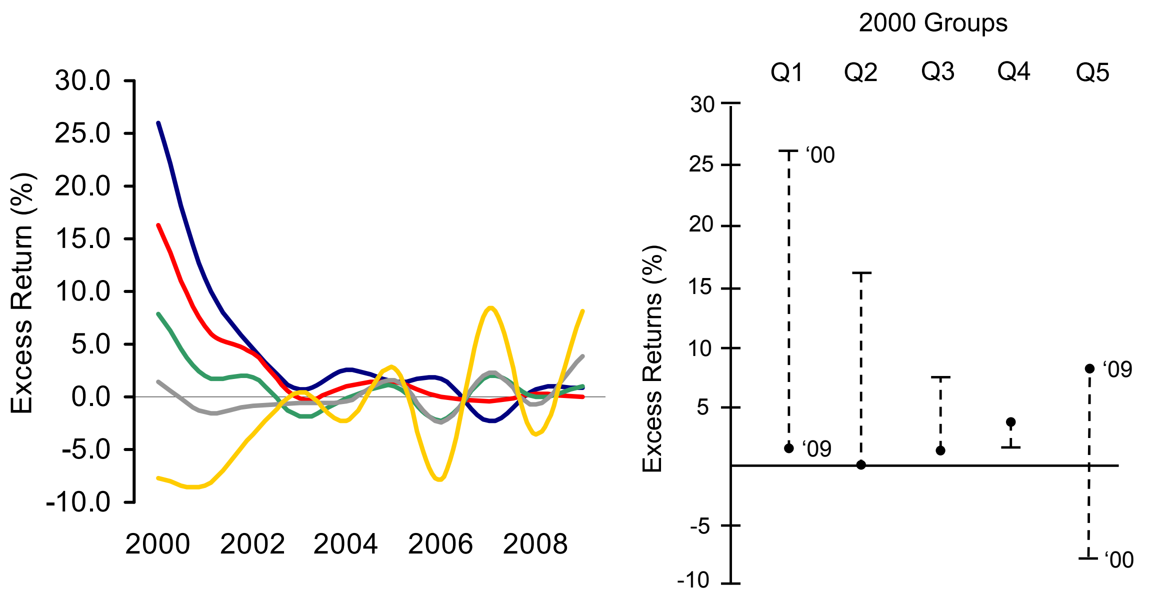


Source: Capital IQ, LMCM analysis.

Research by Robert Wiggins and Timothy Ruefli, professors of management, shows that not only is reversion to the mean in clear evidence for the corporate world, but also that returns are converging at a faster rate today than they did in the past.[45] They note that this phenomenon is not limited to technology companies but rather is evident across all industries. An empirical study of the slope of the rate of decline found that companies with high returns, high cash-flow variability, and high growth faded the fastest. Stable businesses with slow growth rates held the steadiest.[46]

Reversion to the mean is a powerful force in investing, too. Jack Bogle, a luminary of the investment industry, illustrates this by ranking mutual funds in quartiles based on results in the 1990s and seeing how those quartiles performed in the 2000s. The top quartile, which had handily outpaced the average fund in the 1990s, saw a 7.8 percentage point drop in relative performance. Symmetrically, the bottom quartile in the 1990s witnessed a sharp 7.8 percentage point gain in results in the 2000s. Exhibit 14 tracks the excess returns of about 700 large cap mutual funds ranked based on 2000 results. By 2009, the excess returns for the best performing funds in 2000 was effectively zero, while the lowest quintile delivered strong excess returns. Because investing results have a large dose of randomness, reversion to the mean is mighty.[47]

Exhibit 14: Mean Reversion in Mutual Fund Results



Source: Morningstar, LMCM analysis.

Persistence of performance has been one of the most popular topics in mutual fund research.[48] Similar to what we saw with companies, and consistent with the analysis of streaks, there is some evidence of persistence in fund performance.[49] But the strength of the signal is in part a function of the time period a researcher decides to measure, is more pronounced with poor performers than superior performers, and is weakened as academics adjust mutual fund returns for factors in stock price returns (i.e., size, value, momentum).

Importantly, reversion to the mean in the investment business extends well beyond the results for mutual funds. It applies to classifications within the market (small capitalization versus large capitalization, or value versus growth), across asset classes (bonds versus stocks) and spans geographic boundaries (U.S. versus non-U.S.). There are few corners of the investment business where reversion to the mean does not hold sway.[50]

We have mentioned already that reversion to the mean ensnares a lot of decision makers. This is so important for investors, however, that it bears additional comment. The sad fact is that there is significant evidence that investors—both individual and institutional—fail to recognize and reflect reversion to the mean in their decisions. To illustrate, the S&P 500 Index generated returns of 8.2 percent in the twenty years ended 2009. The average mutual fund saw returns of about 7 percent, reflecting the performance drag of fees. But the average investor earned a return of less than 6 percent, about two-thirds of the market's return. The reason investors did worse than the average fund is bad timing: they put money in when markets (or funds) were doing well and pulled money out when markets (or funds) were doing poorly. This is the opposite of the behavior you would expect from investors who understand reversion to the mean.

It is certainly understandable that individual investors react to emotional extremes. But what about the institutional investors who allocate capital for a living? You might guess that they are fully aware of reversion to the mean and work to counter-balance it. Yet that is not at all the behavior that researchers observe. Institutions, often guided by committees, fail to reflect reversion to the mean in their decisions, which ends up costing their beneficiaries billions of dollars.

Amit Goyal and Sunil Wahal, professors of finance, studied how well 3,400 plan sponsors (i.e., retirement plans, endowments, foundations) did in their decisions to hire and fire investment managers over a decade. [51] They found that plan sponsors hired investment managers after they had generated superior returns, only to see post-hiring excess returns revert to zero. Plan sponsors fired investment managers for a multitude of reasons (poor performance topped the list), only to see the managers they fired deliver statistically-significant excess returns.

A separate study, which looked at decisions across a large number of asset classes and over a longer time period, came to a similar conclusion. The study's authors summarized, "Perhaps investment officers—either because they believe it themselves or their supervisors do—find comfort in extrapolating past performance when, in fact, excess performance is random or cyclical." [52] While we would say that results are *mostly* random in the short term, the larger point holds. Both studies are consistent with performance chasing and the belief in hot hands, and inconsistent with an appreciation for the force of reversion to the mean.

Coping with reversion to the mean is not easy in markets, but there is a three-step process that helps guide a decision. The first step is to consider the mix of skill and luck in the activity. As we have seen, the pull of reversion to the mean will be strongest in activities dominated by luck. Second, consider how extreme the result is versus some sense of the average. For example, periods with stock market returns that are substantially above or below the long-term average of 6-7 percent, adjusted for inflation, may be followed by periods that are closer to the average. Finally, consider the expectations reflected in asset prices. [53] Avoid assets that have performed well and embed optimistic expectations, and embrace assets that have performed poorly and embed low expectations. These steps are easy to articulate but difficult to follow due to psychological and institutional constraints.

Transitivity

Transitivity holds when there's a clear pecking order of skill and the better competitor always wins. In reality, matchups between individuals, teams, competitors, or strategies generally yield a lack of transitivity. What allows you to win in one environment may not work in another. As a general rule, transitivity tends to decrease as the complexity of the interaction increases. It is hard to characterize the degree of transitivity thinking only of skill and luck, but the idea remains very useful for decision makers.

The importance of transitivity in sports is quite clear. We already saw how in theory the winner of a tournament might be the result of the order in which the teams played one another (Exhibit 2). Notice that in the setup of that example, all the teams had the same total level of skill, designated as 100 points, and that it was the structure of the matchups that determined the outcome.

The significance of matchups is also evident in practice. Wayne Winston, a professor of decision sciences, analyzed interactions between NBA lineups, as well as between specific players, and found a lack of transitivity. To illustrate, he studied the 2006 playoffs and 2006-2007 regular season and found that Steve Nash outplayed Devin Harris, Harris outplayed Tony Parker, and Parker outplayed Nash. Which player is better depends on the matchup, and there is no way to say that one is best. [54] A similar lack of transitivity exists with strategies in soccer and between face-off specialists in lacrosse. [55]

The degree of transitivity spills over to coaching strategy. KC Joyner, a football analyst at ESPN, separates football coaches into two categories: those who focus on personnel and those who focus on strategy. Personnel coaches try to stack their teams with the most talented players, keep the game plan simple, and try to overwhelm their opponents. Strategy coaches worry less about attracting the finest players and focus instead on outsmarting their opponents with innovative game plans. [56]

Mike Leach, the former coach of the Texas Tech football team, is a great example of a strategy coach. He managed to win over 70 percent of his games in recent years despite playing a highly competitive schedule. The team's success is particularly remarkable since few of the players were highly recruited or considered "first-rate material" by professional scouts. [57]

Leach offset the talent gap by introducing more complexity into the team's offense via a large number of formations. By creating new matchups, these formations changed the geometry of the game and forced opponents to change their defensive strategies. For example, defensive linemen were frequently forced to drop back to cover receivers. Leach explained that "defensive linemen really aren't much good at covering receivers. They aren't built to run around that much. And when they do, you have a bunch of people on the other team doing things they don't have much experience doing." You can certainly argue that Leach was skillful. The key here is that by adding complexity, Leach also made results less transitive.

Transitivity is also evident in business. One example is how a company's product offerings fare under changing economic conditions. For instance, one automobile manufacturer may emphasize small vehicles while a competitor focuses on sport utility vehicles (SUV). When gasoline prices are high the maker of small cars will be in a better position, and when prices are low the producer of SUVs will have the advantage. So the vagaries of the fuel market dictate the outcomes, and there is no strategy that works in all environments.

Clayton Christensen's theory of disruptive innovation is another example of transitivity in business. [58] Christensen studied why great companies with smart managements and substantial resources consistently lost to "disruptors," companies with simpler, cheaper, and inferior products. He describes two ways that this can happen. In one case, the disruptors introduce a product that is at the low end of the market and that is neither profitable for the incumbents nor in demand from the incumbent's current customers. Incumbents are motivated to flee the low-end segment of the market and to focus on more value-added products. This becomes a problem as the disruptors improve their offering and move up market, eventually encroaching on the core business of the incumbent, and doing so with a lower cost structure.

In the other case, disruptors introduce a product that was unavailable to consumers before, effectively competing with non-consumption. A recent example is Nintendo's Wii video game console. Rather than focus on the high end of demanding gamers, as Microsoft's Xbox and Sony's Playstation 3 have, the Wii expanded the market by making the games simpler to play and more intuitive. In these instances, incumbents tend to ignore the market (as Microsoft and Sony largely did initially).

Whether the disruptor's strategy is based on a low-end segment or on non-consumption, stronger incumbents yield to weaker challengers because of asymmetric motivations. [59] As in sports, we see cases where the more "skillful" company loses to the weaker company as the result of strategy choices. Transitivity in head-to-head matchups frequently appears as the result of asymmetric motivations. The Colonel Blotto game, a model from game theory, also sheds light on this conclusion. [60]

Transitivity also exists in the investment industry. For example, the success of different styles tends to rotate. If you are a small capitalization (cap) manager, for instance, there will be times when small cap stocks will outperform large cap stocks and you will do well just by showing up to work. And since the industry frequently seeks to constrain the mandates of individual portfolio managers, success is often about style, not skill.

This effect shows up when we study the mutual fund industry. The decade of the 1990s and the first decade of the 2000s offer an interesting contrast. The 1990s were one of the worst decades for active management, with an average of only 35 percent of funds generating returns in excess of the S&P 500 annually. The 2000s were one of the best decades for active management, with an average of half of all funds beating the index in each year. Few would think of the 2000s as better than the 1990s for active managers, because the absolute returns were so much lower in the 2000s. But on a relative basis, 2000-2009 was a golden decade for active managers, with a rate of beating the benchmark 25 percent higher than the long-term average.

The reason active managers did so much better in the recent decade has little to do with skill and a lot to do with style. Most funds that use the S&P 500 as a benchmark construct portfolios with stocks that have an average market capitalization that is much smaller than that of the broad index. [61] This suggests a simple relationship: when large cap stocks outperform small cap stocks, active managers will struggle. Conversely, when small cap outperforms large cap, active managers will shine. This was the case with the 1990s versus the 2000s. In the 1990s, large cap stocks beat small caps by an average of 6.6 percentage points a year. By contrast, small caps generated returns 4.5 percentage points greater than large caps, on average, in the 2000s. As transitivity suggests, different strategies win from one environment to the next. [62]

Peter Bernstein, who was one of the investment industry's brightest stars, wrote an article in 1998 suggesting that outsized excess returns in the investment industry were unlikely in the future. [63] Bernstein's analysis was a riff off of an essay by Stephen Jay Gould explaining why there would never be another 0.400 hitter in baseball (Ted Williams last achieved the feat in 1941, hitting 0.406.) Gould reasoned that because all players are improving in all facets of the game, the standard deviation of results narrowed. That was in fact true for batting average, which reduced to a miniscule level the probability that even an outlier could reach 0.400.

Bernstein surmised that as markets continued their march toward efficiency, a similar pattern was occurring for money managers. The data backed it up: the standard deviation of excess returns for mutual funds had slowly and steadily declined from 1960 through 1997. In 2004, though, Bernstein reran the numbers and found that the standard deviation had exploded from roughly 10 percent in the late 1990s to almost 20 percent in 1999. He concluded that the 0.400 hitters of the investment industry had returned. [64] But the spike in standard deviations was short-lived and attributable to strong style swings. Specifically, large cap managers were narrowly focused on technology stocks in late 1999, allowing for strong returns relative to other styles. And following the technology stock bubble, small cap managers enjoyed massive relative returns. Since Bernstein's paper in 2004, however, the standard deviations have again shrunk, consistent with his (and Gould's) original thesis.

Conclusion

The two main ways to assess skill and luck are through an analysis of persistence of performance (with streaks being a particularly useful subset of this approach) and its alter ego, reversion to the mean. The research shows evidence for persistence of performance in sports, business, and investing, although the evidence is strongest in sports. Studies of business and investing point to skill in both domains, although the percentage of companies or investors with skill is small.

Reversion to the mean is also clear in each realm. The central insight is that the more the outcomes of an activity rely on luck (or randomness), the more powerful reversion to the mean will be. As important, it is clear that many decision makers do not behave as if they understand reversion to the mean, and predictably make decisions that are, as a consequence, harmful to their long-term outcomes. This is particularly pronounced in the investment industry.

The two-urn model is a useful mental model because it allows for differential skills and accommodates luck. Even Paul Samuelson, the Nobel-prize winning economist and efficient markets advocate, allowed for the possibility of investment skill. He wrote, "It is not ordained in heaven, or by the second law of thermodynamics, that a small group of intelligent and informed investors cannot systematically achieve higher mean portfolio gains with lower average variabilities. People differ in their heights, pulchritude, and acidity. Why not their P.Q. or performance quotient?" [65]

An examination of transitivity also provides insights into where outcomes are most predictable. A lack of transitivity marks large swaths of sports, business, and investing. Since it is not always straightforward to pin low transitivity on skill or luck, the main lesson is to recognize that matchups and strategies can matter a great deal.

We now come to the final part of our discussion—defining skill in the investment business. Even if we can reasonably conclude that there are skilled investors, the challenge is to identify them *before* they deliver superior results. Skill in investing, like other probabilistic activities, is a process that incorporates analytical, psychological, and organizational considerations. If nothing else, the discussion of skill and luck makes clear why focusing on outcomes is less useful than focusing on process. If luck nets to zero over time—you win some, you lose some—then long-term results depend on the process.

Skill in Investing: What Comprises a Good Investment Process?

Here are some thoughts on what makes for a good investment process, or skill in the investment industry. This discussion applies directly to long-term investors, but many of the concepts apply to any type of investment approach. You can think of skill in three parts.

The first part requires you to find situations where you have an analytical edge and to allocate the appropriate amount of capital when you do have an edge. The financial community dedicates substantial resources into trying to gain an edge but less time on sizing positions so as to maximize long-term wealth.

At the core of an analytical edge is an ability to systematically distinguish between fundamentals and expectations. Fundamentals are a well thought out distribution of outcomes, and expectations are what is priced into an asset. A powerful metaphor is the racetrack. The fundamentals are how fast a given horse will run and the expectations are the odds on the tote board. As any serious handicapper knows, you make money only by finding a mispricing between the performance of the horse and the odds. There are no “good” or “bad” horses, just correctly or incorrectly priced ones. [66]

An analytical edge exhibits certain characteristics. For example, assessment of the fundamentals should be consistent with the principles of economics, especially microeconomics. Investors need to grasp notions like supply and demand, economic profits, and sustainable competitive advantage. An edge should also incorporate the outside view rather than relying on the inside view. With the inside view, decision makers tend to gather information about a topic, combine it with their own inputs, and project into the future. In most cases, the inside view leads to conclusions that are too optimistic. By contrast, the outside view asks what happened when others were in a similar situation before. By leaning more on historical base rates than on individual extrapolation, the outside view provides a better grounding for analysis. [67]

An analytical edge should also be repeatable in different environments. This does not mean that an investor must always find an edge; there will be times when the set of potential investments will be limited by either the investor’s correct realization of the limits to his or her competence or by a lack of attractive opportunities. It does mean that the approach to finding an edge will be steadfast over time and can be applied to various industries or asset classes.

Onlookers frequently confuse edge with style. When a certain style is doing well, a manager using that style will fare favorably whether or not he or she actively chose that exposure. Over time, some factors have generated excess risk-adjusted returns. For example, small caps have delivered higher returns than large caps since the mid 1920s. But these long-term results mask the existence of extended periods when those factors don’t work. If you had bet on small caps going into the 1980s and 1990s, as an illustration, you would have fared worse than the S&P 500. Edge means generating excess returns because of mispricing. Style suggests being in the right place at the right time. Sometimes edge and style overlap, sometimes they don’t.

Edge also implies what Ben Graham, the father of security analysis, called a margin of safety. You have a margin of safety when you buy an asset at a price that is substantially less than its value. As Graham noted, the margin of safety "is available for absorbing the effect of miscalculations or worse than average luck." The size of the gap between expectations and fundamentals dictates the magnitude of the margin of safety. Graham expands, "The margin of safety is always dependent on the price paid. It will be large at one price, small at some higher price, nonexistent at some still higher price."[68]

Finding gaps between fundamentals and expectations is only part of the analytical task. The second challenge is to properly build portfolios to take advantage of the opportunities. There are two common mistakes in sizing positions within a portfolio. One is a failure to adjust position sizes for the attractiveness of the opportunity. In theory, the positions in more attractive risk-adjusted opportunities should be more prominent in the portfolio than less attractive opportunities. In some activities, mathematical formulas can help work out precisely how much you should bet given your perceived edge.[69] While this is difficult in practice for most money managers, the main idea remains: the best ideas deserve the most capital. The weighting in many portfolios fails to distinguish sufficiently between the quality of the ideas.

The other mistake, at the opposite end of the spectrum, is overbetting. In the past, funds that have seen their edge dwindle have boosted returns through leverage. This led to position sizes that were too large for the opportunity and ultimately disastrous in cases when the trade didn't perform as expected. The failure of Long-Term Capital Management is one of the best-documented cases of the perils of overbetting.[70] The analytical part of a good process requires both disciplined unearthing of edge and intelligent position sizing aimed at maximizing long-term risk-adjusted returns.

The second part of skill is psychological, or behavioral. Not everyone has a temperament that is well suited to investing, and skillful investors approach markets with equanimity. One such skilled investor is Seth Klarman, founder and president of the highly-successful Baupost Group, who shared a wonderful line: "Value investing is at its core the marriage of a contrarian streak and a calculator."[71]

A large source of mispricing is when the collective becomes uniformly bullish or bearish, opening large gaps between expectations (price) and fundamentals (value). The first part of Klarman's line emphasizes the importance of the willingness to go against the crowd. Academic research confirms what most people know: it is easier and more comfortable to be part of the crowd than it is to be alone. Skillful investors heed Ben Graham's advice: "Have the courage of your knowledge and experience. If you have formed a conclusion from the facts and if you know your judgment is sound, act on it—even though others may hesitate or differ."[72] However, Klarman correctly observed that it is not enough to be a contrarian because sometimes the consensus is right. The goal is to be a contrarian when it allows you to gain an edge, and the calculator helps you ensure a margin of safety.

Exposure to diverse inputs is crucial to developing sound contrarian views. As an idea takes hold in the investment community, it tends to crowd out alternative points of view. Skillful investors constantly seek input from a variety of sources, primarily through reading. Phil Tetlock, a psychologist who has done groundbreaking work on the decision making of experts, writes that "good judges tend to be . . . eclectic thinkers who are tolerant of counterarguments."[73]

This part of the process also acknowledges, and takes steps to mitigate, the biases that emanate from common heuristics. These biases include overconfidence, anchoring, the confirmation trap, and the curse of knowledge, to name just a few.[74] Overcoming these behavioral pitfalls is not easy, especially at emotional extremes. Techniques that are helpful include expressing views in probabilistic terms, constantly considering base rates, and maintaining a decision-making journal.

The last component of this part is maintaining what I call a "Mr. Market" mindset. To express a proper attitude toward markets, Ben Graham created the idea of Mr. Market, a "very obliging" fellow who offers to sell his shares to you or to buy yours. Mr. Market shows up every day, but is sometimes very optimistic and, fearful that you will snatch his shares at a low price, posts a very high price. On other occasions he is distraught, and seeks to dump his shares at a bargain-basement price.

Graham's main lesson is that Mr. Market is there to serve you, not to educate you. You cannot let the prices entrance you. Graham writes, "Basically, price fluctuations have only one significant meaning for the true investor. They provide him with an opportunity to buy wisely when prices fall sharply and to sell wisely when they advance a great deal." [75] This is easy to say but requires a lot of skill to do.

The third part of the process of skill addresses organizational and institutional constraints. The core issue is how to manage agency costs. Costs arise because the agent (the money manager) may have interests that are different than the principal (the investor). [76] For example, mutual fund managers who are paid fees based on assets under management may seek to prioritize asset growth over delivering excess returns. Actions to serve this priority may include heavily marketing products that have been recently successful, launching new products in hot areas, and managing portfolios to look similar to their benchmarks.

Charley Ellis made this point when he distinguished between the profession and business of investing. [77] The profession is about managing portfolios so as to maximize long-term returns, while the business is about generating earnings as an investment firm. Naturally, a vibrant business is essential to support the profession. But a focus on the business at the expense of the profession is a problem. Stated differently, you want the investment professionals focused intently on finding opportunities with edge and building sensible portfolios.

Career risk is also important. Investment managers seeking long-term excess returns will frequently have portfolios that are very different than the benchmark and that have high tracking error. If the time horizon of either the investment company or the clients is shorter than the time horizon necessary to see the fruition of the investment approach, even skilled managers risk getting fired. Professional investors have learned to play close to the index. For example, aggregate active share is down considerably over the past 30 years. [78]

All three parts of investing skill are difficult. Many organizations clear one or two of the hurdles, but few can clear all three. This fits with the conclusion of our analysis of skill and luck in investing: there are differential capabilities, but only a handful of investors can clear the analytical, psychological, and organizational hurdles.

In 1984, Warren Buffett gave a speech at Columbia Business School called "The Superinvestors of Graham-and-Doddsville." [79] He referred to the coin toss metaphor and granted that some investors would succeed by luck. But he went on to point out that a number of successful investors came from the same "small intellectual village that could be called Graham-and-Doddsville." Common to all of the investors was that they searched "for discrepancies between the *value* of the business and the *price* of small pieces of that business." These investors had a common patriarch, Ben Graham, but went about succeeding in different ways. Still, Buffett suggested he anticipated their success based on "their framework for investment decision making." While some luck along the way didn't hurt, their results were all about skill.

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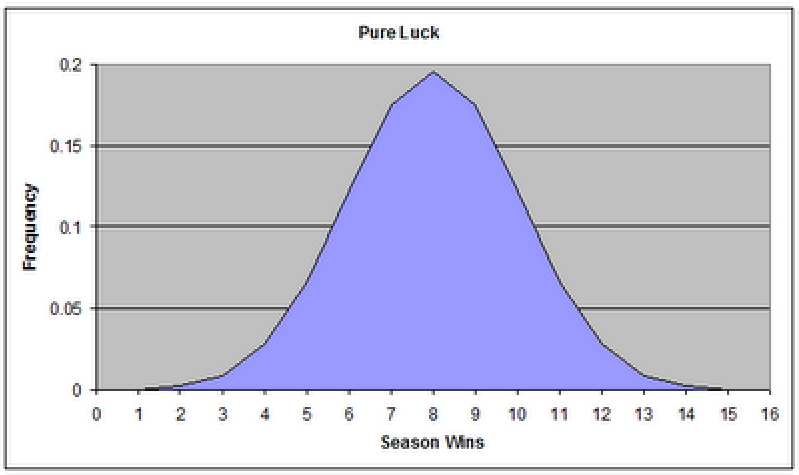
Appendix A: Blending Distributions to Understand Outcomes in the National Football League

This analysis comes from Brian Burke, author of Advanced NFL Stats. This discussion came from a series that started here: http://www.advancednflstats.com/2007/08/luck-and-nfl-outcomes.html.

Burke starts by asking what the distribution of wins and losses would look like in a pure luck world (see Exhibit 15). A binomial, or coin-toss, model expresses this distribution. This is equivalent to assuming outcomes are the combination of draws from a normally-distributed luck urn and a skill urn filled with zeros. About 20 percent of the teams go 8-8, and the probability of going either winless or undefeated is extremely low.

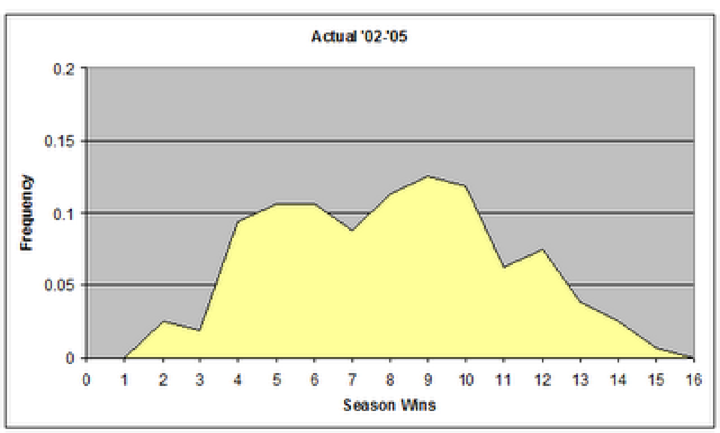
Exhibit 15: NFL Win-Loss Records Assuming a Coin-Toss Model



Source: Brian Burke, Advanced NFL Stats.

He then looks at the actual results for all NFL teams over the 2002-2005 seasons (see Exhibit 16). It's clear that the distribution isn't the same as what the binomial model generates.

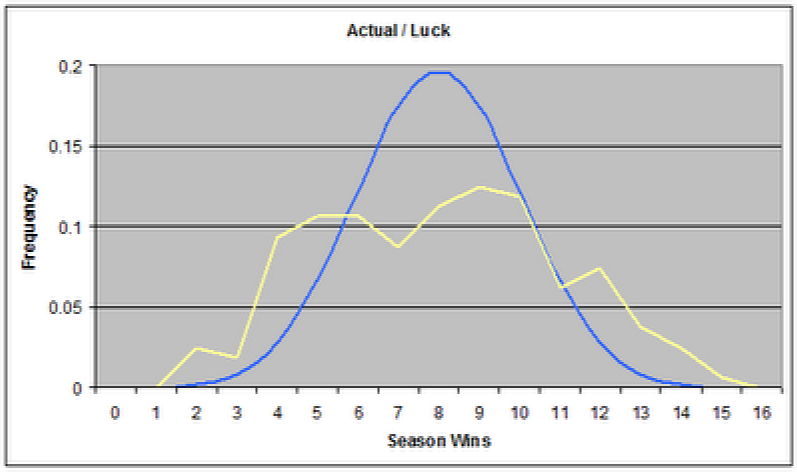
Exhibit 16: Actual NFL Win-Loss Records (2002-2005)



Source: Brian Burke, Advanced NFL Stats.

The next picture provides a contrast between the random model and the empirical results (see Exhibit 17). You can see that the middle of the empirical results is lower than the random model and that there are more extreme events—teams winning or losing lots of games.

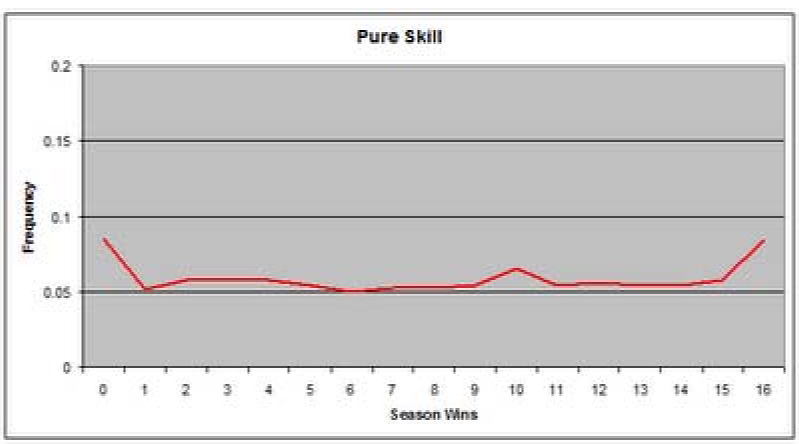
Exhibit 17: Comparison of Coin-Toss to Actual Win-Loss Records



Source: Brian Burke, Advanced NFL Stats.

Burke then turns to a pure-skill distribution (see Exhibit 18). Here he ranks all of the teams from #1 to #32, assumes that the higher-rated team always beats a lower-rated one, schedules games as they do in the NFL, and simulates the outcomes. Burke describes the distribution as "an inverted trapezoid." The rise in undefeated and winless teams is a result of scheduling. For example, there may be some seasons when team #2 never faces team #1, so both teams go undefeated. The same holds for team #31 and team #32. This is equivalent to having a skill urn that ensures the better team always wins and a luck urn filled with zeros.

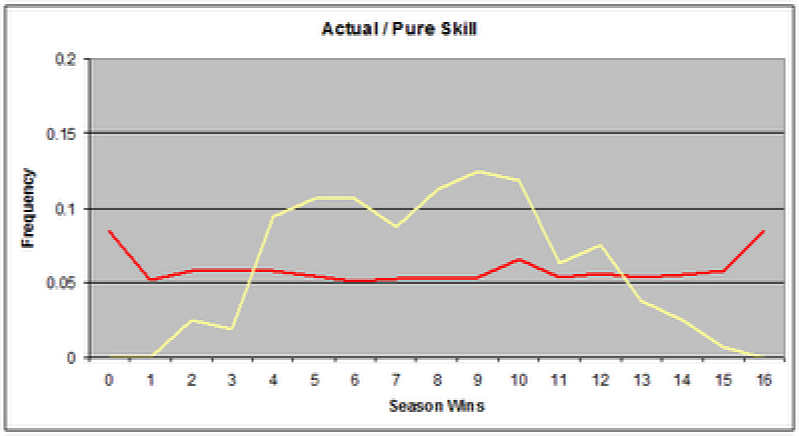
Exhibit 18: NFL Win-Loss Records Assuming Pure Skill



Source: Brian Burke, Advanced NFL Stats.

Next, he provides a contrast between the pure-skill model and the empirical results (see Exhibit 19). The pure-skill model is much too flat and assumes too many records with lots of wins or lots of losses.

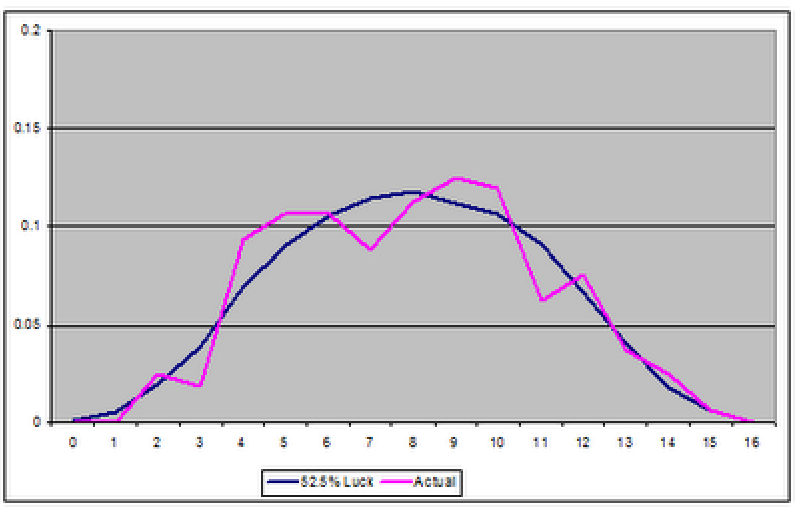
Exhibit 19: Comparison of Pure-Skill to Actual Win-Loss Records



Source: Brian Burke, Advanced NFL Stats.

Finally, Burke blends the pure-skill and pure-luck models together until he gets a distribution that best fits the empirical results (see Exhibit 20). Adding the pure skill to the pure luck model helps stretch out the frequency of win-loss records, and adding the pure luck model to the pure skill model raises the middle of the distribution. Burke finds that the blend that best fits the empirical data is 52.5 percent luck. This is a little lower than the 58 percent we found because he measured the 2002-2005 seasons and we analyzed 2005-2009.

Exhibit 20: Blend of Skill and Luck that Best Fits the Empirical Results



Source: Brian Burke, Advanced NFL Stats.

Burke notes that this degree of randomness suggests NFL game prediction models to be accurate in the 75-80 percent range. He suggests that this is consistent with various computer models and oddsmakers.

Sports results naturally lend themselves to this type of analysis because both extremities are simple to specify. But the idea of comparing empirical results to simulated data is helpful in a number of other activities as well.

Appendix B: Placing the NBA on the Skill-Luck Continuum

	2005-06	2006-07	2007-08	2008-09	2009-10
Boston Celtics	40.2%	29.3%	80.5%	75.6%	61.0%
New Jersey Nets	59.8%	50.0%	41.5%	41.5%	14.6%
New York Knicks	28.0%	40.2%	28.0%	39.0%	35.4%
Philadelphia 76ers	46.3%	42.7%	48.8%	50.0%	32.9%
Toronto Raptors	32.9%	57.3%	50.0%	40.2%	48.8%
Chicago Bulls	50.0%	59.8%	40.2%	50.0%	50.0%
Cleveland Caveliers	61.0%	54.9%	61.0%	80.5%	74.4%
Detroits Pistons	78.0%	64.6%	72.0%	47.6%	32.9%
Indiana Pacers	50.0%	42.7%	43.9%	43.9%	39.0%
Milwaukee Bucks	48.8%	34.1%	31.7%	41.5%	56.1%
Atlanta Hawks	31.7%	36.6%	45.1%	57.3%	64.6%
Charlotte Bobcats	31.7%	40.2%	39.0%	42.7%	53.7%
Miami Heat	63.4%	53.7%	18.3%	52.4%	57.3%
Orlando Magic	43.9%	48.8%	63.4%	72.0%	72.0%
Washington Wizards	51.2%	50.0%	52.4%	23.2%	31.7%
Dallas Mavericks	73.2%	81.7%	62.2%	61.0%	67.1%
Houston Rockets	41.5%	63.4%	67.1%	64.6%	51.2%
Memphis Grizzlies	59.8%	26.8%	26.8%	29.3%	48.8%
New Orleans Hornets	46.3%	47.6%	68.3%	59.8%	45.1%
San Antonio Spurs	76.8%	70.7%	68.3%	65.9%	61.0%
Denver Nuggets	53.7%	54.9%	61.0%	65.9%	64.6%
Minnesota Timberwolves	40.2%	39.5%	26.8%	29.3%	18.3%
Portland Trailblazers	25.6%	39.0%	50.0%	65.9%	61.0%
Oklahoma City Thunder	42.7%	37.8%	24.4%	28.0%	61.0%
Utah Jazz	31.7%	50.0%	65.9%	58.5%	64.6%
Golden State Warriors	41.5%	51.2%	58.5%	35.4%	31.7%
Los Angeles Clippers	57.3%	48.8%	28.0%	23.2%	35.4%
Los Angeles Lakers	54.9%	51.2%	69.5%	79.3%	69.5%
Phoenix Suns	65.9%	74.4%	67.1%	56.1%	65.9%
Sacramento Kings	53.7%	39.5%	46.3%	20.7%	30.5%
Standard deviation(obs)	14.0%	12.9%	17.0%	17.2%	16.3%
Variance(observed)	1.97%	1.66%	2.88%	2.96%	2.66%
Standard deviation(random)	5.5%	5.5%	5.5%	5.5%	5.5%
Variance(random)	0.30%	0.30%	0.30%	0.30%	0.30%

→ variance(skill) = variance(observed) - variance(random)
→ random percentage = variance(random)/variance(observed)

variance(observed)	2.42%	Last 5 regular seasons (average)
- variance(random)	0.30%	
= variance(skill)	2.12%	
random percentage	12.6%	

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