A Fallacy that Will Not Die

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Abstract

Regression to the mean is a pervasive statistical phenomenon that invites causal explanations for random fluctuations. A notorious economic example of this fallacy was exposed more than eighty years ago, yet regression to the mean continues to be overlooked or misinterpreted by economists, even Nobel Laureates.

A Fallacy that Will Not Die

Galton [1886] observed that the children of unusually tall (or short) parents tend to be closer to the average height than are the heights of their parents—a statistical pattern he labeled "regression." We now know that regression to the mean occurs in a great many contexts, including education, medicine, sports, and business. Yet, in all these areas, regression is frequently overlooked or misinterpreted. In investing, this can be an expensive mistake.

Regression Toward the Mean

Imagine a test consisting of 20 randomly selected true-false questions from an enormous test bank of questions about corporate earnings; for example, Apple's return on equity was above 30 percent in 2014: true of false? A person's "ability" is the expected value of his or her score. Someone with an ability of 70 can answer 70 percent of the questions in the test bank correctly. This person has a 70 percent chance of answering a randomly selected question correctly, and the expected value of this person's test score is 70 percent.

A person with an ability of 70 will not get exactly 70 percent right on every test. Sometimes, by the luck of the draw, more than 70 percent of the questions will be ones this person can answer correctly; sometimes, fewer than 70 percent. The score on any single test is an imperfect measure of ability. What we do know, statistically, is that scores will regress toward ability. A person with an ability of 70 who happens to get 90 on one test will probably score below 90 on a second test. A person with an ability of 70 who gets 50 on one test will probably do better on a second test.

Now consider a group of people of various abilities, with an average ability of 60. What, if

anything, can we infer about a person's ability from his or her test score? A key insight is that someone whose test score is high relative to the other people in the group probably also had a high score relative to his or her own ability. Someone who scores 90 on a test where the average score is 60 could be someone of higher ability (perhaps 95) who did poorly, or could be someone of more modest ability (perhaps 85, 80 or 75) who did unusually well. The latter is more likely because there are more people with ability below the 90 than above it.

If this person's ability is below 90, his or her score on a second test is likely to be below 90. More generally, someone who scores far above the group mean probably has an ability that is closer to the mean than was the score, and can consequently anticipate scoring closer to the mean on a second test. Similarly, a person who scores well below average probably had an off day (the score is below his or her ability) and should score somewhat higher on a second test. This tendency of people who score far from the mean to score closer to the mean on another test is an example of regression toward the mean.

This regression principle applies not only to tests about earnings, but also to actual earnings. Let's call the expected value of a firm's return on equity (ROE) for the coming year its "ability." If the firm's actual ROE turns out to be above its ability, and its ability hasn't changed, its subsequent ROE will probably be lower.

Now consider a group of companies with differing abilities. A company whose ROE is high relative to other companies is more likely to have had an ROE that was above it ability than below its ability, and its subsequent ROE will probably be lower. For example, a company with a 30 percent ROE, when the average ROE is 20 percent, is more likely to be a company with an expected ROE below 30 percent than a company with an expected ROE above 30 percent,

because the former far outnumber the latter. Even if its expected ROE is unchanged, its subsequent ROE will probably be less than 30 percent.

Some early studies argued that earnings follow a random walk (Little [1962], Brealey [1967], Lintner and Glauber [1967], Ball and Watts [1972]). However, several later studies found a regression pattern. Although they do not use the label regression to the mean, Freeman, Ohlson, and Penman [1982] find that ROEs regress to the mean and conclude that, "A relatively low rate-of-return implies that earnings are 'temporarily depressed'; similarly, a high rate-of-return implies that earnings are 'unusually good.'" Fairfield, Sweeney, and Yohn [1996]— also conclude that ROEs regress to the mean, though they do not speculate on the reasons. A later section will cite additional evidence of earnings regression by authors who offer explanations.

The Law of Averages

Jacob Bernoulli's *law of large numbers* says that, if a coin has 0.50 probability of landing heads, it will land heads close to 50 percent of the time in the long run. Some people misinterpret this law as saying that, in the long run, the number of heads and tails must be *exactly* equal. If tails come up more often than heads in the first 10, 50, or 100 flips, we are "due" for heads in order to balance things out. This misinterpretation is known as the *law of averages* (or, more aptly, the *gambler's fallacy*)

This belief is wrong, but widespread. For example, one gambler wrote:

Flip a coin 1000 times and it'll come up heads 500 times, or mighty close to it. However, during that 1000 flips of the coin there will be frequent periods when heads will fail to show and other periods when you'll flip nothing but heads. Mathematical probability is going to give you roughly 500 heads in 1000 flips, so that if you get ten tails in a row,

there's going to be a heavy preponderance of heads somewhere along the line. (McQuaid [1971])

This reasoning is fallacious because a coin has no memory and no control over how it lands. A coin is an inanimate object that is tossed in the air and examined by curious humans. If the coin is unbent and fairly tossed, heads and tails are equally likely to appear no matter what happened on the last flip or the last 999 flips.

The paradox is that in a large number of flips, we are increasingly certain that there will be close to 50 percent heads (the correct law of large numbers), but also increasingly certain that the number of heads will not equal the number of tails (contrary to the fallacious law of averages). In 1,000 coin flips, there is a 0.499 probability that the fraction heads will be between 0.49 and 0.51, while the probability of exactly 500 heads is 0.0252. Increase that to 10,000 flips and the respective probabilities are 0.956 and 0.0080.

The *law of averages* is frequently invoked outside of coin flips. Human performance is not a series of coin tosses but, still, there is no statistical reason to believe that every failure makes success more likely, or vice versa. Four baseball hits in a row does not make an out more likely. Losing ten football games in a row does not make a win more likely.

Chemi [2013], the head of data and research at Bloomberg Media, noted that Warren Buffett's Berkshire Hathaway had underperformed the S&P500 for four months in a row, June, July, August, and September, 2013, and concluded that "Berkshire stock is due for a comeback vs. the S&P." This is the gambler's fallacy. Perhaps Buffett had lost his Midas touch, or perhaps he had been unlucky. Either way, underperforming the market does not, by itself, increase the chances of outperforming it.

People sometimes confuse regression to the mean with the gambler's fallacy. In our test example, regression to the mean says that a person who gets a score far from the mean will probably score closer to the mean on a second test. The gambler's fallacy is that the score will swing from one side of the mean to the other—that an above-average score is likely to be followed by a below-average score.

In his best-selling, prize-winning book, *Against the Gods*, Bernstein [1996] wrote that

> The track records of professional investment managers are also subject to regression to the mean. There is a strong probability that the hot manager of today will be the cold manager of tomorrow, or at least the day after tomorrow, and vice versa . . . . [T]he wisest strategy is to dismiss the manager with the best track record and to transfer one's assets to the manager who has been doing the worst; this strategy is no different from selling stocks that have risen the furthest and buying stocks that have fallen furthest.

Bernstein is wise, but this is not wisdom. The idea that the best will be worst and the worst will be best is the gambler's fallacy that good luck must be offset by bad luck. It is false and it is not regression to the mean. Regression to the mean arises because those managers with the best track records probably benefited from good luck and are consequently not as far above average as they seem. Those who make the best stock picks in any given year tend to be closer to average—not below average—the next year. If there is any skill to stock picking, the investment managers with the best track record can be expected to outperform the managers with the worst record, but not by as much in the future as they have in the past. If there is no skill, just luck, we may as well pick managers randomly—or save money by not using a manager at all—but there is no reason to choose the worst manager.

Mean Reversion

The random walk hypothesis holds that stock price changes are unrelated to previous changes, much as coin flips are unrelated to previous tosses, and a drunkard's steps are unrelated to previous steps. However, in a seminal paper, Debondt and Thaler [1985] concluded that portfolios of stocks that had done poorly subsequently outperformed portfolios of stocks that had done well. Fama and French [1988] and Poterba and Summers [1988] also found "mean reversion" in stock returns in that stocks with above-average returns over various horizons tend to subsequently experience below-average returns. Others (Richardson [1989], Richardson and Stock [1989], Kim, Nelson, and Startz [1991]) argue that the evidence for mean reversion is weak; for example, because it is largely due to overlapping observations during the Great Depression and World War II.

Whether it is true or not, mean reversion is different from regression to the mean. Mean reversion is like the gambler's fallacy in its presumption that successes tend to be followed by failures, and vice versa. The difference is that, in the stock market, there is a plausible explanation. Indeed, mean reversion in stock returns may be due to an insufficient appreciation of regression to the mean in earnings, cash flow, and other fundamental determinants of stock prices.

Suppose that a company's ROE fluctuates randomly about a constant expected value, and consequently exhibits regression to the mean. When the ROE in any period happens to be above its expected value, then, by definition, the expected value of ROE in the next period is lower than the current ROE. Extreme values tend to be followed by values that are closer to the mean. If ROEs fluctuate randomly around a constant expected value, the *change* in ROE will exhibit

mean reversion—ROE increases tend to be followed by ROE decreases, and vice versa.

When we look at a group of companies, those companies with the highest ROEs in any given year are more likely to have had a good year than an off year. They typically didn't do as well the year before and won't do as well the year after. Something very similar is true of predicted earnings. The most optimistic predictions are more likely to be overly optimistic than to be excessively pessimistic; so, the companies with the most optimistic forecasts probably won't do as well as predicted. Keil, Smith, and Smith [2004] confirmed that the companies with the most optimistic (or pessimistic) forecasts tended to do better (or worse) than average, but closer to average than predicted.

Now suppose that investors do not fully appreciate regression to the mean. They see an increase in earnings and/or an optimistic earnings prediction and bid up the price of the stock. When earnings regress to the mean, the stock price takes a hit. Thus, a price increase (and high return) tends to be followed by a price decrease (and low return).

This argument that regression to the mean in earnings causes a mean reversion is prices explains the conclusion of Lakonishok, Shliefer, and Vishny [1994]:

> First, a variety of investment strategies that involve buying out-of-favor (value) stocks have outperformed glamour strategies over the April 1968 to April 1990 period. Second, a likely reason that these value strategies have worked so well relative to the glamour strategies is the fact that the actual future growth rates of earnings, cash flow, [and sales] etc. of glamour stocks relative to value stocks turned out to be much lower than they were in the past, or as the multiples on those stocks indicate the market expected them to be.

Statistical Fallacies

An anonymous reviewer once wrote that,

> There are few statistical facts more interesting than regression to the mean for two
> reasons. First, people encounter it almost every day of their lives. Second, almost nobody
> understands it. The coupling of these two reasons makes regression to the mean one of
> the most fundamental sources of error in human judgment.

The core problem is an under-appreciation of the role of luck in our lives—the unpredictable fluctuations of events around the expected value of the outcome. The expected value of a person's test score might be 70 percent, but the actual score may be above or below 70, depending on the luck—good or bad—in the questions selected for the test. The expected value of the number of shots made by a basketball player shooting 10 free throws might be 5, but the actual number may be higher or lower. The expected value of a company's ROE might be 20 percent, but its actual ROE may be higher or lower.

This is not to say that expected values don't change. A person can study; a basketball player can practice, a company can get a new CEO. However, problems arise when we ignore the role of luck and think that every event is an accurate gauge of the underlying expected value. It is a mistake to think that a person who gets 90 percent correct is a 90 percent student. It is a mistake to think that a basketball player who makes 7 of 10 shots is a 70 percent shooter. It is a mistake to think that a company with a 30 percent ROE last year can be expected to have a 30 percent ROE this year.

The mistake is to overlook the role of luck in a success—be it a student, basketball player, or company. When success is partly due to good luck, we cannot count on good luck every year. A

related mistake is to think that all fluctuations must have an explanation. If a student's score goes up, he must have studied. If his score subsequently drops, he must have forgotten what he previously learned. Overlooked is the possibility that his scores are simply fluctuating about an unchanged ability.

Regression to the mean is a purely statistical phenomenon that occurs in a wide variety of everyday contexts, including educational testing (Kelley [1947], Lord and Novick [1968]), medical test results (Bland and Altman [1994a, 1994b]), and athletic performances (Schall and Smith [2000]). We are too quick to conclude that when a student gets the lowest test score, it is because this student is the weakest student in the class, and that when this student gets a higher score on a later test, it is because special tutoring paid off. We are too quick to believe that when a medical test result is outside the normal range, something must be wrong with the patient, and that when a subsequent test result is normal, it is because a treatment was effective. We are too easily persuaded that when a golfer wins a tournament, it is because he is the best player in the world, and that when he appears on the cover of *Sports Illustrated* and doesn't win the next tournament, it is because of the *Sports Illustrated* cover jinx.

Regression is often overlooked or misinterpreted in investing by investors inventing causal explanations for statistical noise. If a company does exceptionally well one year, it must have somehow turned into an exceptional company. If this company is subsequently less exceptional, it must be because of the entrance of new firms and other competitive forces.

It is particularly ironic that the economics profession produced what is arguably the most famous regression-to-the-mean fallacy of all time and, yet, economists—even Nobel laureates—continue to make the same error over and over again. It is a fallacy that will not die.

The Triumph of Mediocrity

Horace Secrist was a distinguished economics professor and director of Northwestern University's Bureau of Business Research. Secrist and his assistants spent ten years collecting and analyzing data for the years 1920 to 1930 for companies in seventy-three different industries. For each firm, Secrist calculated several measures of business success, including the ratios of profits to sales, profits to assets, expenses to sales, expenses to assets. For each ratio, he divided the companies in an industry into quartiles based on the 1920 data. He then calculated the average value of the ratio for the next ten years for the companies in the top quartile in 1920. He did the same for companies in the second, third, and bottom quartiles. In nearly every case, the companies in the top two quartiles in 1920 were more nearly average in 1930, as were the companies in the bottom two quartiles.

He had evidently discovered an economic phenomenon that might explain the cause of the Great Depression, provide a solution, and secure his legacy. His 1933 treatise, *The Triumph of Mediocrity in Business*, was 468 pages long, with 140 tables and 103 charts documenting the fact that American business was converging to mediocrity. Secrist summarized his conclusion:

> Complete freedom to enter trade and the continuance of competition mean the
> perpetuation of mediocrity. New firms are recruited from the relatively "unfit". . . .
> Superior judgment, merchandizing sense, and honesty . . . are always at the mercy of the
> unscrupulous, the unwise, the misinformed, and the injudicious. The results are that retail
> trade is overcrowded, shops are small and inefficient, volume of business inadequate,
> expenses relatively high, and profits small. So long as the field of activity is freely
> entered, and it is; and so long as competition is 'free,' and, within the limits suggested

above, it is; neither superiority or inferiority will tend to persist. Rather mediocrity tends

to become the rule.

The nation's economic problems were apparently due to the new economic principle he had

discovered: competitive pressures inevitably dilute superior talent. The evident solution? Protect

superior companies from competition from less-fit companies.

Before publishing his work, Secrist asked thirty-eight prominent statisticians and economists

for comments and criticism. After publication, the initial reviews were unanimous in their praise.

This book furnishes an excellent illustration of the way in which statistical research

can be used to transform economic theory into economic law, to convert a qualitative into

a quantitative science—*Journal of Political Economy* (King [1934])

The author concludes that the interaction of competitive forces in an interdependent

business structure guarantees "the triumph of mediocrity." The approach to the problem is

thoroughly scientific—*American Economic Review* (Elder [1934])

The results confront the business man and the economist with an insistent and to

some degree tragic problem—*Annals of the American Academy of Political and Social

Science* (Riegel [1933])

Then Hotelling [1933] wrote a devastating review that politely demonstrated that Secrist had

wasted ten years proving nothing at all. What Secrist became famous for was being fooled by

regression toward the mean.

Secrist's Error

The fundamental problem is that Secrust ignored the role of luck. He assumed that if a company

performs exceptionally well, it must be as exceptional as it performance. He concluded that if it

subsequently does not do as well, there must be an explanation, such as competition from less-fit companies.

However, regression to the mean teaches us that, in any given year, the most successful companies are more likely to have had good luck than bad, and to have done well not only relative to other companies, but also relative to their own "ability." The opposite is true of the least successful companies. This explains why the subsequent performance of the top and bottom companies is usually closer to the average company. At the same time, their places at the extremes are taken by other companies experiencing fortune or misfortune. These up-and-down fluctuations are part of the natural ebb and flow of life and do not mean that all companies will soon be mediocre.

Let's work through a detailed example of the statistical regression that fooled so many prominent, sophisticated people in the past and continues to do so today. As Stigler [2000] noted, "the regression fallacy is extremely subtle, and it can as easily hoodwink the mathematically educated as the nonmathematician."

The expected value of a firm's ROE is its "ability." Suppose that in a particular industry, the distribution of abilities across firms is described by a normal distribution with a mean of 20 percent and a standard deviation of 10 percent and that, for each firm, the annual variation of its actual ROE around its ability is described by a normal distribution with a mean of 0 percent and a standard deviation of 10 percent. Thus, 95 percent of the firms have abilities between 0 percent and 40 percent. For a firm with an ability of, say, 30 percent, there is a 95 percent chance that its ROE in any given year will be between 10 percent and 50 percent.

These assumptions were used to generate data for two years, which I will call 1920 and 1930.

Following Secrist, suppose that we group the firms into quartiles based on their observed ROE in 1920. Regression to the mean occurs because firms with observed profits that are far from the mean tend to have abilities that are closer to the mean. Thus, their profits in any other year are closer to the mean. In our example, the firms with observed profits in the top quartile have an average ROE of 38, but an average ability of 29. They averaged 38 in their top-quartile year, but they can be expected to average 29 in any other year. Exhibit 1 shows this convergence when firms are grouped into quartiles based on their 1920 profits.

Exhibit 1 Average ROE, Quartiles Formed Using 1920 Profits

	1920	1930
First quartile, 1920	38.0	29.0
Second quartile, 1920	24.6	22.3
Third quartile, 1920	15.4	17.6
Fourth quartile 1920	2.0	11.0

The firms in the top two quartiles in 1920 tend to have more nearly average profits in 1930. The firms in the bottom two quartiles in 1920 also tend to be more nearly average in 1930.

This regression doesn't depend on which year we use to group the firms into quartiles. Exhibit 2 shows the convergence of 1920 profits using quartiles based on 1930 profits.

Exhibit 2 Average ROE, Quartiles Formed Using 1930 Profits

	1920	1930
First quartile, 1930	29.0	38.0
Second quartile, 1930	22.3	24.6
Third quartile, 1930	17.7	15.4

Fourth quartile 1930   11.0   2.0

Exhibit 3 is a visual demonstration that if we use 1920 to form quartiles, as did Secrist, profits regress in 1930.
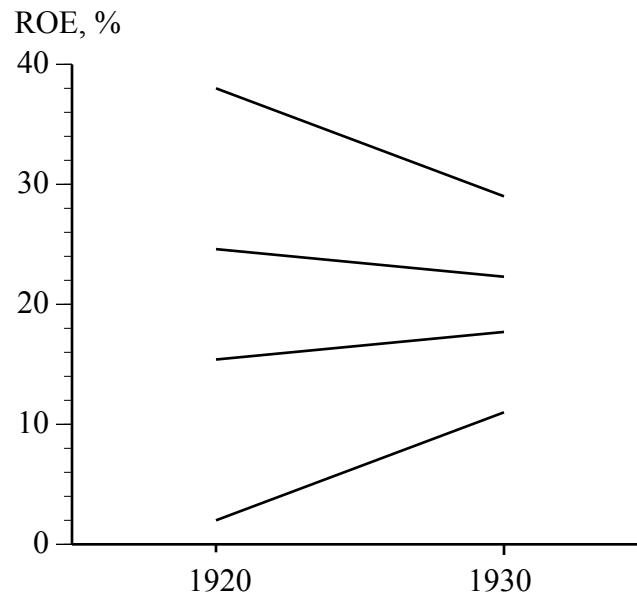
ROE, %

Exhibit 3 Quartiles Based on 1920 Profits Regress in 1930

Exhibit 4 shows that if we use 1930 ROEs to form quartiles, profits regress in 1920.
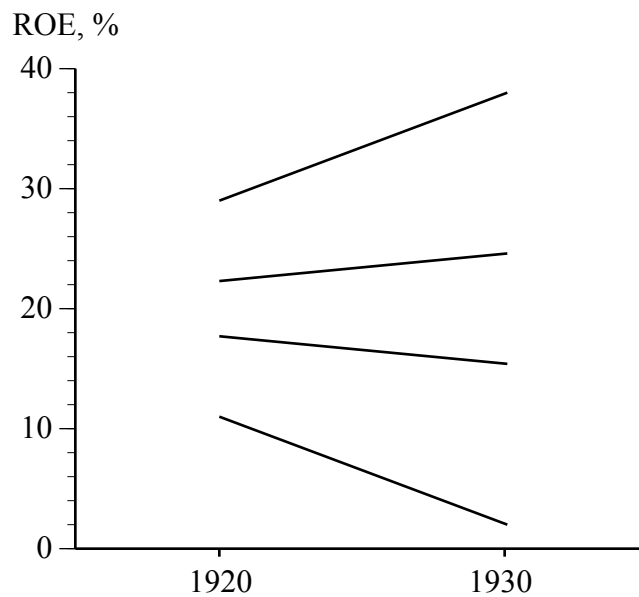
ROE, %

Exhibit 4 Quartiles Based on 1930 Profits Regress in 1920

There is absolutely no convergence in abilities. I assumed that abilities are the same for each firm in each year. Regression occurs simply because profits fluctuate randomly about ability. As Hotelling put it, Secrist's "diagrams really prove nothing more than that the ratios in question have a tendency to wander about."

Do Old Fallacies Ever Die?

Even though Secrist's error was clearly dissected by Hotelling, the error lives on, in that regression is often overlooked or misinterpreted (Tversky and Kahneman [1973, 1974]), and this can be an expensive mistake.

Hirschman [1970], an eminent political economist, wrote that,

An early, completely forgotten empirical work with a related theme has the significant title The Triumph of Mediocrity in Business, by Horace Secrist, published in 1933 by the Bureau of Business Research, Northwestern University. The book contains an elaborate statistical demonstration that, over a period of time, initially high-performing firms will on the average show deterioration while the initial low performers will exhibit improvement.

The author was blissfully unaware of the reason that Secrist's conclusions had no impact. He read Secrist, but overlooked Hotelling.

A investments textbook written by a Nobel laureate (Sharpe [1980]) argued that, "ultimately, economic forces will force the convergence of the profitability and growth rates of different firms." To support this assertion, he looked at the firms with the highest and lowest profit rates in 1966. Fourteen years later, in 1980, the profit rates of both groups were closer to the mean. He concluded triumphantly: "convergence toward an overall mean is apparent. . . . the phenomenon

is undoubtedly real." Déjà vu, déjà vu. Like Secrist fifty years earlier, he did not consider the possibility that this convergence is not due to economic factors, but is simply statistical regression to the mean.

Several years later, two other distinguished finance professors—one, another Nobel Prize laureate—made the very same error. In a lead article in the *Journal of Business*, Fama and French [2000] found regression in earnings data and, like Secrist, attributed it entirely to competitive forces:

> In a competitive environment, profitability is mean reverting within as well as across industries. Other firms eventually mimic innovative products and technologies that produce above normal profitability for a firm. And the prospect of failure or takeover gives firms with low profitability incentives to allocate assets to more productive uses.

Similarly, Haugen [1995], a book that was required reading for the CFA exam, argues that value stocks are superior investments because investors do not appreciate the economic forces that causes earnings to converge:

> Because the value companies tend to reorganize and reinvent themselves or are taken over and forced to do just that, and because growth companies face hungry competitors eager to participate in profitable product markets, the bad and the good become the average much faster than the market realizes."

These arguments makes sense, but their evidence is no more persuasive than was Secrist's evidence. This is not to say that competitive forces are a myth, only that we cannot gauge the strength of these forces without taking into account regression to the mean.

While these authors ignore regression, others have applied the label but incorrectly described

regression as being caused by competitive forces. Two articles in the *Financial Analysts Journal* made this mistake when they used regression to the mean to explain the disappointing performance of companies identified as outstanding in the best-selling book, *In Search of Excellence* (Peters and Waterman [1982]). Clayman [1987] wrote that,

> Over time, company results have a tendency to regress to the mean as underlying economic forces attract new entrants to attractive markets and encourage participants to leave low-return businesses.

Bannister [1990] agreed with this (mis)interpretation:

> [The] key financial ratios of companies tend, over time, to revert to the mean for the market as a whole. The thesis is easily defended. High returns eventually invite new entrants, driving down profitability, while poor returns cause the exit of competitors, leaving a more profitable industry for the survivors.

Regression to the mean is a persuasive reason for anticipating that companies that have been extraordinarily successful in the past will be less extraordinary in the future, but this expectation is purely statistical and does not depend on competitive forces.

Similarly, Hershey [2003], a prolific author and professor muddled the distinction between competitive pressures and statistical regression: "Experienced investors know that competitor entry in highly profitable, high-growth industries causes above-normal profits to regress toward the mean. Conversely, bankruptcy and exit allow the below-normal profits of depressed industries to rise toward the mean."

Another example of a search for a causal explanation is a study (Baruch [1969]) of the financial statements of hundreds of U.S. companies which found that six financial ratios (such as

sales to inventory and income to total assets) tended to regress to industry averages. The author

suggested that industry averages are targets and when a firm observes a deviation between its

ratio and the industry mean, it will adjust its ratios, either by changing its behavior or using the

wiggle room provided by generally accepted accounting rules to smooth out income, inventories,

and other financial data. Once again, the role of statistical regression was overlooked.

Another variation on this recurring error cropped up in a book (Baumol, Blackman, and

Wolff [1989]) and book review (Williamson [1991]), both written by prominent economists,

arguing that the economic growth rates of entire nations converge over time. They assumed too

quickly that there must be a causal explanation. and completely ignored the role of statistical

regression in this convergence.

Friedman [1992] wrote an apt commentary titled, "Do Old Fallacies Ever Die?," which is the

inspiration for the title of this paper. Friedman lamented the tenacity of the regression fallacy:

> I find it surprising that the reviewer and the authors, all of whom are distinguished
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> economists, thoroughly conversant with modern statistical methods, should have failed to
>
> recognize that they were guilty of the regression fallacy. . . . However, surprise may not
>
> be justified in light of the ubiquity of the fallacy both in popular discussion and in
>
> academic studies.

The fallacy is still alive and well.

Conclusion

We are inclined to discount the role of luck in our lives—to believe that extraordinary events are

accurate representations of extraordinary traits, and that subsequent events that are less

extraordinary must be due to a waning of those traits. A company that has a great year must be a

great company. If its subsequent performance is not so great, something must have happened—such as the entrance of new competitors—that undermined its greatness. This fallacy was exposed in 1933, yet it lives on, fooling even Nobel Laureates.

References

Ball, Ray, R. Watts. "Some Time Series Properties of Accounting Income." Journal of Finance, 27 (1972), pp. 663-81.

Bannister, Barry B. "In Search of Excellence: A Portfolio Management Perspective." Financial Analysts Journal, Vol. 46, No. 2 (1990), pp. 68–71.

Baruch, Lev. "Industry Averages as Targets for Financial Ratios." Journal of Accounting Research, Vol. 7, No. 2 (1969), pp. 290-299.

Baumol, William J., S. Blackman, E. Wolff. Productivity and American Leadership: The Long View, Cambridge and London: MIT Press, 1989.

Bernstein, Peter L. Against The Gods: The Remarkable Story of Risk. New York: John Wiley & Sons, 1996.

Bland, J. Martin, D. Altman. "Regression towards the Mean." British Medical Journal, 308 (1994a), p. 1499.

——. "Some Examples of Regression Towards the Mean." British Medical Journal, 309 (1994b), p. 780.

Brealey, Richard. "Statistical Properties of Successive Changes in Earnings." Working paper, Keystone Custodian Funds, (1967).

Chemi, Eric. "Is Warren Buffett Approaching an All-Time Losing Streak?," Bloomberg Businessweek, October 16, 2013.

Clayman, Michelle. "In Search of Excellence: The Investor's Viewpoint." Financial Analysts Journal, Vol. 43, No. 3 (1987), pp. 54–63.

DeBondt, Werner F. M., R. Thaler. "Does the Stock Market Overreact?" Journal of Finance, Vol.

40, No. 3 (1985), pp. 793–805.

Elder, Robert F. "Review of The Triumph of Mediocrity in Business by Horace Secrist."
American Economic Review, Vol. 24, No. 1 (1934), pp. 121–122.

Fama, Eugene F., K. French. "Permanent and Temporary Components of Stock Prices." Journal
of Political Economy, Vol. 96, No. 2 (1988), pp. 246-273.

Fama, Eugene F., K. French. "Forecasting Profitability and Earnings." Journal of Business, 73
(2000), pp. 161–175.

Fairfield, Patricia M., R. Sweeney, T. Yohn. "Accounting Classification and the Predictive
Content of Earnings." The Accounting Review, Vol. 71, No. 3 (1996), pp. 337-355.

Freeman, Robert, J. Ohlson, S. Penman. "Book Rate-of-Return and the Prediction of Earnings
Changes." Journal of Accounting Research, Vol. 20, No. 2 (1982), pp. 639-653.

Friedman, Milton. "Do Old Fallacies Ever Die?" Journal of Economic Literature, Vol. 30, No. 4
(1992), pp. 2129–2132.

Galton, Francis. "Regression Towards Mediocrity in Hereditary Stature." Journal of the
Anthropological Institute, 15 (1886), pp. 246-263.

Haugen, Robert A. The New Finance, Upper Saddle River, New Jersey: Pearson Prentice Hall,
1995.

Hirschey, Mark. Tech Stock Valuation: Investor Psychology and Economic Analysis, Amsterdam,
Boston: Academic Press, 2003.

Hirschman, Albert O. Exit, Voice, and Loyalty, Cambridge, Massachusetts: Harvard University
Press, 1970, p. 11.

Hotelling, Harold. "Review of The Triumph of Mediocrity in Business, by Horace Secrist."

Journal of the American Statistical Association, Vol. 28, No. 184 (1933), pp. 463–465.

Keil, Manfred, G. Smith, M. Smith. "Shrunken Earnings Predictions are Better Predictions."

Applied Financial Economics, 14 (2004), pp. 937–943.

Kelley, Truman L. Fundamentals of Statistics. Cambridge, MA: Harvard University, 1947.

Kim, Myung J., C. Nelson, R. Startz. "Mean Reversion in Stock Prices? A Reappraisal of the

Empirical Evidence." The Review of Economic Studies, Vol. 58, No. 3 (1991), pp. 515-528.

King, Willford I. "Review of The Triumph of Mediocrity in Business by Horace Secrist." Journal

of Political Economy, Vol. 42, No. 3 (1934), pp. 398–400.

Lakonishok, Josef, A. Shliefer, R. Vishny. "Contrarian Investment, Extrapolation, and Risk."

Journal of Finance, Vol. 49, No. 5 (1994), pp. 1541–1578.

Lintner, John, R. Glauber. "Higgledy Piggledy Growth in America." In James Lorie, R. Brealeys,

Eds., Modern Developments in Investment Management, New York: Praeger, 1962.

Little, Ian M. D. "Higgledy Piggledy Growth." Oxford: Institute of Statistics Bulletin, 24 (1962),

pp. 387-412.

Lord, Frederic M., M. Novick. Statistical Theory of Mental Test Scores. Reading, MA: Addison-

Wesley, 1968.

McQuaid, Clement, editor. Gambler's Digest. Northfield, IL: Digest Books, 1971, p. 287.

Peters, Tom, R. Waterman, Jr. In Search of Excellence, New York, Harper & Row, 1982.

Poterba, James M., L. Summers. "Mean Reversion in Stock Prices: Evidence and Implications."

Journal of Financial Economics, Vol. 22, No. 1 (1988), pp. 27–59.

Riegel, Robert. "Review of The Triumph of Mediocrity in Business by Horace Secrist." Annals

of the American Academy of Political and Social Science, 170 (1933), pp. 178–179.

Schall, Teddy, G. Smith. "Baseball Players Regress Toward the Mean." The American

Statistician, 54 (2000), pp. 231-235.

Secrist, Horace. The Triumph of Mediocrity in Business, Evanston, Ill: Northwestern University,

1933.

Sharpe, William F. Investments, 3rd edition, Englewood Cliffs, New Jersey: Prentice-Hall, 1985,

p. 430.

Stigler, Stephen M. Statistics on the Table, The History of Statistical Concepts and Methods,

Cambridge, Mass.: Harvard University Press, 2000, p. 170.

Tversky, Amos, D. Kahneman. "On the Psychology of Prediction." Psychological Review, 8

(1973), pp. 237–251.

Tversky, Amos, D. Kahneman. "Judgement Under Uncertainty: Heuristics and Biases." Science,

185 (1974), pp. 1124–31.

Williamson, Jeffrey G. "Productivity and American leadership: A Review Article." Journal of

Economic Literature, Vol. 29, No. 1 (1991), pp. 51–68.