Biasing Research: Can Science be Trusted?

Hershey H. Friedman
Murray Koppelman School of Business
Brooklyn College of the City University of New York

Robert B. Fireworker
Peter J. Tobin College of Business
St. John's University

Harry Nagel
Peter J. Tobin College of Business
St. John's University

There is a growing body of evidence that indicates that most published research is later found to be wrong. This paper will demonstrate why it is difficult to be certain about a so-called fact even when there is published research supporting it. Different types of biases are examined.

INTRODUCTION

Researchers speak of evidence-based medicine, evidence-based management, evidence-based practice. How reliable is the evidence researchers use to prove their points? Munafo & Flint (2010) indicate that a "substantial proportion of scientific research may in fact be false." They attribute this to several factors including publication bias, low statistical power, "trend for effect sizes to decrease with year of publication," overestimate of true effect size, and source of funding. They conclude:

> In the meantime, readers of scientific journals should perhaps only believe large studies which report on findings in a mature literature (as opposed to early findings in a new field), place less emphasis on nominal statistical significance and focus instead on effect sizes and confidence intervals, and are published in journals with a low impact factor (Munafo & Flint, 2010).

According to Tractenberg, chair of the Committee on Professional Ethics of the American Statistical Association:

> A survey of more than 1,500 investigators, published in a 2016 issue of Nature, showed that more than 70 percent of researchers have tried and failed to reproduce other scientists' experiments, and more than half have failed to reproduce their own experiments (Tractenberg, 2017).

Richard Smith, the former editor of the British Medical Journal, stated: “Most scientific studies are wrong, and they are wrong because scientists are interested in funding and careers rather than truth” (McLain, 2013).

One would think that with so many research issues, scholars would see the dangers of certainty. Unfortunately, this has not been the case. We are observing arrogant people ranging from academics to doctors to politicians who are certain of their facts. Unfortunately, not all the information available to the public is reliable. There is a great deal of bad science, junk science, fake news, and erroneous research available to the public.

Carl T. Bergstrom and Jevin West at the University of Washington have proposed a course with the provocative title of “Calling Bullshit in the Age of Big Data.” The syllabus for the course may be found at http://callingbullshit.org/syllabus.html#Introduction. Their definition of bullshit is: "language, statistical figures, graphics, and other forms of presentation intended to persuade by impressing and overwhelming a reader or listener with a blatant disregard for truth and logical coherence” (Kolowich, 2017). With so much nonsense on the internet, it becomes difficult to distinguish between facts and fiction. The University of Michigan plans to start offering a one-credit course with the title, “Fake News, Lies, and Propaganda: How to Sort Fact from Fiction” starting with the Fall 2017 semester (Hutchinson, 2017).

There are different kinds of errors made by researchers. Some deal with mistakes in statistical reasoning and others are cognitive biases. A cognitive bias is defined as:

> a systematic error in thinking that affects the decisions and judgments that people make. Sometimes these biases are related to memory. The way you remember an event may be biased for a number of reasons and that in turn can lead to biased thinking and decision-making. In other instance, cognitive biases might be related to problems with attention. Since attention is a limited resource, people have to be selective about what they pay attention to in the world around them (Chery, 2016).

This paper will focus on a few key biases that can distort or misrepresent the truth.

The Problem of Sampling on the Dependent Variable

Sampling or selecting on the dependent variable refers to the practice of selecting cases where some measure or phenomenon of interest has been observed and excluding the cases where the measure or phenomenon of interest has not been observed. The selected cases are then used to prove the measure or phenomenon of interest. For example, suppose a researcher looks only at unsuccessful firms as measured by annual returns. She concludes that these firms were headed by leaders who were unethical and concludes that lack of integrity on the part of the CEO will hurt a company. This finding may or may not be true. The flaw in the researcher’s reasoning is that she did not also examine successful firms. It is quite possible that successful firms are also headed by dishonest CEOs.

Much of the research in management is based on sampling on the dependent variable. A researcher might examine the 20 most successful firms and find what they have in common. This then becomes the basis for a book or article. In Search of Excellence by Tom Peters and Robert H. Waterman (1982) is one of the most popular business books. The authors studied 43 of America’s best run companies in order to determine what made them successful and came up with eight basic principles of management. In other words, they sampled based on the dependent variable of “excellent firms in 1982.” The question is what happened to those firms. Eckel (2013) says that “two thirds of them underperformed the S&P 500 over a decade. Some faltered badly, and some even went out of business.” Kodak, K Mart, and Wang Labs are three examples of firms on Peter and Waterman’s (1982) list that went bankrupt. Amdahl, also on the list, was successful until the early 1990s and then starting losing money and was eventually taken over. Baum and Smith (2015) also found that the stock performance of these companies did not stand the test of time.

A similar problem was found with Collins’ research. Collins and his team of researchers identified 11 companies whose stocks performed spectacularly. They found that these companies were headed by "level 5 leaders" who had a great deal of humility and were driven to make their organizations succeed. With the passage of time, these 11 companies did not do very well (Baum & Smith, 2015). Two of the 11 firms had serious problems: The price of Fannie Mae stock plummeted from $80 to $1 from 1001 to 2008 and eventually was delisted; Circuit City went bankrupt (Baum & Smith, 2015).

The above examples demonstrate the dangers of this type of research. There is a widespread belief that people who were molested as children will also become molesters. What kind of research was done to establish this finding? If a researcher only studied child molesters and found that, say, 60% were molested as children, does this prove the relationship between being molested as a child and becoming a molester? To validate this kind of relationship, one should also look at people who were molested as children and perform a longitudinal study to determine what happens to them.

There is one study that did examine this belief in a cycle of sexual abuse. The results supported the finding but only for male perpetrators: 35% of perpetrators of sexual abuse were themselves victims as children (79/225) vs. 11% (56/522) for non-perpetrators. This finding was not true for women. In a sample of 96 females, 43% were victims but only one later became a perpetrator (Glasser et al, 2001).

One study that caused a great deal of harm was the one conducted in 1998 in England by Dr. Wakefield and colleagues claiming that the MMR (measles, mumps, and rubella) vaccine causes autism. Wakefield did not look at the incidence of autism in vaccinated and unvaccinated children. He only examined vaccinated children which made no sense given that 90% of children when and where the study was done received the MMR vaccine. In any case, the study was found to be fraudulent and Wakefield lost his license to practice medicine (Children's Hospital of Philadelphia, 2016). Wakefield had a huge conflict of interest since he was paid by a personal injury lawyer that represented the parents of children supposedly harmed by the vaccine (Park, 2011). Despite all this, many people will not vaccinate their children and the number of children that become ill or die from vaccine-preventable diseases continues to grow.

The Problem of Relying on Correlations Rather Than Randomized Controlled Experiments

Most published research findings in medicine are wrong (Ioannidis, 2005). Why? The ideal method to determine causality is via a randomized controlled experiment. The way this works is that subjects are randomly assigned to, say, two groups: a control (placebo) group and an experimental group. The only thing that distinguishes the two groups is the factor (drug, vitamin, etc.) being tested. However, many studies rely on correlations which do not demonstrate causality. Thus, for many years researchers were finding correlations between low levels of Vitamin D and arthritis. However, low levels of Vitamin D might correlate with another factor that affects arthritis. There is no way to isolate the effects of Vitamin D without conducting a controlled experiment (Gutting, 2013).

Over a five-year period, Corley examined the daily routines of 233 wealthy people and 128 poor people and concluded that there are certain lifestyle changes that increase the chance that poor people will become financially successful (Dindar, 2014). Here are some of his suggestions:

> 70% of wealthy eat less than 300 junk food calories per day vs. 97% of poor who eat more than 300 junk food calories per day
> 44% of wealthy wake up three hours before work starts vs. 3% of poor
> 67% of wealthy write down their goals vs. 17% of poor
> 76% of wealthy exercise four days a week vs. 23% of poor
> 86% of wealthy believe in lifelong educational self-improvement vs. 5% of poor
> 81% of wealthy maintain a to-do list vs. 19% of poor
> 67% of wealthy watch one hour or less of TV every day vs. 23% of poor
> 6% of wealthy admit to gossiping vs. 79% of poor
> 84% of wealthy believe good habits create opportunity luck vs. 4% of poor (Dindar, 2014).

These correlations are the result of other factors that correlate with wealth. It is highly doubtful that making the suggested changes will make one financially successful. Rich people are more likely to eat caviar than poor people but eating caviar will not make one rich. There is a strong correlation between the amount of clothing people wear and the weather. No one, however, suggests that if we all go outside in our bathing suits in the middle of the winter, the temperature will rise. Many significant correlations are spurious and meaningless. Tyler Vigen (2015) wrote a book on spurious correlations. Some examples he gives are: U.S. spending on science, space and technology correlates with suicides by hanging, strangulation and suffocation ($r = .99789$); the divorce rate in Maine correlates with per capita consumption of margarine ($r=.99256$); and the age of Miss America correlates with murders by hot steam, vapours and hot objects ($r= .87013$).

Gutting (2013) cites Ioannidis (2005) and asserts:

> John Ioannidis, in a series of highly regarded analyses, has shown that, in published medical research, 80 percent of non-randomized studies (by far the most common) are later found to be wrong. Even 25 percent of randomized studies and 15 percent of large randomized studies — the best of the best — turn out to be inadequate.

This is due to the fact that it is difficult and costly to conduct randomized controlled experiments. Therefore, most research is based on correlational data. Furthermore, "it is impossible to decipher how much data dredging by the reporting authors or other research teams has preceded a reported research finding" (Ioannidis, 2005). With data mining packages, it becomes very easy to perform hundreds of statistical tests and scour the data and come up with several statistically significant results.

The fact that 80% of non-randomized studies turn out to be wrong, should make us very wary of all kinds of research ranging from health studies to management studies. Pfeffer & Sutton (2006) noted that both medicine and management are not evidence-based. Evidence-based medicine is defined as: "the conscientious, explicit and judicious use of current best evidence in making decisions about the care of individual patients" (Pfeffer & Sutton, 2006). Doctors only make about 15% of decisions using scientifically valid studies.

> Recent studies show that only about 15% of their decisions are evidence based. For the most part, here's what doctors rely on instead: obsolete knowledge gained in school, long-standing but never proven traditions, patterns gleaned from experience, the methods they believe in and are most skilled in applying, and information from hordes of vendors with products and services to sell (Pfeffer & Sutton, 2006).

The same is true when it comes to management decisions. Many management beliefs are not based on hard evidence but opinions. Some examples of management myths cited by Pfeffer & Sutton (2006) include the following: (1) That the use of stock options to compensate corporate leaders will result in better financial performance for the organization; (2) Forced performance ranking of employees (this often means that the bottom 10% to 20% will be terminated) will ensure higher productivity and profits; and (3) the belief that the first company to enter an industry will have a huge advantage over competitors.

Publication bias

Goldacre (2013) posits that publication bias is "endemic throughout the whole of medicine and academia." This bias is a problem when examining evidence from published research papers in academic journals. Glen (2017) defines publication bias as follows:

> Publication bias is when studies with positive findings are more likely to be published — and they tend to be published faster — than studies with negative findings. This means that any meta analysis or literature reviews based only on published data will be biased, so researchers should make sure to include unpublished reports in their data as well. When studies with positive findings are more likely to be published — and they tend to be published faster — than studies with negative findings. This means that any meta analysis or literature reviews based only on

published data will be biased, so researchers should make sure to include unpublished reports in their data as well (Glen, 2017).

The problem of publication bias was first documented by Theodore Sterling, a psychologist, in 1959. He discovered that 286 out of 294 studies reported in major psychology journals showed statistically significant results, i.e., positive findings He found that the same problem existed in 1995. Journals seem to prefer publishing positive findings (Goldacre, 2013).

Similar biases include:

Citation bias: finding literature sources by scanning reference lists from published articles. Less references sources are therefore more likely to be excluded from a meta-analysis.
Dissemination bias: when the nature of a study's direction or the study's results are unevenly reported.

Gray-literature bias: ignoring literature that's harder to find, like government reports or unpublished clinical studies.

Language bias: the exclusion of foreign language studies from your analysis.

Media attention bias: studies that show up in the news are more likely to be included in analyses than those that do not.

Outcome-reporting bias: when positive outcomes are more likely to be included in a meta-analysis than negative outcomes. Negative outcomes can also be misrepresented as positive ones.

Time-lag bias: studies with significant results have a shorter median time to publication (4.7 years) while those with non-significant results have a median time of 8.0. years (Glen, 2017).

The result of these biases is that research tends to be skewed when studies showing non-significant findings are excluded. It is estimated that positive results are about twice as likely to be published as studies that show negative results. Moreover, approximately 50% of clinical trials are never published (probably because they showed negative results). This, of course, skews results (AllTrials, 2015). The problem of not reporting negative results is that this may result in the approval of a drug that is less effective than other medications. For example, if a drug has positive results in one trial and negative results in ten trials conducted by other researchers, it should not be approved. However, if the regulatory agency (e.g., the FDA) is unaware of the negative results, it may approve the drug (Campbell, 2014). Merck, the pharmaceutical firm, hid negative results as well as risks of heart attacks for their new drug Vioxx in the name of profit (Campbell, 2014). Goldacre (2013) asserts that "industry-funded trials are more likely to produce a positive, flattering result than independently funded trials." Thus, researchers studying 500 clinical trials of five categories of drugs found "85 per cent of the industry-funded studies were positive, but only 50 per cent of the government funded trials were.

The net effect of publication bias in medicine is that doctors often prescribe drugs that are no better than existing drugs and frequently have harmful side effects. Instead of helping patients, they may be killing or hurting them (Goldacre, 2013). It is not surprising that many of the major findings in cancer research cannot be replicated (Basken, 2017).

So, while doctors are kept in the dark, patients are exposed to inferior treatments, ineffective treatments, unnecessary treatments, and unnecessarily expensive treatments that are no better than cheap ones; governments pay for unnecessarily expensive treatments, and mop up the cost of harms created by inadequate or harmful treatment; and individual participants in trials, such as

> those in the TGN1412 study, are exposed to terrifying, life-threatening ordeals, resulting in lifelong scars, again quite unnecessarily (Goldacre, 2013).

The Center for Open Science is advocating that scientific journals only accept for publication studies "for which the question being tested was publicly declared and registered in advance" (Basken, 2017). This will enable researchers to more easily find the number of studies that demonstrated negative findings.

Confirmation bias

Psychologists speak about confirmation bias as a major cognitive bias. Once people form an opinion they "embrace information that confirms that view while ignoring, or rejecting, information that casts doubt on it … Thus, we may become prisoners of our assumptions" (Heshmat, 2015). People tend to only listen to information that supports their preconceptions.

There is a great deal of evidence that not only do facts not correct misinformation, but they make it more persistent and potent (Gorman & Gorman, 2017; Kolbert, 2017; Mercier & Sperber, 2017; Wadley, 2012). People get a rush from finding information that confirms that they are right; they would rather win an argument than discover the truth. People may have the ability to see flaws in their opponent's arguments. However, when it comes to their own opinions, that is when they are blind.

Several books have been written about expert predictions which usually turn out to be wrong. Experts do only slight better than random chance. This is what can be said about expert predictions:

> When they're wrong, they're rarely held accountable, and they rarely admit it, either. They insist that they were just off on timing, or blindsided by an improbable event, or almost right, or wrong for the right reasons. They have the same repertoire of self-justifications that everyone has, and are no more inclined than anyone else to revise their beliefs about the way the world works, or ought to work, just because they made a mistake.
>
> Extensive research in a wide range of fields shows that many people not only fail to become outstandingly good at what they do, no matter how many years they spend doing it, they frequently don't even get any better than they were when they started. In field after field, when it came to centrally important skills—stockbrokers recommending stocks, parole officers predicting recidivism, college admissions officials judging applicants—people with lots of experience were no better at their jobs than those with very little experience (Eveleth, 2012).

Kahneman speaks of "adversarial collaboration" as an effective way to avoid confirmation bias which arises when a researcher consciously or unconsciously design an experiment in such a way so as to provide support for a particular position (Matzke et al., 2013). Bringing together two researchers who disagree and having them conduct an experiment jointly often results in better research (Matzke et al., 2013). The goal of adversarial collaboration is to discover the truth, not to win arguments (Kahneman, 2012). With critical thinking, the goal is to solve a problem in an honest way and not be unreceptive to new approaches and different opinions.

Cherry-picking research

There is a great deal of published research. It is not difficult for a researcher to cherry-pick the literature and only reference studies that provide support for a particular opinion (confirmation bias) and exclude others (Goldacre, 2011). Even if individual studies are done correctly, this does not guarantee that a researcher writing a state of the art review paper will write an accurate, undistorted synthesis of the literature. Indeed, Celia Mulrow demonstrated that many review articles were biased (Goldacre, 2011).

Certainty Bias

Robert A. Burton, a neurologist, examined the neuroscience behind being certain and came to the following conclusion:

> Despite how certainty feels, it is neither a conscious choice nor even a thought process. Certainty and similar states of "knowing what we know" arise out of involuntary brain mechanisms that, like love or anger, function independently of reason (Burton, 2008a: xi).

Burton believes that human beings cannot avoid certainty bias but can moderate its effect by an awareness that feelings of certainty are not based on logic and reasoning. These feelings are the result of "involuntary brain mechanisms" that have little to do with the correctness of a belief. This is why intuitions, hunches, premonitions, and gut feelings need to be empirically tested. Burton sees certainty bias as a "potentially dangerous mental flaw." Burton (2008b) explicitly makes the point that people should not believe in politicians that "sound too sure of themselves."

Overconfidence bias

One has to be careful with researchers who are overconfident; overconfidence is also a cognitive bias. Many people are too confident of their true abilities. This is especially true of so-called experts. There is evidence that individuals who are overconfident and certain of their abilities are overrated by others; individuals who are underconfident, are underrated by others as being worse than they actually happen to be (Lamba & Nityananda, 2014). Thus, it definitely pays to be overconfident. This may explain why politicians have no problem with being so sure of themselves and overpromising (Hutson, 2014).

The importance of overconfidence is being used to explain why there is a gender gap in the corporate world. Men are more egotistical than women so this makes them appear more capable (Hutson, 2014). Kahneman (2011) believes that one has to be very careful with people who are overconfident and assertive. Before believing that they know what they are talking about, one has to have some way of measuring this empirically. He concludes that "overconfident professionals sincerely believe they have expertise, act as experts and look like experts. You will have to struggle to remind yourself that they may be in the grip of an illusion.

Some Examples of Dubious Theories Taught in Academe

Academics pride themselves on being careful with their facts. However, there are several examples of theories taught in academe that have little evidence to back them up. Popper and others posited that Marxism is a "pseudo-science" and only worth studying as a "sociological phenomenon dangerous to a society" (Hudelson, 1980). Popper contends that Marx's theory was "historicist" and based on a misunderstanding of the scientific method (Hudelson, 1980). Popper maintains that Marxist theory could not be scientific since it could not be falsified, i.e., proven wrong. This made Marxism as unscientific as psychoanalysis.

> According to Popper, Marx's original theory of the collapse of capitalism was just such a bold conjecture and thus scientific, but it was proven false and should therefore be rejected. "Yet instead of accepting the refutations the followers of Marx reinterpreted both the theory and the evidence in order to make them agree. In this way they rescued the theory from refutation; but they did so at the price of adopting a device which made them irrefutable. They thus gave a 'conventionalist twist' to the theory; and by this stratagem they destroyed its much advertised claim to scientific status (Popper 1963, p. 37).

Popper believed in falsificationism, a philosophy that scientific hypotheses have to be falsifiable and refutable if they are to be scientific. Claims such as those made by Marxists or Freudians that cannot be disproved are not scientific. It is not only the left-wing that has been fooled into believing in fake science.

Rational choice theory "is an economic principle that states that individuals always make prudent and logical decisions. These decisions provide people with the greatest benefit or satisfaction — given the choice available — and are also in their highest self-interest" (Investopedia, 2016a). After the Great Recession of 2008, it became clear to many economists, including Daniel Kahneman, Nobel laureate, that rational choice theory was incorrect (Ignatius 2009).

> In 2008, a massive earthquake reduced the financial world to rubble. Standing in the smoke and ash, Alan Greenspan, the former chairman of the U.S. Federal Reserve once hailed as "the greatest banker who ever lived," confessed to Congress that he was "shocked" that the markets did not operate according to his lifelong expectations. He had "made a mistake in presuming that the self-interest of organizations, specifically banks and others, was such that they were best capable of protecting their own shareholders" (Ariely, 2009).

What is shocking is that Greenspan had already questioned the rational man theory several years earlier because of the Enron crisis. After the Enron debacle, Greenspan, the then-Chairman of the Federal Reserve, voiced his distress at a meeting with how easy it was for CEOs to "craft" financial statements in ways that could deceive the public. He declared: "There's been too much gaming of the system. Capitalism is not working! There's been a corrupting of the system of capitalism" (Suskind, 2008). Clearly, even brilliant people can be fooled by incorrect theories.

Disciplinary Elitism

One problem that may affect the quality of academic research is disciplinary elitism, the belief that one discipline is superior to others and can provide all the answers. This problem is exacerbated by increasing the number of academic departments (Friedman, 2015). Most colleges are probably better known for turf battles than for communication and collaboration across disciplines and even sometimes across sub-areas in the same discipline. Faculty tend to be loyal to their department and discipline; this may affect the quality of academic research. Edwards (1999) maintains that "in so many cases, the most provocative and interesting work is done at the intersections where disciplines meet, or by collaborators blending several seemingly disparate disciplines to attack real problems afresh." Klein (1996: 191) also asserts: "Almost all significant growth in research in recent decades, the committee [National Research Council] concluded, has occurred at the 'interdisciplinary borderlands' between established fields." Research that uses the findings of only one discipline may be imprecise or even erroneous.

Behavioral economics is interdisciplinary and combines findings from psychology and economics. Behavioral economists have been able to demonstrate that consumers do not behave as pure economic models predict; consumers use heuristics (rules of thumb) and often behave in an irrational manner. Ariely (2009) posits:

> We are finally beginning to understand that irrationality is the real invisible hand that drives human decision making. It's been a painful lesson, but the silver lining may be that companies now see how important it is to safeguard against bad assumptions. Armed with the knowledge that human beings are motivated by cognitive biases of which they are largely unaware (a true invisible hand if there ever was one), businesses can start to better defend against foolishness and waste.

This is why people sometimes have to be given a "nudge" to do what is in their own self-interest (Thaler & Sunstein, 2008). The problem is that people are susceptible to all kinds of biases that lead them to make incorrect decisions not in their best interest. The behavioral economists have conducted numerous experiments showing various cognitive biases (Welch, 2010).

Thaler & Mullainatha (2008) describe how in experiments involving "ultimatum" games, we see evidence that people do not behave as traditional economic theory predicts they will. People will act "irrationally" and reject offers they feel are unfair since they care about fairness and justice:

> In an ultimatum game, the experimenter gives one player, the proposer, some money, say ten dollars. The proposer then makes an offer of x, equal or less than ten dollars, to the other player, the responder. If the responder accepts the offer, he gets x and the proposer gets 10 − x. If the responder rejects the offer, then both players get nothing. Standard economic theory predicts that proposers will offer a token amount (say twenty-five cents) and responders will accept, because twenty-five cents is better than nothing. But experiments have found that responders typically reject offers of less than 20 percent (two dollars in this example) (Thaler & Mullainatha, 2008).

The ultimatum game is evidence that greed, which usually is excessive, can boomerang and result in less, not more for the avaricious individual.

Behavioral economists have discovered that the pain of losing something we own outweighs the joy of winning by as much as two to one. Thus, for example, the pain of losing $1000 that you currently have is about double the intensity of the joy you would experience getting $1000. Emel (2013), citing the work of Dan Ariely, makes the following point:

> Loss aversion means that our emotional reaction to a loss is about twice as intense as our joy at a comparable gain: Finding $100 feels pretty good, whereas losing $100 is absolutely miserable. People are more motivated by avoiding loss than acquiring similar gain. If the same choice is framed as a loss, rather than a gain, different decisions will be made

The following example cited by Emel (2013) demonstrates the principle of Loss Aversion.

Participants were told the US is preparing for an outbreak of an unusual disease which is expected to kill 600 people. They could pick one of two scenarios to address the problem:

- 200 people will be saved.
- 1/3 chance 600 people will be saved. 2/3 chance that no people will be saved.

72% of participants chose option 1, while only 28% of participants chose option 2. The same group of people were given two more scenarios:

- 400 people will die.
- 1/3 chance no one will die. 2/3 chance 600 people will die.

22% of participants chose options 1, and 78% of participants chose option 2. People picked the polar opposite answer of their original choice and the only difference was how the options were framed.

There are many other examples that demonstrate that consumers behave in unexpected ways that economic theory does not predict.

Discussion and Conclusion

One biased study that caused a huge amount of harm was conducted by Harvard Researchers in the 1950s. The sugar industry paid (about $50,000 in today's dollars) scientists in the 1960s to be selective in choosing studies in order that the connection between heart disease and sugar be minimized. The researchers were told to focus on saturated fat and make it the villain (O'Connor, 2016). The study was published in 1967 in the New England Journal of Medicine and "cast aspersions on the role of saturated fat." Till this day, Americans are told to reduce their fat intake. In many cases, this resulted in switching to a low-fat, high sugar diet; this increase in sugar consumption may have caused the obesity problem in the United States. Thankfully, journals today have much stricter conflict of interest rules (O'Connor, 2016).

The bottom line is that anyone examining research must do so with an understanding how easy it is for bias – conscious or unconscious – to distort the findings. One cannot even rely on a meta-analysis, unless it is done with extreme care to find the negative findings (this includes searching through dissertations, funded studies that never got published, etc.). An astute researcher will have humility and accept that most findings, even if they appear to be absolutely true, could be incorrect.

REFERENCES

AllTrials (2015, August 20). Half of all clinical trials have never reported results. AllTrials.net. Retrieved from http://www.alltrials.net/news/half-of-all-trials-unreported/

Ariely, D. (2009). The end of rational economics. Harvard Business Review, July-August. Retrieved from https://hbr.org/2009/07/the-end-of-rational-economics

Basken, P. (2017, February 10). Attempt to replicate cancer studies casts doubt on reproducibility itself. Chronicle of Higher Education, A30.

Baum, G. & Smith, G. (2015) Great companies: Looking for success secrets in all the wrong places. Journal of Investing, Fall, 61-72. Available at: http://economics-files.pomona.edu/GarySmith/SuccessSecrets.pdf

Burton, R. A. (2008a). On being certain: Believing you are right even when you're not. New York: St. Martin's Press.

Burton, R. A. (2008b). The certainty bias: A potentially dangerous mental flaw. Scientific American. Retrieved from https://www.scientificamerican.com/article/the-certainty-bias/

Campbell, K. R. (2014, April 1). Negative results from clinical trials need to be reported. KevinMD.com. Retrieved from http://www.kevinmd.com/blog/2014/04/negative-results-clinical-trials-reported.html

Chery, K. (2016). What is a cognitive bias: Definition and examples. Verywell.com. Retrieved from https://www.verywell.com/what-is-a-cognitive-bias-2794963

Children's Hospital of Philadelphia (2016). Vaccines and autism. CHO. Edu. . Retrieved from http://www.chop.edu/centers-programs/vaccine-education-center/vaccines-and-other-conditions/vaccines-autism

Collins, J., (2001). Good to Great, New York: HarperCollins.

Dindar, S. (2014, September). 12 things rich people do that poor people don't. The Loop. Retrieved from http://www.theloop.ca/12-things-rich-people-do-that-poor-people-dont/

Eckel, B. (2013, November). Fake science. Reinventing Business. Retrieved from http://www.reinventing-business.com/2013/10/fake-science.html

Edwards, R. (1999). The academic department: How does it fit into the university reform agenda?" Change, 31, 17-27.

Emel, M. (2013, August 15). The economy of decisions. Retrieved from http://www.metia.com/seattle/mandy-emel/2013/08/the-economy-of-decisions/

Eveleth, R. (2012, July 31). Why experts are almost always wrong. Smithsonian.com. Retrieved from http://www.smithsonianmag.com/smart-news/why-experts-are-almost-always-wrong-9997024/

Friedman, H. H. (2015, October 28). How to destroy a good college: The misuse of the corporate model in academe. Available at SSRN: http://ssrn.com/abstract=2682883 or http://dx.doi.org/10.2139/ssrn.2682883

Glasser, M., Kolvin, I., Campbell, D., Glasser, A., Leitch, I. & Farrelly, S. (2001).
Cycle of child sexual abuse: Links between being a victim and becoming a perpetrator
British Journal of Psychiatry, December, 179 (6), 482-494; DOI: 10.1192/bjp.179.6.482

Glen, S. (2017). What is publication bias? Statistics How To. Retrieved from http://www.statisticshowto.com/publication-bias/

Goldacre, B. (2013). Trial sans error: How pharma-funded research cherry-picks positive results [excerpt]. Scientific American. Retrieved from https://www.scientificamerican.com/article/trial-sans-error-how-pharma-funded-research-cherry-picks-positive-results/

Goldacre, B. (2011). The dangers of cherry-picking evidence. Guardian. Retrieved from https://www.theguardian.com/commentisfree/2011/sep/23/bad-science-ben-goldacre

Gorman, S. E. & Gorman, J. M. (2017). Denying to the grave: Why we ignore the facts that will save us. New York: Oxford University Press.
Gutting, G. (2013, April 25). What do scientific studies show? New York Times. Retrieved from http://opinionator.blogs.nytimes.com/2013/04/25/what-do-scientific-studies-show/?_r=0
Heshmat, S. (2015, April 23). What is confirmation bias? Psychology Today. Retrieved from https://www.psychologytoday.com/blog/science-choice/201504/what-is-confirmation-bias
Hudelson, R. (1980). Popper's critique of Marx. Philosophical Studies: An International Journal for Philosophy in the Analytic Tradition, 37(3), 259-270.
Hutchinson, D. (2017, February 16). University of Michigan to offer class helping students fight fake news. Click on Detroit. Retrieved from http://www.clickondetroit.com/news/university-of-michigan-to-offer-class-helping-students-fight-fake-news
Hutson, M. (2014). It pays to be overconfident, even when you have no idea what you're doing. New York Magazine. Retrieved from http://nymag.com/scienceofus/2014/05/pays-to-be-overconfident.html
Ignatius, D. (2009, February 8). The death of 'Rational Man.' Washington Post. Retrieved from http://www.washingtonpost.com/wpdyn/content/article/2009/02/06/AR2009020602742.html
Investopedia. (2016a). Rational choice theory. Investopedia.com. Retrieved from http://www.investopedia.com/terms/r/rational-choice-theory.asp
Ioannidis, J. P. A. (2005, August 30). Why most published research findings are false. PLOS/Medicine. Retrieved from http://journals.plos.org/plosmedicine/article?id=10.1371/journal.pmed.0020124
http://dx.doi.org/10.1371/journal.pmed.0020124
Kahneman, D. (2012). The human side of decision making: Thinking things through with Daniel Kahneman. Journal of Investment Consulting, 13(1), 5-14.
Kahneman, D. (2011, October 19). Don't blink: The hazards of confidence. New York Times. Retrieved from http://www.nytimes.com/2011/10/23/magazine/dont-blink-the-hazards-of-confidence.html?
Klein, J. T. (1996). Crossing boundaries: Knowledge, disciplinarities, and interdisciplinarities. Charlottesville, VA: University Press of Virginia.
Kolbert, E. (2017, February 27). Why facts don't change our minds. New Yorker. Retrieved from http://www.newyorker.com/magazine/2017/02/27/why-facts-dont-change-our-minds
Kolowich, J. (2017, January 16). The fine art of sniffing out crappy science. Chronicle of Higher Education. Retrieved from http://www.chronicle.com/article/The-Fine-Art-of-Sniffing-Out/238907
Lamba S. & Nityananda, V (2014). Self-deceived individuals are better at deceiving others. PLoS ONE, August, 9(8): e104562. doi:10.1371/journal.pone.0104562
Matzke, D., Nieuwenhuis, S., van Rijn, H., Slagter, H. A, van der Molen, M. W. &Wagenmakers, E. J. (2013). Two birds with one stone: A preregistered adversarial collaboration on horizontal eye movements in free recall. Retrieved from http://dora.erbe-matzke.com/papers/DMatzke_EyeMovements.pdf
McLain, S. (2013, September 17). Not breaking news: many scientific studies are ultimately proved wrong! Guardian. Retrieved from https://www.theguardian.com/science/occams-corner/2013/sep/17/scientific-studies-wrong
Mercier, H. & Sperber, D. (2017). The enigma of reason. Cambridge, MA: Harvard University Press.
Munafo, M. R. & Flint, J. (2010). How reliable are scientific studies? British Journal of Psychiatry, September, 197(4), 257-258. DOI: 10.1192/bjp.bp.109.069849
O'Connor, A. (2016, September 12). How the sugar industry shifted blame to fat. New York Times. Retrieved from https://www.nytimes.com/2016/09/13/well/eat/how-the-sugar-industry-shifted-blame-to-fat.html
Park, A. (2011, January 6). Study linking vaccines to autism is fraudulent. Time. Retrieved from http://healthland.time.com/2011/01/06/study-linking-vaccines-to-autism-is-fraudulent/
Peters, T. & Waterman, R. H. (1982). In search of excellence. New York: Harper & Row.

Pfeffer, J. & Sutton, R. I. (2006). Evidence-based management. Harvard Business Review, January, 63-74.
Popper, K. R. (1963). Conjectures and refutations. London: Routledge and Kegan Paul.
Sacks, J. (2006). The dignity of difference. London: Continuum.
Smith, J. (2015). 67 ways to increase conversion with cognitive biases. Neuromarketing. Retrieved from http://www.neurosciencemarketing.com/blog/articles/cognitive-biases-cro.htm#
Suskind, R. (2008, September 25). The crisis last time. New York Times, A29.
Thaler, R. H. & Mullainathan, S. (2008). How behavioral economics differs from traditional economics. The Concise Library of Economics. Retrieved from http://www.econlib.org/library/Enc/BehavioralEconomics.html
Thaler, R. H. & Sunstein, C. R. (2008). Nudge. New Haven, CT: Yale University Press.
Tractenberg, (2017, February 19). Using statistics ethically to combat 'a scientific credibility crisis'. Science Magazine. Retrieved from https://scienmag.com/using-statistics-ethically-to-combat-a-scientific-credibility-crisis/
Vigen, T. (2015). Spurious correlations. New York: Hachette Books. [see also website: http://www.tylervigen.com/spurious-correlations].
Welch, N. (2010, February). A marketer's guide to behavioral economics. McKinsey Quarterly. Retrieved from http://www.mckinsey.com/insights/marketing_sales/a_marketers_guide_to_behavioral_economics