The Conventional Past, Behavioral Present, and Algorithmic Future of Risk and Finance

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Abstract. *Modern finance is a relatively young field, only a few decades old, and already it has gone through two phase transitions and is perhaps poised to undergo a third. The first transition starting from the 1950s brought modern portfolio theory into the mainstream with econometric and optimization based approaches to portfolio construction and risk management. The second transition starting from the 1990s shifted those conventional approaches based on rational investors into a focus on the actual psychological factors driving investor behavior along with the important concept of limits to arbitrage. The third transition happening now aims to take an algorithmic approach to finance, looking to explore how and why investor heuristics evolve and predominate, how automated processes can respond to unpredictable events, and what the effects will be on the markets as ever-faster computers trained on ever-larger data sets become the predominant and nearly real-time traders.*

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1. Introduction

Both risk and finance are fundamental elements of human life. Every situation has a possibility of future gain or loss, and every contract involves trading off possibilities. While gambling and insurance applications are ancient, modern advances in the past century in both fields have typically relied on analogies from, and applications of, other fields. For example, the study of risk has traditionally been from the perspectives of probability and statistics, while the study of finance has traditionally been as an application of mathematics and economics.

Throughout that time, there have emerged, and currently exist, three relatively disparate approaches to studying both risk and finance. These are: the longstanding conventional approach incorporating mathematics and economics, the more recent behavioral approach incorporating psychology and structural limitations, and the emerging algorithmic approach incorporating computer science and automated processes.

What are the advantages and disadvantages of each? In what circumstances should each be used? What can we ultimately learn about the fundamental concepts of risk and finance from each?

This paper will explore and delineate the similarities and differences between these three approaches and offer examples throughout of their relative strengths and ultimately compare and contrast the approaches to some of the weightiest issues of modern risk and finance. In doing so, the differences will be stressed more than the similarities in order to make the boundaries between them as stark as possible; of course, some overlap can and does occur—for example, quantitative behavioral finance incorporates both mathematics and psychology—but it is useful to be able to separate out the approaches so that each element can be analyzed on its own merits and so the tools proper to the approach can be examined and applied.

Therefore, the approach here is to first describe and consider each approach separately, including its usual data, methods, and techniques, including key examples, and then to consider broad questions of risk and finance and explore the insights and perspectives of each onto those questions. Note that the history and expositions of conventional and behavioral finance below are briefer than that of algorithmic finance not because they are shorter or of less importance, but only because they are likely to be more familiar.

2. The Conventional Past of Risk and Finance

Every origin story needs a visionary who launched the field, and in the case of modern finance it is unquestionably Harry Markowitz. To Markowitz are attributed the concepts of mean-variance efficiency, optimality, and the tangency portfolio. Insofar as there is a second founding father of modern portfolio theory, it is William Sharpe, for whom the ubiquitous Sharpe ratio is named and who was one of the developers of the capital asset pricing model (CAPM).

Much of the credit due them, including their Nobel prizes, is more than justified, but like all origin stories, some details have been lost in the process and some accomplishments misattributed. For example, neither Markowitz (1952) nor Sharpe (1964) provide the optimality formula for determining the efficient frontier. The first paper that did so was Roy (1952).

Arthur D. Roy's paper, published the same year as Markowitz's seminal contribution, was ahead of its time. It provided a far more rigorous and mathematical foundation for portfolio theory. Within its pages can be found the concepts of what would eventually be known as the Sharpe ratio, the idea of using expected returns and standard deviations (rather than variances as per Markowitz), the modern way of labeling the axes, the tangency portfolio, the idea of short-selling, and the specific formulas relating to the covariance matrix. Furthermore, he introduced the concept that we would today refer to as value-at-risk, the idea of minimizing tail risk. All this in a single paper from more than six decades ago.

But Roy's contributions eventually disappeared from view, and he did not share in the Nobel prizes for modern portfolio theory even though he was still alive at the time. Sullivan (2011) describes and compares the papers of Roy and Markowitz, and notes that Roy's approach was more general in scope, more mathematical, and provided an exact solution. He also cites the following quote of Markowitz, offered toward the end of his life:

Comparing the two articles, one might wonder why I got a Nobel Prize for mine and Roy did not for his… the more likely reason was visibility to the Nobel Committee in 1990. Roy's 1952 article was his first and last article in finance. He made this one tremendous contribution and then disappeared from the field, whereas I wrote two books and an assortment of articles in the field. Thus, by 1990 I was still active and Roy may have vanished from the Nobel Committee's radar screen… On the basis of Markowitz (1952), I am often called the father of modern portfolio theory (MPT), but Roy (1952) can claim equal share of this honor.

One major contribution of the conventional approach that is likely to last for centuries is its emphasis on clean data.

✓ **Conventional data.** Conventional financial data is epitomized by the Center for Research in Security Prices (CRSP). This dataset aims to include stocks in the United States back to 1926, as well as various indices, US Treasury bonds, and other custom datasets, including a mutual fund database explicitly constructed to be free of survivorship bias. Other datasets certainly exist and are used by conventional finance, but the epitome of clean historical data is CRSP. CRSP additionally interfaces with another common dataset, Compustat, which provides quarterly fundamental information such as balance sheets, income statements, and other metrics.

Much, perhaps most, conventional empirical financial research uses CRSP/Compustat or a similar dataset. Until recently, monthly or quarterly returns were typically used. Some research now uses daily returns.

✓ **Conventional approach.** The typical approach to analyzing conventional financial data is to rely on sorts and splits. When analyzing cross-sectional equity data in particular, one often sorts stocks by some metric and splits the resulting sorted lists into deciles, or occasionally quintiles or thirds. This sort-and-split is done periodically, usually on a monthly or quarterly basis, and then the properties of the resulting dynamic decile portfolios are analyzed.

Thus, one can speak of the Fama-French (1993) SMB (small minus big size) or HML (high minus low value) factors, defined as the differences between the top and bottom dynamic quantiles based on sorting by market capitalization, or the ratio of book value to market value, respectively. Indeed, one can double-sort or triple-sort to create combinations of size and value portfolios.

One can even sort stocks based on their recent returns. Jegadeesh and Titman (1993) and the flourishing literature on momentum they pioneered does just that, and finds that winners tends to outperform losers.

✓ **Conventional techniques.** How do we know, for instance, that momentum returns are real? The conventional techniques used to answer such questions are econometric and statistical in nature, and ultimately resort to multiple regression analysis. It is no accident that conventional finance focuses so much attention on "alpha," or unexplained outperformance. This is the standard name for the constant term in regressions of returns on various explanatory variables.

The returns of the dynamic momentum portfolio, for example, formed by buying stocks that recently rose and selling stocks that recently fell, when regressed on standard risk factors such as the market excess return and the SMB and HML factors, appears to have both an economically substantive and statistically significant alpha: standard factors do not explain its outperformance. Hence momentum is a puzzle to conventional finance.

Puzzles in conventional finance are resolved in one of only three ways: either the statistical assumptions or techniques are challenged, or, if the anomaly is deemed real, then the search begins to explain it through regression on other risk factors. If that search proves fruitless, the anomaly itself is incorporated as a new risk factor for pricing other assets.

One can imagine the progression as follows. First, the returns on stocks, R_i, net of the risk free rate R_f, are regressed on the market excess return $R_M - R_f$. The coefficient is called the stock's beta, measuring its covariance with the market, and the intercept is its alpha, or unexplained outperformance.

$$R_i - R_f = \alpha_i + \beta_i\left(R_M - R_f\right) + \epsilon_i$$

The CAPM is the model that predicts that all of the α_i are zero for all assets, and tests of that hypothesis essentially involve examining whether the number of non-zero observations can be explained by randomness.

To the extent systemic deviations exist—in other words, to the extent there is real alpha—the conventional approach aims to isolate the factors responsible. For instance, at one time, small stocks and value stocks tended to outperform. Thus, creating the dynamic SMB and HML factor portfolios would likely explain much of that alpha.

$$R_i - R_f = \alpha_i + \beta_i\left(R_M - R_f\right) + \beta_{i,2}SMB + \beta_{i,3}HML + \epsilon_i$$

The Fama-French (1993) asset pricing model predicts that all of the α_i are zero. With the returns on momentum seemingly unexplained by these traditional factors, momentum itself eventually becomes a factor in asset pricing, resulting in the below.

$$R_i - R_f = \alpha_i + \beta_i(R_M - R_f) + \beta_{i,2}SMB + \beta_{i,3}HML + \beta_{i,4}MOM + \epsilon_i$$

The Carhart (1997) four-factor model in the above predicts now that all of the α_i are zero.

Indeed, most generally, this process is neverending and is known as the Arbitrage Pricing Theory of Ross (1976). Factors and portfolios of all kinds can be continually added to the right hand side, with the hope of eventually eliminating any alpha.

In short, and intentionally oversimplifying to facilitate comparison with other approaches, one can say that conventional finance is all about multivariate least squares regressions.

3. The Behavioral Present of Risk and Finance

The origin story of behavioral finance is both more recent and more graphic. The release of Robert J. Shiller's book Irrational Exuberance neatly coincided with the stock market collapse that the book itself argued was imminent.

Of course, behavioral finance has been the result of many authors and researchers, dating at least as far back as Allais (1953). Most significant has been the work of Amos Tversky, Daniel Kahneman, and Richard Thaler. Kahneman and Tversky wrote a series of papers that ultimately produced a normative quantitative model of human decision making under uncertainty, and Thaler used their and other insights to apply psychology to finance, paving the way for many later behavioral finance researchers.

To the extent one can view conventional risk and finance as bridging statistics or mathematics and finance, behavioral finance bridges psychology and finance (and algorithmic finance, as discussed subsequently, bridges computer science and finance). Ultimately the hope from all three approaches is to find the best bridge to reach the other side; as we will see, the best bridge may be different for different applications, and provide different perspectives on the final goal.

✓ **Behavioral data:** The data used in behavioral finance research is in one sense a subset and in another sense a superset of the data used in conventional finance research. How can it be both?

It is a subset in that behavioral finance in its infancy often had to prove its own worth as a discipline, so as a matter of exigency, it tended to focus on the biggest, most obvious pricing discrepancies and anomalies. Smaller discrepancies involving intricate statistics might have been acceptable progress in conventional finance had the explanation for the discrepancy been a rational, risk based one, but not if it were a psychological based one. To a certain extent, this bias towards analyzing only the more egregious violations of conventional finance continues to this day. Thus, behavioral finance tends to focus on only the cleanest and most reliable subset of conventional data.

It is a superset in that behavioral finance typically offers a multi-modal approach. This too is a remnant of its days spent trying to establish itself. In addition to empirical financial data, behavioral research often uses results from laboratory experiments, surveys, or other non-financial data.

This additional data is offered for several purposes: first, to document or confirm known psychological biases and how to exploit them in certain circumstances; second, to show how to neutralize them in those same circumstances with the minimal amount of changes to the setup; and third, to provide causal rather than merely relational evidence that the psychological biases are indeed the ones causing the financial anomaly observed in the empirical markets.

✓ **Behavioral approach:** The idea that the behavioral approach rests on the two pillars of limits to arbitrage and behavioral biases was crystallized by Thaler and Barberis (2003) but, as they report and cite, was originally due to Shleifer and Summers (1990).

One of those two pillars, namely the limits to arbitrage idea that sometimes there are restrictions on the amount or speed with which arbitrageurs can eliminate a pricing discrepancy, has been so successful that it has essentially become a principle of conventional finance. It is even hard to remember a time when the prevailing wisdom assumed that arbitrageurs would bring all prices to equilibrium. (This difficulty of remembering such a time is actually itself an example of the behavioral bias known as the curse of knowledge.)

Traditional limits to arbitrage have always been external limits imposed on arbitrageurs, such as restrictions or large fees on borrowing shares, noise trader risk, transactions costs, and similar. Maymin (2011a) further introduced the idea of self-imposed limits to arbitrage that are voluntary, internal restrictions on arbitrageur activity.

The other pillar is the only remaining point of contention between behavioral and conventional finance: do people have systemic biases, meaning that they tend to make decisions all in the same direction, and therefore have an aggregate effect on prices, or do people simply make relatively random mistakes, and therefore have little to no aggregate effect on prices?

In short, and again oversimplifying, one can say that the behavioral approach is all about biases.

✓ **Behavioral techniques:** Behavioral finance uses as many techniques from standard conventional finance as possible in order to most clearly isolate and delineate the effects of the additional behavioral assumptions. The primary novel techniques of behavioral finance involve decision theories.

Where conventional finance by default, tradition, and mathematical convenience assumes perfect rationality and normative decision theories such as elegant utility-based approaches that satisfy axioms and have nice provable properties, behavioral finance posits and tests descriptive decision theories. Thus, rather than attempting to determine the proper way to make decisions, it studies how human beings actually do so. Thus, descriptive theories almost by definition and construction tend to be more complicated than normative theories.

Far and away the most popular and successful such descriptive theory is the cumulative prospect theory of Kahneman and Tversky (1993). Unlike utility theory in which investors experience a hypothetical, ordinal level of happiness as a typically continuous and concave function of their overall wealth and correctly observed probabilities, prospect theory models investors as experiencing a real, cardinal level of happiness or sadness as a concave function over gains and a convex function over losses, with a discontinuous slope between gains and losses, and incorrectly observed probabilities.

Prospect theory predicts that overall wealth is not as salient as changes, and the empirical research bears this out. (This is no surprise, as prospect theory was intentionally designed to explain the empirical results.)

The discontinuous slope represents loss aversion, the idea that losses cause about twice as much pain as equivalent gains cause pleasure. The probability adjustment is essentially a smooth version of the idea that people observe only three kinds of probabilities: zero, meaning something will never happen; one, meaning something will happen for sure; and about fifty-fifty. An adjustment in an event probability from 0.34 to 0.33 feels substantially different than an adjustment in an event probability from 0.01 to 0.00.

One application of this approach is Benartzi and Thaler (1985) where myopic loss aversion is posited as the explanation for the equity premium puzzle. Myopic loss aversion is regular loss aversion in the prospect theory sense, combined with a high frequency for evaluating an investment. They show that investors who observe their portfolio returns less than once a year will tend to prefer equities while those who observe their returns more frequently, for example, on a monthly basis, will prefer bonds. The reason? On a monthly basis, equity losses are more frequent and cause undue pain; on an annual basis or longer, equity losses are infrequent enough that, even when doubled in weight, are offset by the equity gains.

Thus, while they have their differences, the implicit assumption behind behavioral techniques is precisely the same as that of conventional techniques: the past is indicative of the future. Where conventional finance assumes some kind of linear combination of relationships will tend to continue, behavioral finance assumes the distributions will continue to be the same. More specifically, both implicitly assume that investors in the past knew what the future distributions and risk factor loadings would be, and priced assets accordingly. The behavioral techniques evaluate future realized distributions based on prospect theory; the conventional techniques evaluate future realized linear relationships based on arbitrage pricing theory; both tacitly assume that substantial parts of what actually happened in the future were well predicted and anticipated by the investors in the past, whether it was the frequency of losses or the correlation to a special portfolio.

4. The Algorithmic Future of Risk and Finance

What will happen in the future? Computers are getting faster. Trading frequency is increasing. The amount of data is growing. Eventually, one might imagine that virtually all trading will be automated. Behavioral biases will be accounted for and discarded, just as much a relic of antiquated human trading as exchanges and paper tickets. And with all of the automation, markets will finally be efficient, relative to some market risk factors. In other words, one might imagine that soon if not already both conventional and behavioral approaches will become extinct. Indeed, there may not be much left of finance to study, other than tweaking the trading algorithms or finding better ways of securely storing the data.

In fact, such an idealistic outcome is not only unlikely, it is virtually impossible. The name of the field that studies this new future is algorithmic risk and finance. As conventional finance applied statistics to markets and behavioral finance applied psychology to markets, algorithmic finance applies computer science to markets. And it turns out that the most important problem in computer science is exactly the same as the most important problem in finance.

In computer science, the question is: does P = NP? This question refers to sets of problems that have computational solutions. Some problems are relatively easy to solve in general, such as multiplying two numbers, sorting a list, or, as was recently shown by Agrawal, Kayal, and Saxena (2004), testing for primality. Some problems are relatively hard to solve in general, but a candidate solution can be checked quickly. Examples of this are determining the optimal route among cities, finding a satisfying assignment of variables in a logical statement, and factoring numbers.

Traditionally, problems whose solutions can be computed quickly are known as the set P, where P stands for polynomial. If a general algorithm for a problem can solve an instance of length n in time proportional to some polynomial of n, then that problem is considered to be in P.

On the other hand, problems whose proposed solutions can be verified quickly are known as the set NP, where NP stands for non-deterministic polynomial. If a general algorithm for a problem can verify a candidate for an instance of length n in time proportional to some polynomial of n, then that problem is considered to be in NP.

It is clear that P is a subset of NP. Given a proposed solution of a problem in P, one can simply take a polynomial amount of time to find the solution, and then check if the computed solution equals the proposed solution.

The biggest question in computer science is whether P equals NP, in other words, if there is a polynomial algorithm for solving the traveling salesman problem, or satisfiability, or any other similar sufficiently general NP problem, called NP-complete, which could be used to represent any other NP problem.

Most mathematicians and computer scientists believe that P does not equal NP, although there is no proof either way. The most recent poll by Gasarch (2012) showed that 83 percent of theorists believe that P does not equal NP.

How does this relate to finance?

The most important question in finance is: are markets efficient? If they are, then there is no way to make money relative to the risks you undertake. If they are not, then there is a possibility for a money-making strategy. There are various grades of efficiency, ranging from, in its weakest form, an inability to make money from a history of past prices to, in its strongest form, an inability to make money even from private inside information. Most finance academics believe at least in weak form efficiency: Doran, Peterson, and Wright (2010) report that 92 percent of finance professors do not believe it is possible to make money by predicting future returns from past returns. In other words, they overwhelmingly believe in market efficiency.

Maymin (2011c) showed an equivalence between the two questions: markets are efficient if and only if P = NP. In other words, it can't be the case that both the finance professors and the mathematicians are both correct. One of them must be wrong. If the theorists are correct that P ≠ NP, then markets are inefficient and the finance professors must be wrong. If the finance professors are correct that markets are efficient, then P = NP and the theorists must be wrong.

In practical terms, this means that no matter how much speedup in computation and trading takes place, there is no reason to believe markets will become more efficient unless we also see major advances in fundamental questions of mathematics and computer science.

✓ **Algorithmic data:** The distinguishing features of algorithmic data as compared to conventional or behavioral data are its size and its frequency. Big data and high frequency are often the objects of study in algorithmic finance. Indeed, algorithmic trading is often used synonymously with high frequency trading, although they are different concepts. This is not to say that conventional and behavioral approaches do not use big data or high frequency data, or that algorithmic approaches do not use conventional or behavioral financial data, simply that that realm tends to be most conducive to algorithmic methods and so are often found hand-in-hand.

In addition, where behavioral data added survey and experimental results to conventional financial data sources, algorithmic data further adds the results of simulations and other "computed data."

✓ **Algorithmic approach:** This kind of computed data is a common characteristic of the algorithmic approach. Unlike the sorts and deciles of conventional finance, or the biases and experiments of behavioral finance, exploration and complexity represent the main approaches of algorithmic finance. Rather than the top-down style of explanation that both conventional and behavioral finance attempt, algorithmic finance often adopts a bottom-up approach. In this way of thinking, one attempts to discover the simplest possible models which, when simulated, generate the kinds of complexity and other features of interest to the research.

One example is the minimal model of financial complexity described in Maymin (2011b). The question underlying finance is both a simple and a deep one: what is the smallest model of the market that generates complexity in its time series? It is clear that multiple traders, either identical or different, interacting on multiple assets can, depending on their initial parameters, generate virtually any possible price paths. But what is the smallest model that will do so? Are three traders necessary? Could it be done with just two?

Maymin (2011b) showed that it could be done with a single trader, a representative investor who attempts to trade every day, but finds the price adjusts on zero volume precisely to his indifference level. Further, it can be done with a single asset, the market asset. And finally, the trader relies only on the information in past prices.

The general algorithmic approach for any field, not necessarily risk and finance, as described by Wolfram (2002) is to determine a candidate type for the simplest possible model, and then list and test all possible instances. In the case of financial complexity, the candidate type was a particular kind of computational model called an interated finite automaton, which can be thought of as a machine that follows arrows between internal states depending on the value of the input, and always producing an output on each arrow. There are 256 possible instances of the smallest possible such model in the financial case. Unlike traditional fitting in finance, these are not “tweakable” models because the difference between, say, instances 1 and 2 could be arbitrarily large. Indeed, it is in general not computable beforehand what the differences between two instances would be; the only way to find out, with rare exceptions, is to run both and compare.

Surprisingly, it turns out that only one unique rule generates the sort of complexity observable in financial markets. Even more surprisingly, the complexity generated seems to exhibit much of the troubling features of real markets, including crashes, momentum and mean reversion, skewness, and fat tails. And it achieves all this without any traditional parameter fitting.

✓ **Algorithmic techniques:** The techniques of algorithmic finance are borrowed from computer science in much the same way that the techniques of conventional finance are borrowed from statistics and the techniques of behavioral finance are borrowed from psychology.

It is in general impossible to write a single program that would predict what an arbitrary input algorithm will compute, without merely mimicking the computation itself. Wolfram (2002) calls this the Principle of Computational Irreducibility. Therefore, the only general way to truly know what an algorithmic model will generate is to run it and see.

This kind of exploratory approach, akin to what Wolfram calls “mining the computational universe,” may seem to be a comprehensive search over all possibilities, but as discussed above, the search is among a finite set of distinct models that often do not have any customizable parameters.

Other common algorithmic finance applications of computer science concepts include determining the asymptotic computational difficulty of a particular class of problems. An early example is Kao and Tate (2001) where they show that attempting to design proxies to track indices is almost always computationally intractable.

Finally, the most practically useful approach is a heuristic one. In psychology, and in behavioral finance, heuristics are used somewhat deprecatingly to refer to investor rules of thumb. In that context, the heuristics are considered a mistake, a deviation from rational behavior. In computer science, a heuristic is also a rule of thumb, but it is a term often used laudingly, with praise. The best chess programs, for example, are often ones that have better heuristics for evaluating positions, not just those that can search ever deeper. Todd and Gigerenzer (2012) call this approach ecological rationality, highlighting that the advantages or disadvantages of particular heuristics depend on the context in which they are used. Gilli, Maringer, and Winker (2008) and Schlottmann and Seese (2004) survey and discuss applications of heuristics in finance.

In short, the algorithmic approach is all about heuristics: extracting the implied heuristics used by investors from their investing behavior, developing new heuristics to manage portfolios, and measuring the intensity of heuristics across time, asset classes, and investors.

5. Comparisons

All three major approaches to risk and finance have relative strengths and competitive advantages, and all offer a different perspective on issues. In some cases, a combination of approaches provides the best overall answer; in other cases, one of the three is superior by itself. This section examines some common applications.

✓ **Risk factors:** The conventional approach to risk is that the market determines risk factors. Prices are set so that the expected return of any asset, net of its loading to the correct set of risk factors, is zero, and the realized return of any asset, net of noise, is precisely its loadings on the factors times the factor returns. In terms of variance, assuming the risk factors have been chosen to be relatively independent, the risk of an asset is nothing more nor less than the weighted sum of the risks of the risk factors, with the weights calculated from the factor loadings. We do not know the correct set of risk factors ahead of time, but we can use econometric and statistical methods to determine what they must have been for prices and returns to have behaved as they did.

The behavioral approach to risk is that psychology determines risk factors. Human biases tend to point in the same direction, so portfolios composed to capture those biases should explain the risks of all assets. In addition, decision theories precisely predict how people would have made investment decisions historically.

The algorithmic approach to risk is that risk factors may simply be uncomputable. It may be literally impossible, even with vast amounts of data, and even assuming some risk factors did exist, to accurately determine what those risk factors were. In an algorithmic approach, correlations are almost always transitory and the factors that help price asset returns can change dynamically.

✓ **Regulation:** There are three possibilities for regulation: it can either achieve its desired goals, fail to make any difference whatsoever, or thwart its own desired goals.

The conventional approach to regulation is that regulation will have no effect. All agents in an economy will perfectly adapt to any regulations so that regulatory attempts to reduce systemic risk will merely shift certain portfolios but ultimately have little real effect.

The behavioral approach to regulation is that regulation will work. Humans can be manipulated to perform in a way consistent with the regulator’s goals and properly devised interventions can thus be expected to work and ultimately achieve those goals.

The algorithmic approach to regulation is that regulation will backfire (Maymin and Maymin, 2012). Attempts to reduce complexity in a computational system may appear to work for a period of time but an explosion whose timing and extent are both uncomputable is inevitable. The basic reason why regulation backfires is that objective regulations cause commonality of actions that would otherwise not have happened, for example, the inadvertent but inevitable creation of regulatorily favored assets which require less regulatory risk capital than their true risk would dictate, and which in turn leads to greater systemic risk.

In considering the financial crisis of the beginning of the 21st century, the conventional approach is that such a crisis would have happened no matter what the regulations in place had been, the behavioral approach is that such a crisis could have been averted with better or smarter or more psychologically-informed regulations, and the algorithmic approach is that such a crisis was a direct result of the regulations

(Maymin and Maymin, 2012).

✓ **Alpha:** There are three possibilities for what sign the alpha can be: positive, negative, or zero.

The conventional approach to alpha is that there is no alpha. The right approach for investors with similar risk characteristics as priced by the market is to invest with low-cost passive index funds. The only exception is for investors with substantially different risk preferences from the average, who can then hold more of the particular risk factor that does not affect them. In this approach, any ostensible alpha found in a particular hedge fund, mutual fund, stock, or other investment is an illusion, and merely represents a surprising positive historical run with no further outperformance predicted.

The behavioral approach to alpha is that there is negative alpha (cf. Barber and Odean, 2000). People trade too much and too aggressively, costing themselves substantially. The only real way to benefit from behavioral investors is to attempt to collect their transactions costs as a broker or investment adviser, because even trading against behavioral trends may backfire as prices out of equilibrium go even further from equilibrium.

The algorithmic approach to alpha is that there can indeed be positive alpha. Because it is so costly to search all possible algorithms, indeed because this is in general an irreducibly difficult computational problem, there may exist profitable trading strategies that simply haven't been found or publicly disseminated yet. Hence, there are returns to search, and investors should keep looking.

6. Conclusions

In approaching questions of risk and finance, researchers and practitioners tend to borrow tools from other disciplines. The conventional approach borrowed from statistics and econometrics, the behavioral approach borrowed from psychology and experimentation, and the new algorithmic approach borrowed from computer science and simulations.

None of the approaches is necessarily right or wrong in itself, but the usefulness depends on the context to which it is applied. In the same way that laboratory experiments pushed the boundaries of finance in the recent past, computer experiments may help push the boundaries in the future.

Practitioners and researchers should consider all three approaches to their problems to gain a fuller picture and pursue the one whose techniques and approaches best fit the desired goal.

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