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Simple and Complex Market Inefficiencies: Integrating Efficient Markets, Behavioral Finance, and Complexity

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Traditional capital market theory says that markets are efficient because investors are rational. The new school of behavioral finance says the opposite. Rather than solving problems "rationally," individuals tend to make biased decisions using pattern recognition techniques. However, what is rational and irrational may depend upon the type of problem we wish to solve and the method we use to solve it. If the market inefficiency is a simple objective problem, then "cool reason" should prevail. However, if the market is a complex system, then the value of data would be ambiguous making it more rational to use pattern recognition techniques. In this article we will find that rational investors would indeed keep certain types of mispricing from happening. Likewise, human behavior and the market complexity cause mispricing that cannot be arbitraged away. In the end, investors are irrational if they use the wrong method to solve a particular type of problem. By examining method and object we can find when investors are rational, when they are irrational. A non-mathematical model integrating efficient markets, behavioral finance, and complex systems is presented.

Introduction

The semi-strong Efficient Market Hypothesis (EMH) states that current prices reflect all public information (Fama [1965]). In other words, the market consists of rational investors who collectively value information in a uniform way, and thereby price securities fairly and efficiently. However, behavioral finance proponents have shown that people often fail to use statistical reasoning when making decisions (Kahneman and Tversky [1972, 1973]). Instead, they rely on subjective methods, using heuristics or "rules of thumb," even when presented with objective circumstances.

The results suggest that market inefficiencies can exist, since it is assumed that subjective methods are inferior to statistical techniques. Thus, disciplined investors using quantitative methods, or simply astute traditional managers, can generate low-risk profits at the expense of investors who use subjective methods.

However, this does not take into account the circumstances under which decisions are made. Behavioral finance assumes that market decisions are made under conditions favoring standard quantitative techniques, but actual decisions are often made under ambiguous conditions, or "true uncertainty." True uncertainty exists when we do not know all the possible outcomes of a decision. Hence, calculating probabilities (which depend upon frequency) is impossible. Under such conditions, heuristics may be the rational way to make decisions, but, ultimately, the optimal decision-making method depends on the type of uncertainty faced by the decision-maker. In addition, the way to profit in ambiguous circumstances may be quite different than the way to profit under conditions of objective uncertainty. Since the latter has dominated the efficient markets literature, it would be helpful to examine the former condition as well.

In this article, we examine the types of uncertainty that investors face and we attempt to determine the appropriate decision-making methods for each type. We see that there are two types of inefficiencies: simple and complex. Simple inefficiencies are riskless in the short-term, but can be easily arbitraged away, as described in the EMH literature. This makes them risky in the long term. Complex inefficiencies arise from long-term behavioral biases that cannot be arbitraged away. Thus they have low long-term risk, but also carry short-term risk since the outcome of individual transactions cannot be predicted. Rational and irrational behavior can also be defined. Rational investors match a problem with the appropriate decision-making method. Irrational behavior comes from a mismatch between method and problem.

In addition, we observe that accepting the securities markets as complex systems makes strategies with long-run positive excess expected returns possible without an "inefficient" market. This observation rests on the ambiguous nature of most information,

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and the inability of the market as a whole to agree on its value. Thus the opportunity to profit does not depend on the existence of "irrational" investors, but merely better forecasting methods within an atmosphere of ambiguity. Admittedly, complexity theory in finance has a controversial history, but examining this possibility opens interesting areas for possible future research.

The Nature of Uncertainty

The financial literature is dominated by studies that examine markets under conditions of objective, or statistical, uncertainty. Yet, there is little appreciation of the conditions that are assumed when examining uncertainty with statistical methods. This can lead to errors. Applying statistical methods to cases of true uncertainty can be misleading at best, and dangerous at worst. In the next sections we examine the nature of and conditions for objective and true uncertainty.

Objective Uncertainty

> When you have eliminated the impossible, whatever remains, no matter how improbable, must be the truth! (Sherlock Holmes)

This Holmesian quote (despite originating from a fictional character) sets the conditions for objective reasoning and the application of statistical methods. When applying statistical techniques to a set of data (particularly using time series forecasting methods), we are making specific assumptions about the process under study. The necessary conditions for statistical analysis are:

1. All the possible outcomes are known in advance.
2. The phenomena can be repeated many times under objective conditions to estimate frequency.
3. The results are easily measured.
4. The data are precise and unambiguous.
5. Causality is well defined.
6. Noise is exogenous.
7. The problem has a closed-form solution and can be solved for one optimal answer: the "truth."

There are ways to minimize any violations of these assumptions, however. But relaxing too many of these conditions would make any econometric forecasting analysis unreliable.

For example, "subjective probabilities" are a convenient way to deal with problems that lack most of these conditions. However, like many methods for handling the limits of statistical reasoning, subjective probabilities cannot be derived from first principals. They simply "are," and they sidestep the real problem. How do we estimate the likelihood of something we do not fully understand?

A common question that falls into this category is "What is the probability that the Fed will raise rates?" While most Fed watchers can provide a probability, what does it really mean? If an analyst says there is a "60% probability" that the Fed will raise rates, does that mean that if we repeat current conditions 1,000 times, the Fed will raise rates 600 of those times? Of course not, but this is what is inadvertently implied. Clearly, the question of whether the Fed will raise rates does not lend itself to probabilistic reasoning.

The conclusion is that only well understood problems with limited parameters fall under the category of objective uncertainty. Certainly all problems involving games of chance can be solved using objective methods.

Statistical evaluation of uncertainty has one overriding characteristic: The domain of the problem is well defined. While individual outcomes are unknown, the likelihood of an event is known in advance. And while a particular outcome may have a low probability, we know in advance there is a chance of it happening. Thus the problem can be objectively evaluated.

Unexpected events (those not accounted for in the original realm of possibility) are called "exogenous." They come from outside the system and are often interpreted as noise. However, as Zadeh [1965] says, "As complexity rises, precise statements lose meaning and meaningful statements lose precision." Noise is not always exogenous.

True Uncertainty

> [For] uncertain matters...there is no scientific basis on which to form any calculable probability whatever. We simply do not know! (John Maynard Keynes)

In real life, too many unexpected and significant events occur to call them "noise." In fact, the noise usually ends up being a possibility that was never considered. For examples, consider the 1990 Iraqi invasion of Kuwait and the emerging market crisis of 1997. While unexpected, such events were not exogenous. In fact, in real life most of our decisions are not made under the well-defined parameters needed for objective analysis, and they are not repeatable under the same conditions even if the event itself is repeated. Every time the Fed raises rates the circumstances are different than the last time. In most cases of true uncertainty we are not even sure of all the possible outcomes. These are the conditions of true uncertainty, where circumstances are at best ambiguous and at worst unknown. Applying Holmes' axiom is unwise.

The characteristics of true uncertainty are:

1. All the possible outcomes are not known.
2. Causality is not well understood.
3. The circumstances are unique to each occurrence.
4. The results are not easily measured.
5. The data are ambiguous and imprecise.
6. The noise is endogenous.
7. There is more than one possible solution because the problem does not have a closed-form solution.

Zadeh [1965] proposes that under conditions of ambiguity fuzzy sets are a more rational way to make decisions than statistical methods. Peters [1996] makes an intuitive link between fuzzy sets and the heuristics of behavioral finance.

In the behavioral finance literature, a wide body of research shows that people generally make decisions according to heuristics. Kahneman, Slovic, and Tversky [1982] focus on instances where people continue to apply heuristics to circumstances with known probabilities. For example, consider a well-known case where subjects are shown a line-up of ten people and told that eight are truck drivers and two are accountants. In the first case, members of the line-up are dressed identically. When participants were asked whether a randomly chosen person was a truck driver or an accountant, they overwhelmingly chose truck driver, in keeping with the stated probabilities.

In the second case, however, the members were dressed differently. When asked if a randomly chosen person wearing a suit and carrying a briefcase was a truck driver or an accountant, the majority identified the person as an accountant. Furthermore, they assigned a high *probability* to the fact that the person was an accountant, despite knowing that the odds were five to one against it. Kahneman and Tversky [1973] use these results to illustrate the irrational nature of human decision-making.

Peters [1996] finds that representative heuristics are comparable to fuzzy sets. Fuzzy sets are often used to measure the similarity between two sets of characteristics. In the case of the truck drivers and the accountants, the participants identified a random individual as an accountant because they believed the person had a high level of *similarity* to an accountant. In this instance, our language has made "similarity" and "probability" synonymous.

Likewise, the "probability" that the Fed would raise rates was really a 60% similarity with previous times the Fed had raised rates. Again, our language has confused similar, but different, assessments of uncertainty. We can say that the degree of similarity is subjectively set, but that does not make it irrational.

Consider another example. If you live in the suburbs, you would probably agree that the *probability* of finding an unknown dangerous animal in your backyard is small. However, if you did find a large, hairy beast with bared teeth growling at you, it is likely you would assign a high probability that this animal is dangerous and take appropriate precautions, despite believing that the probability of finding such an animal is small. Such behavior is not irrational. We find a high similarity between this animal and a dangerous one despite the a priori probabilities mentioned earlier.

Many decisions are made under similarly ambiguous conditions. When we change employers we can hardly calculate the probability of success in the next five years. The problem is too complex. However, we can examine whether the conditions exist for success, and make our decisions likewise. Such a decision would be a heuristic. Calculating a "probability" in the true statistical sense is not possible, and any attempt to do so could be considered an irrational attempt to impose order on the unknowable.

A final characteristic of ambiguous systems is that there are multiple possible solutions, as opposed to multiple possible outcomes. Thus, given the ambiguous nature of the inputs, decision-making does not require a precise answer. Such systems are also complex systems.

A growing body of work is attempting to develop a more realistic statistical approach to problems of true uncertainty and ambiguity. Ghirardato and Marinacci [2002] is an excellent survey of many of these methods. We believe that statistical tools will be useful, but it is important to recognize that most of the commonly used statistical tools are not suited to dealing with true uncertainty. Many of the more advanced tools have the same problems.

Our purpose in this article is to define the types of problems we are dealing with, and decide which tools are most appropriate. The choice of tools will change over time as new methods develop. But whatever sophisticated statistical tools are developed, people are more likely to continue to use heuristics to solve problems. Because we aim to understand rational and irrational investor behavior and how best to profit from that knowledge, we currently believe that heuristics is the optimal way to solve complex problems.

Irrationality Defined

Though this be madness, yet there is method in 't.
(*Hamlet* [Act II, scene 2])

We have seen that statistical methods are the rational way to make decisions under conditions of objective uncertainty. Likewise, under conditions of true uncertainty, heuristics are also the rational way to make decisions. Given these two definitions of rationality, we can now define when individuals are being irrational. Irrational behavior (or "madness," as Shakespeare would have called it) occurs when the wrong decision-making method is applied systematically to particular circumstances. Specifically, people are irrational when they apply complex methods to objective circumstances, or objective methods to complex problems.

Table 1 provides an illustration.

The two types of irrationality are caused by a mismatch of methodology and problem. Both problems are behavioral in nature, although only Type I has been addressed in the behavioral finance literature. This table is called the Method and Madness Model (M3), with a nod to Shakespeare because it postulates that irrationality is caused by systematically trying to solve a problem by using the wrong method.

Table 1. *Rational vs. Irrational Behavior*

	Problem	
Methodology	**Objective**	**Complex**
Objective	Rational	Type II Irrationality: Quantitative
Complex	Type I Irrationality: Behavioral	Rational

Type I: "Behavioral" Irrationality

Type I irrational behavior has been widely documented in the behavioral finance literature. The accountant/truck driver problem falls into this category. Individuals have a tendency to use heuristics, or "rules of thumb," even when faced with objective problems. The irrational behavior occurs because most of our daily decisions are made under ambiguous conditions, rather than under the well-defined conditions typically addressed in the behavioral literature. Even Kahneman and Tversky [1973] state:

> These problems differ from those discussed earlier...in that, due to their unique character, they cannot be readily answered either in terms of frequency of occurrence in the past, or in terms of some well-defined sampling process.

We are programmed to face the unknown as ambiguous, so most people automatically use heuristics to make decisions. Only the mathematically inclined are likely to recognize that an objective situation is actually a rare opportunity to use statistical problem-solving methods. But heuristics require less "mental energy." Statistical thinking requires specialized training, so attempts to simplify the problem lead us to use heuristics when they are not appropriate.

Type II: "Quantitative" Irrationality

A less examined, but widespread, phenomenon is the indiscriminant application of statistical methods to ambiguous circumstances. This occurs particularly often when estimating probabilities for highly complex systems or problems. For example, an expert may assert his opinion of the "probability" of a nuclear war. But calculating the true probability of such an event would assume we can know all the possible sequences of events that would lead to a nuclear war *and* the likelihood of their occurring. Such things are unknowable in a large complex system, but we continue to turn to experts on such matters.

Ironically, this overconfidence in analytical methods is a behavioral problem. We want to believe we know the risks we face every day, as well as the odds of those risks coming true. If we know the odds, we believe we have the ability to prevent or minimize these risks from occurring. And on the other hand, if we are ignorant of these risks, or unable to even know what they are, we believe we are helpless in controlling our destiny.

Ellsberg [1961], in the famous "Ellsberg Paradox," showed that people are much more comfortable with known but low probabilities than with situations of true uncertainty, where probabilities are unknown. When we apply statistical reasoning to ambiguous situations, it gives us the illusion that we are facing an easily defined instance of objective uncertainty rather than the uneasy reality of true uncertainty. We would rather impose a model on reality than admit we have no model, and, hence, no control.

Quantitative irrationality also arises when individuals apply the standard "scientific method" to complex problems. The western tradition of scientific investigation solves complex problems by breaking them down into smaller problems that are then linked together. But this method only works for "complicated" systems, not complex ones. Complicated systems are chains of events or modules linked together in a linear sequence. Most manmade systems are complicated. For example, turning the ignition in an automobile sets in motion a sequence of events that starts an internal combustion engine. By examining each step in the sequence, then linking them together, we can understand the total system. The scientific method is best suited to solving such objective problems, closed systems with well defined parameters and properties.

Complex systems, by contrast, do not depend on a set sequence of events. Instead of being a chain, a complex system is like a net or a web. The human brain, for example, is a problem that has not lent itself to the scientific method. We know how the parts work, such as the neurons and the synapses. But we still don't understand how consciousness arises from a mass of neurons. In Type II irrationality, the scientific method is used to explain complex processes. Unfortunately, trying to explain the brain, or the economy, by examining the parts and assembling them together is a cognitive error.

Common Reasons for Irrationality

Quantitative irrationality has at its heart the same causality as behavioral irrationality. Both methods tend to oversimplify. Behavioral irrationality tries to simplify the decision-making process by ignoring any mathematical construct for a conceptual one. Non-mathematical decision-making is easier to develop and implement. Quantitative irrationality, on the other hand, attempts to simplify the problem itself by assuming that it can be broken down into basic elements to be solved by quantitative methods. However, as Einstein is reported to have said, "Things should be as simple as possible, but not one bit simpler." The M3 model states that by oversimplifying the method or the problem, gross mistakes can occur.

Note that both Kahneman and Tversky [1973] and a later study by Dorner [1996] showed that, when presented with unambiguous problems, irrationality did not surface in a meaningful way. The addition of ambiguity is what resulted in systematic irrational behavior. In Kahneman and Tversky [1973], it was the addition of visual data in the form of dress. In Dorner [1996], it was the addition of a time delay between the action of the participants and the reaction of the system. Since most real-life decisions have elements of data or causal ambiguity in addition to statistical uncertainty, we can expect these "irrational" behaviors to continue.

Market "Inefficiencies"

The market has long defined inefficiency as mispricing due to irrational investor behavior. This, of course, assumes markets are at least semi-strong efficient. However, it may be time to revisit this definition. First, inefficiencies are generally defined as *riskless* excess returns. Second, securities are mispriced if investors make mistakes so that more astute investors can profit from their errors. Third, there is little consideration of the investment horizon of the inefficiency.

Classic market inefficiencies are short-term mistakes that can generate no-risk profits for disciplined investors. Such inefficiencies will eventually be arbitraged away. However, given the complexity of the markets as a whole, and the ambiguous nature of information for long-term forecasting, the classic definition of inefficiency may be too narrow. Behavioralists, for example, say that human nature generates long-run inefficiencies that cannot be arbitraged away. Many games have process inefficiencies that can generate long-run low-risk profits that still carry substantial short-term risk, such as card-counting in blackjack.

Finally, simply being a superior competitor in a complex environment can result in superior long-run performance. Two football teams may be great and not prone to errors, but one may be simply better than the other. Clearly, winning is not due to a team's "inefficiency" just because competition is high. A team may lose because of a mistake in judgment, but this mistake would be irrational only if it is systematic. Often, the "right" call is merely the lucky one, and no systematic mistakes are involved.

In the next section we examine each of the four quadrants in M3 and determine which type of investment strategy is appropriate for each.

Simple Inefficiencies

A simple market inefficiency is shown in the quadrant where objective conditions meet objective analysis, the upper left quadrant. Investors in this quadrant are not being irrational. They are applying the correct analysis to the correct environment. It is a classic semi-strong efficient market.

However, the classic EMH has a critical assumption. If the value of information is apparent to everyone, there must be a formula to calculate fair market prices. Once the information is released, it would be plugged into the formula, the fair price would be calculated, and the market price would be adjusted accordingly. In this environment, the only way to profit would be to obtain information before everyone else, which is why insider information is illegal. Much research and analysis is spent looking for "informational" inefficiencies, however, because once the general public becomes aware of the secret information, the market mechanism will price it out.

The earliest example of this scenario occurred during the tulip bulb mania of sixteenth-century Holland (Mackay [1932]). Tulips with green stems were more prized than tulips with yellow stems. As a result, yellow-stemmed tulips were, of course, cheaper. One individual found that if he cross-bred two yellow-stemmed tulips, he could produce a green-stemmed tulip, and sell it for a tidy profit. However, he told others of his discovery, which increased the demand for yellow-stemmed tulips, which in turn increased their price. In a short time, the price of yellow-stemmed tulips rose to a point where the arbitrage was no longer profitable. This tale of tulip-mania illustrates the nature of simple informational inefficiencies.

First, informational inefficiencies are based on having information that no one else has. Second, the value of the information must be readily apparent to those who possess it. Third, the inefficiency must produce *riskless* returns. Fourth, the inefficiency will tend to be short-term in nature. Fifth, once the information becomes generally known, the opportunity to profit is arbitraged away in the manner of efficient markets. Thus, simple inefficiencies can show that investors are generally rational.

Proponents of the EMH have rightly pointed out that such inefficiencies are short-lived. They use this rationale for the theory that any form of active management is not consistent with long-run excess returns.

Since simple inefficiencies are unambiguous, the Kahneman and Tversky [1973] and Dorner [1996] studies show that we can expect them to be recognized and arbitraged away. People tend to react in a uniform way (in aggregate) to problems that have one right answer even when the problem is dynamic, as in Dorner [1996]. So the EMH can be expected to hold for *simple* inefficiencies.

Complex Inefficiencies

Unfortunately, the world is not a simple place. Because of the complexity of our society, we typically make decisions under conditions of extreme ambiguity. This can lead to situations where we treat objective conditions as ambiguous, or ambiguous circumstances as knowable. Both types of cognitive errors result in potential market inefficiencies that are much different than the simple inefficiencies we have discussed up to now.

First, the source of a complex inefficiency is the subjective interpretation of generally available information, even if the participants know of objective circumstances. Second, complex inefficiencies are opportunities that do not produce riskless profits. Third, these inefficiencies are long term in nature. Finally, and perhaps most importantly, they cannot be arbitraged away.

Many people believe these characteristics fail to qualify complex inefficiencies as inefficiencies at all. In many ways this is true. Below, we argue that complex inefficiencies are crucial incentives for market participants to continue trading. But first we address the above characteristics.

Type I Inefficiencies

Type I inefficiencies are attributable to behavioral irrationality. In the table this behavior is shown in the lower left quadrant. As Kahneman and Tversky [1972] showed in examples like the truck driver/accountant problem, people use heuristics to analyze situations even when they are aware of the objective circumstances under which they are making decisions. They confuse the ambiguous conditions of typical decision-making with circumstances when a more analytical approach is appropriate. As a result, people continually interpret much information in a subjective way.

As long as investors use subjective judgment, there cannot be unanimous agreement on the value of information, because it does not have the formulaic interpretation characteristic of simple inefficiencies. Characteristics may overlap with other participants, but each individual still has a unique knowledge base and set of goals.

For example, it is unlikely that a day trader will interpret trade data information the same way an institutional money manager does. Because of the heterogeneous nature of market participants, there will always be a minimal level of disagreement about the value of ambiguous information. There can be consensus, but the minority will always be sizable enough to generate opportunity and ensure that the inefficiency will not be completely arbitraged away.

These behavioral biases tied to Type I cognitive errors will persist into the future. Value investing strategies are closely tied to Type I errors. Individuals, unable to judge the value of a company with no earnings but high prospects, sometimes confuse an expensive stock with a good investment. One of the drawbacks of value investing, and other strategies that center on long-run complex inefficiencies, is that they have significant short-term risk, and can underperform market indices for periods of time.

Type II Inefficiencies

Type II inefficiencies, in the upper right quadrant of the chart, are attributable to quantitative irrationality. Type II cognitive errors have a different source of persistence than their Type I counterparts. Because the future is ambiguous, it is difficult to accept that we cannot know much about it. Ironically, there can be comfort in statistics. So we accept the opinions of experts who say that market returns are normally distributed even when the empirical distribution is otherwise. Portfolio insurance, for instance, was a strategy that slavishly followed the Black-Scholes option pricing model, even though the empirical information showed that market returns are not normally distributed. At the extremes the strategy was doomed to fail, as portfolio insurers discovered on October 19, 1987.

But complex processes can also lead to another type of behavior: the need to impose order. Complex systems are characterized by feedback, delay, and spontaneous organization, but there is no leader or method to the madness. And since our mental abilities are unable to conceive of such a process, we tend to simplify it. Typically, a complex problem is sifted down to one principal cause that either defines the solution, or rationalizes why current behavior is optimal.

Dorner [1996] and an extensive European group of academics have studied how people make decisions when facing complex problems (for example, see Frensch and Funke [1995]). These problems fall under the Type II variety. This work is as important as the work done by Kahneman and Tversky [1973] and their followers on Type I inefficiencies, but is not very well known, as the results have not yet been applied to economic situations.

Dorner [1996] has approached his research differently than the behavioral finance proponents. His subjects were required to control a complex system through computer simulations. These systems included running a town, controlling a village, and trying to fight a forest fire.

Dorner [1996] found that understanding the full workings of a complex system is not necessary. Just one characteristic gave rise to most of the ambiguous situations: time lags. In one classic study, subjects were given the following situation. They are in charge of running a dairy store that sells ice cream. The connection between the thermostat and the rheostat (a mechanism that regulates the strength of electrical currents) no longer functions. It will be several hours before a repairman can come. The subject must manually control the rheostat by looking at the temperature. The problem is that the rheostat is only a dial with numbers from 1 to 100. The subjects have to set the dial and look at the effect on the temperature.

When there was no time delay between setting the rheostat and seeing the change in temperature, subjects had little trouble controlling the temperature and keeping their ice cream from melting. In real life there would always be a time lag, however. When a time delay was added to the problem, the results were much more interesting.

Participants were not told of the time delay, but many assumed there was a direct relationship between setting the rheostat and seeing the temperature change anyway. If the temperature did not change quickly enough, they continued to turn the dial. If the temperature overshot the target, they quickly turned the dial in the other direction. Sometimes they would keep hitting the dial even when it was at its lowest or highest level, like people who continually press an elevator button as if it will make the elevator come faster. Such actions produced wild oscillations in temperature.

This, of course, was a classic case of overreaction. What is interesting is that it was induced by a time delay. Sometimes subjects developed systems to cope with the complexity, assigning mystical significance to certain actions. They would decide that even numbers worked better than odd, or that the number 22 is a "good" setting. Many of these behaviors are classic market behaviors. Interestingly, although the causality of the system was mostly understood, the addition of a time delay added enough ambiguity to the problem to make decision-making difficult.

This situation, where there was a delay between the action and reaction of the system, is similar to conditions faced by the Fed. It is well known that there is a delay between monetary policy and its effect on the economy. Unlike the ice cream problem, the delay changes every time, which adds another layer of ambiguity. But the impact of Fed policy can never be fully anticipated, and opinions on its effect always vary.

In another study, the time delay was in the actual communication of information, and similar behaviors were discovered. The participants tended to assume that their information was current and indicative of current trends, when it was actually delayed and the current state of the system was unknown.

Common to all the studies was a need to impose order on the process, even through oversimplifying the system. This oversimplification usually amounted to imposing a set of rules on a complex process to make it understandable, which led to overconfidence and failure.

Type II irrationality (and complex inefficiency) is probably more widespread than Type I irrationality and simple inefficiency. During the U.S. speculative bubble of 1999-2000, there was widespread overconfidence in investor ability to make money and "beat the market." A low-inflation, high-growth economic environment brought on by "productivity gains" in the "new economy" made buying tech stocks the way to beat the market. Now, after the bear market of 2000-2001, these assumptions have been shown to be just gross oversimplifications that "confused genius with a bull market."

However, profiting from complex inefficiencies is difficult. It is mostly a matter of not making mistakes by distinguishing between long- and short-term effects. Consider this illustration. In June 1999, the Fed began to raise interest rates to slow the economy. There was little effect after a couple of months, so many speculators assumed that earnings growth would be unchanged. These investors ignored the time delay between when interest rates rise, when the economy slows, and when earnings growth slows. They still bought in early 2000 when the U.S. stock market was peaking, because they didn't believe Fed policy would affect earnings. They were proven wrong in the following months.

In this case, profit could have come from acknowledging the delay between action and effect. Like the participants in Dorner's [1996] ice cream problem, these investors assumed that the lack of immediate reaction meant there was no longer a causal connection between interest rate changes and earnings growth, even though the causal relationship is well documented. The time lag resulted in oversimplification and disastrous behavior.

Competitive Opportunities

The only quadrant left to discuss is the lower right quadrant, where we have ambiguous circumstances and rational investors. Like the upper left quadrant, investors here are applying the methodology appropriate to the circumstances. Opportunity does exist for excess returns, but these opportunities combine some of the features of complex and simple inefficiencies. Like simple inefficiencies, these strategies do not require people to make cognitive errors. Like complex inefficiencies, they carry low long-term risk but significant short-term risk, and they cannot be arbitraged away.

Competitive opportunities require a complex adaptive system. Complexity occurs when a large number of agents following their own self-interest spontaneously self-organize due to overlapping knowledge and goals. But no two agents are identical, so no two will interpret or value information the same way. This economic interpretation of complex systems, which integrates subjectivism (or Austrian economics) and complexity, is covered more fully in Peters [1999]. Complex systems are characterized by feedback, non-linearity, and a high level of randomness at the local level that generates a global stability and resilience to shocks. They also evolve and adapt through time.

A striking element of complex systems is that they are not forecastable over the long term. While they can be expressed mathematically, they also have multiple solutions and are considered open systems. The latter two characteristics are crucial in this environment.

As we stated earlier, it has long been assumed that the only way to profit in the market is through the systematic mistakes of others. But in a complex system two different models could come up with two different solutions. Both may be rational, but only one will be right, although it is also possible that neither will be right. But if model A is right one month and model B is wrong, that does not necessarily mean that A is superior to B. Each model may be looking at a different aspect of the total problem. Remember that the "total" problem is unknowable because of its complexity, and individual agents will only be concerned with the part of the problem that concerns them. Hence, two models of market returns can have correlation coefficients of 0.12 with the market, but be uncorrelated with each other. Both models may be tractable, rational, and generate excess returns over the long run.

To explicate further, complex problems have no "right" answers. The actual outcome depends on many interrelated factors, and, as a result, the ultimate winner can often be a matter of luck. However, by modeling the tendency of the system it is possible to tilt the odds in your favor over the long term. Casinos do this in roulette by adding the "00" where the house always wins. The addition of that one space to the wheel ensures that the house will win over the long term.

Complex systems are also open. They are not zero-sum games. Participants enter and leave the market regularly, most often the losers, but sometimes the winners. By creating a better process, markets can be rational but still offer the opportunity for long-run excess returns. These returns will be low-risk over the long run, and high-risk over the short run. Unlike simple inefficiencies, there are no guarantees, just opportunity. And perhaps this is why the quest for simple inefficiencies continues. Like winning the lottery, they are a low-risk way of getting rich quickly.

So how can one profit from complex opportunities? If you win some and lose some, it should end up a zero-sum game. But the real answer is risk control. Controlling the size of bets, maximizing bets in environments where you know you can do well, and minimizing bets in poorer environments can all result in superior long-run returns even when others are behaving rationally. To use a gambling analogy, the classic "know when to hold them, and know when to fold them" strategy tends to win over the long term.

Future Research

The M3 model integrates research done so far on efficient markets, behavioral finance, and complex systems, but much work remains.

First, Dorner's [1996] work (and the rest of the European school) on complex decision-making needs to be more formally integrated into financial economics and behavioral finance. Since it is similar to "experimental economics," however, there can be duplication of their efforts.

Second, we need research that identifies optimal decision-making methods under conditions of ambiguity. While much research has focused on which objective methods best handle ambiguity, we also need research on whether such methods are superior to the pattern recognition techniques used by individuals. Such research would require test subjects in a laboratory environment to measure behavior.

Finally, the M3 model is a positive, or conceptual, model. Further work on a normative, quantitative model needs to be advanced that incorporates the M3 model in a manner similar to Levy, Levy, and Solomon [2000], who quantified traditional behavioral finance.

Summary

Capital market theory has long depended on investors being, in aggregate, rational. That is, as a group, investors were believed to agree on the value of information and make decisions based on statistical methods. Behavioral finance has challenged that view by showing that people typically do not behave in a way that classical economists would consider "rational." However, statistical decision-making may not always be the rational route. We have demonstrated that, under extremely complex conditions, when problems are not well defined, causality is not understood, and the value of information is ambiguous, subjective forms of decision-making may be the "rational" approach.

In the method and madness model (M3), we have defined rationality as the proper matching of problem to decision-making method. Objective problems require statistical techniques. Complex problems require subjective methods based on pattern recognition, such as heuristics. We then define irrationality as systematically using the wrong method to solve a problem.

This article presents a conceptual model for defining rational and irrational behavior. We postulate that different environments coexist simultaneously in a free market. We also offer a view of how investors can successful implement strategies in different rational and irrational environments. We suggest that, in a complex environment, it is possible to profit over the long run even if investors are rational.

In the end, we are left with a picture of the financial markets and investor behavior that is far richer and more complex than what has previously been offered by either efficient market proponents or behavioral finance proponents. It offers opportunity for long-run returns while recognizing the nature of short-term risk. The research needs for the complexity model are vast, but the problem has become much more interesting.

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