Chapter on

Behavioral Finance

for The Handbook of Modern Finance

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Introduction

Behavioral finance as a sub-discipline of finance has always been with us, even in earlier decades when it was not named as such. Academic research in finance focussed on the behavior and decision making of investors and corporate managers as early as the 1930s when Keynes described investors' decisions as "animal spirits" and "beauty contests" and the 1950s when Lintner wrote a famous paper documenting a survey asking managers *why* they pay dividends. However it was not until the 1980s and 1990s that the in-depth study of financial decision making, and, particularly, the examination of differences in financial decisions from what would be predicted by rational economic models of choice, was christened "behavioral finance." That title was given in juxtaposition to "modern finance," which had developed in the 1960s through 1980s as a series of mathematical models with fully rational agents.

Modern finance has as its cornerstone the efficient markets hypothesis, which is the relatively simple and quite reasonable proposition that investors respond immediately to profit opportunities. For example, imagine that with the information available to them, investors were able to determine that the value of a share of stock was $20/share, but that stock was trading at $10/share. Could that pricing persist for very long? The efficient market hypothesis states that it could not. Investors would figure out that the stock price was too low and that, as a result of this mispricing, they could profit by purchasing the stock at $10/share, and indeed at any price up to $20/share. These investors would submit buy orders for the stock as long as it was trading at below $20/share, and the resulting excess demand for the stock would push the price up to $20. Similarly, if the stock were priced at $30/share, investors would short-sell the stock, and the resulting excess supply of the stock would cause the price to be pushed down to $20/share. So, the argument goes, the *equilibrium* price for the stock (the price at which supply would equal demand) would have to be $20/share – the stock's true value.

The idea that investors respond to profit opportunities is certainly correct. But amazingly, this was really not taken into account in finance theory, or in macroeconomic theory prior to the parallel development of the efficient markets hypothesis and the rational expectations theory at the University of Chicago in the 1960's. The rational expectations theory, as developed by Lucas and others, has at its foundation the hypothesis that economic agents can not be "fooled" by fiscal and monetary actions on the part of the government.[1] These agents will figure out what the government's policies are, and will then act in an optimizing manner, and in so doing render the government's actions ineffective.

The efficient markets hypothesis can be viewed as equivalent response in finance theory: the simple underlying idea is that agents would respond to profit opportunities, seeing through "window dressing" on the part of managers or potential information manipulators. Like the rational expectations theory in macroeconomics, the efficient markets hypothesis enjoyed remarkable early success. Almost all of the early empirical work testing the efficient markets hypothesis (see Fama (1970) for a summary) found strong support for the hypothesis that asset prices were equal to asset values, and that, as a result, there were no trading strategies that could consistently "beat the market."

The view that markets were completely efficient, and that security prices fully and completely incorporated all publicly available information.at all times became the status quo among finance scholars. However, on both on the theoretical and empirical level, there is now voluminous evidence that contradicts these strong views.

In this Chapter, we explore this evidence. We begin in Sections 1 and 2 by discussing the precepts of modern finance, and contrasting these with those of

[1] See Lucas (1972), Lucas and Sargent (1981), and Begg (1982).

behavioral finance. In Section 3, we investigate the concept of efficient markets in more depth, and the concept of arbitrage, which underlies the efficient markets hypothesis. We discuss why arbitrage is not always possible, and thus how behavioral biases can cause markets to be inefficient even when there are some agents in the economy who realize that the resulting prices are "wrong."

In Section 4, we discuss how bounded rationality can potentially lead individuals to process information in a way that appears sub-optimal. Individuals make mistakes because they have limited ability to process information, and the decisions they must make are complex, relative to their ability. Also in Section 4.1, we discuss how evolutionary selection could result in human decision making rules being biased and sub-optimal for financial decision making, even though the rules were optimal for survival over a long period. In Sections 5, 6 and 7 of this chapter we summarize some of the behavioral biases identified in the pioneering work of Kahneman and Tversky and others. Their experiments showed that, in fact, individuals exhibit systematic biases in the way they make decisions, and they do make mistakes. In Section 7 we discuss some of the recent analytical models of behavioral finance and Section 8 concludes.

1. Behavioral Finance versus Modern Finance

Behavioral finance, as a response to modern finance, has essentially developed as series of explanations of the inability of traditional "rational" models to explain certain anomalous patterns in asset returns. Research and interest in this sub-field of finance has grown significantly in the decade of the 1990s.

The objective of this chapter is to define behavioral finance by contrasting its paradigms with those of traditional finance. Then, we discuss the results and conclusions offered in the last two decades by researchers in the field. This is not the first, and almost certainly will not be the last, summary of this field. And yet, there is much to summarize already and many possible interpretations of the results.[2] Very likely, no two authors would agree on what the main frameworks and conclusions currently *are* because it is a young sub-field; its results and conclusions are in a state of flux. One of the difficulties in pinning down its exact conclusions is common to most of the social sciences: answers are not uniform, decisions are multi-dimensional, and decision makers are fickle. Often, results can be explained by several competing and yet extremely plausible hypotheses. This is, of course, a major distinction between the conclusions of the "hard" sciences like mathematics and physics where two plus two is universally four and the social disciplines like psychology, sociology, and economics where answers often change over time and certainly differ across individuals. "Modern finance" (like much of modern economics) has been viewed in the last two decades as a hard science, complete with mathematical models and "precise" answers, while behavioral finance has tended to emphasize the less quantifiable social science psychological complexities of human behavior. There are some that would characterize behavioral finance research as "soft" and unscientific while researchers open to the behavioral finance approach respond by pointing to the failure of the modern finance models to accurately explain observed financial practice. (see Fama (1998) in contrast to De Bondt and Thaler (1995)). The goal of this chapter is to demonstrate that the two areas complement the other by explaining an inherently complex system better than either sub-discipline could individually.

Indeed, one cannot appreciate the contribution of behavioral finance without first having an understanding of the standard or "modern" finance paradigms that it attempts to reinterpret. Simply put, behavioral finance exists because the *predictions* of modern finance differ systematically from *actual,* observed decisions made by investors and financial managers. We will examine these differences in this chapter. In some cases, we find that the decision makers make "bad," biased decisions. They *should*

[2] See DeBondt and Thaler (1995), Shefrin, (2000), Shleifer (2000). Statman, (1999) for surveys aimed at

know better, but for some reason they learn slowly, if at all, from their mistakes and consistently repeat them. These mistakes have been documented and explained by researchers in other disciplines, especially psychology.

In other cases, it is not that obvious mistakes are the culprit but that the modern finance predictions are too "perfect": they expect decision makers to make revisions to their beliefs and then act instantaneously, consistently, and, above all, correctly with seemingly flawless *ex post* hindsight. That, of course, is a tall cognitive order for decision makers. Investors with limited cognitive abilities will use *ad-hoc* rules in their decision making. Even if these rules are reasonable, they will often be biased, and they will show up in "imperfect" security prices.

Garrision Keilor, in an amusing novel, *Lake Woebegone Days*, writes of a fictional town where "all children are above average." While clearly this is a mathematical impossibility, it amuses us because we can easily envision virtually all parents able to view their own children that way. Modern finance makes a similar but even bolder claim, that decision makers are not only above average, but are "perfect." Obviously no one believes that claim completely. And yet, there is a subtle, insidious belief among many in the academic finance profession that assuming perfection will cause no great harm in aggregated results and will not change important conclusions.

Behavioral finance takes a different tack. It believes that it is instructive to examine the specific assumptions that make up this unobtainable perfection, as they may lead us to an observed "behavioral finance" real world that is inconsistent with "perfect" decision makers. The unrealistic conclusions of "perfect," modern finance may therefore benefit from a more complete (and in some cases, behaviorally-based) re-interpretation.

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different and various audiences.

2. The Framework of Modern Finance (or, "Rational" Financial Decisions in a "Perfect" World)

Modern financial economics, and thus, its prescription for optimal financial decision making, is based on three over-arching paradigms. The first is that human decision makers are cognitive *maximizers*: that the decision maker can choose from a limited supply of scarce, costly resources. The decision-maker chooses to consume, over his lifetime, the "best" bundle of these resources that he can presently and will in the future, with accurate foresight, be able to afford. Second, decision makers are inherently accurate *Bayesian statisticians*. That is, they appropriately assess the uncertainty in the world around them (for example, they may start with a "fuzzy" opinion about the question "what will be the level of the market at the end of the year?"). Then, they revise and make their opinion more precise and reduce their level of uncertainty as they take in new information. In the third key paradigm, decision makers are posited to have "rational expectations." That is, their *ex ante* collective views are realized accurately *ex post*.

The academic economics literature has tended to call a decision maker who abides by these three paradigms a "rational" decision maker. It is important to realize that this *economist's* definition of "rational" is considerably more specific than one would find in the dictionary, where it simply means "logical" or "sane." Additionally, it is also important to realize that each of these paradigms has subtle implications and assumptions for the behavior of decision-makers. The next few sections of this chapter dwell on these assumptions.

We should keep in mind that the rationality paradigm, like most theoretical models, is a parsimonious model of a more complex world. Just as two dimensional pictures rarely capture the realism of the three dimensional world, it is not surprising that the predictions of any simplified model like the standard rationality model do not completely capture the complexity of financial decisions. In fact, we *expect* deficiencies. The mark of a good model is that its mis-predictions (or "errors") are fairly small, unsystematic, and are not easily explained with a reasonable addition to the original model.

So, it is useful that we examine the assumptions of modern finance carefully since these the inputs drive the outputs (i.e. the predictions of the modern finance model). To early economists such as Smith and Ricardo, rationality meant preferring more to less. While more-is-better is not always so, it is not an egregious assumption. The next significant assumption that the rational or "modern" finance model is that it presupposes that decision makers are "expected utility" maximizers. Interestingly, each of the words, "expected" and "utility," has a specific meaning and importance so we address and explain each of them.

First, the expected utility framework is first based on the concept of utility, or the idea that decision makers can accurately and consistently identify and rank their own preferences among various goods and services. That is, given that they have a total budget of, say, $50,000 they can spend each year, they can order their preferences for purchasing a new refrigerator versus a week's vacation versus a home computer. Naturally, they can also "value" the marginal benefit for their utility of taking two weeks of vacation versus one or none, and they can rank the value of purchasing a fancy computer versus a basic one. Once they have ordered and valued the various options of consumables in their choice set, they will choose a "consumption bundle" that maximizes their utility or "happiness."

Decision-makers in this rational model accurately exhibit their utility preferences and choices in tradeoffs across time, too. For example, the investor's common problem of having money to spend today versus saving it and having more to spend in a year is a utility tradeoff. They, for example, may choose not to consume $5,000 of this year's income (lowering this year's utility), but to save it for the future expected liability of their children's college educations or their retirement (increasing their total lifetime utility).

Next, we examine the first word of the expected utility phrase, "expected." The basic idea of *expected* utility theory is that when the existence of the goods or services will not occur for certain but with probability p (less than 100% of the time), decision makers are assumed to be able to rank their preferences consistently and correctly by calculating the average or "expected value" of their utility by factoring in these uncertain outcomes or "gambles". While there are several variants of the expected utility, the best known is the one made famous by Von-Neumann and Morgenstern (1944).

The essence of the model is that the utility of the decision-maker is a direct calculation of utility if the event or asset were obtained with certainty times the probability of the event or asset occurring. That is:

$$U = \sum p_i u(X_i)$$

Why has this extension been made? The world is an uncertain place. Without a model dealing with future possibilities and the uncertainties inherent in them, no approximation of the world would be complete. Many of the tradeoffs decision-makers deal with involve "gambles" or probabilistic, uncertain potential payoffs.

Expected utility relies on several axioms to complete its coherent theory. One of the most common is *transitivity*. It says, simply, that if A is preferred to B and B is preferred to C, then A is preferred to C. While this seems sensible at first glance,we will show in a later section that even that assumption is non-trivial and sometimes violated by decision-makers.[3]

Utility theory also regularly presupposes that decision-makers are consistent (or, invariant) in their choices. That is, advertising about a product or re- "framing" of a

[3] There are many summaries of the expected utility model available (including most micro-economics textbooks), but a good primer is Schoemaker (1982).

decision problem cannot sway decisions. Thus, rational utility theory assumes that decision makers' preferences are fully developed, not created, and that decision-makers are fully cognizant of *all* the choices they could potentially make and how much they value each of those possible choices.

A final assumption of the expected utility paradigm is *risk aversion*. We call a decision-maker risk averse if he prefers a completely certain outcome A to any risky prospect that has an *expected value* equal to A. In theoretical terms, this is equivalent to saying a decision-maker's utility curve is concave. Practically speaking, this assumption translates to saying that $100 gives a consumer more utility than a 50% chance of $200 and a 50% chance of $0.

The third paradigm, the rational expectations hypothesis, asserts that individuals do not make systematic (predictable) mistakes in forecasting the future (Begg, 1982).[4] Previous attempts at modeling individuals' expectations relied on *ad hoc* assumptions about how they divine the future. The popularity of this rational expectations approach has relied on a simple, logical idea: if individuals were to make systematic mistakes in predicting the future, they would learn from those mistakes and make corrections. Or else, they would die out or lose all their money. Over time, as learning takes place, their beliefs about the future would essentially evolve into "rational expectations."

So, this complete model of decision making assumes that decision makers not only make correct current utility decisions, but also accurately provide for all future contingencies. To do this, the decision-makers must visualize a correct model of the future, on average. Suffice it to say, this assumes considerable talent by the decision-maker in interpreting his informational environment.

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[4] A primer on rational expectations is Begg, (1982)

3. Efficient Markets (or, Information and Its Price Impact in a "Perfect" World)

The rational choice paradigm has generally referred to individual choice, even though market prices are usually determined by the supply-and-demand aggregation of many individuals. The main paradigm in modern finance, which translates the assumptions of rational decision making into market prices of assets, is known as the "efficient market" hypothesis (EMH). While it is, strictly speaking, a hypothesis to be proved or disproved, to many finance academics, it is more of an assumption or even conclusion about what prices actually occur in the real world. The most basic definition of efficient markets is that *market prices for assets reflect all available and relevant information about those assets*. This is an aggregate market concept that is primarily concerned with the appropriate prices of assets, not the supply and demand issues that create assets' trading volumes. It is a concept emphasizing the "price" results of individuals' collective actions, not their decision making processes. The EMH assumes that the consensus of all individual rational decisions will wind up as the correct or "efficient" price.

3.1 A Simple Mental Model of Information Arrival and Market Efficiency

Under the EMH, as new information comes in to the market, prices adjust appropriately and instantaneously. Investors continuously re-value assets as new information arrives. When the revaluation process suggests the asset is cheap, investors will buy it immediately until it is appropriately valued. When the asset is overvalued, investors will sell immediately until the market price equals the new valuation. The idea of efficient markets is that this arbitrage process is virtually instantaneous: as soon as "news" comes out about an asset, its price moves to reflect that information completely. Investors neither undershoot nor overshoot in immediately and correctly revaluing the asset, once information is disseminated.

This paradigm of efficient markets can be illustrated by the price graph of the stock of a hypothetical company in the Figure 1. At any starting point in time, the price (at A) reflects all information available from all sources about the company. This includes information contained in the company's accounting statements, the pronouncements of management and security analysts, press reports, etc. Until a new piece of (positive) information about the company is released (at B), the price of the company should, on average, appreciate at a rate relative to the risk inherent in the company's investments. In modern finance, this risky rate of return is derived from an asset pricing model like the CAPM or a multi-factor model that specifies an appropriate expected rate of return corresponding to the risk of the given company. According to a strict efficient markets interpretation, the stock immediately increases at time B to a new equilibrium level, reflecting the new good news. From time B to time C, it again appreciates consistently until additional (bad) news is released at time C. In the hypothetical scenario of Figure 1, we assume that the risk-return profile changes as the company announces different (riskier) investment decisions. The second piece of negative information released (at C) increased the risk level of the company. This is indicated by the steeper slope of the price per unit of time from time C to D.

[Figure 1 about here.]

Obviously this figure represents an extremely simplified view of how prices change in markets, but considering it illustrates the thorny issues in the EMH assumptions about market pricing and investors' valuation decisions. First, it would appear to be difficult if not impossible for investors to identify all of the relevant information "events" related to a particular stock or asset. The EMH assumes investors can do this. Conversely, the EMH also assumes investors correctly ignore all irrelevant news. Investors also accurately evaluate the sources of information (for example, strategic vs. truthful) they receive and interpret it correctly.

Second, there is an assumption that whatever subset of investors receive and evaluate new information upon its first dissemination, their immediate actions move the stock price immediately and appropriately. Thus their price re-valuations are precise, and effectively, no time is needed to revalue the asset price. Furthermore, the process of prices changing through trading is also "efficient" and frictionless. The theory assumes that there will always be just enough investors with just enough supply of and demand for the stock to move prices to just the right new equilibrium but no further. [5]

It is, of course, quite naïve to think that the investment process works this efficiently. To quote Kenneth Arrow (1987), "the main implication of this extensive examination of the use of the rationality concept in economic analysis is the extremely severe strain on information-gathering and computing abilities" it assumes on the part of the decision maker.

So why do many academics persist in supporting a fully rational worldview? There are at least two justifications. The first argues logically that market forces will enforce a rational "equilibrium." If some market participants are not rational, they will be driven out (and bankrupt) by smarter, more rational players. As Arrow says, "There cannot be any money lying in the street, because someone else would have picked it up already."

The second defense of the "rational financial economics" paradigm does not attempt to opine on whether the financial decision maker *can* reasonably do all that is demanded of him by the paradigm—it just *assumes* he can. This line of argument, the "as if" defense, is often attributed to Friedman.[6] For example, fielders do not know and understand the physics equations behind the trajectory of a baseball hit into the outfield, but nevertheless some trained ones are able to catch it. They act "as if" they understood the theory behind the ball trajectory.

[5] Grossman and Stiglitz (1980) suggest a more reasonable approach to price setting. Expand.
[6] See Friedman (1953) or Friedman and Savage (1948) QRE p. 21.

3.2 Arbitrage, and the Limits of Arbitrage

Most economists don't really believe that all agents are fully rational – there is too much everyday evidence around of people making decisions in foolish ways to believe that each individual acts in a fully rational manner. However, some economists argue that nonetheless security prices will be set "as if" all agents are rational. Perhaps the strongest argument for why this will be is an argument related to the concept of *arbitrage.* The argument is that, if an asset were priced incorrectly, and there were any close substitutes available, it would only take a few wealthy rational agents to eliminate any mispricing through the process of *arbitrage.*

An arbitrage opportunity arises when two securities or portfolios with the same payoff sell for different prices. Given such a situation, an *arbitrageur* could buy the low price security and sell the high price (but identical) security and, with this transaction, earn the difference in prices. The simplest example of arbitrage is when two identical securities sell for different prices. For example, silver is traded on exchanges in both Chicago and in New York. There is a group of silver arbitrageurs constantly monitoring the prices in both markets. If the price in Chicago becomes only a little bit higher than the price in New York, these arbitrageurs will, within seconds, buy silver in New York and sell exactly the same amount in Chicago. Through supply and demand, this will bring down the price in Chicago while raising the price in New York. The presence of these arbitrageurs guarantees that the price of silver in the two markets is almost identical. Thus, even if New York silver traders are "irrational" and don't shop around for the best price, the presence of the arbitrageurs guarantees that the price that they paid will be no different than the price in any other large silver market. Summers (1985) noted correctly that much of modern finance theory is based on the assumption of arbitrage: "…two quart bottles of ketchup invariably sell for twice as much as one quart bottles of ketchup except for deviations traceable to transactions costs."

A similar argument is often used to show that the price of common stocks should not move too far from their fundamental value. If IBM were underpriced, the argument goes, a set of arbitrageurs would come in, buy a large number of shares of IBM, and short sell a portfolio of securities which would have close to the same future value as a share of IBM. Thus, these arbitrageurs would push the price IBM back to its fundamental value.

However, unlike the silver arbitrage example given earlier, this type of arbitrage for stocks can be risky for a couple of reasons. First, there is no portfolio of other assets which is a perfect substitute for a share of IBM. Thus, in taking on this arbitrage “gamble”, the arbitrageur would face the risk that IBM and its mimicking portfolio might diverge in value.

Second, even if there were a portfolio available which was a close substitute for IBM, arbitrage would not be as clear cut as in the silver example. Following the purchase and sale of silver in the two markets, the arbitrageur can close out his position and walk off with his profits. Here, the arbitrageur may have to wait for a very long to realize his profits. He can close out his position only when the market realizes it has made a mistake and push the prices of IBM and the mimicking portfolio back together. If this doesn’t happen, he has to wait until IBM and the mimicking portfolio provide cahs to their shareholders in the form of dividends or repurchases. Thus, particularly if markets remain “irrational” for long periods of time, this latter strategy may be unprofitable.

De Long et. al. (1990a,b) develop two interesting models which illustrate the inability of arbitrageurs to eliminate mispricing. In De Long et. al. (1990a), arbitrageurs have limited risk bearing capacity. Moreover, arbitrageurs face the risk that "noise traders" may cause any mispricing to be exacerbated. De Long et. al.

(1990b) a explores the possibility that the actions of arbitrageurs may actually amplify mispricing rather than the attenuating them. Specifically, if investors behavioral biases cause them to employ "positive feedback strategies," I arbitrageurs actions can cause higher price volatility, and greater deviation of asset prices from their fundamental values.

The Shleifer and Vishny (1997) model illustrates another why arbitrageurs may take on only limited arbitrage positions.. The motivation for limited opportunities is that the arbitrageurs are generally trading with other people's money. Initially, the trading positions taken by arbitrageurs could lose money as prices diverge ever further from fundamental values. Given the uncertainty in the investor's mind about the quality of the arbitrageur in these ostensible losing situations, investors might pull their money out of the arbitrageur's fund. Ironically, this would be exactly the time at which the arbitrage strategy *ex ante* is likely to be most profitable.

The implication of this uncertainty, Shleifer and Vishny point out, is that arbitrageurs will be reluctant to take on large positions in all but the most certain and immediate arbitrage opportunities. Consequently, the argument that arbitrage will eliminate mispricing will not be applicable to most securities.

4. Behavioral Decision Theory (BDT)

As we noted earlier, rational or "modern finance" models of decisions are normative. That is, they are based on how financial decision-makers and prices *should* behave *if* they accept the tenants of "rational" choice described above. Naturally, any theory should be validated by asking, "how accurate are its predictions?" and "when the theory mis-predicts, why does it?" Research in the field of behavioral decision theory (BDT) in the last two decades makes it clear that actual decisions depart systematically from the rational normative theories. Even those that question the usefulness of behavioral research concede that modern economics has been found lacking in describing the real world. Merton Miller (1994), a proponent and Nobel-prize-winning contributor of rational financial theory, stated in *The Economist*:

> *"The blending of psychology and economics will lead nowhere* The mix is becoming popular simply because conventional economics has failed to explain how asset prices are set."

Miller's damning opinion of both psychology-based (behavioral) explanations and his own field, mathematically-based (modern) financial economics notwithstanding, it is instructive to examine whether behavioral decision theory (BDT) and its extension, behavioral finance (BF), can reconcile some of the "failures" of the conventional rational economics model. This is the primary objective of the remainder of the chapter.

A financial decision can be thought of as a series of several steps. The decision maker is typically given an uncertain situation. In the rational paradigm, he "knows" the probability distribution of the potential outcomes (but not which outcome will occur). He must then gather relevant information, and process the information. In the rational paradigm, again, he has access to *all* relevant information available and processes it in an instantaneous and yet unbiased way. Finally he must choose among various courses of action based on the costs and benefits of each course. When engaged in the rational paradigm, he uses his expected utility "calculator" to choose among the alternatives.

However, much financial decision making is sufficiently difficult that we cannot really do it in a way that even remotely resembles the way it is modeled. For example, consider the problem of valuing the stock of a company like Microsoft. We know how to value Microsoft once we have established what the expected future cash flows of Microsoft are (and the riskiness of these cash flows). However, estimating the expected cash flows is an exercise that involves intuitions, hunches, and feelings. How can one incorporate the news about the antitrust proceedings against Microsoft? About the future competitiveness of the industry? About the development of alternative operating systems? About the evolution of alternatives to the personal computer? The decision making that goes into such a valuation is complex.

Herbert Simon suggested a useful starting point, diverging from the rational paradigm, in his pioneering work where he describes decision-makers as "boundedly rational."[7] That is, decision makers usually intend and even attempt to be "rational," and to make all of the calculations necessary to maximize their present and future utility but find the cognitive task overwhelming. It is like expecting a slow personal computer to accomplish a task for which a super computer is needed: at best, the personal computer cannot do it quickly enough, at worst, it will freeze up and never provide a logical answer. Arrow (1987) eloquently states that strict rationality assumptions "imply an ability at information processing and calculation that is far beyond the feasible and that cannot well be justified as the result of learning and adaptation." Simon hypothesized, therefore, that decision-makers devise simplifying strategies to deal with the complicated and seemingly impossible tasks: they "satisfice." That is, they search for the best outcomes over a limited (manageable and most obvious) set of alternatives and then, within a certain time deadline, make a decision. Decisions made in this satisficing way are, of course, potentially and regularly sub-optimal relative to perfectly rational decisions (where *unlimited* cognitive resources can hypothetically be employed). However, boundedly rational decisions are perfectly logical, if the cost and time of mental effort is factored in. Economic rationality, on the other hand, subtly and unrealistically assumes the cost and time involved in mental effort is zero.

4.1 Evolution and Behavioral Biases

Another aspect of the human decision making process that is often ignored is that this process is undoubtedly the result of evolutionary adaptation. Individuals who can make better decisions than others are more likely to survive than others who are less

[7] See Simon (1982).

able. However, human decision making ability is not likely to be optimized for making financial decisions. The ability to make good financial and investment decisions may have enhanced genetic survival in the last several thousand years (and even this is questionable), but certainly not before this. A decision-making process that enhanced genetic survival in a more primitive period might not be optimal for "survival" in today's financial markets. For example, Daniel and Titman (1999) discuss how overconfidence might increase the chance that males would pass on their genes, if those males who *appear* to be the strongest and the smartest are more likely to attract mates and reproduce.[8] Thus, we might expect to see overconfidence as a prevalent characteristic in individuals, even though it probably does not enhance one's chances of "surviving" in fiancial markets. Interestingly, behavioral studies show that overconfidence is more pronounced among males, where it should have had the strongest genetic survival impact according to this theory. Also, in an interesting related study, Barber and Odean (1999) find that males trade more frequently than females, something they attribute to stronger overconfidence among males, and have lower overall portfolio performance as a result.

Another behavioral trait that might be a result of evolutionary survival is that individuals overreact to *salient* information. Klibanoff, Lamont, and Wizman (1998) present evidence that the prices of international closed-end mutual funds move too much, relative to movements in underlying net-asset values, in response to prominent news stories in the US media. The fact that investors overweight salient information is certainly sub-optimal when viewed from an non-bounded rationality perspective. However, in primitive times, the costs of failing to react sufficiently to salient information in a new, unusual, situation might have been large, and the costs of overreacting comparatively small.[9]

[8] Waldman (1994} and Hirshleifer (1999} show how overconfidence among males can be an evolutionarily stable strategy.
[9] Terry Odean suggested this idea.

5. "Irrationality" in The Framing of Decisions

Another alternative formulation of the theory of choice when there is uncertainty suggests that the expected utility model incorrectly describes the choices a decision-maker makes. You should note from the earlier discussion of expected utility theory that it assumes two things commonly associated with rational choice. First, that decision-makers are risk averse and secondly, that their choices are invariant or unchanged by the framing of the problem.

For example, when decision-makers were asked for their preferences in choosing between medical treatments, the contrasting choices illuminate a common violation of the invariance property. You should note that the two versions of Problem 1 are essentially the same.

> **Problem 1 (framed with survival rates): Choose between . . .**
>
> Surgery: Of 100 people having surgery 90 live through the post-operative phase, 68 are alive at the end of one year, and 34 are alive at the end of five years. course identical. (82% chose this)
>
> Radiation: Of 100 people having radiation therapy, all live through treatment, 77 are alive at the end of one year, and 22 are alive at the end of five years. (18% choose this)
>
> **Alternative Problem 1 (framed with mortality rates): Choose between . . .**
>
> Surgery: Of 100 people having surgery 10 die during surgery or the post-operative phase, 32 die by the end of one year, and 66 die by the end of five years. (56%)
>
> Radiation: Of 100 people having radiation therapy, none die during treatment, 23 die by the end of one year, and 78 die by the end of five years. (but now, 44% choose this)

One should notice the significant difference in percentages choosing surgery and radiation, simply as a result of the different "frame" of the problem ("live through" and "are alive" versus "die"). (Rational choice would assume identical percentages choosing surgery given either frame of the problem.)

Another example provides an additional violation of the expected utility assumption of risk aversion.

Problem 2a (framed as a gain)

Assume yourself richer by $300 than you are today. You have to choose between:
a sure gain of $100 *(72% choose this)*
and a 50% chance to gain $200 and a 50% chance to gain nothing *(versus 28%)*

Alternative Problem 2b (framed as a loss)

Assume yourself richer by $500 than you are today. You have to choose between:
a sure loss of $100 *(but now, only 36% choose this)*
and a 50% chance to lose nothing and a 50% chance to lose $200. *(versus 64%)*

What we notice is a substantial reversal in choice, although the final outcomes are the same in both versions of the problem. (Either the decision-maker chooses $400 for sure or a 50-50 chance of $300 or $500.) When the problem is framed as a gain, the decision-maker is risk averse but then it is framed as a loss, he is risk seeking.

Kahneman and Tversky (1979) proposed an alternative to expected utility theory called ***prospect theory***. In it, they noted several important discrepancies between expected utility and the choices generally made by decision-makers. Prospect theory proposed a value function different from the concave shape of the expected utility function. The shape of the value function is more consistent with several observed phenomena from experimental problems like the ones above. Figure 2 shows the prototypical prospect theory value function

[Figure 2 about here.]

The main differences of prospect theory from traditional (rational) expected value theory are as follows: starting from a reference point of the decision-maker's current wealth, the decision-maker analyzes gains and losses differently. First, when choosing among gains (as in Problem 2a) the decision-maker is risk averse, but when saddled with proposition of a loss, the majority of decision-makers are risk seeking as in Problem 2b (meaning they would rather gamble for the *possibility* of a smaller loss rather than accept a larger certain loss). The second feature of the prospect theory value function is that the incremental utility of a loss is larger than that of a gain. That is, the "hurt" of a $1000 loss is more painful than the "benefit" of a $1000 gain.

Prospect theory is a *descriptive* model of how humans regularly make decisions. In simple, transparent decision problems, the decision-maker sometimes follows the axioms of "rationality." But, in more opaque circumstances, like Problem 1 above, he or she often violates rational choice "rules." Thus, the descriptive view presented in prospect theory is consistent with Simon's idea of bounded rationality discussed earlier.

As prospect theory shows, decision-makers evaluate their alternatives relative to a reference point, usually their current wealth. However, in some cases, people appear to make decisions, comparing their chosen alternative to imagined, hypothetical outcomes. This psychological literature is known as ***regret theory***. Often, it suggests, decision-makers attempt to minimize the regret of the anticipated unpleasant choices occurring. In essence, For example, decision-makers may choose $1000 for sure rather than $2500 based on the flip of a coin based on considering their feeling of regret if the coin flip lands against them. Descriptively, regret theory makes the same predictions as prospect theory, but it amplifies a dimension as to why decision-makers are risk averse.

6. Behavioral Biases and Decision-Maker Heuristics

What specific strategies do decision-makers actually employ when faced with difficult and overwhelming decision problems? Psychologists Kahneman and Tversky and many others have shown that satisficing decision makers often use heuristics, or, rules of thumb, as their decision tools. That is, when a problem gets too complex and difficult, they resort to an approximating mental shortcut. For the decision-maker, this approach has significant cognition- and time-saving benefits. However, behavioral decision theory researchers have also found that these simplifications also result in systematic (and thus predictable) decision-making biases. We outline several of these heuristics in this section because they lead to biases with particular application in finance.

Representativeness—This heuristic is used in judging the likelihood of whether particular events or cases belong to a certain class. Regularly, decision-makers judge frequency by comparing the current case with the stereotype of the class. A biased judgment occurs when frequency and similarity are not well correlated. The famous "Linda" laboratory problem illustrates the issue:

> **Description:** Linda is 31 years old, single, outspoken, and very bright.
> As a student, she was deeply concerned with issues of discrimination and social justice, and also participated in antinuclear demonstrations.
>
> **Choose the most likely alternative:**
>
> - A: Linda is a bank teller
> - B: Linda is a bank teller and is active in the feminist movement

It is indisputable that the probability of a conjunction *p*("Linda is a bank teller" & "Linda is active in the feminist movement") cannot be greater than the probability of either of its parts *p* ("Linda is a bank teller") and *p* ("Linda is active in the feminist movement") because some bank tellers are not feminists! (See Figure 3) But, Kahneman and Tversky (1982) found that respondents chose choice B more than 80% of the time. They conclude that as the vividness of a scenario increases, and hence, its probability decreases, its representativeness or apparent likelihood increases too.

[Figure 3 about here]

An important manifestation of representativeness is the failure of decision-makers to regress to the mean in predicting a second outcome after observing a first extreme outcome. This tendency can easily lead decision-makers to overreact to new information. Indeed, many studies have shown that individuals tend to overweight recent information and underweight base rate data. This is at odds with rational Bayesian updating rules discussed earlier which assume that decision-makers can blend the old and new information appropriately.

Anchoring and Adjustment—Another observed phenomenon which leads underreaction to new information is named "anchoring and adjustment." Simply put, decision-makers can be highly influenced by "stakes in the ground" such as an initial suggestive questions such as "How likely is it that the Dow Jones will close over 11,000 (or, 13,000) by the end of the year?" when they are next ask "What will be the Dow Jones close at year end?" Whether the respondent considered 11,000 or 13,000 in the first question will (incorrectly) overly influence his or her answer to the second question.

Availability and Retrievability—Decision-makers often over-use data that are easily available to them. Numerous experiments suggest that humans have an easier time recalling some types of data than others. For example, it is far easier to conjure up words ending in "ing" than words with the next to last letter as "n" (although "ing" words are a far smaller subset of the latter. Decision-makers appear to make decisions based on the world that is familiar to them rather than seek further information to complete their world-view. Manifestations of this tendency appear especially in apparent search problem anomalies such as insufficient international investment, often called the home country bias.

While the errors outlined above result from biased decision heuristics, another groups of decision problems emanate from incorrect and hard-to-correct "cognitive maps" by the decision-maker. For example, consider the decision-maker that believes (incorrectly) that the information he has is more accurate or valuable than it actually is. How will this affect his decision making? We expect that he will "overuse" his information, relative to its true value: he will be overconfident.

Overconfidence—While it would be incorrect to say that decision-makers are universally overconfident, studies have documented that they are overconfident in many, if not most, probabilistic situations, especially when accurate judgments are difficult to make.

For example, Lichtenstein and Fischhoff (1977, 1980) found that when people "thought" they were 65 to 70 percent confident, they were actually correct only about

50 percent of the time, about the same as by random chance. In fact, they report that even when people report being 100 percent sure of their answer, they tend to be only 70 to 85 percent correct.

Of course, decision-makers do "learn" and particularly those who play probabilistic games or make probabilistic forecasts regularly or professionally become better "calibrated", especially when feedback is available. Expert bridge players, professional gamblers, and weather forecasters, for example, exhibit little or no overconfidence (Keren, 1987). But, the preponderance of evidence shows that when individuals are not explicitly thinking probabilistically, they are overconfident relative to the actual precision of the knowledge they possess.

An important question is *why* decision makers are regularly overconfident. Kahneman and Lovallo (1993) provide some interesting insights into this question. They suggest that decision makers have a strong tendency to consider individual problems as unique. In doing so, they neglect past base rates that would give them a statistical distribution to compare their problem to. Overly optimistic forecasts, in their analysis, result from decision makers adopting an "inside view", that their immediate problem is unlike others where they have informed probabilities. They instead advocate "the outside view" which prods decision-makers to construct base rate comparisons.[10]

7. Heuristics and Errors in Financial Decisions

This chapter has thus far presented the modern, rational economic model of the decision-maker and then the systematic discrepancies that are different from the rational *assumptions* about how decision-makers decide versus empirically observed realizations of how they actually decide. How do these discrepancies inform us with regard to the financial decision making process? We observe substantial evidence in financial

[10] We also refer the reader to Griffin and Tversky (1992) and Einhorn (1980) for detailed examinations of the "overconfidence" topic.

decisions of these “irrational” behavioral tendencies. This section describes some salient examples of the tendencies described above in financial markets.

Frame of Reference Effects—A study by Thaler and Johnson (1990) addresses an important question for managers and investors:

> “Consider the case of a manager whose division has lost $10 million under her administration, and who must choose between two projects. Project A will earn a sure $5 million. Project B will earn $20 million with probability 0.5 and lose $5 million with probability 0.5. *Does past history influence the decision?*” (italics ours)

Prior outcomes do appear to influence future choices and change the risk aversion of decision-makers. That is, risk taking by decision-makers is conditional upon prior gains or losses, not invariant to them. The first finding of Thaler and Johnson they call ***the house money effect***, showing essentially that after “winning” in a first round, subjects take more risk in the next round, presumably because they have not immediately or completely internalized the first round’s winnings in their reference point. If the gambler is “up” $500, he is less careful about losing in the future until he is down more than $500.

The second effect, which Thaler and Johnson and Kahneman and Tversky (1979) call ***the break even effect***, is shown in the willingness to gamble after initial losses. We noted earlier that prospect theory predicted more risk seeking (rather than risk averse) behavior in the face of the alternative of certain losses, as decision-makers attempt to avoid losses. The break even effect suggests, more subtly, that decision-makers will take extra risk to attempt to break even or recover to a small gain.

Shefrin and Statman (1985) suggest that people generally sell their winners too early and hold their losers too long, despite a valuable tax benefit for selling losers relative to winners. They label this phenomenon the ***disposition effect***. Terrance Odean (1998) also has confirmed, in a study of discount brokerage firm clients, that individuals tend to sell a higher proportion of their winners than their losers, and that, *ex post*, such sales are sub-optimal (the stocks they sell outperform the stocks they keep).

Evidently, it is quite easy to confuse the value of past history with the likelihood of future gains.

Another important indication of the importance of historical frames of reference comes from the earnings per share literature. Degeorge, Patel, Zeckhauser (1999) examine the reported quarterly earnings of U.S companies and find significant ***threshold effects,*** another manifestation of frames of reference. That is, they find evidence that earnings are "managed" by firms to: 1) not be below last year's earnings, 2) not be below zero (i.e. a quarterly loss), and 3) not be below analysts' consensus expectations. Figure 4 shows earnings relative to the quarter the year before. If earnings were reported "truthfully", we should expect a smooth distribution, but the figure shows an abrupt discontinuity at the zero level (i.e. positive versus last year).

[Figure 4 about here]

These various examples show that frames of reference affect financial behavior significantly. The "behavioral" aspect of that conclusion is that, of course, problems can be reframed, and this reframing can change investor behavior. This naturally is an important challenge to "rational," "efficient" markets where investors are presumed to "see through" cosmetic framing differences, and hence, managers would have no incentives to manipulate earnings to meet or exceed thresholds.

Disposition Bias Effects—A classic example displaying disposition bias by investors is Odean (1998). The study examines the trades of a large set of investors who make their own trading decisions through a discount brokerage house. The study analyzes the buy and sell transactions of individuals. Odean finds that investors are far more likely to sell recent winners than recent losers. He also finds that the stocks that these investors sell outperform the stocks they keep. This relative performance differential is probably attributable at least in part to the momentum effect – recall that Jegadeesh and Titman (1993) show that stocks that have gone up over the previous 6-12 months continue to rise in value (on average) over the subsequent 6-12 month period.

Indeed, it is possible that the momentum effect is to some extent attributable to the very trading patterns Odean identifies in this paper.

Information Processing Effects—Another set of anomalies suggests that financial decision making may diverge from the economist's rationality because of the inherently difficult task decision makers have in acquiring and processing all the information available and needed to make an optimal, rational decision.

Benartzi and Thaler (2000) examine an important choice of workers, their asset allocation decision choices in their own defined contribution retirement plans. Optimal diversification strategies would consider the covariance of the various asset choices and a view of the risk reward tradeoffs among the various asset funds (e.g. stocks, bonds, real estate, etc.). Instead, these researchers find that workers typically us ***the 1/n heuristic***, simply dividing their retirement assets evenly among all the funds offered. When the worker's retirement plan has a high *number* of stock funds relative to bond funds, he invests heavily in equity; when his plan has a higher number of bond funds, he overinvests in bonds. The import of this finding is that the decision-maker, the retirement plan participant, is apparently unable to do the financial calculus necessary for optimal diversification and adopts a naïve strategy that is clearly sub-optimal.

Another example and amusing result documented by Huberman (2000) demonstrates that investors are more likely to invest in companies operating in regional telephone companies (RBOCs) in their local service area rather than in those further away. This ***familiarity bias*** by investors almost surely results in sub-optimal portfolio diversification. Presumably, investors find the effort to evaluate other utility companies too difficult or costly, relative to the comfort and familiarity of investing in the nearby firm. Another example of this same type is home-country bias, the documented fact that investors tend to over-invest in their homeland even though there are demonstrated diversification benefits of a more global approach.

These results offer strong evidence that typical investors appear to be incapable of using and assessing the relevance of *"all available and relevant information"* as the efficient markets hypothesis would assume, and suggests that some investors hold suboptimal portfolios as a result. A final example is unusually dramatic, and suggests that these processing effects can also have large effects on market prices. Cooper, Dimitrov, and Rau (2000) find that investors revalued companies upward by about 80% in a 11-day window around the announcement of the name change when they simply changed their name to include ".com" in 1998-1999. This evidence suggests that investors are unable to "see through" window dressing by the firm managers.

Other evidence suggests that investors mimic or infer new information from the trading of others. At least two scenarios make this result plausible. If some investors acquire information ahead of most investors, they may attempt to beat the crowd in trading before everyone else. Later investors will infer from the changing prices that they have missed valuable information and "jump on board" with further trades. Alternatively, but leading to the same result, some investors may engage in costly activities to ferret out valuable information, and other investors for whom information collection is more costly may attempt to infer the value of the other people's information and then trade in the same direction. These scenarios, which may be called ***cascade effects***, suggest a noisier or, at least, less perfect information dissemination environment than assumed in the purest form of the efficient market hypothesis.

What impact does this have on price formation, i.e. the way in which prices change? Certainly, market prices will not occur with the abrupt changes in valuation when new news is released as in the hypothetical Figure 1 price chart previously. We do not completely understand how information "flows" into stock prices when market participants are watching and keying on other participants' actions. However, we observe in informational event study research that there are some commonalties that indicate how markets "absorb" new information.

A large body of literature now suggests that the prevalent tendency of markets is to under-react to new fundamental information like earnings announcements, dividend changes, stock repurchases, and recommendations by sell-side analysts.[11] This "underreaction" appears to create subsequent and predictable price momentum or "drift" in the same direction as the original announcement return after these well-defined information events. In effect, returns adjust more slowly than if all investors were involved in the valuation calculus as rapidly as information is disseminated.

8. Analytic Models of Behavioral Finance

Economists often attempt to understand the financial environment by creating mathematical models that simplify and approximate the real-world. From these models we hopefully isolate and understand better the driving forces in financial decision making, and extrapolate to forecast behavior in a variety of situations. The last half of the 1990s saw the development of a fresh new set of psychology-based asset pricing models designed to explain the complex set of anomalies uncovered in empirical behavioral finance research. These models serve as a complement to the models discussed in Section 3.2, which study and justify the argument that the presence of arbitrageurs cannot eliminate all of the mispricing effects brought about by behavioral biases. These models therefore assume that mispricing will not be fully eliminated, and thus try to explain the *direction* of the price effects that will result from behavioral biases.

As discussed earlier in this chapter, there is now a considerable body of empirical evidence inconsistent with fully rational models of asset pricing. Among the strongest of these anomalies are: (1) the size effect, (2) the book-to-market effect, (3) the momentum effect, and (4) the reversal effect. The size effect is the anomaly that a diversified portfolio of small market-capitalization firms has historically outperformed a

[11] See Ikenberry and Ramnath (2000) for a survey of the underreaction phenomenon and Bernard (1991), Michaely, Thaler, and Womack (1995), Ikenberry, Lakonishok and Vermaelen (1995), and Womack (1996) for specific details on the four types of events mentioned.

diversified portfolio of large market-capitalization firms. Similarly, the book-to-market and momentum anomalies are the empirical findings that high book-to-market (or low market-to-book) stocks outperform low book-to-market portfolios, and high momentum portfolios outperform low momentum portfolios. Here, momentum is defined as the prior six-months to one-year return of the stock. Another anomaly which finds considerable empirical support is the reversal effect: this is the empirical observation that stocks which have performed well in the past 3-5 years do poorly in the future (and vice-versa).[12]

A portfolio designed to exploit these effects would have earned unusually high returns relative to the apparent risk. Moreover, recent studies have shown that these high returns are not unique to U.S. stock markets, or to the time periods in which they were initially uncovered.[13] Researchers (see, especially Fama and French (1993, 1996)) have attempted to explain the higher returns of these portfolios as a risk premia. However, these risk-based hypotheses would predict that the returns to these strategies should be highly correlated with movements in risk-based macroeconomic variables. So far, the evidence is not convincing that macro variables explain these return differentials.

Because of this inconsistency with rational models, researchers have attempted to explain these anomalies with behaviorally-based theories. However, according to Fama, the interpretations given to this evidence can appear contradictory. For example, the momentum effect is often interpreted as evidence of under-under-reaction, while the size and book to market effects are interpreted as evidence of over-reaction. As Eugene Fama, an eloquent defender of the efficient markets paradigm, has pointed out, the usefulness of a model depends on its descriptive and predictive ability. He states that:

> {in the behavioral literature] ... [a]pparent anomalies argue that one at a time, and the same authors, examining different events, seemed content

[12] See De Bondt and Thaler (1985, 1987)
[13] See Daniel, Hirshleifer, Subrahmanyam (1998) for a summary of the empirical literature, and for an extensive list of citations

> with over-reaction or under-reaction and willing to infer that both warrant cropping market efficiency (Fama, 1998)

In other words, he argues, finding evidence inconsistent with the rational expectations model does not mean that the rational expectations model is a bad model. It is important to keep in mind that every model in the social sciences is a simple approximation to a very complex world, and hence is undoubtedly "incorrect" at some level. To invalidate the efficient markets model, Fama claims, an alternative model must be proposed to which does a better job explaining the world than does the efficient markets model:

> The alternative [to market efficiency] has a daunting task. It must specify what it is about investors psychology that causes simultaneous under-reaction to some types of events and over-reaction to others. The alternative must also explain the range of observed results better than the simple market efficiency story. (Fama, 1998)

In response to Fama's criticism, and others like it, a several researchers have begun to develop new models based on investors psychology which to attempt to explain the range of observed results, and which offer new, testable, empirical predictions. We will discuss here the models proposed by Barberis, Shleifer and Vishny (BSV, 1998), Hong and Stein (HS, 1999), and lastly that of Daniel, Hirshleifer, and Subramanyam (DHS, 1998, 2000). All three attempt to explain the puzzling, simultaneous presence of short-horizon momentum (apparent underreaction), and long-horizon reversals (apparent overreaction). In addition, the DHS papers attempt to indentify and explain several other security price regularities, as discussed below.

The model of Barberis, Shleifer and Vishny (BSV)(1998) tries to model the two behavioral phenomena of *conservatism* and *representativeness*. To understand the effects of conservatism and representativeness in their model, consider the following setting: assume that a particular firm could be either a “low-growth" or a "high-growth" firm. If it is a high growth firm, its earnings have a 60% probability of going up each quarter, but if it is low growth firm this number is only 40%. Also, assume that initially there is a 50-50 chance that the firm is high or low. Now, if the firms' earnings do grow in the first quarter, and investors do correct Bayesian updating, they will shift toward the "high growth" belief by just the right amount, to a 60% probability that the firm is high. However, in the BSV model, the conservatism bias causes investors to overweight their prior beliefs and therefore underreact to this new information. As a result of the conservatism bias, investors might change the assessed probability that the firm is high to only 55%. Thus the firm's share price underreacts to this good earnings news (and to other information releases) at short horizons, which also results in stock return momentum.

However, the BSV model also tries to explain the representativeness bias. Continuing with the example from the last paragraph, assume that this firms' earnings continue to grow for another two consecutive quarters (for a total of 3). In the BSV model, given this longer string of earnings increases, representativeness comes into play. Investors will view this longer string of earnings increases as far more likely to have come from the high-growth firm, and hence will shift their priors toward the firm being high-growth far more than they should. For this example, the correct probability that the firm is high is about 75%, but investors will believe that it is far higher. Thus, investors will *overreact* to the information in this longer string of increases, pushing up the stock price too far, resulting in mean reversion later. This later prediction is thus consistent with long-run reversals and the familiar book to market effect.

The Hong and Stein (1999) model is different from the BSV and DHS models (which we will discuss shortly) in that it describes (1) the interaction of *two* different types of irrational agents and (2) the slow diffusion of information that result in short-term underreaction and long-term overreaction. They assume all agents are either "news-watchers" or "trend-chasers." The news-watchers learn information about security values and trade on this information, but don't watch and extract information from security prices (as a rational agent should). Hence, since the news-watchers learn information about firms at different times, and the price rise in response to a single piece of information will be slow, leading to momentum.

The trend-chasers in the HS model trade on and exacerbate the momentum generated by the behavior of news-watchers. However, more importantly, these momentum traders (effectively) assume that any momentum will continue indefinitely. Hence, they continue pushing up the price of a security even when the price is above the fundamental value, resulting in overreaction and (eventual) correction.

The model explored in Daniel, Hirshleifer, and Subramanyam (DHS, 1998, 2000) is an attempt to explain a somewhat wider range of anomalies with a parsimonious behavioral model. In addition to the (1) size and book-to-market effects (and other price-scaled variable effects), (2) the momentum effect, and (3) the reversal effect, the DHS model also attempts to explain (4) the consistent underreaction to public information releases,[14] and, in DHS (2000), (5) the weak relation between standard measures of risk (such as the CAPM beta) and return, after controlling for characteristics such as size and book-to-market.

The DHS model is based on the single behavioral phenomenon of overconfidence. As noted by De Bondt and Thaler (1995), "... perhaps the most robust finding in the psychology of judgment is that people are overconfident." As we discussed in Section 6 of this Chapter, people perceive themselves as more able to the actually are, more able than average, and more favorably than others view them. Most importantly for the DHS model, individuals underestimate their prediction error variance in experimental settings. For example, Christensen-Szalanski and Bushyhead (1981) presented physicians with a set of patient symptoms, and asked them to determine what illness was causing these symptoms. The physicians gave their prognosis. The physicians were then asked what the likelihood was that their prognosis

[14] DHS (1998) show that the empirical results documented in the finance literature are consistent with underreaction to public news events in the case of seasoned offerings, repurchase announcements, insider

was correct. The average prediction was higher than the actual success rate -- this, and a number of other experiments, are consistent with the interpretation that the physicians were overconfident in their ability to make an accurate diagnosis, and hence underestimated the prediction error variance.

In the simplest version of the DHS model, there are analysts/investors who collect information and then process this information to come up with private information or “signals” of security value. As with the physicians, the overconfident investors in DHS overestimate the precision of the estimates that they generate. The key result from the DHS model is that investors will therefore overreact to private information, and underreact to public information. Both phenomena are a direct result of investors placing too much weight on private information relative to public information. This constant overconfidence model is consistent with effects 1, 3, 4 and 5 above -- that is, all but the momentum effect.

The momentum effect is not be explained within the simple static overconfidence model of DHS. But DHS point out that agents’ level of overconfidence is not static. Rather, investors continually update their estimate of the quality of the information they have generated. Most importantly for the DHS model, they do this updating in a biased fashion, consistent with behavioral biases. Specifically, they exhibit "self-attribution bias," which basically means that they overweight information that is consistent with their views, or consistent with their having superior talent, and so they underweight inconsistent information.

A good example of self-attribution bias comes from a study done by Lord, Ross, and Lepper (1979). In this study, a number of subjects were surveyed on their beliefs about whether the death penalty was an effective deterrent to crime. Then, the researchers selected a set of subjects who had moderate views on this issue. These subjects were given a set of studies to read through. These studies presented evidence

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trade announcements, analysts’ buy and sell recommendataions, stock splits, divdiend initiations and on the question of whether the death penalty was an effective deterrent to crime; some results were consistent and some were inconsistent with this view. After looking through these studies, the subjects were asked how their views on the death penalty had changed. Interestingly, their views became more polarized. That is, those who had previously believed that the death penalty was an effective deterrent became even more convinced this was the case, and *vice versa*. Had these subjects been doing standard Bayesian updating (see Section 2 of this Chapter) their views should have converged rather than diverged. Instead, the subjects placed more weight on the studies that were consistent with their prior beliefs, and discounted the findings which were inconsistent with their priors.

In the DHS model, self-attribution bias results in investors becoming more confident about their signal over time, on average. Imagine an investor who gathers information, processes it, and forms a positive view about the valuation of a firm. The investor initially places too much weight on this information, and hence pushes the price up too high.[15] Moreover, subsequent to this process, the investor receives new public information about the firm value, such as earnings, or other announcements by the firm's management. This information is unbiased. But, since this investor *interprets* information inconsistent with his views as being of poor quality, and information consistent with his views as high quality, on average he will become more overconfident. Therefore he will start putting even more weight on his private signal, thus pushing the price up even further. This results in stock price momentum. In contrast to the standard interpretation of momentum as underreaction, the DHS claim that momentum is instead a process of *continuing overreaction*. In recent work, Jegadeesh and Titman (1999), find evidence consistent with this interpretation. They

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omissions, merger announcements, and venture capital distributions. See DHS (1998) for citations.

[15] Actually, there is no reason that they might not react correctly or even initally underreact to their information. The behavioral evidence is consistent with people being overconfident *on average*. It could be that investors begin underconfident, and then through self-attribution bias become overconfident over time.

find that portfolios of high-momentum stocks perform well for about 1-1.5 years after the portfolio formation date, but after 3 years the prices of these portfolios start to decline.

What is necessary for the progress of behavioral finance to mature as a science is testing, verification, and potentially modification of these models and others like them. This has begun, and will undoubtedly progress in the next decade. These tests will tell whether these models can provide the predictive power that they must have to useful descriptions of the world.

These models are not the last word – they are too simple and do not incorporate enough of the obvious complexities of the real world. One of the missing ingredients from all of these models is *learning*. How learning takes place is something that none of these models has addressed. To the extent that investors learn about their behavioral biases and take actions to correct these, the resulting price effects will be mitigated. Also, if a larger class of investors learns about the effects of these biases and take actions to profit from a these effects, they will disappear. The size effect of was very strong from the mid 1920s up through the early 1980s. A set of academic articles published in 1981-83 pointed out the size effect, and since then it has declined to zero, or less. The book to market effect has perhaps also declined in magnitude since investors "learned" about it. It became a subject of intense discussion following the papers of Fama and French (1992, 1993) and Lakonishok, Shleifer, and Vishny (1994). The two years 1998-99 have been the two worst consecutive years for the book to market effect since at least 1928. However, other more complicated strategies involving book to market and momentum appear to have been more persistent (see Daniel and Titman (1999).)

9. Summary and Conclusions

The earliest models of modern, "rational" finance in the 1960s and 1970s delivered a series of predictions based on the theories of rational expectations and efficient markets. These straight-forward assumptions are inherently logical and reasonable, but have, with more recent further examination, been shown to be systematically biased. Modern finance is normative, but it is not fully descriptive. It is not that modern finance is "wrong", it is that it is incomplete.

One key reason for increasing our understanding of behavioral decision traits is to recognize and embrace the reality that most financial decisions are made by human subjects, replete with their cognitive limitations. Decision makers in a non-behavioral framework are theoretically asked to determine the accuracy, credibility, and relevance of dozens if not thousands of information sources, and to do it rapidly and without bias. Not surprisingly, the amount of information processing needed to make perfectly rational and unbiased decisions strains credibility. So, as discussed, the natural response of decision makers is to take shortcuts, creating heuristics to simplify and shorten the decision process.

Shortcuts, however, often lead to biased decisions. The typical decision maker's decisions are *approximately* right, but *predictably and slightly* wrong. By understanding these psychological divergences from "rational" choice models, we may be more accurate in predicting what financial decision makers will do prospectively.

Behavioral finance as a sub-field of finance seeks to move our understanding of financial decision making to higher ground that is more descriptively accurate than that obtained by rational models alone.

Bibliography

Arrow, Kenneth, 1987, Rationality of Self and Others in and Economic System, published in *Rational Choice: The Contrast between Economics and Psychology*, edited by Robin M. Hogarth and Melvin W. Reder, University of Chicago Press, 200-215.

Barber, Brad M. and Terrance Odean, 1999, Boys will be Boys: Gender, Overconfidence, and Common Stock Invesment, University of California, Davis Working Paper.

Barberis, Nicholas, Andrei Shleifer and Robert Vishny, 1998, A Model of Investor Sentiment, *Journal of Financial Economics* 49, 307-343.

Bernard, Victor, 1991, Stock Price Reactions to Earnings Announcements: A Summary of Recent Anomalous Evidence and Possible Explanations, *Advances in Behavioral Finance*, Russell Sage Foundation Press

Begg, David K. H., 1982, *The Rational Expectations Revolution in Macroeconomics: Theories and Evidence*, Baltimore: The Johns Hopkins University Press.

Bernarzi, Shlomo, and Richard Thaler, 1997, Myopic Loss Aversion and the Equity Premium Puzzle, *Quarterly Journal of Economics* 110, 73-92.

Bernarzi, Shlomo, and Richard Thaler, 2000, Naïve Diversification Strategies in Defined Contribution Saving Plans, forthcoming *American Economic Review*.

Christensen-Szalanski, Jay J. and James B. Bushyhead, 1981, Physicians' Use of Probabilistic Information in a Real Clinical Setting, *Journal of Experimental Psychology: Human Perception and Performance* 7, 928-935

Cooper, Michael, Orlin Dimitrov, and P. Raghavendra Rau, 2000, A Rose.com by any Other Name, Working Paper, Purdue University.

Daniel, Kent D., David Hirshleifer and Avanidhar Subrahmanyam, 1998, Investor Psychology and Security Market Under- and Over-reactions, *Journal of Finance*, 53, 1839-1886.

Daniel, Kent D., David Hirshleifer and Avanidhar Subrahmanyam, 2000, Covariance Risk, Mispricing, and the Cross Section of Security Returns, NBER Working paper #7615, March.

Daniel, Kent D., and Sheridan Titman, 1999, Market Efficiency in an Irrational World, *Financial Analysts' Journal* 55, 28-40.

De Bondt, Werner F. M., and Richard H. Thaler, 1985, Does the Stock Market Overreact?, *Journal of Finance* 40, 793-808.

De Bondt, Werner F. M., and Richard H. Thaler, 1985, Further Evidence on Stock Market Overreaction and Stock Market Seasonality, *Journal of Finance* 42, 557-581.

De Bondt, Werner F. M., and Richard H. Thaler, Financial Decision-Making in Markets and Firms: A Behavioral Perspective, in Robert A. Jarrow, Voijslav Maksimovic, and William T. Ziemba, ed.: *Finance, Handbooks in Operations Research and Management Science*, vol.9, chap.13, pp. 385--410 (North Holland: Amsterdam).

Degeorge, Francois, Jayendu Patel, and Richard Zeckhauser, 1999, Earnings Management to Exceed Thresholds, *Journal of Business* 72, 1-33.

Einhorn, Hillel J., 1980, Overconfidence in Judgment, *New Directions for Methodology of Social and Behavioral Science*, 4, 1-16.

Fama, Eugene F., 1970, Efficient Capital Markets: A Review of Theory and Empirical Work, *Journal of Finance* 25, 383-417.

Fama, Eugene F., 1998, Market Efficiency, Long-Term Returns and Behavioral Finance, *Journal of Financial Economics*, 49

Fama, Eugene F. and Kenneth R. French, 1993, Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics* 33, 3-56.

Fama, Eugene F. and Kenneth R. French, 1996, Multifactor Explanations of Asset Pricing Anomalies, *Journal of Finance*, 51, 55-84.

Freidman, Milton, 1953, The Case for Flexible Exchange Rates, in *Essays in Positive Economics*. Chicago : University of Chicago Press..

Freidman, Milton, and xxx Savage, 1948, in *Quasi-Rational Economics*, p. 21.

Griffin, Dale and Amos Tversky, 1992, The Weighing of Evidence and the Determinants of Confidence, *Cognitive Psychology* 24, 411-435.

Grossman, Sanford J. and Joseph E. Stiglitz, 1980, On the impossibility of informationally efficient markets, *American Economic Review* 70, 393-408.

Hirshleifer, David, 1999, An Adaptive Theory of Self-Deception, Ohio State University Working Paper.

Hogarth, Robin M. and Melvin W. Reder, 1986, *Rational Choice: The Contrast between Economics and Psychology*, The University of Chicago Press.

Hong, Harrison and Jeremy Stein, 1999, A Unified Theory of Underreaction, Momentum Trading and Overreaction in Asset Markets, *Journal of Finance,* 54.

Huberman, Gur. 2000. Familiarity Breeds Investment, Working Paper, Columbia University, New York, NY.

Ikenberry, David L., Josef Lakonishok, and Theo Vermaelen, 1995, MarketUnderreaction to Open Market Share Repurchases, *Journal of Financial Economics* 39, 181-208.

Ikenberry, David L., and Sundaresh Ramnath, 2000, Underreaction, Working Paper, Rice University.

Kahneman, Daniel, and Dan Lovallo, 1993, Timid Choices and Bold Forecasts: A Cognitive Perspective on Risk Taking, *Management Science* 39, 17-31.

Kahneman, Daniel, and Amos Tversky, 1979, Prospect Theory: An Analysis of Decision Under Risk, *Econometrica*, 47, 263-291.

Kahneman, Daniel, and Amos Tversky, 1981, The Framing of Decisions and the Psychology of Choice, *Science*, January 30, 453-458.

Kahneman, Daniel, and Amos Tversky, 1982, *Judgment Under Uncertainty: Heuristics and Biases*. New York: Cambridge University Press.

Klibanoff, Peter, Owen Lamont and Thierry A. Wizman, 1998, Investor Reaction to Salient News in Closed-End Country Funds, Journal of Finance 53, 673-699.

Jegadeesh, Narasimhan and Sheridan Titman, 1999, Profitability of Momentum Strategies: An Evaluation of Alternative Explanations, NBER working paper #7159.

Keren, H. H., 1987, Facing Uncertainty in the Game of Bridge: A Calibration Study, *Organizational Behavior and Human Decision Processes*, 39, 98-114.

Lichtenstein, Sarah and Baruch Fischhoff ,1977, Do Those Who Know More Also Know More About How Much They Know? *Organizational Behavior and Human Performance*, 20, 159-183.

Lichtenstein, Sarah and Baruch Fischhoff ,1980, Training for Calibration *Organizational Behavior and Human Performance*, 26,149-171.

Lord, Charles G. and Lee Ross and Mark R. Lepper, 1979, Biased Assimilation and Attitude Polarization: The Effects of Prior Theories on Subsequently Considered Evidence, *Journal of Personality and Social Psychology*, 37, 2098-2109.

Lucas, Robert E. Jr., 1976, Econometric Policy Evaluation: A Critique, in Karl Brunner and Allan H. Meltzer (eds.) *The Phillips Curve and Labor Markets*, pp. 19-46, Carnegie Rochester Conference Series on Public Policy, vol. 1, (North-Holland: Amsterdam).

Lucas, Robert E. Jr,. and Thomas J. Sargent, 1981 Rational Expectations and Econometric Practice, introductory essay in R.E. Lucas Jr. and Thomas J. Sargent, eds., *Rational Expectations and Econometric Practice*, (University of Minnesota Press:Minneapolis).

Michaely, Roni, Richard H. Thaler, and Kent L. Womack, Price Reactions to Dividend Initiations and Omissions: Overreaction or Drift? *Journal of Finance* 50, 573-608.

Miller, Merton, quoted in “Mind Over Matter”, *The Economist*, April 23, 1994, V 331, 73.

Odean, Terrance, 1998, Are Investors Reluctant to Realize Their Losses?, *Journal of Finance* 53, 1775-1798.

Plous, Scott, 1993, *The Psychology of Judgment and Decision Making*, New York: McGraw Hill.

Schoemaker, Paul J. H., 1982, The Expected Utility Model: Its Variants, Purposes, Evidence and Limitations, *Journal of Economic Literature*, 20, 529-563.

Shleifer, Andrei and Robert Vishny,, 1997, The Limits to Arbitrage, *Journal of Finance* 52, 35-55

Shleifer, Andrei, 2000, *Inefficient Markets: An Introduction to Behavioral Finance*, Oxford University Press.

Shefrin, Hersh, 2000, *Beyond Greed and Fear: Understanding Behavioral Finance and the Psychology of Investing*, Boston: Harvard Business School Press.

Shefrin, Hersh, and Meir Statman. 1985. The Disposition to Sell Winners Too Early and Ride Loser Too Long: Theory and Evidence, *Journal of Finance* 40, 777-790.

Simon, Herbert A., 1982, *Models of Bounded Rationality*, Cambridge: MIT Press.

Statman, Meir, 1999, Behavioral Finance: Past Answers and Future Questions, *Financial Analysts Journal* 55, 18-27.

Summers, Lawrence H., 1985,. On Economics and Finance, *Journal of Finance* 40, 633-635.

Thaler, Richard H., 1987, The Psychology of Choice and The Assumptions of Economics, in *Laboratory Experimentation in Economics: Six Points of View*, Cambridge: Cambridge University Press.

Thaler, Richard H., ed., 1993, *Advances in Behavioral Finance*, Russell Sage Foundation

Thaler, Richard, and Eric Johnson, 1991. Gambling with the House Money and Trying to Break Even: The Effects of Prior Outcomes on Risky Choice. In *Quasi-Rational Economics*, edited by Richard Thaler, 48-73. New York: Russell Sage Foundation.

Von-Neumann, J. and O. Morgenstern, 1944, *Theory of Games and Economic Behavior*, Princeton, N.J.: Princeton University Press.

Waldman, Michael, 1994, Systematic Errors and the Theory of Natural Selection, American Economic Review 84, 482-497.

Womack, Kent L., 1996, Do Brokerage Analysts' Recommendations Have Investment Value? *Journal of Finance* 51, 137-167.

Figure 1—Market Efficiency and The Arrival of Information

This hypothetical stock, which begins trading in the Figure 1 at time A and is fairly valued, increases consistently at its fair rate of return relative to its risk until time B when new good news arrives. The stock immediately adjusts to reflect the value change in the news, and then continues to appreciate at its fair rate of return. At time C, bad news is announced, which drops the stock price significantly. Suppose that this bad news also signals an increase in the risk of the company. The stock will appreciate at a higher rate per unit of time after C to satisfy rational investors who demand more return for taking more risk.

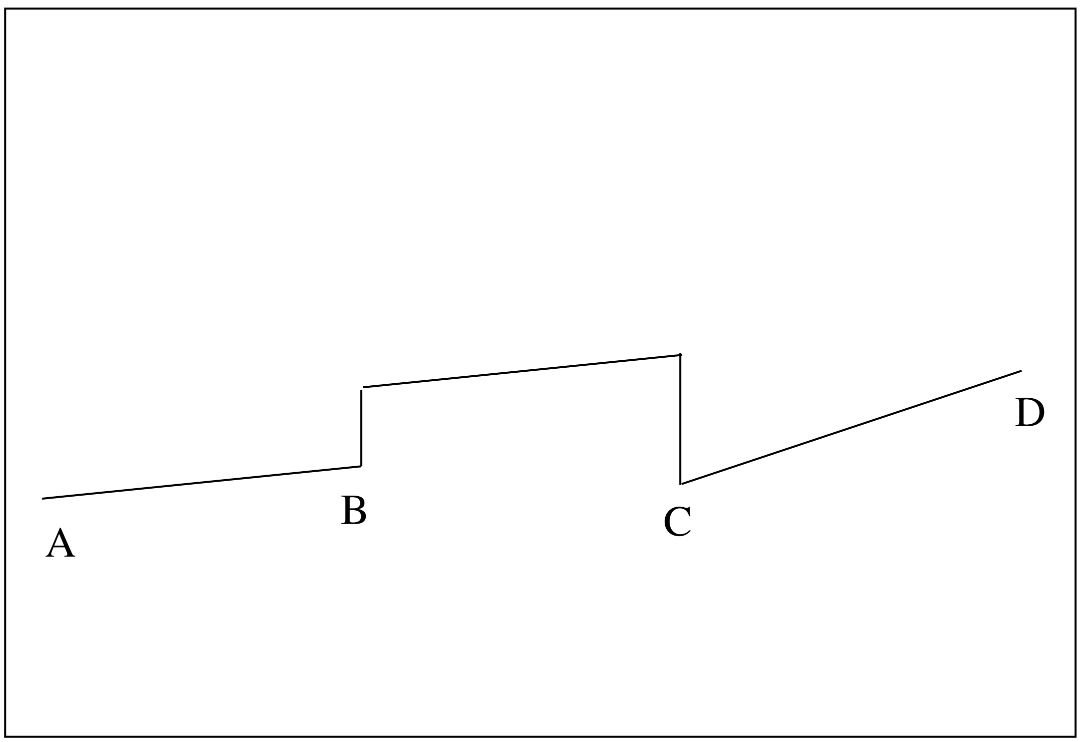

Figure 2—Prospect Theory Value Function

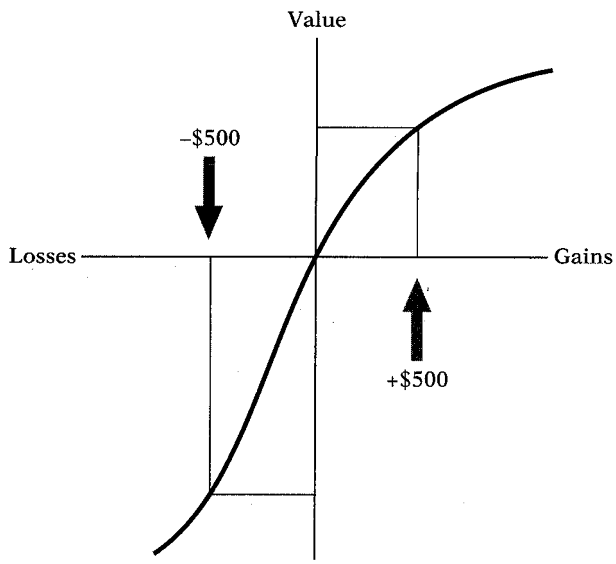

Figure 3—The Conjunction Fallacy

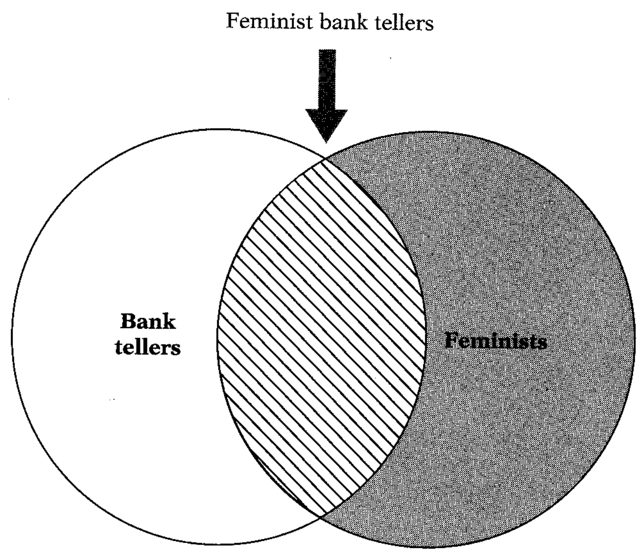

Figure 4—Quarterly Earnings versus Year Ago

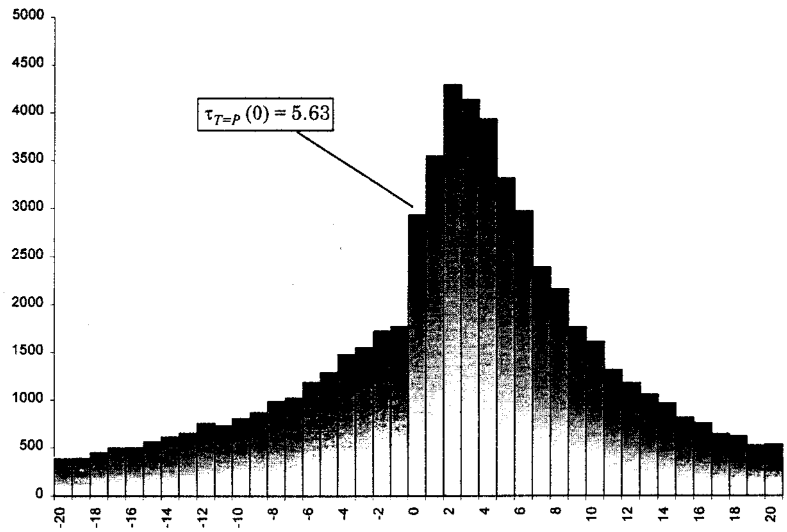

FIG. 5.—Histogram of change in EPS ($\Delta EPS = EPS_t - EPS_{t-4}$): exploring the threshold of "sustain recent performance."