Examining Financial Puzzles From An Evolutionary Perspective

by

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Abstract

In this thesis, we examine some puzzles in finance from an evolutionary perspective. We first provide a literature review of evolutionary psychology, and discuss three main findings; the frequentist hypothesis, applications from risk-sensitive optimal foraging theory, and the cheater detection hypothesis. Next we introduce some of the most-researched puzzles in the finance literature. Examples include overreaction, loss aversion, and the equity premium puzzle. Following this, we discuss risk-sensitive optimal foraging theory further and examine some of the financial puzzles using the framework of risk-sensitive foraging. Finally, we develop a dynamic patch selection model which gives the patch selection strategy that maximizes an organism's long-run probability of survival. It is from this optimal patch strategy that we observe loss aversion. Throughout the thesis, we stress the following: humans' behavior in financial markets is neither inherently irrational, nor is it rational. Rather the puzzles occur as a consequence of evolutionarily-optimal cognitive mechanisms being utilized in environments other than the ancestral domain in which they evolved to adapt in.

Thesis Supervisor: Andrew W. Lo
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Chapter 1

Introduction

1.1 The "Heuristics and Biases" Program and Evolutionary Psychology Reconciled

Mainstream economics assumes that in decision-making under uncertainty, an individual is rational. Consequently, given a set of choices and probabilistic beliefs on these choices, a person rationally selects the option that maximizes his/her expected utility. However, research on human decision-making in the 1970s suggested otherwise; researchers were able show instances in which human decision-making systematically deviated from normative standards of rationality. This eventually gave rise to the "heuristics and biases" program. Continued research in the 1970s and 1980s resulted in hypotheses such as base-rate neglect [17], the conjunction fallacy [53], the ambiguity effect [14], and the framing effect [52] to name a few. The large number of instances of systematic deviation from rationality appeared to paint a bleak picture of human cognitive decision-making mechanisms.

However, evolutionary psychology, which emerged in the early 1990s, painted a picture of human rationality different from that of the "heuristics and biases" program. Drawing on arguments such as competition, and natural selection in human evolution, evolutionary psychologists examined some of the instances of human irrationality documented by the "heuristics and biases" program, and were able to elicit rational responses from subjects. These findings appeared to put evolutionary psychology in direct conflict with the central theme of the "heuristics and biases" program.

More recently, philosophers such as Richard Samuels, Stephen Stich, and Michael Bishop [44] have attempted to reconcile the apparent conflict between evolutionary psychology and the "heuristics and biases" program. They argue that both schools of thought are complementary; humans' cognitive mechanisms are rational in solving adaptive problems in the environment in which humans evolved. The instances of departures from rationality described in the "heuristics and biases" literature are a result of these evolutionarily-rational cognitive mechanisms being used out of their evolutionary context, and the rationality argued by evolutionary psychologists is a consequence of considering these same instances in the evolutionary domain.

1.2 Thesis Motivation

Much like economics, the literature in finance has also documented various instances in which observed behavior in financial markets deviate from that predicted by standard finance theory, with overreaction [15], loss aversion and the disposition effect [49], and the equity premium puzzle [38] to name a few. In this thesis, we adopt the approach of evolutionary psychology to examine some of these financial puzzles. Essentially, we recast the puzzles in the environment in which humans evolved, and argue rationality in this domain. However, we hasten to conclude human rationality in general. Rather, we argue human rationality in the evolutionary domain, and furthermore, that these puzzles are a result of the evolutionarily-rational mechanisms being taken out of the domain in which they evolved to adapt in.

1.3 Thesis Outline

The next chapter is a literature review of evolutionary psychology, discussing its main ideas and findings thus far. Chapter 3 introduces some of the most-researched puzzles in finance. In Chapter 4, we examine the puzzles using the risk-sensitive optimal foraging framework in an attempt to rationalize them by casting them back in their evolutionary domain. We introduce a dynamic patch selection model in Chapter 5 where loss aversion can be observed in the survival-maximizing patch selection strategy. Chapter 6 reiterates some of the main themes of the thesis and concludes.

Chapter 2

Evolutionary Psychology

2.1 Background

Evolutionary psychology is an approach to psychology applying concepts from evolutionary biology such as natural selection and competition. Contrary to conventional orthodoxy which views the human brain as a small collection of general-purpose and domain-general mechanisms governing learning and reasoning, evolutionary psychology views the human brain as a large collection of functionally-specific and domain-specific mechanisms, each adept at solving an adaptive problem that our ancestors faced during our species' evolutionary history [13].

From the perspective of evolutionary psychology, our neural mechanisms were designed by natural selection. Nature selected these mechanisms because they were better at solving adaptive problems than alternative mechanisms were. Consequently, the higher survival and reproduction rates of these mechanisms eliminated other alternatives.

Oftentimes, evolutionary psychology is viewed as being in conflict with the "heuristics and biases" program. This conflict is due in part to the research of the former, which often takes biases documented in the "heuristics and biases" literature, casts them in an evolutionary context, and seeks to rationalize them. Hence, while the "heuristics and biases" program focuses on systematic departures from human rationality and argues for human irrationality, evolutionary psychology in contrast argues for human rationality in the evolutionary domain.

However, in recent years, philosophers have argued that evolutionary psychology and the "heuristics and biases" program are complementary [34], [43], [44]. These philosophers contend that the heuristics used by humans yield approximately optimal solutions in the environment in which humans evolved, but cause the systematic biases observed by the "heuristics and biases" program when taken out of their evolutionary context. Similarly, we argue that the financial puzzles discussed in the next chapter result from evolutionarily-optimal heuristics operating in an environment in which they were not evolved to adapt.

In the remainder of this chapter, we examine the frequentist hypothesis, risk-sensitive optimal foraging theory, and the cheater detection hypothesis, show how they lead to systematic biases when taken out of the evolutionary domain, and then how these biases can be rationalized from the perspective of evolutionary psychology.

2.2 The Frequentist Hypothesis

Essentially, the frequentist hypothesis posits that our reasoning mechanisms take natural frequencies as input and produce natural frequencies as output. Cosmides and Tooby [12] contend that in ancestral environments, the only information available from which to reason inductively was from one's own observations, and those communicated by the handful of other individuals with whom one lived. Consequently, our ancestors could not observe the probability of a single event, which either happened or did not happen. Instead, what our ancestors could observe were encountered frequencies of actual events – for instance, that we could find food six of the last ten times we hunted on a particular resource patch. As a result, if humans had mechanisms for inductive reasoning, one might expect these mechanisms to receive natural frequencies as input. Gigerenzer [24] makes a similar argument, postulating the human mind as an "intuitive frequentist."

Given that humans' reasoning mechanisms process information in terms of natural frequencies, we discuss three biases from the "heuristics and biases" literature – base-rate neglect, the conjunction fallacy, and overconfidence – and show how they can be rationalized when considered from an evolutionary perspective.

2.2.1 Bayesian Reasoning and Base-Rate Neglect

In 1978, Casscells, Schoenberger and Graboys [11] presented the following problem to 60 students and staff from Harvard Medical School.

> If a test to detect a disease whose prevalence is 1/1000 has a false positive rate of 5%, what is the chance that a person found to have a positive result actually has the disease, assuming you know nothing about the person's symptoms or signs?

Almost half of the subjects judged the probability that the person actually had the disease to be 0.95. The mean answer was 0.56, and only 18% of the participants responded 0.02, which is the normatively correct answer obtained from applying Bayes' rule. Consequently, it was concluded that subjects seemed to ignore the base rate when computing their answers and researchers used "base-rate neglect" to describe this phenomenon. Base-rate neglect appeared to suggest that humans were unable to reason probabilistically using Bayes' rule. These results were replicated in further studies [3], [17].

With their view of the human mind as a frequentist, Cosmides and Tooby [12] asserted that in the original study carried out by Casscells, Schoenberger and Graboys, the subjects' apparent inability to engage in Bayesian reasoning stemmed not from the absence of probabilistic reasoning mechanisms in the human mind. Rather, it occurred because these mechanisms were not evolved to take percentages as input. They replicated Casscells' original study, but with the problem phrased in terms of natural frequencies. The following question appeared in their study:

> 1 out of every 1000 Americans has disease X. A test has been developed to detect when a person has disease X. Every time the test is given to a person who has the disease, the test comes out positive (i.e., the "true positive" rate is 100%). But sometimes the test also comes out positive when it is given to a person who is completely healthy.

> Specifically, out of every 1000 people who are perfectly healthy, 50 of them test positive for the disease (i.e., the "false positive" rate is 5%).
>
> Imagine that we have assembled a random sample of 1000 Americans. They were selected by lottery. Those who conducted the lottery had no information about the health status of any of these people.
>
> Given the information above, on average, how many people who test positive for the disease will actually have the disease? _________ out of _______ .

Cosmides and Tooby found that by recasting the problem in frequencies, the number of people who exhibited Bayesian reasoning significantly increased to 76% compared to 12% in the original non-frequentist version of the same problem. Furthermore, by requiring the subjects to create a concrete, visual frequentist representation of the problem, the number of subjects who reasoned by applying Bayes' rule increased to 92%.

A similar study by Gigerenzer and Hoffrage [26] found that expressing problems in natural frequencies produced a significant increase in Bayesian reasoning from 16% to 50%. More recently, Zhu and Gigerenzer [57] conducted two similar experiments on children in China who had never been exposed to Bayes' rule, percentages, and probability theory. They found that while none of the children from fourth through sixth grades could carry out Bayesian reasoning when the problems were phrased in terms of probabilities, their performance improved to an average of 19%, 39% and 53% amongst the fourth, fifth, and sixth graders respectively when the same problems were presented in natural frequencies. Based on the results of their study, Zhu and Gigerenzer argued that it was further evidence that our probabilistic cognitive mechanisms evolved to process natural frequencies.

2.2.2 The Conjunction Fallacy

The original demonstration of the conjunction fallacy was done by Tversky and Kahneman [53] with problems of the following kind:

> Linda is 31 years old, single, outspoken and very bright. She majored in philosophy. As a student, she was deeply concerned with issues of discrimination and social justice, and also participated in antinuclear demonstrations.
>
> Which is more probable?
> (a) Linda is a bank teller.
> (b) Linda is a bank teller and is active in the feminist movement.

85% of the 142 subjects chose (b). Kahneman and Tversky argued that this was a violation of the laws of probability because the conjunction of two events cannot be greater than one of its constituents. Consequently, this was interpreted as an instance of human irrationality and termed the "conjunction fallacy."

Postulating the human mind as an "intuitive frequentist", Gigerenzer [24] argued that the conjunction fallacy in the Linda problem could be made to "disappear" by recasting it in natural frequencies. To substantiate his point, Gigerenzer referred to Fiedler's [20] study of the Linda problem using natural frequencies. Below is Fiedler's frequentist version of the problem.

> Linda is 31 years old, single, outspoken and very bright. She majored in philosophy. As a student, she was deeply concerned with issues of discrimination and social justice, and also participated in antinuclear demonstrations. There are 100 people who fit the description above. How many of them are:
> (a) bank tellers?
> (b) bank tellers and active in the feminist movement?

In his study, Fiedler first replicated Tversky and Kahneman's [53] results using the original formulation of the problem; 91% of the subjects judged the feminist bank teller option to be more probable than the bank teller option. However, in the frequentist version above, the number of subjects who committed the conjunction fallacy decreased significantly; only 22% of the subjects judged that there would be more feminist bank tellers than bank tellers.

2.2.3 Overconfidence

The overconfidence bias is typically studied with questions such as the following [24]:

> Which city has more inhabitants?
> (a) Hyderabad
> (b) Islamabad
>
> How confident are you that your answer is correct?
> 50% 60% 70% 80% 90% 100%

The subject chooses what he/she believes to be correct and then rates his/her confidence in the answer. After the experiment, the subjects' mean answer to the second question is compared to the relative frequency of correct answers for the first question. The overconfidence bias is the observation that the average confidence is systematically higher than the relative frequency of correct answers.

Gigerenzer [24] notes that studies reporting the overconfidence bias ask for single-event confidences. He contends that since humans' reasoning mechanisms process natural frequencies, asking for single-event confidences takes these mechanisms out of their evolutionary domain and lead to the overconfidence bias. Consequently, Gigerenzer argues that a frequentist version of the problem would cause the overconfidence bias to disappear. In a study by Gigerenzer, Hoffrage, and Kleinbolting [25], subjects were given a list of 50 questions similar to the one above. In addition to their inference and their confidence in each inference, the subjects were asked at the end of the study how many of the 50 questions they thought they got correct. In the study, the average overconfidence was 15% when single-event confidence estimates were compared to actual relative frequencies of correct answers. However, when comparing the subjects' estimated frequencies of total correct inferences to actual frequencies of total correct inferences, the overconfidence bias disappeared.

2.3 Risk-Sensitive Optimal Foraging Theory

Risk-sensitive foraging theory provides a basis for predicting the circumstances that cause organisms to avoid uncertainty and those that cause them to prefer it based on the expected payoffs, variability of expected payoffs, and the current minimum requirement [50]. Essentially, risk-sensitive foraging theory predicts the following: given two resource patches with the same mean payoff but different payoff variance, a forager ought to forage on the lower variance patch unless the minimum requirement exceeds the mean payoff of the patches. In that event, it is optimal for the forager to forage on the higher variance patch because the more variable distribution provides an increased probability of obtaining the necessary amount of food. We will discuss risk-sensitive foraging theory in further detail in Chapter 4. The remainder of this section examines the ambiguity effect, and framing and preference reversal using risk-sensitive foraging theory.

2.3.1 The Ambiguity Effect

The ambiguity effect has often been observed in studies involving questions such as the following proposed by Ellsberg [18]:

> Consider the following gamble: One box contains 50 black and 50 white balls; another box also contains 100 black and white balls but in an unknown composition. Suppose you may pick a ball from one of these boxes and receive $100 if the ball is black. Which box would you draw from?

From the perspective of expected utility theory, both options are equivalent since the probability of picking a black ball is 0.5 in both boxes. Hence, rational subjects should be indifferent between the two options. However, studies [10], [14] have shown that a majority of the subjects prefer the 50/50 box, suggesting that subjects prefer options in which information on probabilities are explicitly stated over options in which probability information is missing. This preference for options with explicitly stated probabilities is the "ambiguity effect."

Rode, Cosmides, Hell, and Tooby [41] contend that in the original studies of the ambiguity effect, people attended to the fact that the unknown probability parameters indicated that the expected payoff of the ambiguous option was highly variable. Consequently, even though the two options had the same expected payoff, they were not equivalent. Therefore, risk-sensitive foraging theory predicts that the subjects should choose the unambiguous option. Examined in the context of risk-sensitive foraging theory, they argue that the ambiguity effect is not evidence of human irrationality, but rather proof of a highly elegant mechanism for decision-making in uncertain environments.

2.3.2 Framing and Preference Reversal

A demonstration of the framing effect was provided by Tversky and Kahneman [52] in a study using a problem known as the Asian disease problem. The Asian disease problem involves a hypothetical group of 600 anonymous people infected by a fatal disease. The subjects are asked to evaluate two alternative medical plans to rescue the infected people. Plan A is a sure thing, while Plan B is a gamble of equivalent expected payoff. The two plans are framed either under a positive or negative framing condition. In the positive framing condition, the outcomes are phrased in terms of lives saved; in Plan A, one-third of the lives will be saved for sure, while in Plan B, there is a one-third probability that all the patients will be saved and two-thirds probability that none will be saved. In the negative framing condition, the outcomes are framed in terms of lives lost; in Plan A, two-thirds of the people will die for sure, while in Plan B, there is a one-third chance that none of the patients will die, and two-thirds probability that everyone will die.

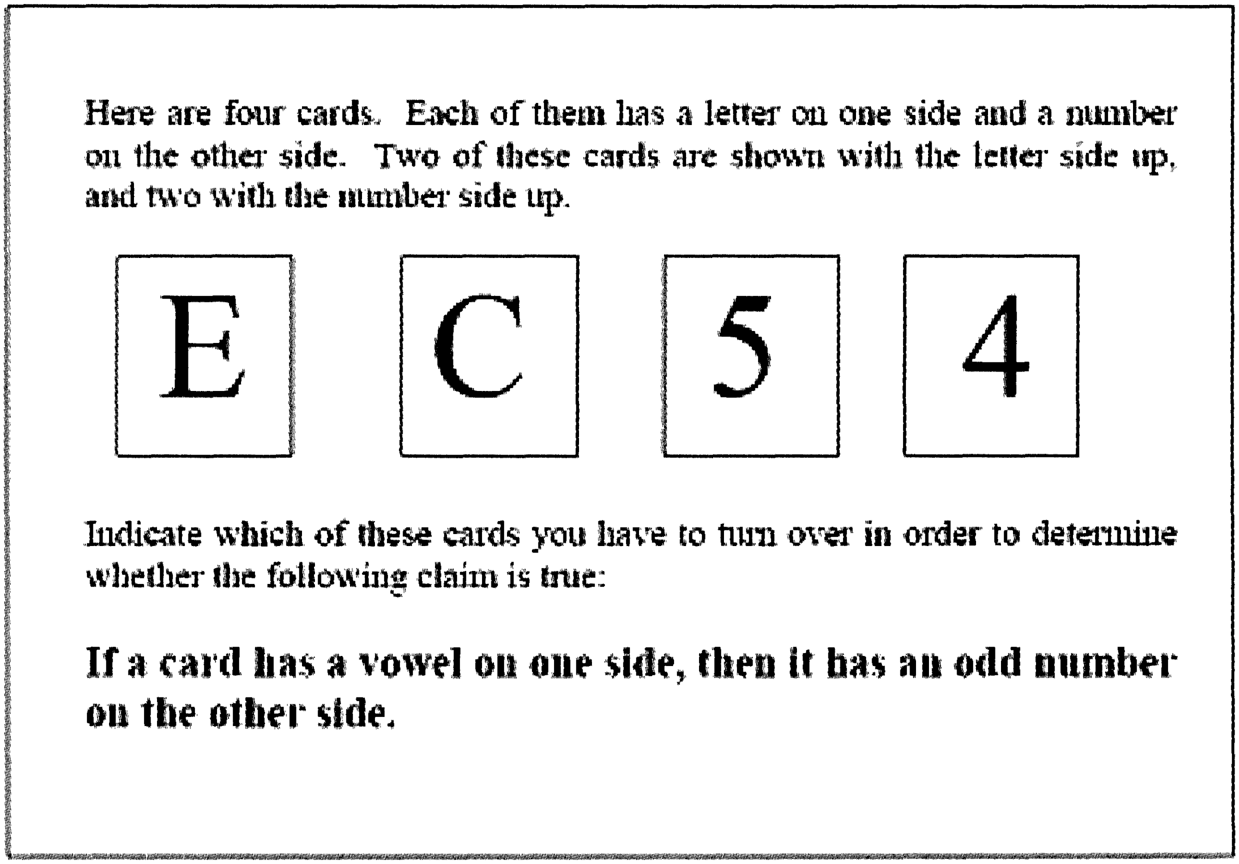
Tversky and Kahneman demonstrated a preference reversal as a result of how the problem was framed. In the positive framing condition, 72% of the subjects preferred the sure outcome (Plan A) to the gamble (Plan B). However, in the negative framing condition, 78% of the subjects preferred the gamble (Plan B) to the sure outcome (Plan A). Such a preference reversal violates the invariance principle of expected utility theory, which requires a rational decision maker to have a consistent preference order among choice prospects independent of the way the prospects are presented or framed.

Risk-sensitive foraging theory can be applied to examine the irrational preference reversals caused by framing effects. From the perspective of evolutionary psychology, Rode and Wang [42] argue that the situation in which 600 lives are at stake is "evolutionarily novel and naïve". Through evolution, humans lived in hunter-gatherer societies, each consisting of households of about 25 members, and which rarely exceeded 100 people, a contrast to the 600 unrelated people in the Asian disease problem.

In a series of studies carried out by Wang and Johnston [54], it was found that the irrational risk preference reversal occurred only when the problem was presented in a large-group context with either 6,000 or 600 anonymous lives involved. With smaller group sizes of 6 and 60, the framing effect was absent. Furthermore, if framed in a kinship context, the majority of the participants became even more risk seeking. Risk-sensitive foraging arguably sheds light on why the risk-seeking preference was amplified in small-and kinship-group contexts. If we assume that for the group to survive as a whole, the number of group members has to be above a certain threshold (minimum requirement for group survival), the risk-seeking option would be favored when the expected value of the sure option is below the survival threshold.

2.4 The Cheater Detection Hypothesis

The cheater detection hypothesis was posited by Cosmides and Tooby to examine subjects' performance in Wason selection tasks [55], in which a subject is asked to look for violations of a conditional rule of the form "If P, then Q". Figure 2.1 on the next page is an example.



Here are four cards. Each of them has a letter on one side and a number on the other side. Two of these cards are shown with the letter side up, and two with the number side up.

E C 5 4

Indicate which of these cards you have to turn over in order to determine whether the following claim is true:

If a card has a vowel on one side, then it has an odd number on the other side.

Figure 2.1: Example of a Wason Selection Task

Wason found that subjects performed very poorly on questions like this. Although most of them responded correctly that the E card must be turned over, many also insisted that the 5 card must be turned over although this card cannot falsify the claim no matter what is on the other side. Furthermore, a majority of the subjects maintained that the 4 card need not be turned over, despite the fact that there is no way of knowing whether it has a vowel on the other side without turning it over.

Cosmides and Tooby [13] examined subjects' performance in the Wason selection task from the perspective of evolutionary psychology. They argued that in a hunter-gatherer society, it will sometimes happen that one hunter has been lucky on a particular day and has an abundance of food, while another hunter is unlucky and cannot find food, and is near starvation. If a pair of hunters can count on each other to help when one has food while the other has none, then the chances that they survive in the long run are greatly increased. On the other hand, if the hunters only fend for themselves and do not engage in such social exchanges, then their long-run probability of survival is greatly diminished, and this gene eventually becomes extinct. Therefore, evolution selects those humans with genes that incline them to engage in reciprocal exchanges with non-kin.

However, such reciprocal exchanges are susceptible to cheating, where individuals accept the benefits of the reciprocal arrangements and share the food of others, but fail to share their own food with other people in the arrangement. Hence, Cosmides and Tooby contend that if stable social arrangements are to exist, "then the organisms involved must have cognitive mechanisms that enable them to detect cheaters, and to avoid helping them in the future." [13] And since humans are apparently capable of entering into stable social exchanges, Cosmides and Tooby assert that humans must have evolved one or more mental modules responsible for recognizing social exchanges, and for detecting cheaters in such an exchange.

Put in the context of the Wason selection task, Cosmides and Tooby contend that if the task is phrased in the context of a social exchange, subjects will be able to reason according to the rules of logic ("If P, then Q"). For instance, in a study done by Griggs and Cox [27] shown in Figure 2.2 on the next page, 75% of the subjects were able to reason logically.

In support of their hypothesis, Cosmides and Tooby examined previous studies done with the Wason selection task and noted the following: "whenever the content of a problem asks subjects to look for cheaters in a social exchange – even when the situation described is culturally unfamiliar and even bizarre – subjects experience the problem as simple to solve, and their performance jumps dramatically. In general, 65% - 80% of the subjects get it right." [13] In contrast, subjects' performance was generally low in those studies that were not presented in the context of social exchange.

In its crackdown against drunk drivers, Massachusetts law enforcement officials are revoking liquor licenses left and right. You are a bouncer in a Boston bar, and you'll loose your job unless you enforce the following law:

"If a person is drinking beer, then he must be over 20 years old."

The cards below have information about four people sitting at a table in your bar. Each card represents one person. One side of a card tells what a person is drinking and the other side of the card tells that person's age. Indicate only those card(s) you definitely need to turn over to see if any of these people are breaking the law.

drinking beer	**drinking coke**	**25 years old**	**16 years old**

Figure 2.2: Selection task provided by Griggs and Cox

Chapter 3

Financial Puzzles

In this chapter, we begin with a citation count of some puzzles in finance to compare the relative extent in which research has been carried out on each puzzle. Following the citation count, each financial puzzle is discussed, together with explanations for it provided thus far by the behavioral finance literature.

3.1 Citation Count

A literature review was done to compile a list of financial puzzles examined by scholars thus far. To assess the relative importance of the puzzles, a citation count was done using the Social Sciences Citation Index (SSCI) and the Social Science Research Network (SSRN). The SSCI provides cited references for academic papers in over 1,700 of the world's leading scholarly social science journals, while the SSRN contains a database with abstracts of over 99,800 scholarly working papers and forthcoming papers.

To measure the relative importance of each financial puzzle, we conducted two searches for each puzzle: a general search where the keyword searched appeared in either the abstract or title of a paper, and a title-only search where the keyword searched appeared only in the title. The relative importance of a financial puzzle was judged by the number of academic papers written about the topic. Table 3.1 on the next page shows the citation count for each financial puzzle using the SSCI and SSRN.

Table 3.1: Citation Count of Financial Puzzles

Financial Puzzle	**Keyword Searched**	**SSCI Citation Count***	**SSRN Citation Count***
Overreaction	Overreaction	260(65)	144(27)
Loss Aversion	Loss Aversion	233(51)	156(31)
	Disposition Effect	11(1)	65(12)
Equity Premium Puzzle	Equity Premium Puzzle	118(26)	120(31)
Home Bias Puzzle	Home Bias	104(20)	240(55)
Post-Earnings Announcement Drift	Post-Earnings Announcement Drift	26(12)	42(12)
	Underreaction	72(19)	36(9)
Dividend Puzzle	Dividend Puzzle	7(3)	27(4)
Closed-end Fund Puzzle	Closed-end Fund Puzzle	2(1)	26(7)
Volatility Puzzle	Volatility Puzzle	2(0)	61(5)

**Number in parenthesis indicates title-only citation count.*

As we can see in Table 3.1, the citation count shows overreaction, loss aversion and the equity premium puzzle to be among the most researched puzzles in the behavioral finance literature. In addition, we also compiled a list of the most important papers for each financial puzzle. This can be found in Appendix A.

We next provide a brief review of each financial puzzle, together with explanations provided thus far in behavioral finance.

3.2 Financial Puzzles

3.2.1 Overreaction

The weak form of the Efficient Market Hypothesis (EMH) postulates that successive one-period stock returns are independently and identically distributed; that is, they resemble a 'random walk' [19]. This implies that future stock returns cannot be predicted using past stock returns as a forecaster. However, empirical studies have shown to violate the weak EMH. Kleidon [31] found that stock price movements are strongly correlated with the following year's earnings. Furthermore, De Bondt and Thaler [15] report that over the last half-century, loser portfolios of 35 stocks outperform the market by, on average, 19.6%, 36 months after formation. On the other hand, winner portfolios earn about 5.0% less than the market, thus lending support to their hypothesis that the stock market overreacts.

De Bondt and Thaler [16] attribute this overreaction to the bias created by the representativeness heuristic. They hypothesize that due to this heuristic, investors associate a recent winner in the stock market with further increases and hence become overly optimistic. Similarly, investors associate a recent loser in the stock market with further losses and consequently become overly pessimistic. Consequently, De Bondt and Thaler propose buying losing stocks over the preceding 36 months and selling winning stocks in the same period.

3.2.2 Loss Aversion and the Disposition Effect

Loss aversion is the phenomenon in which the disutility of a loss relative to a reference point is greater than the utility of a gain of the same magnitude [30]. One of the consequences of loss aversion in finance is the tendency hold on to losing positions for too long and close winning positions too early; what Shefrin and Statman [49] term the "disposition effect." Shefrin and Statman provide empirical evidence of the disposition effect. Odean [40] shows further evidence of this effect, reporting in his study that individual investors are more likely to sell stocks that have gone up in value relative to the purchase price, rather than stocks which prices have gone down.

To go beyond the realm of finance, the disposition effect has also been found in the sale of residential housing [23], and among professional traders [29], [35], and Israeli investors [46].

Shefrin and Statman [49] provide some explanations for the disposition effect. Their first explanation draws on prospect theory and mental accounting. Essentially, Shefrin and Statman contend that investors open a mental account for each stock they purchase. The disposition effect consequently comes from a combination of several features. First, investors frame choices before them in a particular way in the "editing stage." Specifically, they frame all choices in terms of gains/losses relative to a reference point (the purchase price). Next, investors use an S-shaped utility function which is concave in the gains region and convex in the losses region. Prospect theory therefore predicts that when faced with a gain, investors are risk-averse and sell the winners, and when faced with a loss, they become risk-seeking and hold on to the losing stock.

Another reason for the disposition effect provided by Shefrin and Statman is that of pride-seeking and regret-avoidance. Essentially, closing a stock account at a loss induces regret, while closing one at a gain induces pride. The quest for pride and avoidance of regret hence leads to a disposition to realize gains early and defer losses to a later time.

3.2.3 The Equity Premium Puzzle

Essentially, the equity premium puzzle involves the discrepancy between the return on stocks and that on fixed income securities. Since 1926, the annual real return on stocks has been 7% while that on treasury bills has been less than 1% [7]. While risk aversion appears to be a plausible explanation for this puzzle, research by Mehra and Prescott [38] shows this to be improbable. Specifically, Mehra and Prescott show that the combination of a high equity premium, a low risk-free rate, and smooth consumption is difficult to explain with plausible levels of risk aversion. They estimate that investors would have to have coefficients of relative risk aversion in excess of 30 to explain the historical equity premium. This is in conflict with actual figures from previous estimates which put the coefficient of relative risk aversion to be approximately 1.0. Given the significantly high return on stocks compared to fixed income securities, it is puzzle why investors are willing to hold the latter.

Benartzi and Thaler [7] postulate "myopic loss aversion" to explain the equity premium puzzle. Essentially, the unwillingness of investors to hold stocks is a result of loss aversion and a short evaluation period. First, when given a choice between a risk-free asset (treasury bill) and a risky asset (stock), aversion to losses causes investors to prefer the former. Next, suppose an investor has to choose between a risky asset with an annual expected return of 7% with standard deviation 20% and a risk-free asset that pays an annual 1% return for sure. Benartzi and Thaler argue that the attractiveness of the risky asset will depend on the time horizon of the investor. The longer the investor intends to hold the asset, the more attractive the risky asset will appear as long as the investment is not evaluated frequently. Conversely, a short evaluation period will make the risky asset appear less attractive to the investor. Hence, Bneartzi and Thaler argue that it is a combination of loss aversion and short evaluation periods that creates the equity premium puzzle.

3.2.4 The Home Bias Puzzle

Since the economies of different countries do not necessarily move in tandem, conventional finance predicts that investors hold assets in different countries to diversify their portfolios. However, empirical studies run contrary to this prediction. French and Poterba [22] find significant domestic ownership of corporate equity in the United States (92.2%), Japan (95.7%), the United Kingdom (92%), Germany (79%), and France (89.4%). In the same study, French and Poterba report that at the end of 1989, United States and Japanese investors held approximately 94% and 98% of their respective portfolios in domestic equities. A separate study by Grinblatt and Keloharju [28] echoes the findings of French and Poterba. In their study, Grinblatt and Keloharju found Finnish investors more likely to hold and trade stocks of Finnish firms located close to them geographically.

French and Poterba argue that impediments to holding foreign assets such as tax burdens, transaction costs, and capital controls are insufficient to justify the low level of cross-border equity investment. Essentially, their explanation for the home bias focuses on investor behavior. French and Poterba contend that investors know less about foreign markets and firms compared to domestic ones. Consequently, this lack of knowledge causes investors to impute extra risk to foreign investments and hence concentrate their investment portfolios on domestic equities.

Barberis and Thaler [6], and Shefrin [47] make a similar argument, using ambiguity aversion and preference for familiarity to explain the lack of diversification. They assert that investors may find their national stock market less ambiguous than foreign ones, and may hence be more attracted to invest in domestic equities.

3.2.5 Underreaction and Post-Earnings Announcement Drift

The efficient markets hypothesis implies that all information is fully reflected in the prices of stocks. However, empirical evidence suggests the inefficiency of markets in incorporating information regarding earnings. Benard and Thomas [9] show that in the 60 trading days following an earnings announcement, firms with extreme good earnings news experience a mean abnormal return of nearly 2% while firms with extreme bad news experience a negative abnormal return of approximately the same magnitude. Benard [8] shows evidence indicating an average initial underreaction to earnings announcements. Furthermore, Mendenhall [39] and Abarbanell and Benard [1] present evidence that analysts underreact to earnings information when they revise their forecasts. Consequently, one surprise follows another. Other studies showing the post-earnings announcement drift include Ball and Brown [2], Freeman and Tse [21], and Wiggins [56].

A number of theories have arisen to explain the post-earnings announcement drift. Shefrin [47] attributes this to conservatism caused by the anchoring-and-adjustment bias. As a result, analysts do not adjust their earnings predictions sufficiently in response to the new information contained in earnings announcements and are hence surprised by subsequent announcements.

Another explanation from Barberis, Shleifer, and Vishny [5] argues that analysts and investors have difficulty interpreting earnings information and vacillate between two different mind-sets. In the first mind-set, analysts and investors believe the change to be temporary and expect earnings growth to revert. In the second mind-set, analysts and investors believe earnings to be in a growth-spurt phase and that earnings will soar. Barberis, Shleifer, and Vishny argue that analysts are prone to the first (mean-reverting) mindset. Hence, when a permanent positive change in earnings takes place, analysts fail to recognize it and underreact. They hence get positively surprised by the next earnings announcement. Following a succession of surprises, analysts and investors rethink their position and shift to the second mind-set. In doing so, they extrapolate past growth rates and consequently overreact.

3.2.6 The Dividend Puzzle

In the absence of taxes and transactions cost, dividends and capital gains are generally accepted to be perfectly substitutable. Hence, investors should be indifferent between capital gains and dividends. Furthermore, since the tax on cash dividends exceeds that on capital gains, investors should prefer capital gains to dividends. However, in reality, individuals show a strong preference for cash dividends, with a case in point being that reported by Loomis [36] involving General Public Utilities Corporation.

Shefrin and Statman [48] provide three explanations for the dividend puzzle. Their first explanation draws on the idea of self-control. Essentially, many people have self-control problems and in order to not indulge in something, people typically set rules for themselves. Consequently, an individual who wishes to safeguard long-run wealth might set a rule such as to finance consumption from dividend and not from capital. Hence, investors may prefer dividends because dividends help them overcome self-control problems.

A second explanation for the dividend puzzle draws upon prospect theory and the concept of mental accounting. Dividends enable firms to increase the utility of investors by separating gains from losses. To illustrate, consider a firm which value has just increased by $10 per share. The firm has one of two choices; first, to not pay a dividend and return this increase in value to investors as a \$10 capital gain and second, to pay a \$2 dividend and return an \$8 capital gain. Under prospect theory, due to the concavity of the utility function in the gains region, investors derive higher utility from the latter option than the former. Similarly, suppose the firm's value declines by \$10 per share. The firm again has one of two choices; first, to offer a \$10 capital loss and second, to pay a \$2 dividend gain combined with a \$12 capital loss. This time, due to the convexity of the utility function in the losses region (under prospect theory), the second option will result in a higher perceived utility. Shefrin and Statman argue that the key to the utility enhancing trick in this example depends on whether investors segregate the overall gain or loss into different components. By paying dividends, firms make it easier for investors to perform this segregation.

Finally, Shefrin and Statman argue that investors prefer cash dividends because it helps them avoid regret. Consider the case of an investor who has to decide whether or not to sell a stock to finance consumption. If the investor sells the stock and stock's price subsequently rises, the investor will feel a sense of regret at having sold the stock in the first place. This sense of regret could have been avoided if the investor was able to finance consumption through a cash dividend.

3.2.7 The Closed-End Fund Puzzle

Closed-end funds are funds that issue a fixed number of shares that are traded on exchanges. To buy a share of a closed-end fund, one must go through an exchange and purchase it at the prevailing price. Essentially, the closed-end fund puzzle is the observation that fund share prices deviate from the net asset value (NAV) of the portfolio that the fund holds. Specifically, when closed-end funds are first created, they trade at a premium to NAV, but within a few months, the typical fund trades at a discount of 10% on average to NAV. This discount can vary. When closed-end funds are terminated either through liquidation or an open-ending, fund share prices rise and the discounts fall.

Lee, Shleifer, and Thaler [32] attribute the closed-end fund puzzle to noise-traders (who are primary owners of closed-end funds) who exhibit irrational swings in their expectations about future fund returns. They are sometimes overly optimistic and other times overly pessimistic; it is these changes in their sentiment that cause fund share prices to deviate from its NAV. Consequently, owners of closed-end funds are faced with two sources of risk: fluctuations in the value of the funds' assets, and fluctuations in noise trader sentiment. Lee, Shleifer, and Thaler argue that since entrepreneurs typically choose to create closed-end funds at times of investor exuberance, closed-end funds are hence often sold at a premium. Next, if the noise trader risk is systematic, then rational investors will demand compensation for it, which explains why fund share prices trade at a discount to NAV. Finally, when a closed-end fund is liquidated, rational investors no longer have to worry about changes in noise trader sentiment because they know that at liquidation, the fund price will equal NAV. They therefore no longer demand compensation for this risk, and the fund price rises towards NAV.

3.2.8 The Volatility Puzzle

Standard finance theory postulates that stock prices are determined by the present value of the rationally expected stream of future real dividends. However, empirical studies have contradicted this theory. Robert Shiller [45] examined stock prices in the United States from 1871-1979 and concluded them to be between five and thirteen times too high to be attributed to new information about future real dividends. LeRoy and Porter [33] report similar findings about the stock market volatility.

Essentially, the volatility puzzle is that stock market levels appear to vary too much to be explained by standard models of finance. Barberis and Thaler [6] provide several belief-based explanations for the volatility puzzle. First, they argue that investors believe the mean dividend growth rate to be more variable than it actually is. Consequently, when they see a surge in dividends, they believe that the dividend growth rate has increased, thus pushing prices up relative to dividends, and adding to the volatility of returns. Barberis and Thaler attribute this investor exuberance in pushing up prices to a bias generated by representativeness known as the law of small numbers.

Their next belief-based explanation is a consequence of overconfidence in private information. Suppose an investor has seen public information about the economy and has formed a prior opinion about future cash growth. Next suppose the investor does his own research and becomes overconfident in his private findings. Consequently, the investor over-weights the private information relative to public information. Hence, if the private information is positive (negative), the investor will push prices up (down) too high (low) relative to current dividends, which contributes to volatility.

Barberis, Huang and Santos [4] provide a model to explain the volatility puzzle based on investor preferences. The key to their argument lies on the findings of Thaler and Johnson [51] that after prior gains, subjects become more risk-seeking, and after prior losses, they refuse gambles that they would normally accept. Consequently, good news that pushes stock prices up generate gains for investors, causing them to be less risk-averse since any losses will be cushioned by the accumulated gains thus far. This causes them to seek gambles they would otherwise not take, pushing prices further upward relative to current dividends, and adding to volatility.

Chapter 4

Applying Risk-Sensitive Foraging Theory to Financial Markets

4.1 Risk-Sensitive Foraging Theory

In this chapter, we examine some of the financial puzzles discussed in Chapter 3 from the perspective of evolutionary psychology. Specifically, we apply risk-sensitive foraging theory to explain these puzzles. We first begin with a discussion of risk-sensitive foraging theory, and how it can be applied to financial markets. Next, we examine overreaction, the equity premium puzzle, the home bias puzzle, and the dividend puzzle using the framework of risk-sensitive foraging theory.

4.1.1 Background

Rode, Cosmides, Hell, and Tooby [41] assert that choosing between alternative patches to forage on is an adaptive problem that our ancestors faced during our species' evolution. Hence, we should arguably have developed reasoning mechanisms that enable us to evaluate and choose amongst alternative patches on which to forage. Risk-sensitive foraging theory provides such a patch selection framework based on three factors: expected payoffs of the patches, variability of the expected payoffs, and the current minimum requirement for survival. To illustrate, suppose the minimum requirement for survival is 250 calories. Further suppose that two resource patches have the same expected payoff of 250 calories but differ in that the variability of the expected payoff in one patch is higher than the other. Risk-sensitive foraging theory states that a forager should forage on the lower variance patch because this patch is more likely to satisfy the minimum requirement of 250 calories. However, if the minimum requirement is higher than the expected payoff of the patches (for example a minimum requirement of 300 calories), then the best hope for survival is to forage on the higher variance patch because its more variable outcome distribution provides an increased probability of obtaining the required amount of nutrition.

Rode, Cosmides, Hell, and Tooby [41] studied decision-making using the framework provided by risk-sensitive foraging theory. Essentially, subjects in their study had to choose between two options that had the same expected payoff but that differed in the variability of the expected payoffs. They found that in general, subjects' choices corresponded to that predicted by risk-sensitive foraging theory. The participants preferred the high-variability option when the minimum requirement exceeded the expected payoff of the options, and selected the low-variance option when the expected payoff of the options exceeded the minimum requirement.

4.1.2 Ellsberg Problem Revisited

Using the framework of risk-sensitive foraging theory, we revisit the Ellsberg problem presented in Section 2.3.1. Essentially, the problem involves choosing between two boxes, with one containing 50 black and 50 white balls, and the other containing 100 balls in an unknown composition. We note that the probability distribution for the first box is known, while that of the second box could be one of 101 different combinations, ranging from zero black balls to 100 blacks balls. We next compute the expected payoff and the variability of the expected payoff for each of the boxes.

The expected payoff for the known-probability box is as follows:

$$\text{Expected Payoff} = \$100(0.5) + \$0(0.5) = \$50$$

The expected payoff for the ambiguous box is as follows:

$$\text{Expected Payoff} = \frac{1}{101}\sum_{x=0}^{100} \$100\left(\frac{x}{100}\right) + \$0\left(\frac{100-x}{100}\right) = \frac{1}{101}\frac{(100)(101)}{2} = \$50$$

Next, we find the variability of the expected payoffs for each option. We observe that there is no variability in expected payoff for the unambiguous box since its distribution is known. On the other hand, the ambiguous box has expected payoffs ranging from $0 to $100, one for each of the 101 possible distributions it can take. The variability of the expected payoff for the ambiguous box is computed as follows:

$$\text{Standard Deviation} = \sqrt{\sum_{x=0}^{100} \frac{1}{101}(x-50)^2} = \sqrt{850} = \$29.15$$

From the computations, it is clear that while both options have the same expected payoff, they differ in the variability of the expected payoffs; the ambiguous box is more variable than the one with known probability. Risk-sensitive foraging theory consequently predicts that a forager should choose the low-variance, unambiguous box.

Rode and Wang [42] assert that in ambiguity studies, selecting the box of known probability is neither a bias nor an aversion to ambiguity. Rather, it is a choice that would maximize the probability of satisfying subjects' current need. They further note that while subjects' behavior in the Ellsberg problem deviate from "19^{th}-century normative models of rational choice", it "is fully consistent with models of rational choice that have been proven to be adaptive and functional in an uncertain natural environment."

4.2 Risk-Sensitive Foraging in Financial Markets

4.2.1 Background

We propose that the risk-sensitive foraging framework can be applied to examine behavior in financial markets. In this framework, an investor is akin to a forager; profits correspond to food; and financial assets such as stocks and bonds represent potential resource patches on which a forager can forage. A forager (investor) therefore needs to choose amongst alternative patches (financial assets) to forage so as to find enough food (profit) to meet the minimum requirement for survival. In making such a decision, the risk-sensitive foraging framework considers three factors: expected payoffs, variability of expected payoffs, and minimum requirement. Using this framework, we now examine and provide explanations for the following financial phenomena: overreaction, the equity premium puzzle, the home bias puzzle, and the dividend puzzle.

4.2.2 Overreaction

Suppose a forager has to choose between two resource patches (financial assets) to forage and knows from recent history that food can be found (asset prices are rising) in Patch A, while food cannot be found (asset prices are falling) in Patch B. Patch A therefore has a positive payoff while Patch B has a negative payoff; that is, the payoff from Patch A is higher than that of Patch B. In order to ensure long-term survival, it is rational for the forager to forage on Patch A (buy Asset A). At the same time, other foragers who also see the higher expected payoff of Patch A will also choose to forage there. The increase in foraging activity on Patch A corresponds to an increase in demand for Asset A in the financial market domain. The increased demand for Asset A pushes its price up. Eventually, as more and more foragers hunt in Patch A, competition increases and food supplies (profit opportunities) dwindle. The expected payoff of Patch A decreases, which causes foragers to abandon Patch A as a foraging ground, corresponding to a decrease in demand for Asset A in the financial market domain. This decrease in demand pushes the price of Asset A down.

At the same time, since the chance of finding food in Patch B is initially low, few, if any, foragers will choose to hunt on Patch B. This corresponds to a decrease in demand for Asset B which causes its price to decrease. Eventually, the lack of hunting on Patch B helps to replenish resources on the patch. Now, seeing the opportunity for food (profit opportunity) in Patch B, foragers will move to hunt on this patch. The increase in hunting activity corresponds to increased demand for Asset B in the financial market domain and causes its price to rise.

4.2.3 The Equity Premium Puzzle

One major difference between stocks and fixed income securities is that the latter has a constant stream of coupon payments. Furthermore, assuming an investor purchases it at its issuance, protection of the principal is assured when fixed income securities expire. They are hence arguably less risky compared to stocks. If the constant stream of coupon payments (food) meets the investor's (forager's) minimum requirement for survival, risk-sensitive foraging theory predicts that it is optimal for the forager to forage on the low-variance resource patch (hold bonds).

To illustrate, suppose that the return on fixed income securities is guaranteed to be 1%, while that on stocks is expected to be 7% but with high variability. Further suppose that the current minimum requirement is a return of 1%. While the expected return on stocks is higher than fixed income securities, the high variability associated with the stocks' expected return means that there is some probability that the minimum requirement would not be met. In contrast, since the return on fixed income securities is guaranteed to be 1%, there is no chance that its return would not meet the minimum requirement. Consequently, risk-sensitive foraging theory predicts that we should forage on fixed income securities since they provide a higher probability of meeting the minimum requirement and hence of survival. Note that the situation we have illustrated here essentially describes the equity premium puzzle. Risk-sensitive foraging theory therefore explains why investors are willing to hold fixed income securities in spite of the high premium of stocks over fixed income securities.

4.2.4 The Home Bias Puzzle

Apart from unfamiliarity with foreign assets relative to domestic ones perhaps due to a greater difficulty in acquiring information on the foreign asset, etc., purchasing foreign assets comes with the added risk of foreign exchange fluctuations. These uncertainties arguably make the expected return on foreign assets more variable compared to domestic ones. If the expected return from domestic assets meets the forager's minimum requirement, risk-sensitive foraging theory predicts that the forager should choose the low-variance resource patch (domestic asset) to forage on.

To illustrate, suppose domestic and foreign assets have the same expected return of 5% and the current minimum requirement is 5%. All things equal, the expected return on foreign assets is arguably more variable for the reasons just discussed such as susceptibility to foreign exchange risk and a lack of information. Risk-sensitive foraging theory consequently predicts that a forager should pick domestic assets to forage on since their expected returns have relatively lower variance, while meeting the minimum requirement. The examination of the home bias puzzle from an evolutionary context in this case shows holding domestic assets to be optimal for long-run survival.

4.2.5 The Dividend Puzzle

Clearly, the difference between dividend-paying and other stocks is the stream of dividends from the former. Similar to the argument made when examining the equity premium puzzle within the risk-sensitive foraging framework, foragers arguably prefer cash dividends because it provides an expected return with certainty. On the other hand, the expected return from non-dividend-paying stocks is highly variable since it is dependent on stock-price fluctuations. If the expected return from the dividend of a dividend-paying stock meets a forager's their minimum requirement for survival, risk-sensitive foraging theory predicts that the forager ought to forage on this patch (prefer the dividend-paying stock) to maximize long-run survival. This explains why investors prefer stocks that pay dividends to those that do not.

Chapter 5

Dynamic Modeling and Loss Aversion

In this chapter, we examine loss aversion from an evolutionary context using a patch selection model from the literature on behavioral ecology. Essentially, we adopt Mangel and Clark's [37] dynamic patch selection model which provides the patch selection strategy that maximizes a forager's long-run probability of survival. We observe loss aversion from this survival-maximizing patch selection strategy. The next section develops the dynamic patch selection model. Following that, we implement the dynamic model using MATLAB and present some results and observations. We next compare long-run survival probabilities given by the dynamic model to standard models of rationality.

5.1 Dynamic Patch Selection Model

In this model, a forager's current state is represented by the state variable $X(t)$. $X(t)$ can be interpreted in several ways, such as the forager's amount of energy reserves at time t. At each time period, the forager has to choose among alternative patches to forage. Each patch is defined by the parameters on the next page:

α_i	Cost per period (measured in terms of decrement of the state variable) of choosing patch i
β_i	Probability of predation during any one period if patch i is chosen
λ_i	Probability of finding food during any one period if patch i is chosen
Y_i	Increment in the state variable (if food is discovered) in the i^{th} patch

We introduce a lifetime fitness function $F(x,t,T)$, defined as the maximum value of the probability that the forager survives from period t to period T, given that the forager is alive at period t, and the value of $X(t)$ is x. Mathematically,

$$F(x,t,T) = \max \Pr(\text{forager survives from } t \text{ to } T \mid X(t) = x) \qquad (5\text{-}1)$$

In addition, we assume that there is a critical value for the state variable denoted by x_c, such that if $X(t)$ reaches or falls below this value at any time, the forager dies. Hence,

$$F(x,t,T) = 0 \text{ if } x \le x_c \qquad (5\text{-}2)$$

We introduce a capacity constraint C on $X(t)$ such that $X(t)$ can never exceed C. That is, $X(t) \le C$ for all t. Furthermore, we assume in this model that $x_c \le X(t) \le C$. Hence, if $X(t)$ falls outside this range, we set it according to the following "chop" function:

$$chop(x; x_c, C) = \begin{cases} C & \text{if} \quad x > C \\ x & \text{if} \quad x_c \le x \le C \\ x_c & \text{if} \quad x < x_c \end{cases} \qquad (5\text{-}3)$$

At the terminal period T, since the forager is either dead or alive, we can determine the following:

$$F(x,T,T) = \begin{cases} 1 & \text{if} \quad x > x_c \\ 0 & \text{if} \quad x \le x_c \end{cases} \tag{5-4}$$

We now derive the dynamic programming equation that $F(x,t,T)$ satisfies. To do this, suppose that at some period t, $X(t) = x$. Further suppose that the forager chooses patch i to forage on. Then, if the forager survives predation (which occurs with probability $1-\beta_i$), the value of the state variable depends on whether the forager finds food on patch i. It becomes

$$X(t+1) = \begin{cases} chop(x-\alpha_i + Y_i; x_c, C) & \text{with probability } \lambda_i \\ chop(x-\alpha_i; x_c, C) & \text{with probability } (1-\lambda_i) \end{cases} \tag{5-5}$$

Let us consider $t = T-1$. Assume that $X(T-1) = x$, and suppose that the forager hunts on patch i in period $T-1$. Then, the forager will survive period $T-1$ if it is not killed by a predator, which happens with probability $(1-\beta_i)$. Its state variable will change from $X(T-1) = x$ to $X(T)$ as given by Equation (5-5). Also, the forager will survive the final period T if and only if $X(T) > x_c$. We can therefore express this as follows:

$$\begin{aligned} &\Pr(\text{survive from } T-1 \text{ to } T \mid \text{choose patch } i \text{ in period } T-1) \\ &= \Pr(\text{survive period } T-1 \mid \text{choose patch } i \text{ in period } T-1) \\ &\quad * \Pr(\text{survive period } T \mid \text{ choose patch } i \text{ in period } T-1) \end{aligned} \tag{5-6}$$

We know that

$$\Pr(\text{survive period } T-1 \mid \text{ choose patch } i \text{ in period } T-1) = 1-\beta_i \tag{5-7}$$

Furthermore, by the Law of Total Probability,

$$\begin{aligned}&\Pr(\text{survive period } T \mid \text{choose patch } i \text{ in period } T-1)\\ &= \lambda_i \Pr(\text{survive period } T \mid X(T) = x'_i) + (1-\lambda_i)\Pr(\text{survive period } T \mid X(T) = x''_i)\end{aligned}$$

where

$$\begin{aligned}x'_i &= chop(x - \alpha_i + Y_i; x_c, C)\\ x''_i &= chop(x - \alpha_i; x_c, C)\end{aligned} \qquad (5\text{-}8)$$

By the definition of $F(x,T,T)$, we have

$$\Pr(\text{survive period } T \mid X(T) = x) = F(x,T,T) \qquad (5\text{-}9)$$

Substituting Equations (5-7), (5-8), and (5-9) into (5-6), we have the following:

$$\begin{aligned}&\Pr(\text{survive from } T-1 \text{ to } T \mid \text{choose patch } i \text{ in period } T-1)\\ &= (1-\beta_i)\left[\lambda_i F(x'_i,T,T) + (1-\lambda_i)F(x''_i,T,T)\right]\end{aligned} \qquad (5\text{-}10)$$

Since by definition, $F(x,T-1,T)$ is the maximum of these probabilities over all the i patches, we have the following:

$$F(x,T-1,T) = \max_i\ (1-\beta_i)\left[\lambda_i F(x'_i,T,T) + (1-\lambda_i)F(x''_i,T,T)\right] \qquad (5\text{-}11)$$

Applying the same line of reasoning for any $t < T$, relating fitness in period t to fitness in the next period $t+1$, we thereby obtain the general form of the dynamic programming equation:

$$F(x,t,T) = \max_i\ (1-\beta_i)\left[\lambda_i F(x'_i,t+1,T) + (1-\lambda_i)F(x''_i,t+1,T)\right] \qquad (5\text{-}12)$$

5.2 Implementing the Model

5.2.1 Model Validation

We implemented the dynamic patch selection model on MATLAB (please refer to Appendix B for MATLAB code). To verify the validity of our MATLAB code, we attempted to replicate the results of Mangel and Clark [37] (please refer to Appendix C.1 for the results of Mangel and Clark). For this study, $x_c = 3$ and $C = 10$. The input parameters used are shown in Table 5.1.

Table 5.1: Input Parameters for Validation Study

Patch Number	β_i	α_i	λ_i	Y_i
1	0	1	0	0
2	0.004	1	0.4	3
3	0.02	1	0.6	5

As Table 5.1 shows, Patch 1 is the safest patch, since there is no chance of predation. However, there is no chance of finding food on Patch 1. Patch 3 is the riskiest patch in terms of predation, but its expected return of 3.0 is the highest among the alternatives, and greater than the expected return of 1.2 in the relatively safer Patch 2. Hence, in this study, Patch 1 is the safest, followed by Patch 2 and then Patch 3.

The results of our study (please refer to Appendix C.2) replicated those of Mangel and Clark, which shows our MATLAB code to be valid.

5.2.2 Observations

One of the main results of the dynamic patch selection model is loss aversion. It is observed in each time period that as the level of energy reserves decreases, the optimal strategy is to forage on the riskier patches. This is shown in Figure 5.1 on the next page at $t = 1$.

Referring to the Figure 5.1, when $X(1) = 10$, the survival-maximizing strategy is to choose Patch 1 (the safest patch) to forage on.. When the state variable decreases to 9, the optimal patch to forage on is Patch 2. At $X(1) = 7$, the riskiest patch (Patch 3) offers the maximum probability of long-run survival. That is, a decrease in the amount of energy reserves is accompanied by increasing risk-seeking behavior. From this observation, we postulate that when faced with the possibility of extinction (the forager dies whenever $X(t) \leq 3$), the optimal behavior for long-run survival is to be increasingly risk-seeking. This behavior is essentially loss-aversion. When we face a loss relative to a reference point, it increases the probability of extinction and the dynamic patch selection model consequently predicts risk-seeking behavior to be the strategy that maximizes long-run survival.

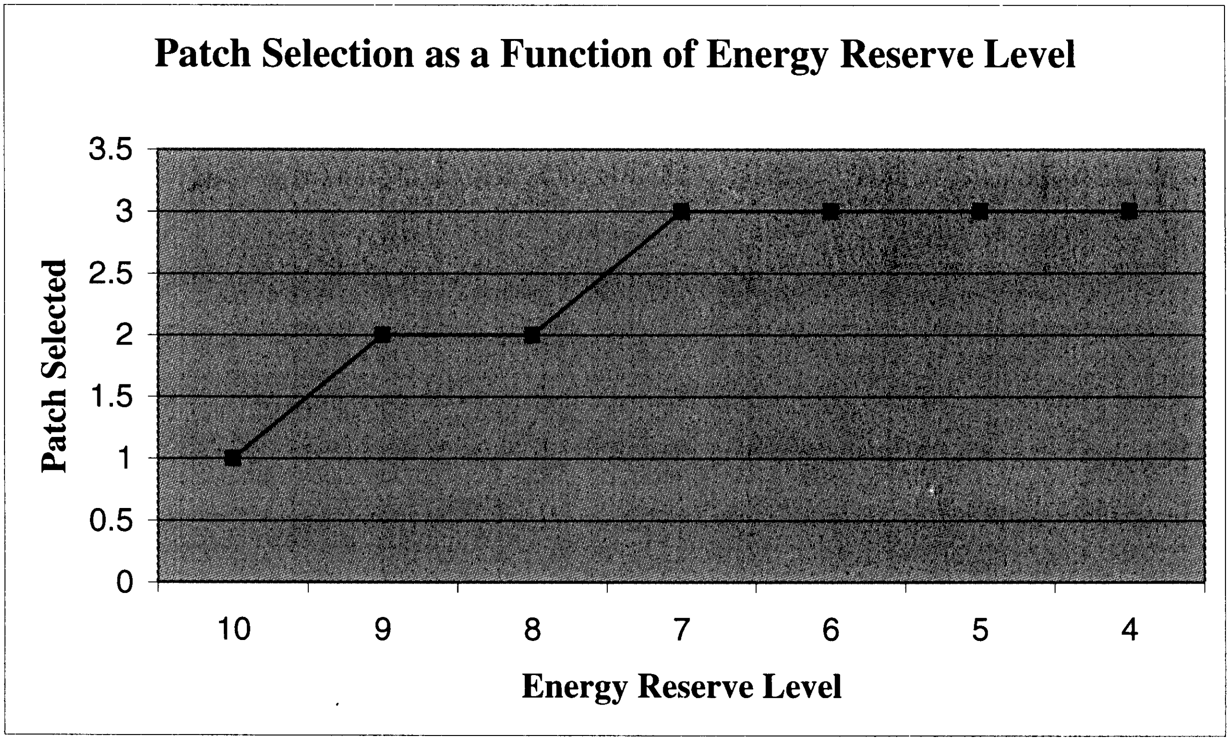


Figure 5.1: Patch Selection as a Function of Energy Reserve Level

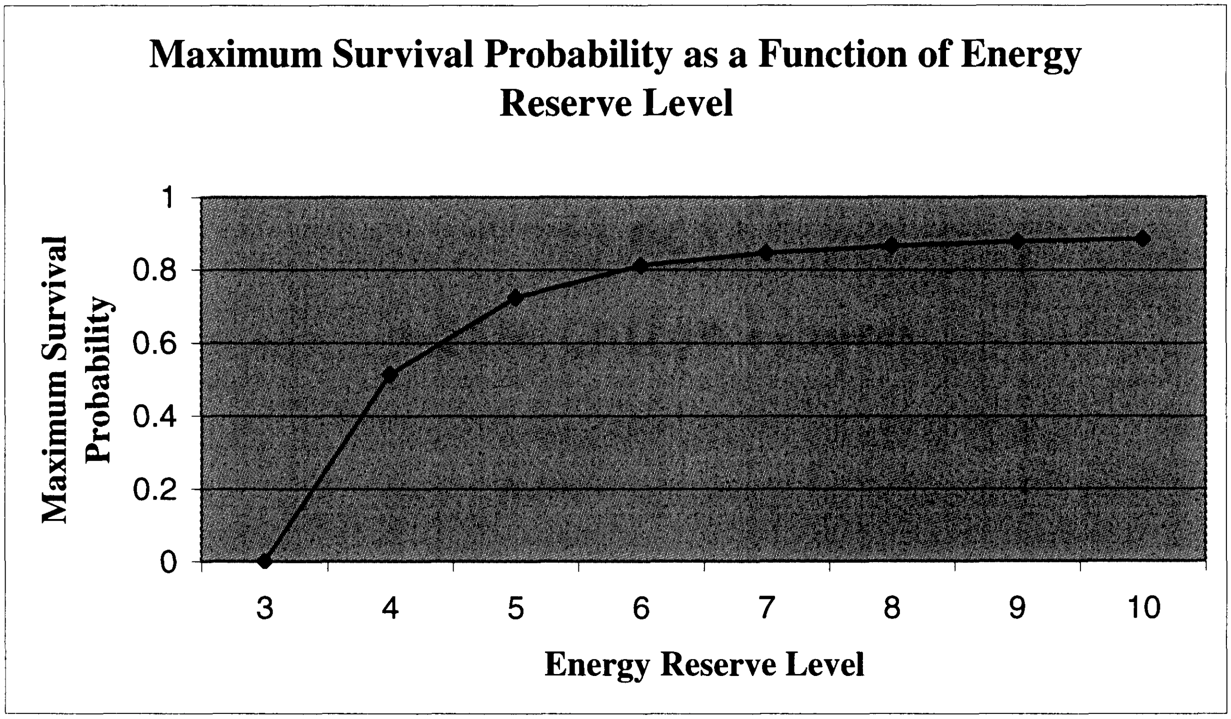


Figure 5.2: Maximum Survival Probability as a Function of Energy Reserve Level

The following observations are similar to those made by Mangel and Clark [37]. First, we note that at each time t, as the state variable moves further away from the critical level x_c, the maximum probability of survival is non-decreasing. This is illustrated in Figure 5.2 above. Figure 5.2 shows how the maximum probability of survival varies with the level of energy reserves at $t = 1$. The figure shows that a higher energy reserve level is accompanied with a higher maximum survival probability, which makes intuitive sense.

Next, we observe that for a given energy reserve level, the maximum probability of survival decreases as t moves further away from the final time period T. Figure 5.3 on the next illustrates this observation.

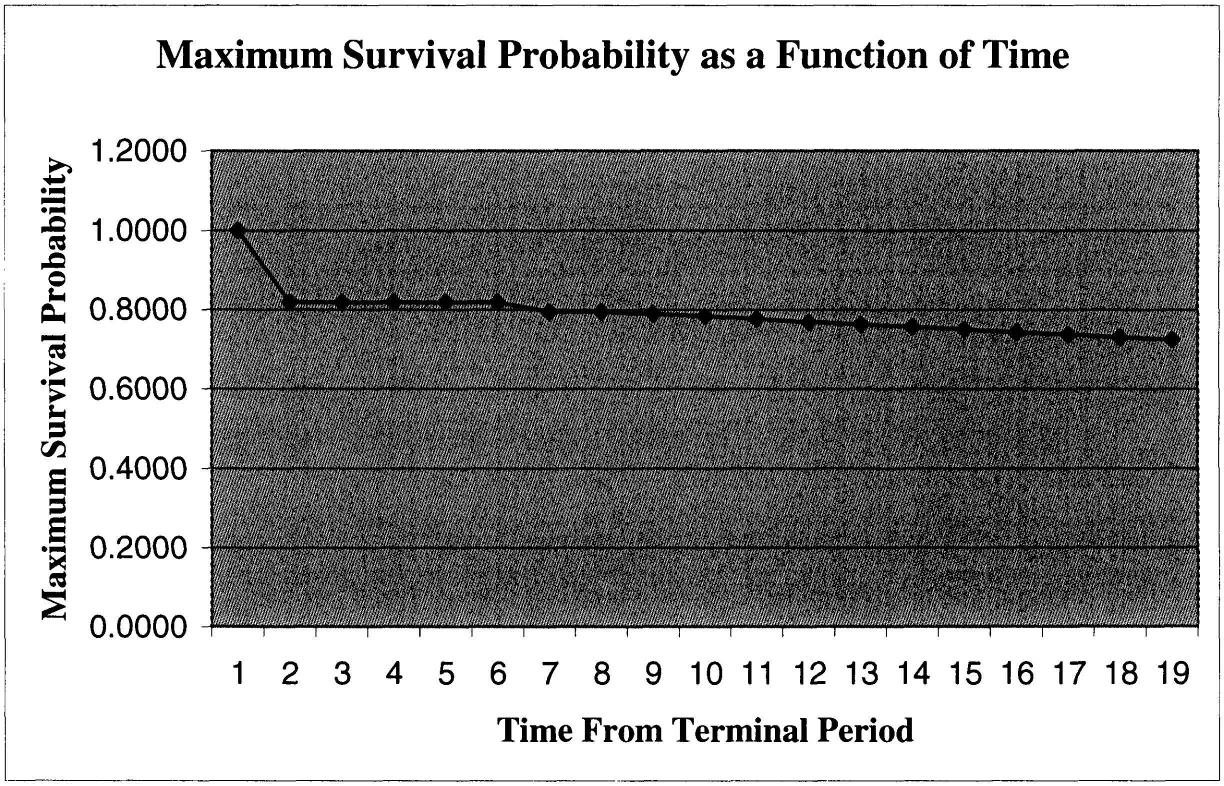


Figure 5.3: Maximum Survival Probability as a Function of Time

The figure above shows how the maximum survival probability varies as we move further away from the terminal time period for $X(t) = 5$. We see that the maximum probability of survival is a non-increasing function of the time from the terminal period, which makes intuitive sense.

Finally, we observe steady-state behavior for a given energy reserve level. For a given energy reserve level, as the time t moves away from the final period T, there comes a point beyond which the optimal patch for survival remains constant. Figure 5.4 on the next page illustrates this steady-state observation. We see that for each energy reserve level, the optimal patch to forage on eventually reaches steady state.

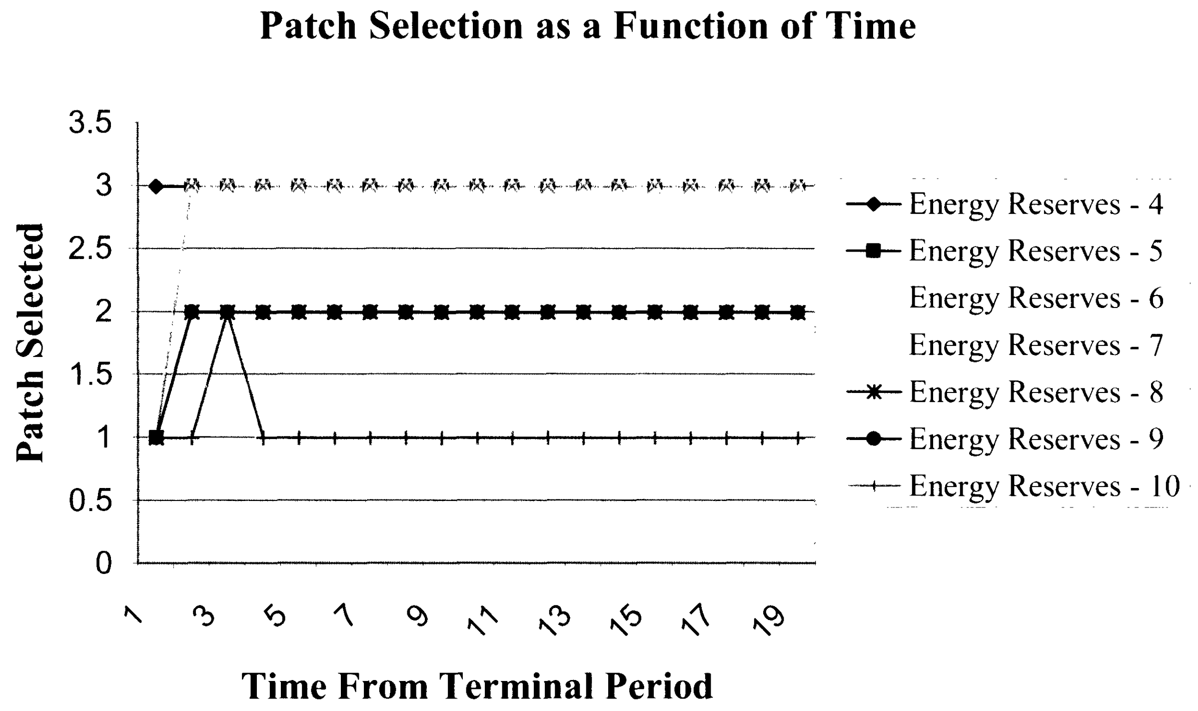


Figure 5.4: Patch Selection as a Function of Time

5.3 Examining the Model Further

5.3.1 Input Parameters

After verifying the validity of our MATLAB code, we proceeded to examine the patch selection model using different input parameters. Essentially, we wanted to find out if, with different input parameters, we could still observe loss aversion in the survival-maximizing patch strategy, or if the loss-averse phenomenon that we observed was merely a result of the particular set of input parameters used by Mangel and Clark.

We observed that in the dynamic patch selection model, the risk associated with each patch was two-pronged. First, there was the risk associated with the probability of finding food. Next, there was the risk associated with the probability of predation. Hence, we carried out three studies that we will describe next.

In Study 1, the probability of finding food was varied while keeping the expected return and probability of predation constant. Table 5.2 below shows the input parameters.

Table 5.2: Input Parameters for Study 1

Patch Number	β_i	α_i	λ_i	Y_i
1	0	1	0.5	1
2	0	1	0.25	2
3	0	1	0.125	4

Essentially, we set the probability of predation to zero. In this study, Patch 1 is the safest patch, with the highest probability of finding food; Patch 2 is the next safest patch; and Patch 3 is the riskiest patch with the lowest probability of finding food. Please refer to Appendix C.3 for the results of this study.

Study 2 aimed to examine the effect of the predation probability. The probability of finding food was kept constant while the predation probability was varied. Table 5.3 below shows the input parameters.

Table 5.3: Input Parameters for Study 2

Patch Number	β_i	α_i	λ_i	Y_i
1	0.01	1	0.4	1
2	0.02	1	0.4	2
3	0.04	1	0.4	4

Here, Patch 1 is the safest patch with the lowest predation probability. Patch 3 is the riskiest patch since it has the highest probability of predation. Patch 2 is in between Patches 1 and 3 in terms of risk. The results of this study are presented in Appendix C.4.

In Study 3, the expected return was kept constant, while allowing predation probabilities and probability of finding food to vary. Table 5.4 on the next page shows the input parameters.

Table 5.4: Input Parameters for Study 3

Patch Number	β_i	α_i	λ_i	Y_i
1	0.01	1	0.5	1
2	0.02	1	0.25	2
3	0.04	1	0.125	4

In this study, Patch 1 is the safest patch with the highest probability of finding food and lowest probability of predation. Patch 3 is the riskiest patch with the lowest probability of finding food and highest probability of predation. Patch 2 is intermediate between Patches 1 and 3 in terms of risk. The results of this study are presented in Appendix C.5.

5.3.2 Observations

Figures 5.5, 5.6, and 5.7 on the next two pages show the steady-state optimal patch strategy as a function of energy reserve level for Study 1, Study 2, and Study 3 respectively.

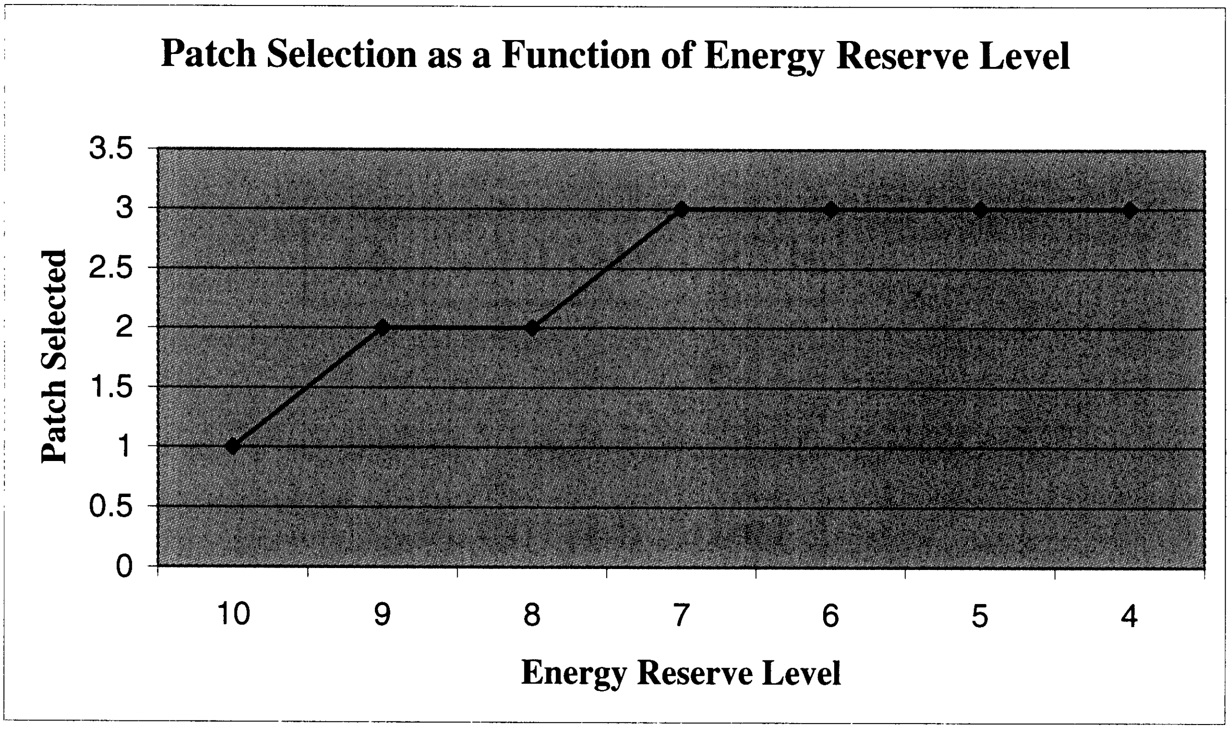


Figure 5.5: Steady-State Patch Selection as a Function of Energy Reserve Level, Study 1

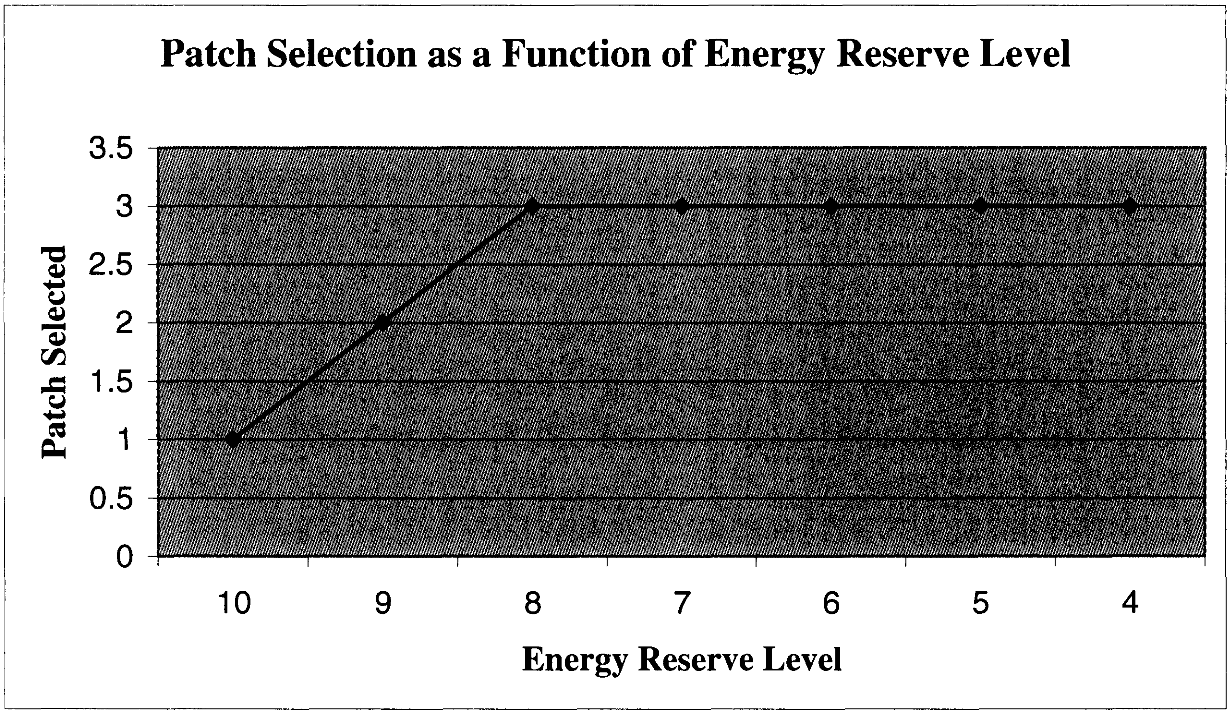


Figure 5.6: Steady-State Patch Selection as a Function of Energy Reserve Level, Study 2

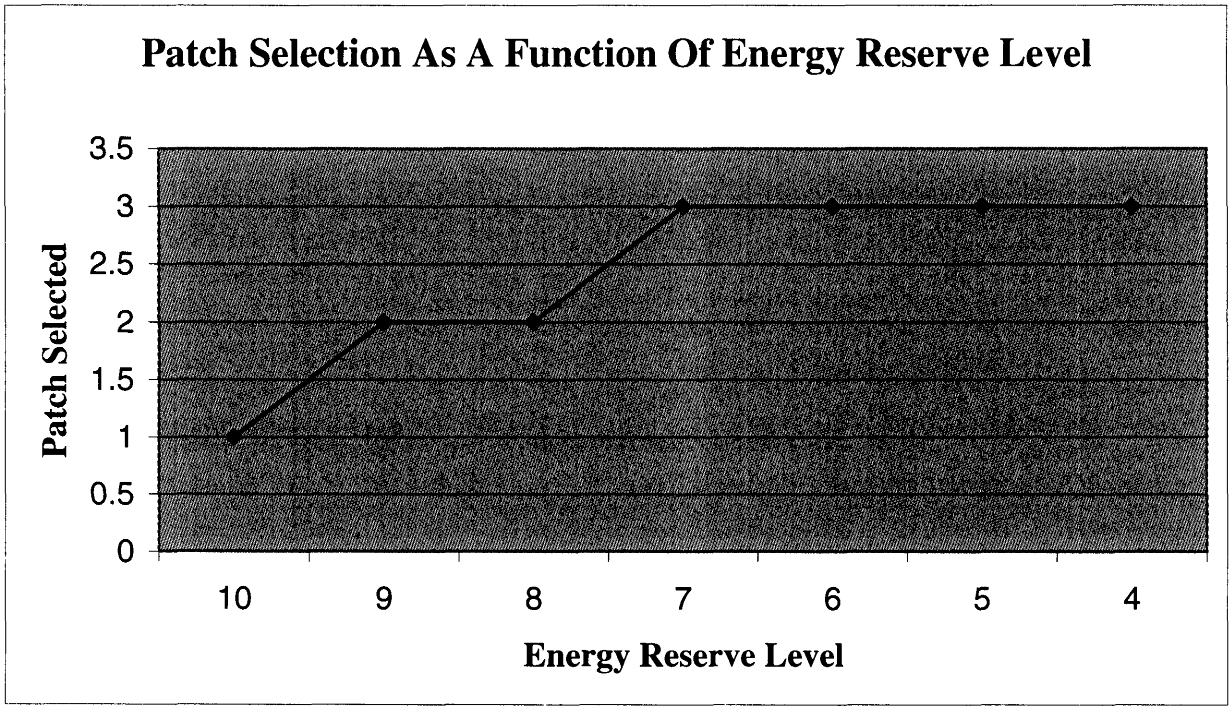


Figure 5.7: Steady-State Patch Selection as a Function of Energy Reserve Level, Study 3

In the three studies, we observe from the survival-maximizing patch selection strategy that a decrease in the energy reserve level is accompanied by increasing risk-seeking behavior. This increasing risk-seeking behavior when faced with a loss is essentially the phenomenon of loss aversion. Moreover, this loss-averse behavior was obtained with sets of input parameters different from the ones used by Mangel and Clark [37], which provides further evidence of our initial assertion of loss aversion as the optimal strategy for an organism to avoid extinction.

5.4 Comparison of Dynamic Model with Standard Models of Rationality

Having observed loss aversion as a forager's optimal response strategy when faced with the threat extinction, we next attempt to examine how our dynamic model compares to standard models of rationality in terms of survival probabilities.

5.4.1 Input Parameters

In this study, $x_c = 1$ and $C = 12$. A forager has nine patches from which to choose to forage on. These patches differ in terms of the probability of finding food, and the increase in the level of energy reserves if food is found. The input parameters for the nine patches are shown in Table 5.5 on the next page.

Table 5.5: Input Parameters

Patch Number	β_i	α_i	λ_i	Y_i
1	0	1	0.61	1
2	0	1	0.3	2
3	0	1	0.2	3
4	0	1	0.15	4
5	0	1	0.12	5
6	0	1	0.1	6
7	0	1	3/35	7
8	0	1	0.075	8
9	0	1	1/15	9

We let the return of Patch 1 be X_1 and calculate its mean and variance as follows:

$$E(X_1) = 1(0.61) + 0(1-0.61) = 0.61$$
$$E(X_1^2) = 1^2(0.61) + 0^2(1-0.61) = 0.61$$
$$Var(X_1) = E(X_1^2) - [E(X_1)]^2 = 0.2379$$

Proceeding similarly for the other eight patches, we obtain the mean and variance of the return for each patch. They are presented in Table 5.6 below.

Table 5.6: Mean and Variance of the Resource Patches

Patch Number	$E(X_i)$	$Var(X_i)$
1	0.61	0.2379
2	0.6	0.84
3	0.6	1.44
4	0.6	2.04
5	0.6	2.64
6	0.6	3.24
7	0.6	3.84
8	0.6	4.44
9	0.6	5.04

We observe that Patches 2 through 9 have an expected return of 0.6, while Patch 1 has an expected return of 0.61. Hence, expected utility theory predicts that a forager should choose to forage on Patch 1 in each time period regardless of the energy reserve level since Patch 1 has the highest expected return. Next, we note that Patches 1 through 9 have increasing variance in returns and are hence increasingly risky. Hence, Patch 1 is the safest patch on which on forage, Patch 2 is riskier than Patch 1, Patch 3 riskier than Patch 2, and proceeding in this fashion, Patch 9 is the riskiest patch.

5.4.2 Results and Observations

Using the input parameters presented in Table 5.5, we obtained the patch selection strategy and survival probabilities using our dynamic model (please refer to Appendix C.6 for results). We also obtained long-run survival probabilities if the forager, in accordance with expected utility theory, chose Patch 1 to forage on in each time period regardless of the level of energy reserves (please refer to Appendix C.7 for results).

Figure 5.8 on the next page compares the patch selection strategy given by our dynamic model to that given by expected utility theory. As the figure shows, the dynamic model selects increasingly risky resource patches to forage on as the energy reserve level decreases and the forager approaches extinction. In contrast, in accordance with expected utility theory, since Patch 1 has the highest expected return, it is optimal to select Patch 1 regardless of the energy reserve level.

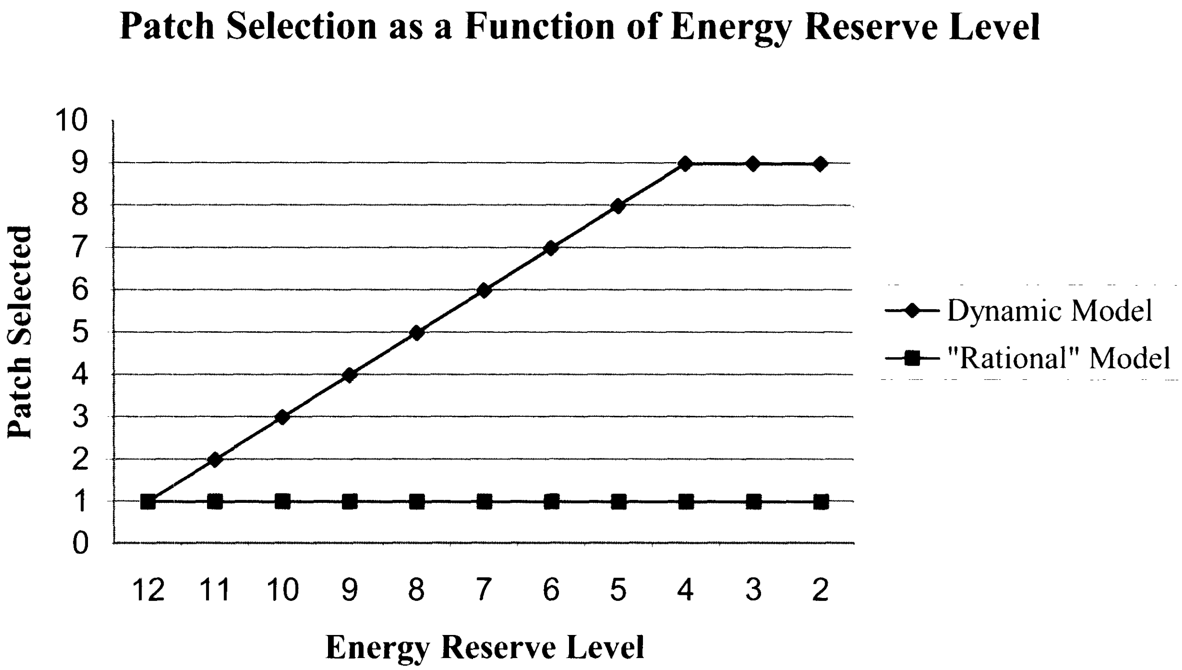


Figure 5.8: Patch Selection as a Function of Energy Reserve Level

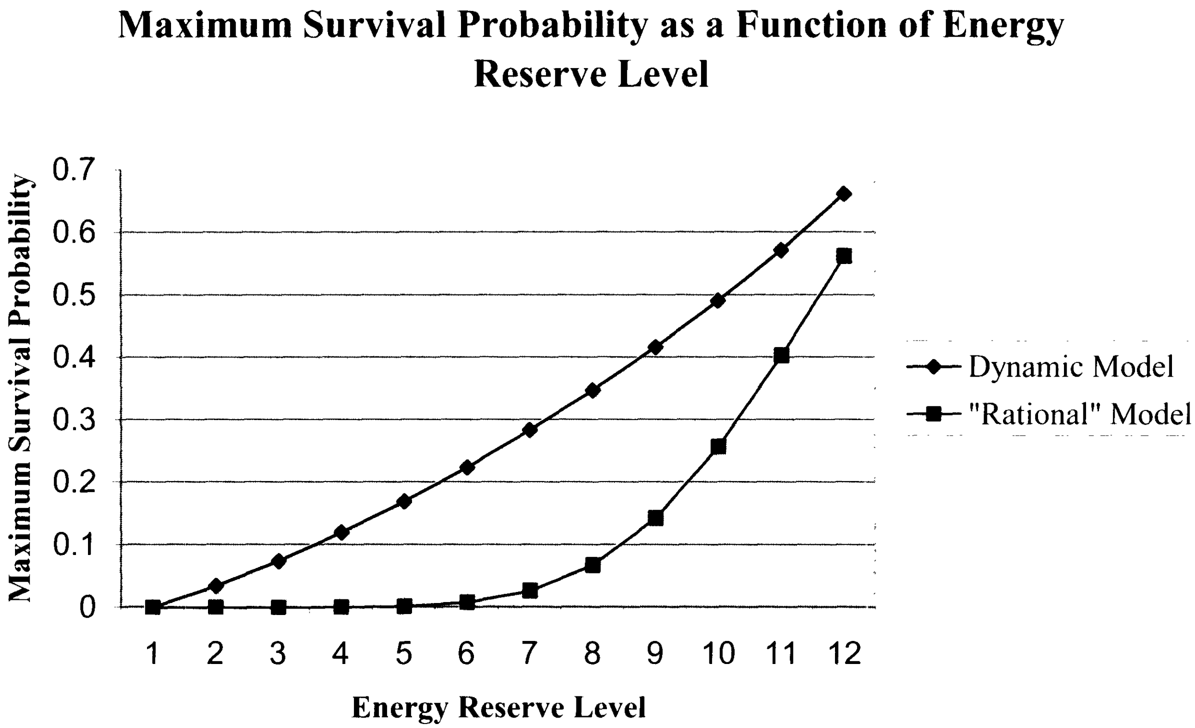


Figure 5.9: Maximum Survival Probability as a Function of Energy Reserve Level

Given the different patch selection strategies between the dynamic model and that predicted by expected utility theory, we compare their steady-state long-run survival probabilities. Figure 5.9 on the previous page shows the steady-state survival probabilities as a function of the energy reserve level for the two strategies. As the figure illustrates, the dynamic patch selection model clearly provides the forager with a higher long-run survival probability at all energy reserve levels compared to the expected utility model. For each energy reserve level, the increase in survival probability for the dynamic model over the expected utility model is shown in Table 5.7 below and illustrated in Figure 5.10 on the next page.

Table 5.7: Increase in Survival Probabilities of Dynamic Model over Expected Utility Model

Energy Reserve Level	Dynamic Model	Expected Utility Model	Increase
1	0	0	0
2	0.0345	0.000002	0.034498
3	0.0742	0.00005	0.07415
4	0.1197	0.0004	0.1193
5	0.1697	0.0022	0.1675
6	0.2244	0.0087	0.2157
7	0.2839	0.0271	0.2568
8	0.3481	0.0684	0.2797
9	0.4170	0.1437	0.2733
10	0.4914	0.258	0.2334
11	0.5725	0.4042	0.1683
12	0.6626	0.5631	0.0995

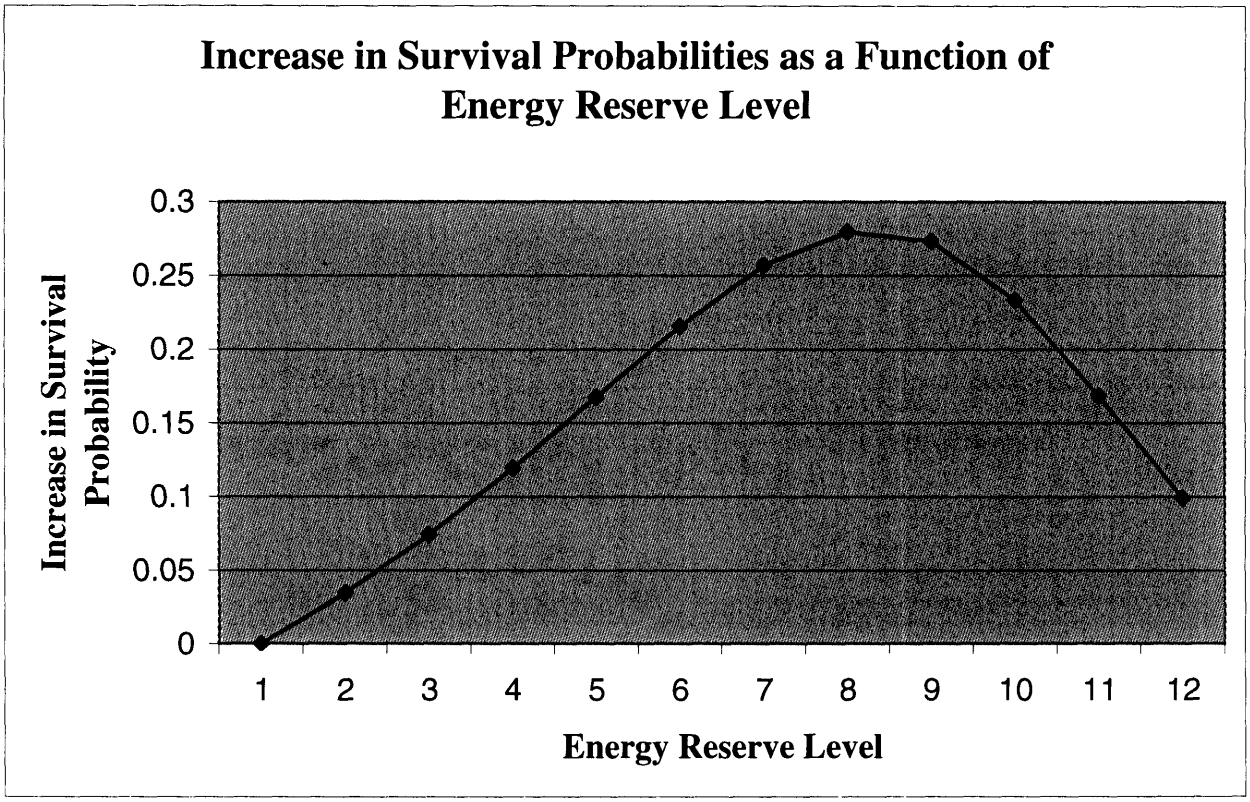


Figure 5.10: Increase in Survival Probabilities as a Function of Energy Reserve Level

Chapter 6

Conclusion

In this thesis, we introduced the approach of evolutionary psychology, which essentially involves applying the idea of competition and natural selection to examine human behavior. In particular, proponents of evolutionary psychology have used ideas such as the frequentist hypothesis to rationalize some of the biases documented by advocates of the "heuristics and biases" program. Our aim, however, is to use the same approach in the field of finance. Consequently, we discussed some of the most-researched puzzles in finance in Chapter 3 and, through a citation count, identified the relatively more important puzzles such as overreaction, loss aversion and the disposition effect, and the equity premium puzzle.

In Chapters 4 and 5, we began to use the approach of evolutionary psychology to examine some of the financial puzzles discussed. Essentially, we introduced two models designed to solve the adaptive task of finding food to ensure survival. The first model is risk-sensitive optimal foraging theory, in which a forager selects from alternative resource patches to forage based on the patches' expected payoffs, variability of the expected payoffs, and the current minimum requirement. Using this framework, we examined overreaction, the equity premium puzzle, the home bias puzzle, and the dividend puzzle.

The patch selection model in Chapter 5 used the concept of dynamic programming, essentially working step-by-step back in time to determine a survival-maximizing patch selection strategy. Arguably, the most important observation from this optimal patch selection strategy is the phenomenon of loss aversion. What the patch selection found was that being increasingly risk-seeking when faced with the possibility of extinction was optimal for long-run survival. We further examined this model to determine if this loss-averse behavior occurred as a result of the particular set of parameters used in Mangel and Clark's [37] study. Our results showed this to not be possible since we were able to observe loss-averse behavior even with alternative input parameters. Finally, we compared survival probabilities of this dynamic patch selection strategy to the strategy predicted by expected utility and found the former to provide a higher probability of long-run survival compared to the latter.

As we have emphasized in this thesis, our aim is not to "rationalize" the financial puzzles, but rather to point out that the financial puzzles observed are a result of evolutionarily-optimal cognitive mechanisms operating outside the environment in which they evolved to survive in. Arguably, determining the long-run survival probabilities and hence optimal patch selection strategy using the dynamic model was no computationally trivial task. Hence, examined in the evolutionary domain, the loss-averse behavior we observed appeared to suggest the work of a highly elegant computational mechanism in humans, adapted for long-term survival. Lo's [34] analogy aptly describes our point: "A more accurate term for such behavior might be 'maladaptive'. The flopping of a dish on dry land may seem strange and unproductive, but under water, the same motions are capable of propelling the fish away from its predators."

Appendix A

Table A.1: Papers on Overreaction

Author(s)	Title	SSCI Citation Count	SSRN Citation Count
De Bondt, Werner and Thaler, Richard	Does the Stock Market Overreact?	384	--
Jegadeesh, N. and Titman, S.	Returns To Buying Winners and Selling Losers: Implications For Stock-Market Efficiency	226	--
De Bondt, Werner and Thaler, Richard	Further Evidence On Investor Overreaction And Stock-Market Seasonality	182	--
Daniel, K., Hirshleifer, D., and Subrahmanyam, A.	Investor Psychology And Security Market Under- And Overreactions	160	--
Barberis N., Shleifer A., Vishny R.	A Model of Investor Sentiment	121	79

Table A.2: Papers on Loss Aversion and the Disposition Effect

Author(s)	Title	SSCI Citation Count	SSRN Citation Count
Kahneman, D. and Tversky, A.	Prospect Theory: Analysis Of Decision Under Risk	3546	--
Shefrin, Hersh and Statman, Meir	The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence	111	--
Odean, T.	Are investors reluctant to realize their losses?	91	435
Dhar, Ravi and Zhu, Ning	Up Close and Personal: An Individual Level Analysis of the Disposition Effect	--	1123
Frazzini, Andrea	The Disposition Effect and Under-reaction to News	--	787

Table A.3: Papers on the Equity Premium Puzzle

Author(s)	Title	SSCI Citation Count	SSRN Citation Count
Mehra, Rajnish and Prescott, Edward C.	The Equity Premium: A Puzzle	609	--
Constantinides, G.M.	Habit Formation: A Resolution Of The Equity Premium Puzzle	256	--
Weil, P.	The Equity Premium Puzzle And The Risk-Free Rate Puzzle	132	17
Benartzi, Shlomo and Thaler, Richard	Myopic Loss Aversion and the Equity Premium Puzzle	97	52
Mehra, Rajnish	The Equity Premium: Why is it a Puzzle?	3	98

Table A.4: Papers on the Home Bias Puzzle

Author(s)	Title	SSCI Citation Count	SSRN Citation Count
French, Kenneth and Poterba, James	Investor Diversification and International Equity Markets	133	--
Tesar, L.L. and Werner, I.M.	Home Bias And High Turnover	66	16
Lewis, K.K.	Trying to explain home bias in equities and consumption	64	--
Kang, J.K. and Stulz, R.M.	Why is there a home bias? An analysis of foreign portfolio equity ownership in Japan	54	6
Brennan, M.J. and Cao, H.H.	International portfolio investment flows	50	--

Table A.5: Papers on the Volatility Puzzle

Author(s)	Title	SSCI Citation Count	SSRN Citation Count
Shiller, Robert	Do Stock-Prices Move Too Much To Be Justified By Subsequent Changes In Dividends	500	--
LeRoy S.F. and Porter R.D.	The Present-Value Relation: Tests Based On Implied Variance Bounds	186	--
Barberis, N., Huang, M. and Santos, T.	Prospect theory and asset prices	41	1906

Table A.6: Papers on Underreaction and the Post-Earnings-Announcement Drift

Author(s)	Title	SSCI Citation Count	SSRN Citation Count
Bernard, V.L. and Thomas, J.K.	Evidence That Stock-Prices Do Not Fully Reflect The Implications Of Current Earnings For Future Earnings	139	--
Bernard, V.L. and Thomas, J.K.	Post-Earnings-Announcement Drift: Delayed Price Response Or Risk Premium	129	--
Barberis N., Shleifer A., Vishny R.	A Model of Investor Sentiment	121	79
Abarbanell, J.S. and Bernard, V.L.	Tests Of Analysts Overreaction Underreaction To Earnings Information As An Explanation For Anomalous Stock-Price Behavior	71	--
Mendenhall, Richard	Evidence On The Possible Underweighting Of Earnings-Related Information	39	--

Table A.7: Papers on the Dividend Puzzle

Author(s)	Title	SSCI Citation Count	SSRN Citation Count
Shefrin, Hersh and Statman, Meir	Explaining Investor Preference for Cash Dividends	62	--
Bernheim, B.D.	Tax Policy And The Dividend Puzzle	20	4
DeAngelo, Harry and DeAngelo, Linda	Payout Policy Irrelevance and the Dividend Puzzle	--	716
Lee, Yul W. and Moore, Keith M.	The Premium-Discount Puzzle of Closed-end Bond Funds: An Empirical Examination of the Dividend Yield Preference Hypothesis	--	117

Table A.8: Papers on the Closed-End Fund Puzzle

Author(s)	Title	SSCI Citation Count	SSRN Citation Count
Lee, Charles, Shleifer, Andrei, and Thaler, Richard	Investor Sentiment and the Closed-End Fund Puzzle	116	--
Doukas, John A. and Milonas, Nikolaos T.	Investor Sentiment and the Closed-end Fund Puzzle: Out-of-Sample Evidence	--	249

Appendix B

Implementation of Dynamic Patch Selection Model using MATLAB

```
%Initializes parameters.
%B = Probability of predation.
%A = Cost per period (in terms of energy expended per period).
%L = Probability of finding food.
%Y = Increment in state variable/energy if food is found.
B=[0, 0.004, 0.02];
A=[1, 1, 1];
L=[0, 0.4, 0.6];
Y=[0, 3, 5];

%t0 = Initial time, T = Final time
%x_c = level of extinction, x_cap = maximum amount of food/energy stored.
t0 = 1;
T = 20;
x_c = 1;
x_cap = 8;

%Initializes the vectors to store maximum survival probabilities
%and optimal survival patches.
f0 = zeros(1, (x_cap - x_c + 1));
f1 = zeros(1, (x_cap - x_c + 1));
D = zeros(1, (x_cap - x_c + 1));

%Finds F(x, T, T)
for i = x_c:x_cap
   if i <= 1
      f1(i) = 0;
   else
      f1(i) = 1;
   end
end
```

```
%Loops over time, energy level, and patches from time T-1 to t0.
for t = (T-1):-1:t0
   f1(x_c) = 0;

   for j = (x_c + 1):x_cap

      for i = 1:3
         x_food = j - A(i) + Y(i);
         x_nofood = j - A(i);

         %Performs "chop" function.
         if x_food < x_c
            x_food = x_c;
         elseif x_food > x_cap
            x_food = x_cap;
         else
            x_food = x_food;
         end

         if x_nofood < x_c
            x_nofood = x_c;
         elseif x_food > x_cap
            x_nofood = x_cap;
         else
            x_nofood = x_nofood;
         end

         V(i) = (1-B(i))*( L(i)*f1(x_food) + (1-L(i))*f1(x_nofood));
      end

      [value, index] = max(V);

      f0(j) = value;
      D(j) = index;
   end

   %Prints out the current time, maximum survival probabilities
   %and corresponding patches, then sets f1 to f0.
   t
   f0
   D

   f1 = f0;
end
```

Appendix C

C.1 Original Results of Mangel and Clark

Energy Reserves	F(x, t, T)	i*	F(x, t, T)	i*	F(x, t, T)	i*	F(x, t, T)	i*	F(x, t, T)	i*
	t = 19		t = 18		t = 17		t = 16		t = 15	
4	0.588	3	0.588	3	0.588	3	0.588	3	0.588	3
5	1.000	1	0.818	3	0.818	3	0.818	3	0.818	3
6	1.000	1	1.000	1	0.909	3	0.909	3	0.909	3
7	1.000	1	1.000	1	1.000	1	0.944	3	0.944	3
8	1.000	1	1.000	1	1.000	1	1.000	1	0.963	2
9	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1
10	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1
	t = 14		t = 13		t = 12		t = 11		t = 10	
4	0.566	3	0.566	3	0.566	3	0.561	3	0.556	3
5	0.818	3	0.794	3	0.794	3	0.790	3	0.784	3
6	0.909	3	0.909	3	0.888	3	0.884	3	0.878	3
7	0.944	3	0.944	3	0.933	3	0.921	3	0.914	3
8	0.963	2	0.963	2	0.955	2	0.945	2	0.935	2
9	0.974	2	0.974	2	0.966	2	0.959	2	0.950	2
10	1.000	1	0.980	2	0.974	1	0.966	1	0.959	1
	t = 9		t = 8		t = 7		t = 6		t = 5	
4	0.550	3	0.546	3	0.541	3	0.537	3	0.532	3
5	0.776	3	0.769	3	0.763	3	0.756	3	0.750	3
6	0.871	3	0.863	3	0.854	3	0.848	3	0.840	3
7	0.908	3	0.900	3	0.891	3	0.884	3	0.876	3
8	0.928	2	0.921	2	0.912	2	0.904	2	0.897	2
9	0.941	2	0.933	2	0.925	2	0.917	2	0.909	2
10	0.950	1	0.941	1	0.933	1	0.925	1	0.917	1
	t = 4		t = 3		t = 2		t = 1			
4	0.527	3	0.523	3	0.518	3	0.514	3		
5	0.743	3	0.737	3	0.730	3	0.724	3		
6	0.833	3	0.826	3	0.819	3	0.812	3		
7	0.869	3	0.861	3	0.854	3	0.846	3		
8	0.889	2	0.881	2	0.874	2	0.866	2		
9	0.901	2	0.893	2	0.886	2	0.878	2		
10	0.909	1	0.901	1	0.893	1	0.886	1		

C.2 Survival Probabilities of Validation Study

Energy Reserves	F(x, t, T)	i*	F(x, t, T)	i*	F(x, t, T)	i*	F(x, t, T)	i*	F(x, t, T)	i*
	t = 19		t = 18		t = 17		t = 16		t = 15	
4	0.5880	3	0.5880	3	0.5880	3	0.5880	3	0.5880	3
5	1.0000	1	0.8185	3	0.8185	3	0.8185	3	0.8185	3
6	1.0000	1	1.0000	1	0.9089	3	0.9089	3	0.9089	3
7	1.0000	1	1.0000	1	1.0000	1	0.9443	3	0.9443	3
8	1.0000	1	1.0000	1	1.0000	1	1.0000	1	0.9627	2
9	1.0000	1	1.0000	1	1.0000	1	1.0000	1	1.0000	1
10	1.0000	1	1.0000	1	1.0000	1	1.0000	1	1.0000	1
	t = 14		t = 13		t = 12		t = 11		t = 10	
4	0.5661	3	0.5661	3	0.5661	3	0.5614	3	0.5558	3
5	0.8185	3	0.7944	3	0.7944	3	0.7898	3	0.7837	3
6	0.9089	3	0.9089	3	0.8878	3	0.8840	3	0.8775	3
7	0.9443	3	0.9443	3	0.9327	3	0.9206	3	0.9144	3
8	0.9627	2	0.9627	2	0.9548	2	0.9453	2	0.9349	2
9	0.9737	2	0.9737	2	0.9659	2	0.9585	2	0.9497	2
10	1.0000	1	0.9803	2	0.9737	1	0.9659	1	0.9585	1
	t = 9		t = 8		t = 7		t = 6		t = 5	
4	0.5497	3	0.5459	3	0.5414	3	0.5365	3	0.5318	3
5	0.7763	3	0.7686	3	0.7627	3	0.7561	3	0.7495	3
6	0.8708	3	0.8627	3	0.8543	3	0.8477	3	0.8403	3
7	0.9076	3	0.8998	3	0.8913	3	0.8836	3	0.8762	3
8	0.9283	2	0.9208	2	0.9124	2	0.9044	2	0.8965	2
9	0.9406	2	0.9331	2	0.9250	2	0.9170	2	0.9090	2
10	0.9497	1	0.9406	1	0.9331	1	0.9250	1	0.9170	1
	t = 4		t = 3		t = 2		t = 1			
4	0.5272	3	0.5227	3	0.5182	3	0.5137	3		
5	0.7429	3	0.7365	3	0.7302	3	0.7239	3		
6	0.8330	3	0.8257	3	0.8186	3	0.8115	3		
7	0.8686	3	0.8610	3	0.8535	3	0.8462	3		
8	0.8889	2	0.8812	2	0.8736	2	0.8660	2		
9	0.9011	2	0.8934	2	0.8856	2	0.8780	2		
10	0.9090	1	0.9011	1	0.8934	1	0.8856	1		

C.3 Survival Probabilities of Study 1

Energy Reserves	F(x, t, T)	i*	F(x, t, T)	i*	F(x, t, T)	i*	F(x, t, T)	i*	F(x, t, T)	i*
	t = 19		t = 18		t = 17		t = 16		t = 15	
4	0.5000	1	0.2500	1	0.1875	2	0.1250	2	0.1172	3
5	1.0000	1	0.7500	1	0.5000	1	0.3594	2	0.2656	2
6	1.0000	1	1.0000	1	0.8750	1	0.6875	1	0.5234	1
7	1.0000	1	1.0000	1	1.0000	1	0.9375	1	0.8125	1
8	1.0000	1	1.0000	1	1.0000	1	1.0000	1	0.9688	1
9	1.0000	1	1.0000	1	1.0000	1	1.0000	1	1.0000	1
10	1.0000	1	1.0000	1	1.0000	1	1.0000	1	1.0000	1
	t = 14		t = 13		t = 12		t = 11		t = 10	
4	0.1016	3	0.0835	3	0.0669	3	0.0557	3	0.0479	3
5	0.2236	3	0.2002	3	0.1705	3	0.1407	3	0.1177	3
6	0.4023	2	0.3347	2	0.2924	3	0.2565	3	0.2178	3
7	0.6680	1	0.5352	1	0.4459	2	0.3836	2	0.3384	3
8	0.8906	1	0.7793	1	0.6572	1	0.5515	1	0.4771	2
9	0.9844	1	0.9375	1	0.8584	1	0.7578	1	0.6547	1
10	1.0000	1	0.9922	1	0.9648	1	0.9116	1	0.8347	1
	t = 9		t = 8		t = 7		t = 6		t = 5	
4	0.0423	3	0.0369	3	0.0319	3	0.0277	3	0.0244	3
5	0.1016	3	0.0892	3	0.0776	3	0.0674	3	0.0587	3
6	0.1848	3	0.1597	3	0.1404	3	0.1224	3	0.1066	3
7	0.2949	3	0.2548	3	0.2217	3	0.1951	3	0.1705	3
8	0.4174	2	0.3628	2	0.3159	2	0.2753	2	0.2416	2
9	0.5665	2	0.4993	2	0.4360	2	0.3813	2	0.3331	2
10	0.7447	1	0.6556	1	0.5775	1	0.5067	1	0.4440	1
	t = 4		t = 3		t = 2		t = 1			
4	0.0213	3	0.0186	3	0.0162	3	0.0142	3		
5	0.0515	3	0.0450	3	0.0394	3	0.0344	3		
6	0.0930	3	0.0816	3	0.0713	3	0.0624	3		
7	0.1488	3	0.1299	3	0.1140	3	0.0997	3		
8	0.2111	2	0.1846	2	0.1613	2	0.1414	2		
9	0.2922	2	0.2555	2	0.2236	2	0.1955	2		
10	0.3886	1	0.3404	1	0.2979	1	0.2608	1		

C.4 Survival Probabilities of Study 2

Energy Reserves	F(x, t, T)	i*	F(x, t, T)	i*	F(x, t, T)	i*	F(x, t, T)	i*	F(x, t, T)	i*
	t = 19		t = 18		t = 17		t = 16		t = 15	
4	0.3960	1	0.3881	2	0.3764	3	0.3726	3	0.3211	3
5	0.9900	1	0.6273	1	0.6124	2	0.5894	3	0.5835	3
6	0.9900	1	0.9801	1	0.7607	1	0.7404	2	0.7084	3
7	0.9900	1	0.9801	1	0.9703	1	0.8361	1	0.8119	2
8	0.9900	1	0.9801	1	0.9703	1	0.9606	1	0.8770	1
9	0.9900	1	0.9801	1	0.9703	1	0.9606	1	0.9510	1
10	0.9900	1	0.9801	1	0.9703	1	0.9606	1	0.9510	1
	t = 14		t = 13		t = 12		t = 11		t = 10	
4	0.3118	3	0.2969	3	0.2939	3	0.2763	3	0.2673	3
5	0.5217	3	0.5061	3	0.4809	3	0.4729	3	0.4473	3
6	0.7013	3	0.6452	3	0.6252	3	0.5955	3	0.5827	3
7	0.7732	3	0.7655	3	0.7195	3	0.6961	3	0.6653	3
8	0.8502	2	0.8069	3	0.7907	2	0.7504	3	0.7260	2
9	0.8976	1	0.8690	2	0.8296	2	0.8079	2	0.7702	2
10	0.9415	1	0.9060	1	0.8749	1	0.8393	1	0.8123	1
	t = 9		t = 8		t = 7		t = 6		t = 5	
4	0.2555	3	0.2486	3	0.2373	3	0.2292	3	0.2198	3
5	0.4327	3	0.4141	3	0.4016	3	0.3841	3	0.3707	3
6	0.5534	3	0.5355	3	0.5127	3	0.4963	3	0.4754	3
7	0.6475	3	0.6180	3	0.5969	3	0.5725	3	0.5531	3
8	0.6951	3	0.6729	2	0.6444	3	0.6215	2	0.5969	3
9	0.7453	2	0.7142	2	0.6902	2	0.6618	2	0.6382	2
10	0.7792	1	0.7513	1	0.7217	1	0.6957	1	0.6686	1
	t = 4		t = 3		t = 2		t = 1			
4	0.2124	3	0.2037	3	0.1964	3	0.1887	3		
5	0.3558	3	0.3433	3	0.3297	3	0.3175	3		
6	0.4586	3	0.4404	3	0.4246	3	0.4079	3		
7	0.5306	3	0.5114	3	0.4914	3	0.4734	3		
8	0.5754	2	0.5529	3	0.5323	3	0.5119	3		
9	0.6131	2	0.5907	2	0.5678	2	0.5467	2		
10	0.6439	1	0.6192	1	0.5961	1	0.5733	1		

C.5 Survival Probabilities of Study 3

Energy Reserves	F(x, t, T)	i*	F(x, t, T)	i*	F(x, t, T)	i*	F(x, t, T)	i*	F(x, t, T)	i*
	t = 19		t = 18		t = 17		t = 16		t = 15	
4	0.4950	1	0.2450	1	0.1801	2	0.1189	2	0.1081	3
5	0.9900	1	0.7351	1	0.4851	1	0.3404	2	0.2492	2
6	0.9900	1	0.9801	1	0.8490	1	0.6604	1	0.4954	1
7	0.9900	1	0.9801	1	0.9703	1	0.9006	1	0.7727	1
8	0.9900	1	0.9801	1	0.9703	1	0.9606	1	0.9213	1
9	0.9900	1	0.9801	1	0.9703	1	0.9606	1	0.9510	1
10	0.9900	1	0.9801	1	0.9703	1	0.9606	1	0.9510	1
	t = 14		t = 13		t = 12		t = 11		t = 10	
4	0.0927	3	0.0753	3	0.0594	3	0.0480	3	0.0402	3
5	0.2013	3	0.1785	3	0.1504	3	0.1224	3	0.0999	3
6	0.3724	2	0.3018	2	0.2548	3	0.2213	3	0.1858	3
7	0.6277	1	0.4951	1	0.3996	2	0.3353	2	0.2858	3
8	0.8385	1	0.7258	1	0.6043	1	0.4969	1	0.4158	2
9	0.9268	1	0.8738	1	0.7918	1	0.6911	1	0.5881	1
10	0.9415	1	0.9248	1	0.8903	1	0.8326	1	0.7542	1
	t = 9		t = 8		t = 7		t = 6		t = 5	
4	0.0343	3	0.0296	3	0.0251	3	0.0214	3	0.0183	3
5	0.0837	3	0.0713	3	0.0612	3	0.0520	3	0.0444	3
6	0.1545	3	0.1299	3	0.1107	3	0.0950	3	0.0810	3
7	0.2465	3	0.2095	3	0.1781	3	0.1522	3	0.1308	3
8	0.3542	2	0.3030	2	0.2576	2	0.2200	2	0.1879	2
9	0.4969	1	0.4231	2	0.3635	2	0.3104	2	0.2657	2
10	0.6644	1	0.5749	1	0.4940	1	0.4245	1	0.3638	1
	t = 4		t = 3		t = 2		t = 1			
4	0.0157	3	0.0134	3	0.0115	3	0.0098	3		
5	0.0379	3	0.0325	3	0.0278	3	0.0.238	3		
6	0.0691	3	0.0591	3	0.0507	3	0.0433	3		
7	0.1117	3	0.0955	3	0.0817	3	0.0700	3		
8	0.1612	2	0.1377	2	0.1179	2	0.1008	2		
9	0.2273	2	0.1949	2	0.1666	2	0.1426	2		
10	0.3116	1	0.2667	1	0.2285	1	0.1956	1		

C.6 Survival Probabilities – Dynamic Model

Energy Reserves	F(x, t, T)	i*	F(x, t, T)	i*	F(x, t, T)	i*	F(x, t, T)	i*	F(x, t, T)	i*
	t = 26		t = 25		t = 24		t = 23		t = 22	
2	0.6100	1	0.3721	1	0.2544	2	0.1987	2	0.1664	3
3	1.0000	1	0.8479	1	0.6623	1	0.5032	1	0.3887	2
4	1.0000	1	1.0000	1	0.9407	1	0.8321	1	0.7039	1
5	1.0000	1	1.0000	1	1.0000	1	0.9769	1	0.9204	1
6	1.0000	1	1.0000	1	1.0000	1	1.0000	1	0.9910	1
7	1.0000	1	1.0000	1	1.0000	1	1.0000	1	1.0000	1
8	1.0000	1	1.0000	1	1.0000	1	1.0000	1	1.0000	1
9	1.0000	1	1.0000	1	1.0000	1	1.0000	1	1.0000	1
10	1.0000	1	1.0000	1	1.0000	1	1.0000	1	1.0000	1
11	1.0000	1	1.0000	1	1.0000	1	1.0000	1	1.0000	1
12	1.0000	1	1.0000	1	1.0000	1	1.0000	1	1.0000	1
	t = 21		t = 20		t = 19		t = 18		t = 17	
2	0.1408	3	0.1254	4	0.1105	4	0.1014	5	0.0917	5
3	0.3277	2	0.2798	3	0.2476	3	0.2206	4	0.2007	4
4	0.5810	1	0.4822	1	0.4168	2	0.3670	3	0.3292	3
5	0.8360	1	0.7365	1	0.6373	1	0.5513	1	0.4860	2
6	0.9635	1	0.9137	1	0.8446	1	0.7638	1	0.6809	1
7	0.9965	1	0.9836	1	0.9564	1	0.9128	1	0.8547	1
8	1.0000	1	0.9986	1	0.9928	1	0.9786	1	0.9529	1
9	1.0000	1	1.0000	1	0.9995	1	0.9969	1	0.9897	1
10	1.0000	1	1.0000	1	1.0000	1	0.9998	1	0.9986	1
11	1.0000	1	1.0000	1	1.0000	1	1.0000	1	0.9999	1
12	1.0000	1	1.0000	1	1.0000	1	1.0000	1	1.0000	1
	t = 16		t = 15		t = 14		t = 13		t = 12	
2	0.0855	6	0.0787	6	0.0741	7	0.0691	7	0.0656	8
3	0.1832	5	0.1696	5	0.1573	6	0.1474	6	0.1382	7
4	0.2988	4	0.2738	4	0.2531	5	0.2352	5	0.2201	6
5	0.4347	2	0.3964	3	0.3624	4	0.3361	4	0.3119	5
6	0.6049	1	0.5404	2	0.4923	2	0.4513	3	0.4178	3
7	0.7869	1	0.7159	1	0.6475	1	0.5869	1	0.5393	2
8	0.9146	1	0.8648	1	0.8067	1	0.7446	1	0.6831	1
9	0.9754	1	0.9517	1	0.9178	1	0.8745	1	0.8238	1
10	0.9952	1	0.9874	1	0.9735	1	0.9518	1	0.9216	1
11	0.9994	1	0.9978	1	0.9937	1	0.9858	1	0.9726	1
12	1.0000	1	0.9998	1	0.9990	1	0.9969	1	0.9926	1

Energy Reserves	F(x, t, T)	i*	F(x, t, T)	i*	F(x, t, T)	i*	F(x, t, T)	i*	F(x, t, T)	i*
	t = 11		t = 10		t = 9		t = 8		t = 7	
2	0.0618	8	0.0589	9	0.0559	9	0.0527	9	0.0493	9
3	0.1306	7	0.1234	8	0.1174	8	0.1116	9	0.1060	9
4	0.2067	6	0.1951	7	0.1847	7	0.1755	8	0.1672	8
5	0.2925	5	0.2744	6	0.2595	6	0.2453	7	0.2335	7
6	0.3887	4	0.3640	4	0.3421	5	0.3231	5	0.3060	6
7	0.4990	3	0.4648	3	0.4352	4	0.4093	4	0.3866	5
8	0.6270	1	0.5800	2	0.5396	3	0.5062	3	0.4757	4
9	0.7690	1	0.7136	1	0.6615	1	0.6147	2	0.5763	2
10	0.8835	1	0.8388	1	0.7900	1	0.7399	1	0.6911	1
11	0.9527	1	0.9257	1	0.8918	1	0.8521	1	0.8083	1
12	0.9848	1	0.9723	1	0.9541	1	0.9298	1	0.8995	1
	t = 6		t = 5		t = 4		t = 3		t = 2	
2	0.0461	9	0.0431	9	0.0406	9	0.0383	9	0.0363	9
3	0.0999	9	0.0938	9	0.0880	9	0.0828	9	0.0782	9
4	0.1589	9	0.1509	9	0.1425	9	0.1343	9	0.1267	9
5	0.2221	7	0.2117	8	0.2014	8	0.1905	8	0.1798	8
6	0.2910	6	0.2771	7	0.2643	7	0.2512	7	0.2377	7
7	0.3663	5	0.3483	6	0.3319	6	0.3161	6	0.3001	6
8	0.4499	4	0.4260	5	0.4054	5	0.3860	5	0.3670	5
9	0.5423	3	0.5124	3	0.4858	4	0.4620	4	0.4392	4
10	0.6463	1	0.6084	2	0.5748	3	0.5451	3	0.5177	3
11	0.7626	1	0.7172	1	0.6748	1	0.6372	2	0.6038	2
12	0.8639	1	0.8244	1	0.7826	1	0.7406	1	0.7002	1
	t = 1									
2	0.0345	9								
3	0.0742	9								
4	0.1197	9								
5	0.1697	8								
6	0.2244	7								
7	0.2839	6								
8	0.3481	5								
9	0.4170	4								
10	0.4914	3								
11	0.5725	2								
12	0.6626	1								

C.7 Survival Probabilities – Conventional Rational Model

Energy Reserves	F(x, t, T)	i*	F(x, t, T)	i*	F(x, t, T)	i*	F(x, t, T)	i*	F(x, t, T)	i*
	t = 26		t = 25		t = 24		t = 23		t = 22	
2	0.6100	1	0.3721	1	0.2270	1	0.1385	1	0.0845	1
3	1.0000	1	0.8479	1	0.6623	1	0.4925	1	0.3545	1
4	1.0000	1	1.0000	1	0.9407	1	0.8321	1	0.6997	1
5	1.0000	1	1.0000	1	1.0000	1	0.9769	1	0.9204	1
6	1.0000	1	1.0000	1	1.0000	1	1.0000	1	0.9910	1
7	1.0000	1	1.0000	1	1.0000	1	1.0000	1	1.0000	1
8	1.0000	1	1.0000	1	1.0000	1	1.0000	1	1.0000	1
9	1.0000	1	1.0000	1	1.0000	1	1.0000	1	1.0000	1
10	1.0000	1	1.0000	1	1.0000	1	1.0000	1	1.0000	1
11	1.0000	1	1.0000	1	1.0000	1	1.0000	1	1.0000	1
12	1.0000	1	1.0000	1	1.0000	1	1.0000	1	1.0000	1
	t = 21		t = 20		t = 19		t = 18		t = 17	
2	0.0515	1	0.0314	1	0.0192	1	0.0117	1	0.0071	1
3	0.2492	1	0.1721	1	0.1172	1	0.0790	1	0.0527	1
4	0.5650	1	0.4419	1	0.3366	1	0.2511	1	0.1840	1
5	0.8343	1	0.7293	1	0.6172	1	0.5078	1	0.4077	1
6	0.9635	1	0.9131	1	0.8414	1	0.7540	1	0.6580	1
7	0.9965	1	0.9836	1	0.9561	1	0.9114	1	0.8500	1
8	1.0000	1	0.9986	1	0.9928	1	0.9785	1	0.9523	1
9	1.0000	1	1.0000	1	0.9995	1	0.9969	1	0.9897	1
10	1.0000	1	1.0000	1	1.0000	1	0.9998	1	0.9986	1
11	1.0000	1	1.0000	1	1.0000	1	1.0000	1	0.9990	1
12	1.0000	1	1.0000	1	1.0000	1	1.0000	1	1.0000	1
	t = 16		t = 15		t = 14		t = 13		t = 12	
2	0.0044	1	0.0027	1	0.0016	1	0.0010	1	0.0006	1
3	0.0350	1	0.0230	1	0.0151	1	0.0098	1	0.0064	1
4	0.1328	1	0.0946	1	0.0667	1	0.0466	1	0.0322	1
5	0.3204	1	0.2472	1	0.1877	1	0.1405	1	0.1039	1
6	0.5603	1	0.4668	1	0.3812	1	0.3057	1	0.2413	1
7	0.7751	1	0.6913	1	0.6038	1	0.5169	1	0.4346	1
8	0.9124	1	0.8589	1	0.7935	1	0.7195	1	0.6405	1
9	0.9751	1	0.9507	1	0.9149	1	0.8675	1	0.8098	1
10	0.9952	1	0.9873	1	0.9730	1	0.9503	1	0.9180	1
11	0.9994	1	0.9978	1	0.9937	1	0.9856	1	0.9719	1
12	1.0000	1	0.9998	1	0.9990	1	0.9969	1	0.9925	1

Energy Reserves	F(x, t, T)	i*	F(x, t, T)	i*	F(x, t, T)	i*	F(x, t, T)	i*	F(x, t, T)	i*
	t = 11		t = 10		t = 9		t = 8		t = 7	
2	0.0004	1	0.0002	1	0.0001	1	0.0001	1	0.0001	1
3	0.0041	1	0.0027	1	0.0017	1	0.0011	1	0.0007	1
4	0.0222	1	0.0151	1	0.0103	1	0.0069	1	0.0047	1
5	0.0759	1	0.0550	1	0.0394	1	0.0281	1	0.0198	1
6	0.1877	1	0.1441	1	0.1093	1	0.0821	1	0.0610	1
7	0.3592	1	0.2923	1	0.2345	1	0.1857	1	0.1453	1
8	0.5608	1	0.4818	1	0.4079	1	0.3403	1	0.2800	1
9	0.7438	1	0.6722	1	0.5979	1	0.5238	1	0.4522	1
10	0.8758	1	0.8243	1	0.7650	1	0.6998	1	0.6312	1
11	0.9509	1	0.9216	1	0.8837	1	0.8374	1	0.7837	1
12	0.9845	1	0.9714	1	0.9520	1	0.9253	1	0.8910	1
	t = 6		t = 5		t = 4		t = 3		t = 2	
2	0.000031	1	0.000019	1	0.000012	1	0.000007	1	0.000004	1
3	0.0004	1	0.0003	1	0.0002	1	0.0001	1	0.0001	1
4	0.0031	1	0.0021	1	0.0014	1	0.0009	1	0.0006	1
5	0.0139	1	0.0097	1	0.0067	1	0.0046	1	0.0032	1
6	0.0449	1	0.0328	1	0.0238	1	0.0171	1	0.0123	1
7	0.1124	1	0.0861	1	0.0653	1	0.0491	1	0.0367	1
8	0.2275	1	0.1826	1	0.1450	1	0.1139	1	0.0886	1
9	0.3851	1	0.3236	1	0.2686	1	0.2204	1	0.1789	1
10	0.5614	1	0.4926	1	0.4267	1	0.3650	1	0.3086	1
11	0.7243	1	0.6607	1	0.5952	1	0.5295	1	0.4653	1
12	0.8492	1	0.8005	1	0.7460	1	0.6872	1	0.6257	1
	t = 1									
2	0.000002	1								
3	0.00005	1								
4	0.0004	1								
5	0.0022	1								
6	0.0087	1								
7	0.0271	1								
8	0.0684	1								
9	0.1437	1								
10	0.2580	1								
11	0.4042	1								
12	0.5631	1								

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