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Portfolio Construction: The Efficient Diversification of Marketing Investments

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ABSTRACT

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M.S., Florida Atlantic University, 1976
B.S., Florida Atlantic University, 1973

Dissertation Submitted in Partial Fulfillment
of the Requirements for the Degree of
Doctor of Philosophy
Applied Management and Decision Sciences

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ABSTRACT

Efforts in the marketing sciences can be distinguished between the analysis of individual customers and the examination of portfolios of customers, giving scarce theoretical guidance concerning the strategic allocation of promotional investments. Yet, strategic asset allocation is considered in financial economics theory to be the most important set of investment decisions. The problem addressed in this study was the application of strategic asset allocation theory from financial economics to marketing science with the aim of improving the financial results of investment in direct marketing promotions. This research investigated the components of efficient marketing portfolio construction which include multiattribute numerical optimization, stochastic Brownian motion, peer index tracking schemes, and data mining methods to formulate unique investable asset classes. Three outcomes resulted from this study on optimal diversification: (a) reduced saturative promotional activities balancing inefficient advertising cost and enterprise revenue objectives to achieve an investment equilibrium state; (b) the use of utility theory to assist in the lexicographic ordering of goal priorities; and (c) the solution approach to a multiperiod linear goal program with stochastic extensions. A performance test using a large archival set of customer data illustrated the benefits of efficient portfolio construction. The test asset allocation resulted in significantly more reward than that of the benchmark case. The results of this grounded theory study may be of interest to marketing researchers, operations research practitioners, and functional marketing executives. The social change implication is increased efficiency in allocation of large advertising budgets resulting in improved corporate performance.

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DEDICATION

To all my friends and family who have provided encouragement and endearing support. To my wife Debbie who was there every step of the way.

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I was fortunate enough to stand on the shoulders of these giants.

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CHAPTER 1: INTRODUCTION TO THE STUDY

Background

Many innovative ideas separate contemporary society from societies past. Transportation, communication, and computation are but a few. The capacity to manage risk and make forward-looking choices is one of the great dividers between modern and past times. Bernstein (1996) commented that the capability to look into the future and select the preferred outcomes from the possible options is at the very core of defining present-day societies.

Managing risk changes the way people think and behave. The mathematics of risk management has been a core contribution that has paralleled society's behavior. The quantitative process of understanding irregularities, volatilities, and the consequences of adversity allows us to express a utility for the strength of our desire for a particular outcome. If one can think about future outcomes, one begins to think differently about aversion to risk.

Most advancement in risk management has been related to the financial services and insurance industries (Crouhy, Galai, & Mark, 2001). Indeed, society has benefited greatly by having more choices in investments, insurance, and home ownership. But, should the science of risk management isolate itself to just financial matters?

Personal security and safety after 9/11 are being redefined. In the process, a completely new industry acknowledging new types of risks previously not thought of has been spawned. Dealing with risks creates new opportunities for society to advance. Risk therefore, is the story about the mathematics and management of social choice, outcomes, and preferences.

Just as security and safety concerns bring new opportunities, understanding and managing the risks the marketing function of an enterprise takes with respect to substantial investments in direct customer contact may prove to be a new source of improvement in corporate performance. This research effort was designed to explore and develop operational components of strategic marketing asset allocation as a way to manage the risks inherent in large promotional investments. Strategic marketing asset allocation is defined as the set of strategic processes and tradeoffs an enterprise engages in order to minimize the investment risk inherent in executing promotional allocation decisions.

Operational efficiencies gained from deploying this process may result in a dramatic reduction in promotional saturative conditions that negatively impact customer perceptions of contact relevance. Re-directing promotion investment from saturative segments into under-funded segments should create a new potential source of revenue opportunity. The underlying hypothesis of this study is that these opportunities can be maximized by utilizing specialized portfolio optimization techniques, well known to financial economics practitioners but void in the marketing sciences literature.

Statement of the Problem

Despite gains within the discipline of marketing science in understanding and predicting customer buying behavior, the optimal allocation of advertising investments across customer groups is a problem area not well understood by marketing practitioners and is the specific problem area to be studied in this research. Because of the increasingly large amounts being spent on promotions, this inefficiency is becoming a growing concern to chief marketing officers, chief financial officers, and chief executive officers (Kotler, 1994). This creates an emerging need to treat the customer contact process as a procedural investment strategy. A premise of this study, based on prior research efforts (Bibelnieks, Gliozzi, & Haydock, 2000), is that the poor results achieved with marketing campaign investments are primarily due to a current orientation surrounding the selection of individual customers into discrete campaigns versus developing a strong investment strategy and allocation across groups prior to treating individual customers.

Burger (1959) referred to the nature of marketing campaigns as volatile relative to the consistency of financial returns. He argued that marketing had matured as a loose grouping of capabilities around the individual advertisement or contact media, rather than as a set of integrated operational processes that leverage many variables in order to take some of the unpredictability out of promotional revenue expectations. Smith (2001) reported that from 1995 to 2000 direct marketing investment increased 7.8% annually while overall revenues from promotional spend lagged, increasing at only 5.9%. Over the 40 year period from Burger's observation to Smith's, inefficiency regarding the return on marketing investment has not been adequately addressed.

Researchers and practitioners have primarily focused efforts on explaining individual customer behavior, or what makes good a buyer (Haydock, 2005a). Customer investment has previously been reduced to a decision based on a profit or revenue score applicable to a particular time period coinciding with a promotional investment. Analytical methods determine the scores, these scores are then sequenced from most favorable to least favorable, and an arbitrary cutoff determines how deeply the customer selection from the list is made.

Recency of purchase, frequency of purchase, and monetary value are the driving attributes underlying such a scoring and selection process. Haydock and Bibelnieks (1999) described the consequences of such a model, that did not compensate for the saturative effect of advertising on customer behavior. This key insight established an alternative method of individual customer investment. Establishing an optimal stream of promotions across time where individual customer actions at every time period are considered significantly outperformed the single period selection models typical of the industry (Haydock, 2005a).

Still, a gap existed when considering an efficient investment process. Greene (1969) argued that individual customer purchase observations were mostly sparse and that there was an unmistakable tendency for marketing managers to ignore this risk element in their investment choices. In the same work, Greene described the need for a more strategic and structural approach to understanding the risks in a marketing investment, assessing what marketing program goals and priorities should be, and argued that marketing should initiate a strict quantitative process for assessing courses of action.

Haydock (2006c) identified that current industry practices have not moved beyond the single period sequential decision criteria for investment allocation. The use of a single tactical process for customer selection into a campaign leaves a void in the management of risk surrounding strategic investment allocations. This void accounts for fluctuations in performance results and unanticipated losses (Greene, 1969).

Direct marketing firms may spend between 15 and 20% of revenues on customer promotions (Haydock, 2005a) creating a large pool of investment dollars. Firms estimate that their waste is between 5 and 7% of investment (Haydock, 2005c) and possibly more, but are unable to remove the waste without removing an entire promotion. Removing an entire promotion removes the associated revenue potential and is therefore at present, a poor choice.

Since direct marketing firms do not currently make use of strategic asset allocation processes, the possibility of serendipitous revenue maximization is extremely low. What may occur is that market segments with revenue payoff potential do not receive enough investment, while other market segments receive too much. The solution to the problem, therefore, is how to improve marketing program results through the construction of an optimal asset allocation procedure. That construction is a goal of this study.

Nature of the Study

This research deployed the grounded theory method to establish the efficient set of portfolio construction procedures. The grounded theory approach is recommended because of the current lack of understanding and documentation regarding this marketing science issue. Grounded theory is generated from the data and advocates a loosely structured research design that allows theoretical ideas to emerge during the course of the research.

In addition to the grounded theory, an extensive test was undertaken in an effort to demonstrate areas of improvement to the return on marketing investment achieved through the use of these proposed asset allocation techniques. This test simulated the possible choices and preferences for risk a marketing executive has in crafting a course of investment action. The risk averse and risk taking marketing investors may not operate under the same expected utility.

Research Questions

Marketers clearly value revenue returns and financial performance in the execution of their promotional programs, but the observation noted by Greene (1968) is that sales outcomes from promotions rarely exceed expectations, are very expensive to execute, and result in contacting the same customer over and over again. These characteristics describe a type of risk that should be identified, understood, explored, explained, and systematically dissipated prior to the marketing executive making any investment decision on any particular customer.

Therefore the core research questions under investigation in this study are:

1. How should a marketing executive consider risk and how do these risks affect utilities that the marketing investor seeks to optimize?

2. What role does an understanding of promotional saturation play in the dissipation of risk when investing in discrete customer market segments?

3. What are the portfolio construction components and investment procedures appropriate for the marketing function that simultaneously maximizes the profit potential

of investable market segments and minimizes any waste in saturating customers with ineffective promotions?

4. In what ways can quantitative models be used by the marketing function to efficiently allocate customer contact investments in order to maximize marketing program return on investment?

5. Which risk management metrics can be engaged in measuring marketing program profitability in order to compare competing investment procedures?

Research questions 1, 2, 3, and 4 are directly related to the development of the grounded investment theory that specifies procedures for constructing an optimal portfolio which would efficiently allocate marketing resources. Research Question 5 is related to the development of risk management metrics that can be tested to identify the amount of investment value attributable to competing portfolio methods.

Significance of the Study

The strategic asset allocation process in financial economics is considered by the investor to be the single most important set of investment decisions (Sharpe & Alexander, 1990). In finance, the asset allocation step precedes the selection of the specific investable instruments. Customer investments made by marketers should follow the same sequence, but have not previously had a tool to allow them to do so.

Without the asset allocation process to balance risk and return, marketers will consistently saturate their customer base with irrelevant advertising in search of promotion driven sales results. This activity creates a new type of risk that is unsystematic and specific to each firm. This risk is an inflationary gamble resulting from a bet on a diminishing return function in the hope that by increasing advertising spend a sale, at any cost, will be eventually generated.

The solution sought in this study is significant for several reasons.

1. *Reduction of saturation*: Saturation can be thought of as a type of promotional inflation, too many dollars chasing too few customers. As an example, for a firm with $1.0 billion in revenues and $150.0 to $200.0 million in customer contact budget, a 5-7% waste reduction optimization would add between $7.5 and $14 million to firm profits prior to the customer contact activity. An added benefit from the standpoint of the consumer is potential to reduce irrelevant communications.

2. *Increased revenue potential:* The optimal allocation process should balance investment inequities to an equilibrium state. Too much investment in a saturative market segment results in unproductive promotional expenditures with little or no marginal revenue return. Too little investment in a higher potential market segment results in lost sales opportunity. In Haydock (2006c), an estimate of revenue gains from implementation of an optimal asset allocation process was 7.1%.

3. *Improved customer perception of relevancy:* Relevancy of customer communications is paramount in developing any consumer relationship. Market segmentation and investment techniques will be used to determine the appropriate resource allocations addressing the frequency of contacts. Although individual relevancy was not addressed in this work, the benefits of segment attribution relative to messaging and its proper sequential organization will be utilized as investment criteria.

4. *Operations research and marketing science contributions:* Several technical contributions were required in order to solve the asset allocation optimization problem relative to its use by the marketing function. These contributions include: (a) The application of financial indexing theory, Brownian motion, and binomial lattice development to assist with setting the probabilities of customer arrivals and expenditure amounts in a time dimensioned uncertain environment; (b) the use of utility theory to assist in the lexicographic ordering of goal priorities; and (c) the detailed solution approach to a multi-period linear goal program with stochastic extensions.

Social Change

Researchers in both the marketing sciences and operations research will benefit from this study because of the unique and original approach to the consideration of a multi-process methodology to the efficient allocation of marketing spend. Several appropriate quantitative techniques were applied to the steps within the process. This construction of a unified asset allocation procedure made up of these complex quantitative processes is something not found in searches through the current marketing sciences literature.

Perhaps the largest contribution to social change occurs with the re-engineering of investments procedures related to those responsibilities of the chief marketing officer of an enterprise. These individuals are charged with the accountability to efficiently spend scarce resource dollars to acquire, re-activate, and retain profitable customer relationships for the firm. The asset allocation capabilities to be proposed would be considered new processes and a potential new source of enterprise financial performance. More than the possession of unique quantitative methods or enhanced procedural insights, the asset allocation capability will effectively allow marketing executives to think differently about the stochastic nature of demands and permit the executive to shape outcomes to meet the firm's marketing program profit objectives.

Lastly, consumers will benefit as a result of organizations adopting this unified approach. The personal experience of opening a residential postal mailbox to find it full of promotional enticements that do not meet a family unit's needs may serve as an example of the economic inefficiency that exists, even in what may be considered the best of breed direct marketing firms. Open an electronic mailbox and the situation may be worse. The quantity of irrelevant e-mails appearing in in-boxes is so high (Demery, 2004) that it has generated government activity in the form of the U.S. Congress passing the CAN-Spam Act that will attempt to separate what is information from what is spam.

Purpose of the Research

The purpose of this quantitative grounded theory study was to develop an optimal strategic asset allocation investment procedure in order to improve the financial results of marketing investment in direct customer contact. This unified strategy weaves together multiple complex quantitative processes resulting in operationally optimal customer portfolios that minimize the inflationary effects of advertising saturation while simultaneously maximizing the revenue and profit potential of the investment.

Research Overview

This study extends the tactical contact optimization procedure first proposed by Haydock and Bibelnieks (1999) and successfully implemented at a retail direct mail cataloger (Campbell, Erdahl, Johnson, Bibelnieks, Haydock, Bullock, & Crowder, 2001). That solution subsequently relied on a series of optimal budgets set at the strategic level, which if misappropriated, would negate the effect of removing saturation at the customer level. The observation at the time: (Bibelnieks et al., 2000) was that the largest gains came from two areas: (a) saving dollars by removing saturation; and (b) ensuring that customer groups, who could use more information, and more expenditure, received the correct allocations in order to maximize revenues and marketing program profits.

The focus of this research was to develop an optimal strategic asset allocation investment procedure in order to improve on these financial areas of gain. Strategic asset allocation was selected, as opposed to either tactical or dynamic allocation methods because this particular procedure frames the preferences of the marketing department relative to available utilities and their risks while trading off revenue opportunities within customer groups seeking the highest probability payoff decisions. A thorough literature search described in chapter 2 confirmed that this research is unique as applied to the marketing investment function of an enterprise.

This research does position itself on the shoulders of some groundbreaking theoretical work in the financial services industry beginning with Markowitz (1952), continuing with Sharpe (1964), and Arnott and Fabozzi (1988). There is a significant difference, though, in the motivations of the financial investor and those of the marketing investor. For example, the financial services asset classes are typically pre-defined where the marketing asset classes require a process of discovery. The investment data in a financial services environment are plentiful as instruments are commonly traded and therefore frequently observed. Consumer shopping behavior on the other hand is infrequently observed by any single firm, as there are many shopping choice options, and the data are therefore sparse.

Most importantly, the strategic asset allocation process is not typically thought of as a part of the marketing function. This is in spite of the large amount of investment dollars being spent on risky promotions and in contrast to the financial services strategic asset allocation process, which would be considered a critical first step in investment optimization decisions. The opportunity, therefore, is to define, construct, and test this new framework.

Scope of Research and Delimitations

The following fell within the scope of this research.

1. A description only of the segmentation and clustering process that does not include details of the algorithms used which create separable partitions in the creation of marketing asset classes. References to detailed work leveraged in the test to produce the market segments are given in chapter 2.

2. The development of a binomial tree to capture the stochastic nature of customer counts and demand amounts in future time periods. Time periods were described in quarters, appropriate for strategic actions. The binomial lattice is the discrete time paradigm for the stochastic Brownian motion exhibited by consumer demands.

3. The development of an index linked to the product offerings of the firm that can be used to predict the highest probability path through the binomial lattice. Demands and customer counts are shown to be path-dependent through time.

4. Use of economic utility theory to determine selection and lexicographic ordering of goal priorities.

5. A comprehensive review of the development of multiattribute optimization featuring a multiperiod linear goal program with stochastic extensions was used to perform the allocation function. This included all algorithms utilized and a data dictionary (inputs) as well as all recommended outputs. Interpretation of the numerical optimization results is included in the results section. These interpretations are consistent with items important to managerial decisions as well as professionals engaged in operations research.

6. A case utilizing operational data was run against the clustering, the binomial lattice, and asset allocation procedures so that results of these models can be articulated and contrasted. These trials provide the venue to apply the scientific method to insure model quality and validity.

7. Identification and articulation of how these complex models can be applied by marketing executives to improve managerial decision-making and drive enterprise profitability. These models can provide large scale social change opportunities, but only if they are practical and useable. The scope of the computational models was limited to operations against market segments that are appropriate for the types of strategy decisions under investigation in this research.

This study was limited to examples, data, and other assumptions consistent with the retail direct marketing industry. Extensions to this study may have applicability to many industries with customer contact inefficiencies. Implementation issues surrounding the organizational transformations that may occur upon execution of this suite of procedures are touched on, but not in great depth. This study was designed to construct the asset allocation framework, detail the mathematical procedures, and demonstrate increased investment value of the methods through case simulations.

This study was designed to provide a significant improvement in contact strategies as opposed to contact tactics and will confine itself to strategy models only. Contact strategies are focused on the market segment investments with the motivation of providing the optimal allocation of dollars to the segments with the most potential. This allocation procedure could provide budgets for the tactical mail stream optimization at the customer level. The mail stream tactic is an equally complex area, but will not be dealt with in this study. Information on the tactical area can be seen in Haydock and Bibelnieks (1999).

Assumptions

The most important general assumption is that the data used for the applications and case study is representative of the data of other firms engaged in the same industry. An assumption of normality was made in the design of the Monte Carlo simulator. The data used are actual purchase, promotional response, and demographic observations which have been carefully selected and are related to the retail apparel industry. The data appear in quarterly time increments that are suitable for strategy level analysis.

It will be assumed in the proposed simulation environment, that a change made to an advertising investment allocation and/or a marketing mix scenario modification will result in a change to the return on investment performance of a market segment. All return on investment responses will be consistent with actual customer performance captured in the profile of that market segment, and represented in the data. These response functions could be either linear or non-linear in nature, and vary by market segment.

A convention used in this study is that the discussion of probabilities will refer to the language and semantics appropriate for Bernoulli trials and binomial logic. These procedures will be used to describe the up-down movements, valuations, and uncertainties surrounding the use of the proposed binomial lattice. The movements of the indices through time with the associated transition probabilities will also leverage these conventions.

Related to the economic scenarios that were generated from the binomial lattice, an assumption was made that there is a constant investment pool available. The costs that may impact a typical direct merchant were considered as stationary for the purposes of this research. These costs could include items such as postage, the cost of paper for direct contact promotional purposes (in the form of a catalog), and the cost of merchandise (such as fabrics).

Finally the objective function and constraint sets of the multi-period linear goal program were considered linear. They were in fact either linear in their original formulation or were made into a linear form through a series of mathematical transformations. All other assumptions are identified as they occur in the formulation of the algorithms.

Barriers to the Research

This research did not require the collection of data from interviews or surveys typical of qualitative studies. The data were generated from archival sources. The study is quantitatively focused and the data required are transactional and were readily accessible to the researcher. Other data used in the creation of the indices were accessible through the Internet and exist on U.S. Government-sponsored Web sites and are of high quality. These data were considered archival as well. No live subjects were interviewed as a result of the research process. A description of the archival data is articulated in chapter 3 that details the design of the research approach.

Since the research was designed as a quantitative grounded theory, the focus was on developing a cohesive series of allocation procedures referred to as portfolio construction. The research questions center around how these procedures can be constructed in order to provide benefits to marketing managers with revenue generation responsibility accomplished through customer contact activities. The details of making this unified theory work efficiently temporarily overshadow the implementation issues that may prove more organizational than technical. Some recommendations are made regarding implementation issues, but these are secondary to the technical solutions proposed. There are no known barriers to the completion of this research as described in the scope of the study.

Limitations

This study is quantitative in nature and relies on the outcomes of mathematical models to provide knowledge about investment allocation and marketing program immunization. The limitations are generally those encountered with the construction and use of statistical and operations research methods. Weaknesses may occur in the formulation of the model equations as key terms may be inadvertently omitted or accidentally misrepresented.

Despite these weaknesses, models are very powerful tools to represent business processes. Often these models are the only means to explore investment decision alternatives or predict future customer demands. Because of the importance of the models used in this research, assessing model accuracy was done by careful inspection of terms and calibrating the models to gain better agreement between observation and model output.

Definition of Terms

For the purpose of this study, a few general terms will now be defined. These may or may not be in the reader's field of expertise. Many of the terms originate in the financial economics area and may be unfamiliar to the marketing researcher.

Asset allocation: The process of efficiently assigning marketing investment into customer market segments. The purpose of the allocation is to ensure that market segments receive enough investment to maximize the revenue potential of the segment, but not so much that they saturate consumers with irrelevant offers. Another motivation is to diversify within recency groups so that objectives can be achieved at minimum risk.

Asset class: Synonymous with market segment.

Binomial lattice: A multiperiod tree-like representation of the up-down stochastic movements that capture the possible values of demand and customer counts at future points in time. The journey through the lattice from the root node to a terminal node is called a *path*. Each path is associated with a probability of occurrence. The total number of possible paths are 2^n where *n* is equal to the number of time periods. The binomial method deployed will provide a discrete time model of a continuous time Brownian motion stochastic process. A *trinomial lattice* (up, down, and same) was rejected as a solution technique as there is virtually no chance that customer counts and demands from the previous time period would be identical to the current time period.

Composite index: The development of a data type that can serve as a proxy for all competitors participating in a retail sense in a selected marketplace. This index will measure aggregate retail sales for all participants in the index. These data are provided as monthly sales updates to the North American Industry Classification System (NAICS) retail categories from the U.S. Census Bureau.

Down movement within a binomial lattice: Referring to one of two possible movements of customer counts and demands determined by the probability of an event moving from a prior state in a previous time period, to a lower state in the current time period as it moves through time represented by the lattice.

Dynamic asset allocation: The shift in portfolio investment strategy in an effort to correct an investment position in a customer group caused by short term adversity or short term opportunity in the marketplace. Dynamic asset allocation is the period to period correction to the overall strategic allocation process. In this research, the corrective triggers will occur as a result of market conditions sensed from customer counts and demands as they move through the binomial lattice.

Financial engineering: A cross-disciplinary field that relies on mathematical finance, numerical methods and computer simulations to make trading, hedging and investment decisions, as well as facilitating the risk management execution of those decisions. Practitioners of computational finance aim to precisely determine the financial implications of risks and rewards in creating optimal portfolio positions.

Linear goal program: A specialized formulation of a linear program that allows for multiple objectives and priorities through the use of deviational variables. This formulation is highly applicable to marketing investment situations.

Marketing engineering: A cross-disciplinary field that relies on mathematical modeling, numerical methods and computer simulations to make product, customer service, and promotional investment decisions, as well as facilitating the management execution surrounding those decisions. Practitioners of marketing engineering, relative to this study, aim to precisely determine the financial implications of risks and rewards in creating optimal customer portfolio positions.

Modified Hamming distance formula: A measure of a multidimensional distance developed for use in a data driven market segmentation, named in honor of mathematician Richard Hamming (1915-1998).

Optimal portfolio: Relative to this study, the optimal portfolio would contain the exact monetary promotional investment positions to be taken by an enterprise in each of several market segments. Each market segment is made up of customers with like, but not identical attributes. These investments are made in various promotions executed by the enterprise in order to generate sales and profits. The optimal portfolio is the one that is preferred over all other competing portfolios and that maximizes revenue, profit objectives, or other utilities of the firm with the minimal amount of risk.

Path through a binomial lattice: There are several routes that can be taken through a binomial lattice. These routes through the lattice are determined by the probabilities of an up or down state at any time period, as customer counts and demands move from period to period. There are 2^n possible paths where n is the number of time periods in the lattice.

Portfolio insurance: The process of protecting a marketing strategy investment from adverse market conditions.

Portfolio immunization: A type of protection against adverse market conditions that would ensure cash flows related to marketing programs. Immunization is the motivation for the hedging activity mentioned in this study.

Program hedge: Establishing a position in a synthetic investment instrument that provides the ability to minimize adversity in market conditions.

Rational man: An economic concept forming the basis for a majority of economic models which makes the assumption that decision-makers are rational and will seek to maximize their utility of either money or nonmonetary preferences.

Strategic asset allocation: The *long term* investment strategy the marketer will deploy to insure the maximization of retention, re-activation, and acquisition of customers measured by *long run* customer file growth and increased customer equity. Long term and long run in this study will refer to six business quarterly time periods.

Up movement within a binomial lattice: Referring to one of two possible movements of customer counts and demands determined by the probability of an event moving from a prior state in a previous time period, to an increased state in the current time period as it moves through time represented by the lattice.

Value at Risk (VaR): The worst loss that might be expected from holding a portfolio of customers over a given period of time (in this case a fiscal quarter) and given a specified level of probability of the loss (known as the confidence level). This measure allows the marketing executive to quantify overall portfolio risk across all market segments.

Additional terms are defined as necessary as they arise in the study and add clarity to the text and concepts being described. Formulas are completely defined and all terms articulated at the time the formulas are introduced. Illustrations are used to help illuminate complex concepts and processes.

Summary

Chapter 1 opened by introducing the concept that risk management can provide the capability for firms to shape future outcomes based on preferences. This capacity has fundamentally shaped the world we live in today. The science of financial economics has utilized the asset allocation function as the primary way to model a risk management strategy. The marketing function has yet to adopt an adequate risk management paradigm or a procedural way to model the substantial investments made in customer contacts. Adopting these procedures may provide a new and important source of improvement to corporate performance.

The focused problem area studied in this research is the optimal allocation of direct marketing advertising investments across customer asset classes. A grounded theory method will be deployed because of the current lack of understanding and documentation regarding this marketing science issue. The research questions center around defining marketing risk, identifying the nature of saturation, documenting the specific portfolio optimization components and computational models, and determining the appropriate metrics that measure return on marketing investment.

A major outcome of this study is the opportunity for social change that could occur as a result of this research. These outcomes include: (a) reductions in saturative contacts as dollars are constrained as over-promoted conditions are uncovered; (b) increased revenue generation as more productive market segments are identified; (c) an increase in the customer perception of promotional relevancy; and (d) the specification of a new source of marketing science and operations research framework that deals with the allocation of scarce resource.

In chapter 2, an extensive review of the literature addresses the components of classical asset allocation as it applies to financial economics. A similar review of the marketing science literature is articulated and compared to the financial economics literature. The areas covered are those that would comprise the construction of the optimal marketing portfolio. These include a review of portfolio optimization, choice preferences and utility theory, multi-period linear goal programming, multiattribute portfolio analysis, stochastic processes and Brownian motion, multiperiod binomial trees, indexing theory and techniques, market segmentation and clustering methods, and concepts surrounding unified portfolio models.

The literature review reinforces that there is sparse marketing science documentation relative to the portfolio optimization investment function and that this research can provide a contribution to knowledge. The connection of prior research to the problem statement is made and the proposed solution is briefly described. The literature review is decomposed by the topical components of portfolio optimization as they relate to the marketing function and the proposed solution.

Chapter 3 describes the research design used in this study. Prior to articulating the research design, a knowledge acquisition strategy must be determined so that claims to knowledge can be properly justified. The post-positivism strategy was selected from four alternatives since its procedures lead directly to a study utilizing the scientific method.

Data collection methods are described and are those governing the use of archival data. A large set of customer observations was acquired that contains detailed purchase summaries and is appropriate to test the portfolio optimization concepts. Another important archival data source that is described comes from the U.S. Census Bureau and includes detailed data on retail category sales used in index development.

Chapter 4 describes the asset allocation optimization construction. Each process component was dissected and articulated using the grounded theory approach. Examples are given in a series of tables and figures that help the reader work through the complexity of the models. A thorough description of the data is presented with characteristics and examples. The hypothesis test is described and is accompanied by a series of tests that help judge the performance of some of the assumptions made concerning normality.

Chapter 5 provides a summary of the research findings. Conclusions are drawn from what was learned from the data and on the overall performance of the asset allocation optimization procedure. The research problem and research questions are re-visited to insure those leading questions were answered with the research findings. Areas for further research and exploration are identified that provide a future research agenda beyond this study

CHAPTER 2: LITERATURE REVIEW

Introduction

The purpose of this study was to develop an optimal strategic asset allocation process in order to improve the financial results of investing in direct customer contact. The investigator executed an extensive review of both the marketing science and financial economics literature addressing the components of classical asset allocation in order to provide this quantitative grounded theory study with a solid theoretical foundation. This theoretical foundation includes the areas of portfolio optimization, choice preferences using utility theory, multiperiod linear goal programming, multiattribute portfolio analysis, stochastic processes including Brownian motion, multiperiod binomial trees, peer indexing theory, and market segmentation using clustering methods.

Selected components of this asset allocation framework, as they apply to the marketing function, have been developed in earlier work by this researcher. These will be reviewed in this literature review as well. Figure 1 provides an illustration of the components studied in this research effort to construct efficient marketing portfolios. An attempt has been made to trace the most important contributions found in the literature, especially as they apply to portfolio construction methodologies.

Figure 1 may also serve as an illustrated way to quickly move through the literature sequence being presented. One key finding that resulted from the literature review was the absence of the notion of portfolio in marketing science contributions. Fortunately, the study of financial economics provides a rich set of documentation, though the motivation for the use of certain components of portfolio construction bifurcates at the point of instrument analysis. Financial engineers study the behavior of financial assets and derivatives, marketing engineers study the behavior of customers and products.

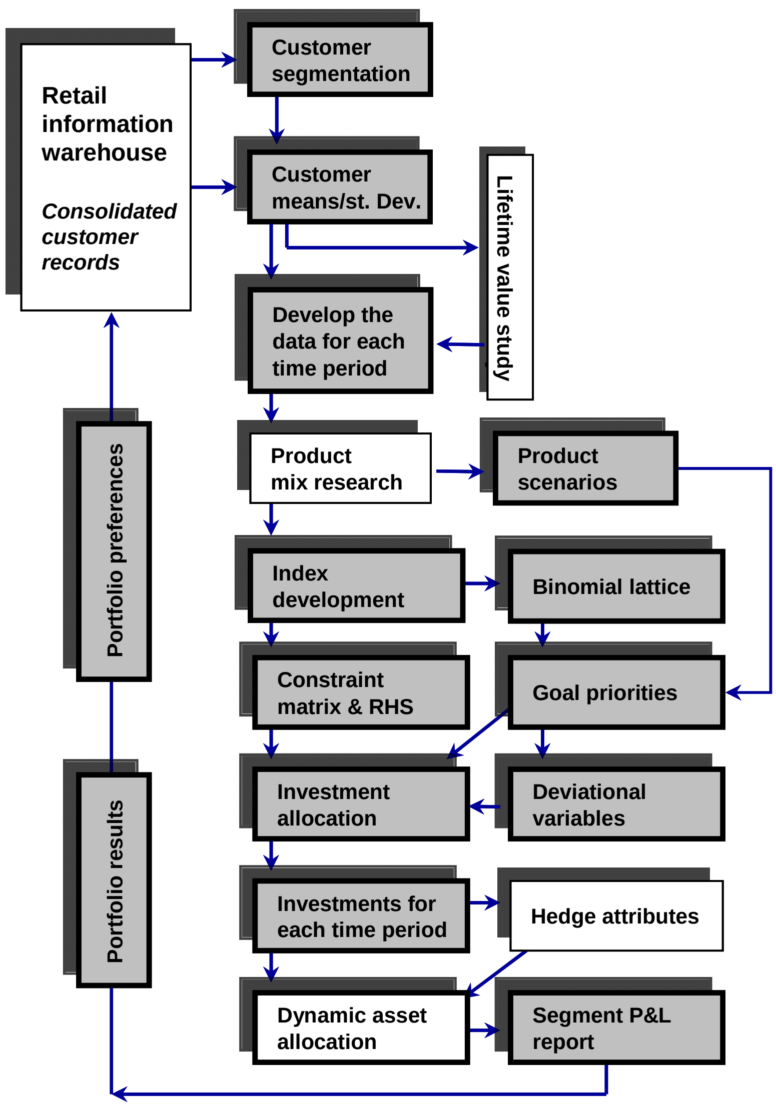


Figure 1. The proposed portfolio construction process and components.

Yet, they both must invest in the effort to derive the maximum return from their respective asset targets, while striving to minimize the uncertainty surrounding the investments. As Figure 1 demonstrates, there are many considerations when constructing a marketing portfolio. The literature was selected in order to construct a foundation for the research. The items highlighted in gray in Figure 1 are reviewed in detail in this portion of the research as these are key missing components in the marketing literature, and foundational aspects of the portfolio construction process detailed in chapter 4.

Borrowing from the way a financial engineer may view the problem of portfolio construction, a selection of preferences for return and risk enveloping the entirety of the portfolio would be the first series of choices. This would certainly predate, and ultimately assist in the preferences surrounding the detailed selection of investable instruments. Using this paradigm, the marketing science literature has concerned itself primarily on the latter aspect of the investment process focusing on the stimulus and response activities of their investable instruments (customers and products). To that end, the marketing science literature is certainly rich, articulate, and well respected.

Prior to the operational selection of specific customers into a portfolio, should the marketing investor not express strategic preferences for return and risk? The topic of a quantitative investment allocation processes prior to mining the customer base for opportunities is a potential source of corporate improvement that can effectively increase the revenue opportunity of the customer base, lower the uncertainty of these returns, and cut costs through dissipating the saturative effect of over promotion.

Marketing engineering, up to this point, has primarily concerned itself with customer selection without regard to investment risk. Financial engineering, in contrast, seeks a firm understanding of the risks surrounding the investment process and in doing so has created procedures that identify, manage, and ultimately leverage these risks. Since the financial economics concept of portfolio optimization is a centerpiece of any study of portfolio construction, a description of its origin will begin the literature review.

Portfolio Optimization

The portfolio optimization process can be thought of as maximizing the expected return of the portfolio subject to rules regarding risk constraints (Leibowitz, Henriksson, & Krasker, 1988). Haydock (2005a) argued that financial economics and marketing science should share similar definitions of risk, both disciplines centered on the uncertainty in the return of an asset class. In financial economics, asset classes are composed of various investment instruments, in marketing science, an asset class will be synonymous with a market cluster with customers as the ultimate investment targets.

This point of risk centered similarity is the juxtaposition of finance and marketing from which their processes begin to diverge. Haydock (2005a) described the current state of marketing investment science as being in a nascent stage focused on the return on an individual customer. Not unlike that of financial investment theory that found itself in the first half of its history principally concerned with the return of an individual security. That all changed with the observations and curiosity of a young researcher.

Harry Markowitz is considered the father of modern financial portfolio theory. In 1950, Markowitz was contemplating his doctoral dissertation topic at the University of Chicago. He was referred to Professor Marshall Ketchum from the Business School, who introduced the young Markowitz to a book by John Burr Williams *The Theory of*

Investment Value. Markowitz noted that Williams' premise was to maximize discounted expected returns of individual securities (Markowitz, 1952).

This premise disturbed Markowitz because all that had to be done to invest using this method was to select the security with the highest return and invest everything in that single asset. This formulation could be represented by (Markowitz, 1959):

$$P = \sum_{t=1}^{n} \frac{A_t}{(1+r)^t} .$$

Where:

P = the present value of the investment,

A_t = the cash income of the investment at time period t;

r = the interest rate sought by the investor, and

n = the number of time periods in the investment.

Markowitz (1952) noted that investors diversify in practice. Investors knew that the payouts in future time periods were not known with certainty and that in fact returns of various securities varied from their original expectations. So, Markowitz developed a rule that defined the expectation of returns, and the variance of returns.

This rule was based on his observation of diversification. Markowitz defined the yield of the portfolio as the weighted sum of the random variables (the investment instruments): $R_P = \sum R_i X_i$ or $E_P = \sum_{i}^{n} X_i \mu_i$.

Where:

R_P = the overall return on the portfolio,

R_i = the returns from the individual securities *i*, which are random variables,

X_i = percentage weights of individual securities selected by the investor where $\sum X_i = 1$,

R_i is independent of X_i, $X_i \geq 0$,

E_P = the overall return on the portfolio where *E* represents the expected value,

n = the number of securities in the portfolio, and

μ_i = the mean value of the random variable R_i;

The variance of the portfolio was defined as:

$$\sigma_P^2 = V_P = \sum_{i=1}^{n} \sum_{j=1}^{n} \sigma_{ij} X_i X_j \; .$$

Where:

$\sigma_P^2 = V_P$ = the variance of the portfolio, and

σ_{ij} = the covariance of the security pairs weighted by *X*.

Markowitz (1952) correctly identified that just a strategy of diversification was not good enough by itself. The covariance of the assets should be offsetting as well. The observation was that securities in the same industries moved more or less together. This meant that allocation across different industries that move in the opposite direction of each other would provide more of the diversification that he had in mind.

The result was a rule for investing in industries with different economic characteristics that would have a lower portfolio covariance than just investing in firms within the same industry. So, the initial step, prior to the selection of any individual investment would be the selection of the industries into asset categories. Missing in the investor's paradigm was not just the individual risks of the securities, but the risk of the overall blended portfolio.

This blend in fact created a new type of asset, synthesized from the combination of weighted assets, and in turn created a different type of risk. The notion of a two stage investment process, removing risk at each stage had taken shape. This led theoreticians in the field to further diversify into the broad categories of cash or equivalents, bonds or debt, and stocks or securities (Sharpe & Alexander, 1990) in addition to industries.

Lastly, Markowitz described the portfolio selection process given two portfolios with identical expected values (Markowitz, 1952). His advice was to choose the portfolio with the lowest variance of returns. The proof included a geometric explanation that fundamentally changed the way tradeoffs were made in finance. His portrayal turned out to be a description of efficient sets. In an explanation of how to achieve the highest return with the minimum amount of risk, Markowitz (1959), also described linear programming and referenced the work of George Dantzig's simplex method.

Markowitz left the University of Chicago in 1951 for the RAND Corporation. There, about a year later, he met Dantzig, also working at RAND. Dantzig was leading the development of applications utilizing linear programming algorithms. This chance encounter was the progenitor of portfolio optimization. Dantzig's linear program formulation (1963) can be described as follows:

Minimize: $c^T X$

Subject to: $AX = B$; $X \geq 0$

Where:

A = the coefficient matrix of constraints with risks on the diagonals,

B = the column vector of right hand sides,

c^T = a vector of coefficients of the objective function, and

X = a column vector of the problem variables.

Since expected return is a linear function of portfolio investments, selecting the portfolio with the highest expected return is inherently a linear programming problem (Markowitz, 2002). Because variance utilizes a squared term, there was a need to describe the minimization of risk utilizing a nonlinear method. Philip Wolfe was also working at the time for the RAND Corporation. His work was known to Markowitz because they had exchanged papers as referees for the same journal. They decided to review each other's work that would lead Markowitz to the formulation of the portfolio selection model as a quadratic programming problem. This problem can be expressed as (Wolfe, 1962):

Minimize: $f(X) = c^T X + \frac{1}{2} X^T VC \times X$

Subject to: $AX = B$; $X \geq 0$

Where:

A = the coefficient matrix of constraints,

VC = the variance-covariance matrix or the quadratic matrix,

B = the column vector of right hand sides,

c = a column vector of linear coefficients of the objective function, and

X = a column vector of the problem variables.

These efforts and discoveries led to the development of financial economics as a new field of research. Maybe more important was the insight into a methodology that would convert the inherently risky task of making large financial bets into a process in which preferred outcomes could be engineered with greater degrees of certainty. Significant contributions were subsequently made by Sharpe (1964), Leibowitz, Henriksson, and Krasker (1988), and Black and Litterman (1990).

The void in the marketing science milieu is this concept of portfolio and a view into the associated risks of the portfolio devised of various customer profiles, response to offerings, and the effects of various advertising or promotional strategies. Absent the quantification of portfolio, choices could be made, but uncertainty would drive the behavior of the marketing executive to saturate the customer communication stream, with disappointing financial returns (Haydock & Bibelnieks, 1999).

The preference to shape certain outcomes drove Markowitz (1959) to create a rational man who was required to make decisions under uncertainty. If this rational man were seeking only the maximization of expected return, then he would never diversify the portfolio in order to dissipate the risks. Because of the uncertainty, the rational man would instead seek the utility of expected return.

Each possible random outcome could have a value associated with a utility, and when deciding among chance outcomes, the rational man would select the outcome with the greatest expected value of the utility. Utility therefore, also captures the idea of preferences, especially those surrounding the certainty of an outcome. The importance and implications of utility theory on portfolio construction are detailed in the next section.

Utility, Portfolio Choice, and Outcomes Under Uncertainty

Utility theory in the context of portfolio construction will be used to assist in the lexicographic ordering of goal priorities. These priorities affect the linear goal programming solution sequence and ultimately portfolio outcomes. Outcome preferences are certain, utility payoffs are expected values and are therefore governed by the statistical properties of uncertainty. The task in lexicographic ordering is to identify that whenever one goal is preferred over another, that the expected utility of the preferred goal is larger than the expected utility of an alternative goal.

Sharpe (1964) proposed a financial economics model that gained near universal acceptance named the Capital Asset Pricing Model (CAPM). Sharpe's aim was to construct a set of priorities that would limit the number of securities in a risky portfolio of capital markets' instruments. Sharpe highlighted the difficulty in predicting capital markets behavior under uncertainty. He articulated that at the time, there was no microeconomic theory that dealt with conditions of risk.

Sharpe explained that Markowitz' portfolio optimization model can be broken down into two parts:

1. The choice of a unique optimal combination of risky assets; and
2. A separate choice concerning the allocation of funds between a combination of risky assets and a single risk-less asset.

Sharpe (1964) identified that the market presented primarily two prices to each portfolio: the price of time, represented by owning a risk-less asset and accumulating the interest on that asset, and the price of risk, which is the premium for owning a risky asset. Sharpe and Alexander (1990) described the utility function of the investor as being $U = f(E_{w,} \sigma_w)$, where E_w described the expected future wealth of the investor and σ_w represented the standard deviation or dispersion around future wealth. Investors, accordingly, would prefer a higher expected future wealth than a lower value $(\partial U / \partial E_w > 0)$. Investors generally exhibit risk aversion preferring a lower value of σ_w over a higher value that says that given a specified level of E_w the investor would prefer that $\partial U / \partial \sigma_w < 0$.

Sharpe's paradigm is very useful in that it introduces the concept of the standard deviation of returns and preferences around these volatilities. A classic earlier work by von Neumann and Morgenstern (1947) described utility as the outcome of a lottery. The user would prefer for instance the lottery L_1 over lottery L_2 if and only if the expected utility of lottery L_1 is greater than the expected utility of L_2.

In their view, a good of any type that is consumed supplies this type of utility. The higher the consumption preference, the higher the total value of the utility. It is this choice over uncertain lotteries that first described the univariate nature of risk aversion.

Figure 2 illustrates this utility concept. Let *y* be a random variable representing in this case wealth that can take on two values $[y_1, y_2]$, and let *p* be the probability that y_1 occurs and (1 - *p*) the probability that y_2 occurs. The expected outcome could be represented by the convex combination $E(y) = p(y_1) + (1 - p(y_2))$ that is shown on the horizontal axis of the figure. If $\Re$ represented a vector of outcomes with $x \in \Re$, then values along the vector reflect an elementary utility function and are concave (von Neumann & Morgenstern, 1947). The expected utility could be thought of as $E(u) = p(u(y_1) + (1 - p)(u(y_2))$.

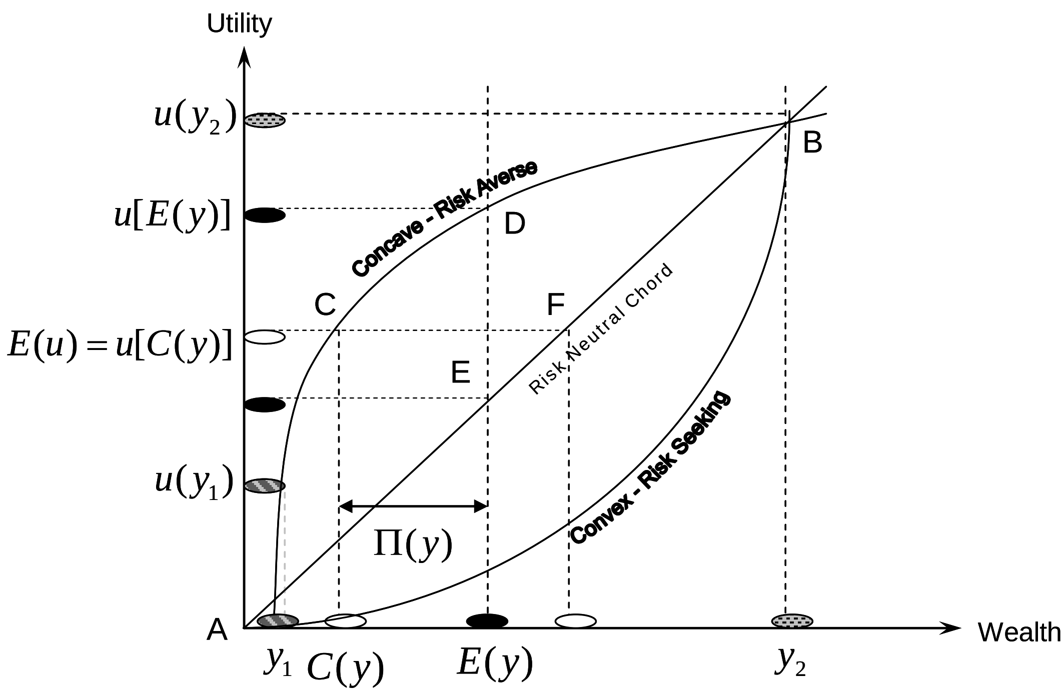


Figure 2. Utility theory: Risk-averse and risk-neutral behavior with risk premium.

The notion of a lottery could be derived from Figure 2 as well. Suppose there are two lotteries, one that pays *E*(*y*) with certainty and another that pays y_1 or y_2 with probabilities *p* and (1 – *p*) respectively. From the prior description, *E*(*u*) = *u*[*C*(*y*)] as *E*(*y*) is received with certainty. The utility of the second lottery is $u(y_1, y_2)$ with probability *p* and (1 – *p*) is $p(u(y_1) + (1 - p)(u(y_2))$ =*E*(*u*). The wealth received at *C*(*y*) is much less than that of $E(y)$ if the $u[C(y)]$ with certainty is selected over the risky $E(u)$. Von Neumann and Morgenstern (1947) described the difference in wealth as the premium that one is willing to pay for certainty, represented by the amount $E(y) – C(y) = \Pi(y)$.

Let $C^U(y)$ represent the certain result and $\Pi^U(y)$ represent the risk premium where *U* represents the utility shape characteristics of certainty and the risk premium. Let the line segment *A*,*B* in Figure 2 represent the chord partitioning the concave set (lying above the chord) and the convex set (lying beneath the chord). Following the concepts depicted in Figure 2, von Neumann and Morgenstern (1947) described the following generalities:

1. If $C^U(y) <$ E(y); or $\Pi^U(y) > 0$ for all $y \in \Re$, then the agent is said to be risk averse and the utility function can be represented by a concave shape.

2. If $C^U(y) =$ E(y); or $\Pi^U(y) = 0$ for all $y \in \Re$, then the agent is said to be risk neutral and the utility function can be represented by a straight line.

3. If $C^U(y) >$ E(y); or $\Pi^U(y) < 0$ for all $y \in \Re$, then the agent is said to be risk seeking and the utility function can be represented by a convex shape.

Applying these concepts to the marketing choices under investigation, the marketing executive may consider the metric for utility to be related to the utility of benefits achieved from an investment. A certainty is related to the certainty of investing and achieving a positive return. In this case, the risk neutral chord (line segment *AB*) provides the investment strategy yielding the most balance. The marketer would prefer an environment in where there is a steady state relationship between investing and financial returns (every investment dollar yields a sale).

The convex shape (in Figure 2) identifies a situation where choices are made as if risk doesn't matter. Risks are taken unnecessarily, with little chance of reward. If the horizontal axis were to represent revenue instead of wealth, when making choices in this area the marginal cost (*MC*) of the choice would on average be greater than the marginal return (*MR*). Risk and reward are unbalanced (King, 2007).

The risk taker in this instance has not surmised the opportunity, and consequently increases advertising spending in an effort to achieve increased revenues, saturating the customer base with promotions. As the advertising expense is increased, the requirement for revenue increases at an increasing rate (as it progresses up the convex curve). Moving up the convex curve increases the bet at an increasing rate.

The prospect of a movement from left to right on the wealth axis (Figure 2) represents a movement away from the expected value of wealth $E(Y)$ to a risky lower probability bet (y_2). This investment strategy results in saturating the customer base and creates a type of unsystematic risk. This unsystematic risk will be referred to as saturation risk (too many dollars, chasing too few customers). The firm has imposed this risk on itself because of the way it invests, and is therefore company specific (Haydock, 2005a).

The risk neutral shape, represented by the line segment *AB* in Figure 2, lying between the concave and convex surfaces is also a choice. Here the opportunity to balance risk and return is achieved through efficiently allocating resources to the point of risk indifference. Movement from the convex region to the chord *AB* is a clear choice to dissipate saturation risk and minimize the variance of return. The opportunity is perceived and an expectation around revenue is formed. By seeing, and acting on the opportunity, the marketing executive has preferred a level of certainty over uncertainty.

Each marketer seeks to create a market for their goods and services. Their efforts are hopefully rewarded with a growing customer base of where each consumer exhibits independent random purchase behavior (Assael, 1981). The collective attributes of these consumers are the sum total of the attributes of the market created. The advertising response from these attribute sets will eventually exhibit a diminishing returns pattern as the number of promotional exposures increase (Lilien, Kotler, & Moorthy, 1992).

This presents another type of investment risk that will be referred to as market risk. This risk is more systematic and consequently more difficult to diversify away. The concave region in Figure 2 illustrates this diminishing returns pattern. Again, the marketing investor would prefer a move toward more certainty, or risk aversion in this case. As the ratio of additional investment to payout reaches a point of diminishing returns (point *D* in Figure 2), the choice of a guaranteed return with certainty is desired to the point where the risk-averse marketing investor should be willing to pay a small price (the risk premium), to achieve the revenue target with certainty.

Moving from the concave region to the chord *AB* is an effort to move from an environment of diminishing returns to an environment of positively sloping returns for the same dollar invested. In fact, the marketing executive may see the opportunity very clearly and prefer to increase the level of the bet, while guaranteeing a certain floor level of return, but with all the upside of the perceived opportunity. Bookstaber (1991) argued that this preference creates the need for a type of hedge framework with certain guaranteed outcomes shaped by the properties of co-varying diversified investments. This is not the avoidance of risk, but instead the management of risk.

Dorfman, Samuelson, and Solow (1958) described leveraging the shape of the utility curve to explain how a limited budget is allocated among diverse alternatives. They identified that the allocation decision was more important than explaining which commodity was selected for consumption and which were not. They articulated that the convex or risk seeking shape represents the concern where the purchase of a lottery ticket is preferred to the purchase of insurance to hedge against a small loss (the behavior depicted in the concave shape). To contrast, the risk seeking agent in fact pays a premium to undertake this gamble (the price of saturation in the case of the marketing agent), where the risk-averse agent also pays a premium, but to purchase insurance.

Extending these utility concepts from a single attribute (wealth) to a portfolio of investments being optimized over multiple attributes is a contribution articulated best by Markowitz (1987). Markowitz described an investor who splits wealth (W_t) between consumption (R_t) (which in the case of the marketing portfolio could be referred to as revenue attainment) and investment (I_t). This investor allocates I_t to various securities (S_t) (which in the case of the marketing investment would be allocated to various market segments). The returns on the various investments, $r_{1t}, r_{2t}, r_{3t}, \ldots, r_{kt}$, determine the next period starting wealth $W_{t+1} = \sum_i r_{it} S_{it}$. This process is repeated for all time periods and under various scenarios, prescribing a multiperiod optimization under uncertainty.

Von Neumann and Morgenstern (1947) assumed that the investor would choose a strategy from all scenarios such that a vector of revenue outcomes $R_1, R_2, R_3, \ldots, R_T$ would be produced where T represents the number of outcomes. These outcomes could be placed in an m by n matrix M where m is the number of outcome rows and n is the number of scenario state columns, and let s_{ij} represent the probability that the ith outcome will occur if the jth scenario is selected as the strategy. This presented a way to clarify outcomes and the probability of an outcome occurring.

Markowitz (1987) explained that there are some m number of ordinal utilities $u_1, u_2, u_3, \ldots, u_m$ which represents the utility of each strategy outcome, in effect, deploying utilities as a way to prioritize outcome preferences or goals. This feature translates well into the requirement of marketing portfolio construction to have a lexicographic ordering of priorities.

Markowitz (1987) also prescribed that the single period utility function could be considered an optimal solution that attempts to maximize ending period wealth. This may have notable implications for the marketing manager maximizing revenues or profits over many time periods. He showed that an action in the first time period (Act_1) could be multidimensional (simultaneously investing in multiple asset categories) and that the second time period action (Act_2) is a function of information learned in the first time period (Inf_1). This could be represented as $Act_2(Inf_1)$.

The third time period action would be a function of information gained in time periods one and two ($Act_3(Inf_1, Inf_2)$), and so forth through the terminal time period

($Act_t(Inf_1, Inf_2, Inf_3, \ldots, Inf_{t-1})$). This is very similar in concept to a Markov decision process that has the dual characteristics of probabilistic actions and assumes that the effects of the actions are fully observable. These activities provide feedback for the next state. This observation leads to the benefits of a multiperiod optimization using discrete time periods.

To conclude, Markowitz (1959) asserted that the utility of the returns of the portfolio in any time period, $u_t(R_t)$, or revenue in the case of marketing allocation, should be strictly concave following the shape of risk aversion (Figure 2). This implies that the investor should prefer a given return with certainty (R_c) over a distribution of returns with mean $E(R_c)$ and variance $V(R_c) > 0$. This suggestion was postulated prior to the concept that an insurance activity could provide a method to offset the diminishing returns properties of a concave function.

The advantage of using utility functions is premised on understanding the risk bearing attitudes of the investor. This review of the properties of utility functions is important in that it provides the mechanisms to describe multiattribute analysis and allows for a classification of preferences and order of the associated risks. The topic of extending from a single attribute describing preference into a set of multiattribute choices, some may be in conflict with each other, provides the focus for the next section.

Multiattribute Portfolio Construction

The move from a single-attribute utility to a portfolio of utilities illustrates that the decision-making problems are usually too complex and ill-structured to be thoroughly examined by a single-attribute criterion. The single criterion approach is usually a simplification of a problem that may have multiple goals that are often not aligned with each other. The foundation for such decisions is formed by the mathematics of optimization under multiple criteria (Ehrgott, 2005).

Pareto (1896) was the first to introduce the concept of efficiency in evaluating multicriteria decision-making. Von Neumann and Morgenstern (1947), as described earlier, had introduced the expected utility theory, setting up a way to evaluate multiple criteria. Keeney (1971) extended the work of von Neumann and Morgenstern by explicitly dealing with multiple independent utility functions showing how they could each be handled as an objective function in a numerical optimization.

Keeney (1974) argued that in most complex decision problems more than one attribute was needed to describe the consequences over all possible outcomes. Keeney recommended that the most common way for evaluating multicriteria consequences is through the additive utility function. This may be written as follows:

$u(x_1, x_2, x_3, \ldots, x_n) = \sum_{i=1}^{n} u_i(x_i)$, where $u_i(x_i)$ is a utility function defined over a vector of attributes x_i.

Keeney's contribution spawned a resurgence of interest in multiattribute optimization. The preference for outcomes could be communicated as a set of priorities. These priorities could be in the form of an ordered vector *P* such that $P_1 > P_2 > P_3 > \ldots > P_n$. As an example, from a marketing perspective, these priorities could be expressed as:

1. P_1 = An overall marketing budget that must not be exceeded.

2. P_2 = A floor allocation for new customers that must be spent in a specified time period.

3. P_3 = Customer retention is a priority and should receive a preset allocation.

Ehrgott (2005) identified that utility is not a simple ordinal measure but a cardinal measure over the vector of attributes. This feature can be exploited and used to identify the degree of preference of one attribute over the other, in effect assigning weights w_i to the ordered preferences P_i. So, the decision criteria can be clearly quantified as to order and degree $w_i P_i$. This can be formulated as follows:

$$u(P_1, P_2, P_3, w_1, w_2, w_3) = w_1 P_1 > w_2 P_2 > w_3 P_3 .$$

Where $w_1 P_1$ is preferred over $w_2 P_2$, and $w_2 P_2$ is preferred over $w_3 P_3$.

Schniederjans (1984) reasoned that the value of lexicographic or preemptive goal programming is that it can be solved as a series of linear programs. He argued that lexicographic goal programming should be used where there is a clear priority ordering among the goals to be achieved. The decision-maker also had the option of interjecting weights where differentiating the degree of importance was critical to the decision.

Deviations were utilized in a financial example (Schniederjans & Zorn, 1993) that appeared on either side of the priority value allowing the solution to proceed through multiple objectives while minimizing the sum over all deviations. A Chebyshev procedure can be used to minimize the maximum deviation, or the method used by Dash and Kajiji (2005) and Schniederjans and Zorn (1993) that minimizes the sum of the deviations to produce the optimal decision. The formulation for minimizing the sum of the deviations follows Schniederjans (1984):

Minimize: $Z = \sum_{i=1}^{m} P_k (d_i^- + d_i^+)$ (for k = 1,2,3,…,K)

Subject to: $\sum_{j=1}^{n} a_{ij} x_j + d_i^- - d_i^+ = b_i$ (for i = 1,2,3,…,m);

and $x_j, d_i^-, d_i^+ \geq 0$.

Where:

Z = the objective function that serves as the minimized value of all negative deviations (d_i^-), and all positive deviations (d_i^+), in m goal constraints,

P_k = the set of preemptive objective function priorities, these are ranked as goal constraints such that $P_1 > P_2 > P_3 >>>> P_K$,

k = the number of objective function priorities (goals) in their order,

K = the maximum number of objective function priorities (goals),

d_i^- = a set of negative deviational variables related to each goal,

d_i^+ = a set of positive deviational variables related to each goal,

i = the index of deviational variables,

a_{ij} = the technological coefficients in the problem,

x_j = the decision variables in the problem,

j = the index of the decision variables, and

b_i = the right hand side goal values.

Schniederjans and Zorn (1993) also described that the linear goal program model's decision variables x_j, represent the number of dollars that should be allocated to the *j*th asset category. The set of goal constraints that represent the investors' total wealth would be expressed by: $\sum_{j=1}^{n} X_j + d_i^- - d_i^+ = (boundary)_i$. In the marketing sciences context, Haydock (2005b) argued this boundary could, as an example, be the marketing budget limitations. Because the budget can not be exceeded, it is set as the highest priority of P_1 .

Haydock (2006a) describes the typical objectives that may be found in a marketing sciences, contact strategy setting may be as follows:

1. The maximization of revenues.
2. The maximization of marketing income (marketing's version of profit).
3. The growth of the customer file over time.
4. The maximization of sales per advertising dollar.
5. Minimization of wasted or ineffective advertising expenses.

The marketing manager utilizing goal programming would rank these objectives and possibly weight them as to their ordinal importance, most important to the least important. This turns out to be a very good exercise for most managers who may have not previously considered the importance of one objective over another. Also, the recognition of multiple objectives is more closely aligned with the actual way that a business person is measured relative to performance and achievement.

Neither Ehrgott (2005) or Schniederjans (1984) adequately illustrated the stochastic nature of the data that would form the foundation of a marketing objective function. If demands and customer counts are considered key inputs into the attribute sets, then an opportunity may exist to make an improvement to the application of linear goal programming under uncertainty. In fact, the actual problem required by the marketing executive would be to construct an efficient portfolio allocation of a budget across multiple time periods. The literature is very sparse with regards to multiperiod linear goal programming with stochastic extensions.

Extensive research into the literature has only turned up a few cases where goal programming was used in a marketing context; most interesting was the article by McGlone and Calantone (1992). These authors described an allocation model using multiattribute utility theory and multiattribute decision-making. They did not consider multiple time periods or the stochastic nature of the inputs into the allocation. Consumer behavior and the nature of retail demands are clearly dominated by uncertainty (Kotler, 1994).

Can the problem of demand and customer count uncertainty be structured in such a way that its elementary components and possible forces acting upon it can be better understood and leveraged? The next section introduces the continuous time Brownian motion model as a way to describe the drift, perturbations, and ultimately valuations of these stochastic demands and counts. A binomial tree approach to model discrete time portfolios is also introduced as a way to convert the continuous time models into discrete time periods, useful in optimization.

Stochastic Customer Demands, Brownian Motion, and the Binomial Tree

The proper determinations of the stochastic nature of demands and customer counts for each time period are key ingredients for the construction of a customer portfolio. This section deals with how expected demands and customer counts can be accounted for and measured for any *n* number of time periods on the planning horizon. The importance of generating these expected values rests with the assignment of investment returns and utility values generated by these customers.

Lilien, Rangaswamy, and Matanovich (1998), Greene (1968), Lilien, Kotler, and Moorthy (1992) described the stochastic nature of customer counts and demands. Most marketers do treat demands as weighted probabilities at a customer level when determining tactical promotional response, but this methodology does not adequately aggregate these demands for use in strategic planning (Kotler, 1971).

Marthe and Ryan (2005) recommended additional research be conducted toward development of a practical method appropriate for use in a marketing portfolio having the feature of being built upon a multiperiod linear goal program and modeling the process as a Brownian motion. Marthe and Ryan made this recommendation as a result of their study on the various uses of Brownian motion in various parts of an enterprise. The areas of the firm that they identified as generating the most value in utilizing a Brownian motion method were those that dealt with complex risks and how to model them, with an interest toward dissipating those risks.

The geometric Brownian motion model, not typically applied in a marketing setting, has its roots in the physics of motion of a heavy particle suspended in a medium of light particles. The lighter particles move around feverishly, randomly crashing into the heavier particle, slightly displacing it. The direction and magnitude of any one collision is independent of all the other prior collisions, referred to as an independent, identically distributed random event (Kasper, Sullivan, & Weithers, 1991).

These heavy particle displacements occur over time and as a normally distributed random event are represented with a mean and standard deviation and demonstrate a path and time dependency. This displacement can be described as the percentage change in movement from one time period to the next. In this context, Brownian motion precisely describes the probability distribution of the future value of demands being composed of numerous independent identically distributed random variables.

Bachelier (1900) described the independence of individual stock price movements as random variables. The increments between the movements were described as normally distributed with a mean of zero and a variance that is proportional to the amount of time involved in the measurement. He articulated that any future stock movement depended only on the level of the variable from its present state and not on its history. This essentially means that the variable has no memory.

This characteristic, when applied to demands, models a random walk diffusion process where the actual value of demands do not follow the Brownian motion process, but the percentage increase or decrease in demands from one time period to the next would. This can be described as the increase (or decrease) in demand between today and a future time period (Δt) as being normally distributed. The mean of the distribution may be represented as μ times the amount of time ($\mu \cdot \Delta t$), and the standard deviation is σ times the square root of the amount of time ($\sigma \cdot \sqrt{\Delta t}$) (Chriss, 1997).

The volatility of the random variable is what gives the Brownian motion this up-down movement along a path. For instance, if a demand level of say $1.0 million in a time period grew at a 10% rate of increase per period then the function could be modeled as always increasing upward. But, if volatility were present then the movement could be described as up or down along the path. If we assigned a probability to the movement, say a 50% chance of a movement up and a 50% chance of a movement down by the 10% rate, then we could envision a random series of up/down movements.

Chriss (1997) described two components to the movement: the first is the movement in the up or down direction and the second is the amount of the increase or decrease in demands and customer counts. These movements have also been described by Cox, Ross, and Rubenstein (1979) as jolts to a system. The expected value of an up movement in the example of demand would be $1.0 million + ($1.0 million x 10%) = $1.1 million with 50% probability. The expected value of a down movement would be $1.0 million - ($1.0 million x 10%) = $0.9 million with 50% probability. Thus the set of possible changes to demand is symmetrical around a mean of zero.

Volatility makes an important difference in demand when a 10% movement up occurs in one period and an equivalent amount occurs as a down movement in the next period. In the example, a 10% increase in the first period brings the demand value to $1.1 million from the original $1.0 million starting point. In the next period the $1.1 million is multiplied by .90 (10% down) that gives the value of $.99 million, slightly below the starting point. A positive return, followed by an equal, but opposite negative return provides a slightly lower return overall. This can be expressed mathematically as

(1 + x)(1 - x) = $(1-x^2)$ = .99, where *x* would represent the change in demand (0.1 in the example).

The average amount the stochastic component depresses in a single move would then be dominated by the value of the average of the variance $\sigma^2/2$ because X^2 is the result of moves that take place in two time periods. This result is exactly what Bachelier (1900) described in his thesis. Chriss (1997) argued that this Markov property comes from the notion that only the previous time period and value provide information into the next move. The random walk has no memory beyond where it is now.

This gives the properties of a random walk as mean = $\left(\mu-\frac{\sigma^2}{2}\right)\times(T-t)$ where *T* is a time period in the future with a standard deviation of $\sigma\sqrt{T-t}$. The standard deviation of returns increases in proportion to the square root of time. In this continuous time model, if the short run standard deviation of returns are estimated then the long run standard deviation varies as the square root of time, times the short run volatility (Chriss, 1997). The randomness of the short term behavior will not be smoothed out by time alone over the long run.

Converting the continuous time random walk represented by the Brownian motion into a discrete time model has many advantages. The computational simplification of a discrete time, multiperiod numerical optimization model with stochastic extensions is among them. Another advantage is the understanding gained by inspecting the circumstances and visualizing the decisions that must be made at each time step. The movement from a continuous time model to a discrete time model was more importantly recognized by Cox, Ross, and Rubenstein (1979) in their work on replicating and simplifying an options pricing approach.

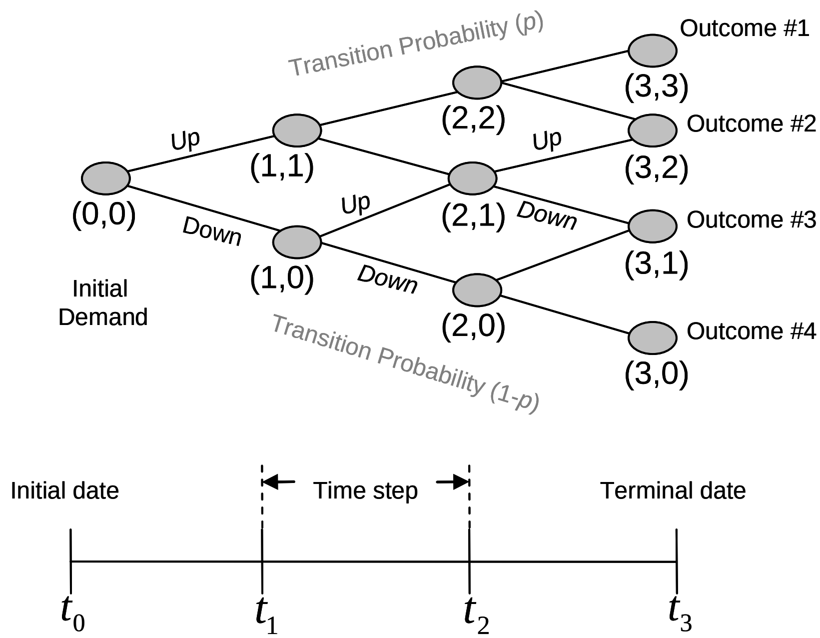


Figure 3. Binomial tree example with transition probabilities and outcomes.

Figure 3 illustrates the binomial tree described by Cox, et al (1979). Let the position in the tree structure be represented by (*i*,*j*) with *i* representing the time period and *j* representing the specific location within the time period. So for instance, the (1,0) position would represent the first time period and the down position.

Let demand at the initial time period be represented by $D_{(0,0)}$, which would be a known demand today. Let the up value of demand be represented by D_u and the down value of demand be represented by D_d. The expected value of D would therefore be

(Cox et al., 1979): $p(D_u)+(1-p)D_d$, where *p* is the up transition probability. $D_u / D_{(0,0)}$ represents the up ratio and $D_d / D_{(0,0)}$ would represent the down ratio.

The binomial tree will mimic the motions of the geometric Brownian motion model with one very important difference. The binomial tree will allow for a flexible rate of volatility as it moves through time where the geometric Brownian motion model assumes a constant rate of volatility. This feature will prove to be very important in the later description of how the trees will be used, especially in the development of the theoretical hedging activity.

The binomial distribution is a sum of *n* Bernoulli random variables (Aczel & Sounderpandian, 2002). The binomial tree representation of the random walk may precisely represent the demands of large quantities of independent and identically distributed random variables. If these random variables are the observations of purchase decisions by the firm's customer base, what may be driving these random walk perturbations?

Haydock and Bibelnieks (1999) were among the first to describe the effects of advertising saturation on a customer base. These saturative effects were described in more detail in Haydock (2005a) and were modeled as the loss of revenues between two promotions that had: (a) overlapping similarities between merchandise categories; (b) similarities between properties of the advertising instrument (the medium) itself; and (c) the amount of time between promotions. Haydock (2005a) described the requirement to eliminate all saturative effects if possible as they constituted a heavy cost on the business. This cost comes in the form of a marginal return on advertising investment and a negative image with the consumer receiving advertising communications that are not relevant to their household needs.

This constant drift effect due to the volatility of the random variable creates an erosion of the revenue base of the direct marketing firm as the firm moves through time. This erosion has been identified by direct marketers (Haydock, 2005c) but is not a well documented phenomenon, and is consequently one of the central areas of risk that should be diversified away in the marketing portfolio. An extensive literature search did not produce insight into this problem beyond that cited in Haydock and Bibelnieks (1999) and Haydock (2005a).

Saturation can be thought of as a risk that the firm has imposed on itself by the way in which it promotes its customer base. This risk therefore can be considered a type of unsystematic risk – unique and specific to each firm based on their promotional strategy and how they have allocated their resources into market segments. A central premise of this proposed grounded theory is to capture the nature of this saturative random variable in an effort to construct an optimal portfolio that allocates the advertising resources of the firm in such a manner as to completely diversify away saturation risk.

Using the utility theory concepts developed earlier, the risk taker prefers to assume this risk, motivated to do so seeking revenue, but not understanding the market opportunity. The result is the introduction of a type of inflationary effect "too many promotional dollars chasing to few customers" (Haydock, 2005a, p. 11). The revenue results begin to decay to the point of suffering erosion over time from sending irrelevant promotions.

The risk-neutral investor would prefer to diversify away this risk through careful market segmentation and efficient allocation of resources utilizing the facility of an optimal asset allocation. This investor sees the opportunity and takes steps to correct misspent advertising resources. If the saturative effect of the volatility component σ^2 in the mean value represented by $\left(\mu - \frac{\sigma^2}{2}\right) \times (T - t)$ can be diversified away to approach zero, the firm would experience more certainty of returns across the same revenue base.

Certainty is clearly a desirable objective and a logical preference for the risk-averse investor. The transition from a risk-averse choice to a risk-neutral preference would be a move to protect the firm from the probability of a sudden, unexpected revenue shortfall due to adverse market conditions. The binomial lattice described previously outlines the amount of the possible shortfall along with the probabilities of this occurring. An unexpected shortfall due to adversity may be considered an extreme event.

The study of extreme events is recognition of the impact these events can have on the value of the firm, and ultimately serves as the motivation for developing a marketing hedged position. Avoidance of these downside extremes creates a need to understand and model these phenomena in the portfolio construction process. A review of the literature regarding value at risk and extreme event theory is the focus of the next section.

Extreme Value Theory and the Value at Risk

Extreme risks are by definition uncommon events. A challenge in understanding extreme risks is the difficulty in acquiring enough observations of severe events in order to apply traditional statistical processes. Methods used in financial risk management will be reviewed as they have recent theoretical grounding in predicting events that can be considered rare or infrequent.

In a marketing setting these events may be classified as revenue or profit shortfalls from a marketing program target. Financial economists refer to value at risk (VaR) as a measure of market and portfolio risk. The term VaR will also be used in this study to refer to the amount of the portfolio that is at risk if an extreme event is realized.

Siegl and West (2001) described VaR as a measure of the maximum estimated loss in the market value of a given portfolio that can be expected until the position can be neutralized. Fong and Lin (1999) provided a more precise description stating that VaR is the $100(1-\alpha)\%$ quantile x_p of the distribution of an extreme loss (where α may typically represent .05 or a 5% chance of an extreme loss). Cruz (2002) showed that the estimates of probability of an event using traditional statistical methods are well suited for making inferences over regions where the majority of the data can be observed. These traditional methods however were not well suited for estimating over the extreme quantiles.

Since VaR concerns itself with the maximum amount of loss that the firm can incur, then the behavior of the tails of a distribution of losses may contain information necessary to understand these extreme events (Khoury, 2003). The application of extreme event theory supports these types of distributions (Cruz, 2002). A more salient point may be that extreme value theory allows for the computation of the probability of events that have not been previously observed.

At the heart of extreme value theory is the extremal types theorem proposed by Fisher and Tippett (1928) and refined by Gnedenko (1943). This theorem states that for a re-centered sequence of observations $X_1, X_2, X_3 ..., X_N$ the maximum random variable $X_{1,S}$ (the minimum value in the case of a revenue shortfall), is defined by the characteristics of a location, scale and shape parameter. The tail distributions for the extreme values are defined by one of three types (Aczel & Sounderpandian, 2002):

1. Frechet: $G(x) = \begin{Bmatrix} 0, x \leq \mu \\ \exp(-(\frac{x-\mu}{\sigma})^{-\gamma}) \end{Bmatrix}, x > 0$ describing heavy tails.
2. Gumbal: $G(x) = \exp(-\exp(-\frac{x-\mu}{\sigma})), -\infty < x < \infty$ describing light tails.
3. Weibull: $G(x) = \begin{Bmatrix} \exp(-(-\frac{x-\mu}{\sigma})^{\gamma}) \\ 1, x > \mu \end{Bmatrix}, x \leq \mu$ describing bounded tails.

Where:

μ = a location parameter,

σ = a scale parameter, and

γ = a shape parameter that characterizes the tail of the distribution.

With these estimates of the parameters of the tail distributions the VaR model will be able to determine the quantiles, or the amount corresponding to the probability of some revenue shortfall that may require alternative courses of marketing actions. This would most likely be driven by some extraordinary market condition rather than a normal market situation. The recognition of an advanced probability of an extreme event would provide an early warning system that a portfolio shortfall is immanent. This portfolio capability has currently not been articulated in the marketing sciences literature.

Social Systems Segmentation

The segmentation of a whole population of individuals into distinct clusters with multiple attributes has many applications in learning about the behavior of organizational entities. The goal of such partitioning is to gain insight into particular structures inherent in a population or in the case within a business environment, to develop a customized or optimal strategy (Michaud, 1997). These optimal strategies, based on skilled clustering results, are an additional source of performance attributed to the asset allocation process.

Strauss (2002) argued that the task of partitioning should be extended to include the concept characteristics described in Von Bertalanffy's social systems theory. This would provide the opportunity for the marketing manager to know about the present state of the social system, and more importantly, to understand the trajectory of the population as a self-organizing entity. The task of clustering leads to asset class determination and is a procedure taken in the marketing sciences that is both rich in the descriptive literature and is unique in its frequency of use.

The asset classes utilized in finance are typically well known, while marketing segments must be discovered (Haydock, 2006b). Consider an asset class, then, as a subpopulation of investable entities that have more in common with the characteristics of population members within their group than they do with population members outside of their group. Giudici (2003) argued that another way this could be articulated is to say that across their respective multiattribute space, the best asset class segmentation will have a minimum of differences within a group, and a maximum of difference between the groups. The characteristics of customer asset classes may differ on dimensions such as spend, treatment productivity, length of time as a customer, products bought, and a risk adjusted financial return profile, as an example.

The risk in not segmenting properly is the missed opportunity to diversify and categorize the firm's most important asset, their customers. The risk and return dispositions of the asset classes are different, and they subsequently require different marketing treatment investment (Haydock, 2006a). So, financial performance is gained in the asset allocation process by a first step that introduces an optimal partitioning.

An excellent treatise and informed discussion on the topic of data mining and knowledge discovery using large scale databases (KDD) is by Fayyad and Stolorz (1997). The authors described the use of techniques that can interrogate large scale databases without a specific query in mind, but with the target of understanding the structure or hidden patterns within the data. This computer driven exploration approach to the data is very different from human-driven exploration in that the computer is not forming a hypothesis about the data as the human analyst must to execute a directed query.

The role of data mining in pattern detection and classification is to accumulate the collection of observations that are connected in space, time, or both, and to discern the structure of an underlying pattern (Schurmann, 1996). These patterns should exhibit certain regularities in such a way that a concept can be developed about the data. Michaud (1997) eloquently described various clustering algorithms that create partitioning cuts within the data as a way to aggregate data into discernable groupings.

A detailed selection of segmentation and clustering procedures can also be found in Haydock (2006b) that describe the specific techniques used to create asset categories prior to the allocation step. The methodology leverages the contributions of Fayyad and

Stolorz (1997) where large amounts of data can be considered in the clustering and Michaud (1997) for his concept of utilizing a binning process to create multiple bins to smooth out the data values in these massive data stores. Schurmann (1996) described alternative distance algorithms that subsequently stimulated a unique formulation that proved especially promising in Haydock (2006b).

Arrow's (1951) thoughts on clustering and classification of objects into distinct segments is one of the first documented works on the importance of these techniques to economics. His unanimity principal sought to insure that the concept of twins with identical attribute values across multidimensional space should reside in the exact same cluster. This unanimity principal was the focal motivation for the development of a novel clustering technique by Haydock (2006b) that has proved quite effective in marketing environments. In Haydock (2006b) there is a comparison of results utilizing this method with other available commercially available software.

Summary

The focus of this research is the improvement of investment strategies and financial results that marketing executives can achieve through the utilization of asset allocation and portfolio optimization. As this chapter revealed, the great majority of investment theory has been grounded in the financial economics industry. Each section within this chapter was selected for the role that component of financial theory would play in the construction of an optimal marketing portfolio.

The chapter began with an illustration of the sequence of components of portfolio construction (Figure 1). The foundations of modern portfolio theory were then reviewed with the major contributions to portfolio optimization detailed in the form of a time line. The next section detailed the key concepts surrounding portfolio choice and utility theory. This section also introduced the economic motivations behind risk taking, risk neutral, and risk avoidance behavior.

The nature of a marketing portfolio adds a dimension of utility not usually considered in financial economics. The ability to rationalize actions by the marketing manager towards their disposition on saturative behavior is represented as a new attribute analyzed through the use of utility theory . Motivations regarding the preference for the certainty of an outcome should drive the marketing manager to consider utilizing portfolio optimization methods to manage the possibility of an adverse marketing program result. Certain portfolio positions may have an added insurance cost that must be considered.

The chapter then moved from a single attribute environment that described risk, to a multiattribute analysis where multicriteria decision-making drive a more complex utility definition and portfolio requirement. Linear goal programming was determined to be a practical method that captures the multiattribute decision-making environment under constraints. The use of goal programming is an area where there was some evidence of marketing engineering contribution, providing little similarity to what is being proposed in this study.

The stochastic nature of demands and customer counts were modeled through the use of geometric Brownian motion. Brownian motion is inherently a continuous time formulation of stochastic drifts, and the binomial tree was introduced as a way to transform a continuous activity into a discrete time set of activities. There are many advantages in making this transformation, utilizing a multiperiod stochastic decisioning model that can be solved for each discrete time step is among the chief reasons for its consideration.

Extreme value theory is an insurance notion for which financial economics has developed the concept of Value at Risk (VaR). This aspect of portfolio construction creates an understanding of the probabilities of an extreme event, such as the unexpected loss of revenue from a promotional program. This measure will be used as an early warning system, forecasting adverse events and their effect on the customer portfolio.

In financial economics asset class designations are mostly pre-selected and well defined. With regard to marketing engineering, the asset classes are derived from the discovery of market segments in massive amounts of transactional data. This section detailed the key contributions in this area where marketing science has made a significant contribution.

Chapter 3 describes the research design in which archival data collected over a three year period detailing apparel and home furnishing purchase transactions for 1.449 million U.S. retail apparel consumers. The test compared the results of current methods of customer aggregation and portfolio selection with the results of a proposed portfolio construction method incorporating the concepts detailed in chapter 2 of this research. Chapter 3 will also describe aspects of the nature and composition of the data captured and used in the test.

CHAPTER 3: RESEARCH DESIGN

Introduction

The first chapter of this research introduced the idea that we can distinguish efforts in the marketing sciences between the analysis of individual customers and the analysis of portfolios of customers. The analysis of individual customers is an area rich in the marketing literature with significant contributions and experiments describing purchase behavior, buyer motivations, brand selection, and many other useful individual consumer oriented models. The subject of efficient customer portfolio construction is an area generally void at present of marketing science contribution.

The second chapter highlighted portfolio developments primarily in the financial economics industry. Since there is no body of literature that articulates the construction of a marketing portfolio of customers, a review of the developments in financial economics also provided a theoretical grounding for each of the elements of portfolio construction that the marketing executive should be considering. The exception was the description of clustering and segmentation techniques, an area where the marketing sciences have excelled.

The purpose of this study was to develop an optimal strategic asset allocation investment process for the marketing executive in order to improve the financial results of direct customer contact marketing investment. Because of the lack of supporting literature in this area, the researcher turned again to the methods used in financial economics to test such portfolios. These methods primarily consist of providing a grounded theory about a desired performance improvement that has significant economic value, then leveraging the scientific method in challenging an incumbent procedure by way of a test of the grounded theory with marketplace data.

This was essentially the strategy of Markowitz (1955) and Nash (1950) and will be the strategy deployed in this research. Portfolio construction is inherently a numerical methods process that is highly quantitative. Questions regarding this particular research effort do not lend themselves to the qualitative interviewing of subjects. However, qualitative research of this nature will be highly valuable in subsequent efforts to understand various ways in which marketing portfolios can be utilized.

Epistemology in this study will be comprised of a strategy of knowledge acquisition focusing first on what should be included in the core elements of a marketing portfolio construction effort, then measuring how well the proposed portfolio enhances the performance of marketing programs. The former subject will be approached as a grounded theory, articulating the core elements and defining each individually while operating as a synthetic whole (Creswell, 2003). The latter subject will be tested by collecting data and applying the grounded theory to the data in a scientific environment that involves the interplay between the theoretical ideas and empirical evidence as suggested by Singleton and Straits (2005).

A theoretical perspective and philosophical stance for portfolio construction methods will be articulated in the grounded theory component. Unlike most quantitative grounded theory studies where the inquirer may generate a theory during the study and place the resulting theory at the end of the study, this research effort will base the grounded theory aspect on portfolio components previously detailed in chapter 2 of the literature review and instead present it first. This approach was recommended for quantitative studies by Creswell (2003).

Creswell (2003) recommended three steps central to the design of research: (a) the selection of the knowledge claims strategy being made in the theoretical aspect of the study; (b) the presentation of the techniques of inquiry that will lead to specific scientific procedures; and (c) the determination of the methods of data collection, data analysis, and testing that will be deployed in the study. Creswell (2003) argued that the four types of knowledge claims are advocacy/participatory, constructivism, pragmatism, and post positivism. Of the four presented, each has attractive characteristics that could be deployed in this study. Constructivism and advocacy/participatory methods were rejected because they appear to be most appropriate for studies where human subjects can articulate preferences or concerns toward some social issue.

Pragmatism is attractive because it is concerned with practical applications that work. This is clearly an intended result from this study. Creswell (2003) described knowledge claims in pragmatism to be a result of actions, consequences, and situations. The focus of a pragmatic study would be to take an existing theory and make a series of practical changes so as to fit the circumstances of individuals.

Pragmatist researchers also seek to understand what to research, which related to this study, is known. Pragmatic designs appear to allow for a less rigid methodological approach to data analysis, where warranted. Since this study is designed to uncover and describe a new approach to managing marketing results, a study that embraces strict scientific methods would be preferred. These aspects assist in rejecting the pragmatism approach.

Creswell (2003, p. 6) referred to the post positivism method as representative of the scientific method. The term post positivism challenges the traditional notion of proving absolute truth recognizing that it is difficult to be positive about all claims of knowledge. An attractive feature of the post positive method is that it is reduction-oriented in nature, preferring to collapse ideas into a small set that can be tested.

The post positive lens relies on careful observation and measurement to make claims about knowledge. Theory is developed first, data are then collected, the theory is tested with the data, and the results are reported. Adjustments to the theory are made as a result of measurement and observation.

Since a post positivism truth can not be absolutely proven, instead of trying to prove a specific hypothesis, we would indicate instead a failure to statistically reject. In this case, the null hypothesis would state that the performance of the asset allocation optimization method is less than or equal to the performance of the benchmark method. The alternative hypothesis would state that the performance of the asset allocation optimization method would provide a reward greater than that of the benchmark method.

The application of an inferential statistical method, such as the *t*-test is used to determine if the difference between two samples is statistically significant, that is the difference is unlikely to have occurred strictly through chance. An alpha is then established, which is the percentage chance of a false positive; for example, that a difference would be detected when one in fact does not exist (a type I error). For these reasons, this method was selected.

Table 1

Alternatives for Research Design (adapted from Creswell, 2003)

Research approach	Knowledge claims	Strategy of inquiry	Research methods
Quantitative	Post positivism	Experimental design	Measurement, observation, rating theory outcomes
Qualitative	Constructivist	Ethnographic design	Field observations
Qualitative	Advocacy/ participatory	Narrative design	Open-ended interviewing
Mixed methods	Pragmatism	Mixed methods design	Closed-ended measures, open-ended observations

Table 1 from Creswell (2003, p. 20) compares the research approaches, knowledge claims, strategy of inquiry, and research methods. The post positivist selection was determined as most appropriate for this study. The remainder of this chapter is focused on describing the hypothesis to be tested, the data collection method to be used, and the research design to measure portfolio performance.

Hypothesis To Be Tested

The purpose of studying the portfolio construction process is to make significant improvements to the marketing investment activity as a proposed new source of corporate performance. Investment is typically measured in terms of the return on an investment. The return on a marketing investment could be thought of as having two significant characteristics:

1. The optimal investment strategy should generate more customer revenue (demand) as compared to an equivalent amount invested using a less efficient strategy.

2. The overall amount of the investment pool should be decreased if there is evidence of promotional saturation (too many dollars chasing too few customers).

Return on marketing investment (RMI) therefore can be thought of as a random variable used for measurement and represented as:

$$RMI = \frac{\sum_{i=1}^{N} Demands_i}{Investment - Saturation}.$$

Where:

i = a customer asset class, and

N = the number of customer asset classes.

Since the population mean and standard deviation are not known in advance a simulation will be used to estimate both parameters. The test group values can take on the form: $\mu RMI_{test} = \dfrac{\sum_{i=1}^{N} \mu Demands_{i,test}}{Investment - \mu Saturation_{test}}$, which will represent the sum of the mean values across all asset classes of the test group in the proposed portfolio optimization procedure. These demand values will be generated from the estimates derived from traversing through the stochastic binomial lattice.

The control observation value (using the incumbent investment procedure) may be represented by: $RMI_{control} = \dfrac{\sum_{j=1}^{J} \mu Demands_{j,control}}{Investment - \mu Saturation_{control}}$, which represent the sum of the values across all recency categories of the control observation using the benchmark method. The demand values used in the control observation will be the actual planning values reported for that period, not having the binomial lattice available as a treatment component. The expectation of the value of saturation in the control observation would be zero, since saturation is currently not an industry consideration. The mean difference between the $\mu RMI_{test} - RMI_{control}$ could be expressed as $\mu RMI_{Difference}$, or the difference between the two measures.

The return on marketing investment is measurable from the research data available and can be contrasted between the two competing procedures (use of the portfolio construction treatment and not). The research hypothesis therefore may be articulated as:

> H_0: The performance of the proposed asset allocation optimization test procedure does not perform as well as, or is equal to, the performance of the current control benchmark investment procedure ($\mu RMI_{test} \leq RMI_{control}$).
>
> H_a: The proposed asset allocation optimization test procedure provides a reward over the control observation using the incumbent investment procedure ($\mu RMI_{test} > RMI_{control}$).

The examination of this hypothesis should utilize a one-tailed test since an acceptance of the null hypothesis (H_0) could occur if the return on marketing investment of the test group was either less than or equal to the return on marketing investment of the control observation. A *t*-test will be utilized to determine rejection or acceptance of the null hypothesis. The population standard deviation for the test group is unknown so there will be a simulation to determine the sample standard deviation (s).

The control observation will be measured for the $RMI_{control}$ value utilizing the incumbent benchmark investment procedure. Only the test group will be exposed to the portfolio optimization procedures. The μRMI_{test} of the test group will be computed and then compared to the control results utilizing a t-statistic. The t-test is recommended where large samples are being used and the population standard deviation is not known.

The t-test responses allow for a measurement of the significance of the differences between the test and control results. The procedure also assumes that the test population is normally distributed (Singleton & Straits, 2005). The α value will be set to .05 as the level of statistical significance in testing the hypothesis. The t-test can be represented by (Aczel & Sounderpandian, 2002):

$$t = \frac{\bar{x} - \mu}{s / \sqrt{n}} .$$

Where:

$\bar{x}$ = the sample mean RMI observed as a result of applying the treatment,

n = the sample size of observations (number of runs in the simulation),

μ = the mean RMI of the control observation under the null hypothesis,

and

s = the sample standard deviation of the RMI metric over n runs.

Concerning the portfolio optimization concepts utilized in the portfolio construction process, context validity and content validity may serve as measures of qualitative fit of the portfolio theory proposed to the intended marketing problem. Because of the lack of portfolio optimization references in the marketing literature, context validity will be assessed by the appropriate closeness to financial economic theory of the application of portfolio optimization concepts in the construction of high performance marketing portfolios in the test group. Content validity deals with the amount of coverage a theory has with regards to all facets of the business problem being studied (Singleton & Straits, 2005). The coverage fit will also be assessed in the practical application, as the theory components are those detailed in chapter 2.

Data Collection Methods

The target subjects for this research are retail catalog buyers. The data represent the purchasing behavior of 1.449 million retail catalog consumers from a large retail catalog firm from 2003-2005 (3 years) and is considered archival data. There was no strategy in this research to directly interview either consumers, or marketers of the firm.

These consumer data were compiled from individual purchase transactions over the three-year period described. The final format of the data for each household is a consolidated record where all purchase activity over the three-year period was summarized into this single household record, one row per household. This file was generated from a random sample of the total active household population of the firm representing approximately 7.5% of their total available customer universe. The qualification for inclusion into the sample was a purchase within the period 2002-2005. These consumers were considered as the most active.

The quality of the data is considered to be excellent for each of the years represented. Each transaction or customer contact was meticulously recorded by the firm's information technology system, which is considered an example of best practices in the retail industry (Faherty, 2004). There are 479 fields of information contained in the sample file for each of the households. These fields represent order quantities, order amounts, merchandise categories purchased, the amount of promotional spending received, and some demographic information.

A secondary data source utilized was government data on retail sales. These data were used in the construction of the index and the assignment of probabilities regarding future demands and customer counts. These economic data exist for multiple retail categories such as food and beverage, electronics and appliances, apparel and apparel accessories, health and beauty products, sporting goods, furniture and home furnishings, and motor vehicle parts and gas stations sales. These data are provided as monthly sales updates to the North American Industry Classification System (NAICS) retail categories from the U.S. Census Bureau.

The data for each category represent total sales across all business participants in that category. None of the business participants are individually visible in the data. These data have been accumulated from 1998 to the present and are updated monthly by the government for each category. The categories of interest in this study were those relating to retail apparel for men, women, kids, and home furnishings. These data were subsequently converted into an index and used in the binomial tree computation to understand stochastic customer demands.

Research Design

This section describes the planning, execution, and interpretation of the research. This research is broken into two distinct components: (a) The development of the theoretical concepts required in the construction of an efficient marketing portfolio using the grounded theory method; and (b) testing the proposed optimal portfolio allocations against incumbent investment methods typically found in the retail direct marketing industry with the objective of seeking significant performance improvements over these current methods.

Grounded Theory of Portfolio Construction

Figure 1 in chapter 2 identifies the proposed portfolio optimization procedures in the form of a step-by-step sequence of activities. These procedures taken in the aggregate comprise the portfolio treatment. Each of these components in Figure 1 was considered in the proposed research treatment to attain performance optimality and is articulated in the grounded theory description. These components are briefly summarized below.

1. Multiperiod linear goal programming with stochastic extensions was used as a way to articulate portfolio objectives and constraints in a complex multiattribute environment. The optimal portfolio must handle multiple time periods with stochastic inputs in order to make optimal investment decisions. The output of the portfolio provides the optimal investment quantities for each market segment, for each time period.

2. An adaptation of utility theory was used to assist in the development of the goal and constraint equations that specifically detail the diversification of unwanted

saturative risk. Utility theory also served as a vehicle to prioritize the goals that appear in the objective function and were required by the linear goal programming method.

3. The development of a binomial lattice assisted in portraying the boundaries of uncertainty in determining stochastic customer counts and demands over multiple future time periods. An index was constructed that attempts to mirror the aggregate performance of all firms engaged in this set of retail categories being studied. Forecasting the index forward allows for an estimate of expected market results in future time periods. The index was then used as an overlay to the binomial lattice identifying the most probable path through the lattice over all time periods versus all other eligible possible paths. Path-dependent probabilities were developed for use in computing stochastic demands and uncertain customer counts for each time period. The linear goal program utilized the probabilities output from the binomial lattice to determine the optimal portfolio investment weights for each time period.

4. Extreme value theory (EVT) was used to identify the probabilities and amounts by which an extreme loss could occur in the execution of a set of marketing programs over any time period. It is possible these extreme amounts have not been seen in the data previously and it was therefore necessary to project the value at risk (VaR) for the portfolio at any time period. The VaR metric may be used by the marketing executive as an alert that there is a strong indication in a future time period of a revenue shortfall.

5. Numerical clustering techniques are recommended that utilize the multiattribute nature of the data captured on the individual consumers in the sample to partition these consumers into separable groups. Performance gains in the asset

allocation process are described in terms of segment performance as these clusters were used to build efficient and investable market segments.

Portfolio Simulation and Performance Test

A series of experiments identified the actual performance differences in the two competing portfolio methods over various scenario conditions. The control observation was measured for their $RMI_{control}$ value as achieved from the incumbent benchmark investment method. The test group will be subjected to the portfolio treatment process and will be measured for its contribution to μRMI_{test}.

The exact nature of the experiments was determined via the grounded theory process. Investment portfolios are typically subject to economic uncertainty and are stress tested by volatile scenarios. The number of relevant experiments may be determined by the types of economic conditions retail marketers have been exposed to during the period of the observed data (2003-2005). Stress conditions may be simulated by adjusting the volatility and adding extreme uncertainty scenarios. Both types of experiments were used to illustrate under which conditions the asset allocation optimization makes reasonable investment decisions.

The portfolio treatment is comprised of those procedures previously described in the grounded theory of portfolio construction. A portfolio simulation, or experiment, can be conducted by applying the treatment procedures to the customer data and observing the outcomes. Each experiment is comprised of running 1,000 Monte Carlo trials at each of six nodes, one node per time period. Each row represents the outcome of one experiment. The result is a table with 1,000 rows and six columns. Each column represents an economic value for each of the six time periods.

The mean and standard deviation are taken for each node (column of 1,000 trials) and it is the six mean economic values that are presented as economic inputs into the portfolio optimization model. Each of the six nodes is independent of the values of any other node before or after it. Figure 4 illustrates a one period march through the lattice and how the Monte Carlo trials will be utilized to generate a distribution of outcomes.

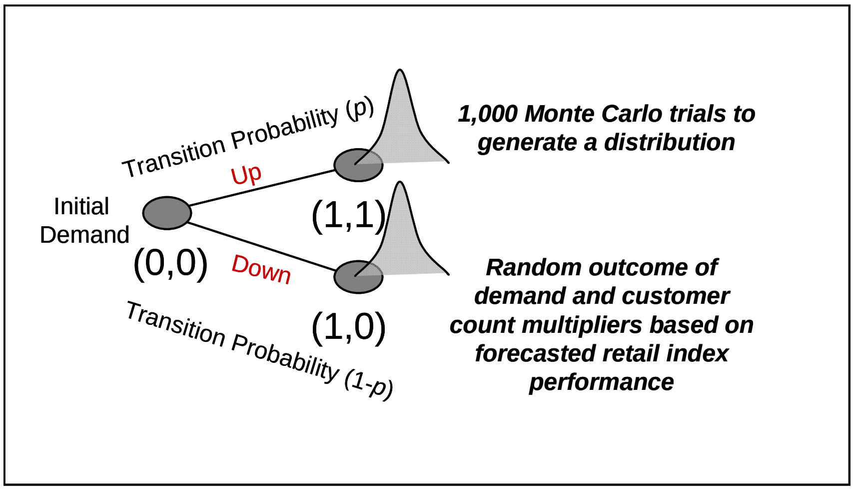


Figure 4. Monte Carlo trials generate a distribution used to simulate uncertainty.

The variation in treatment conditions is only determined by the uncertainty encountered by traversing the binomial lattice across all time periods. The portfolio optimization objectives and constraints remained constant across all scenarios and reflected typical corporate objectives and restrictions irrespective of economic scenarios. These portfolio characteristics represented preferences for outcomes. The market segments and product mix factors remain constant, so only the economic factors derived from the stochastic binomial lattice affect the decisions made by the asset allocation optimization application.

An observation of the RMI_{test} was taken at the conclusion of each experiment. Observations of revenue, saturation, total advertising spend, and RMI_{test} were recorded in a table, each row representing the experiment results. In this way the results could be easily analyzed and reported on.

An experimental design was selected so that the output of the experiments can be observed and easily compared (Singleton & Straits, 2005). This design, depicted in Figure 5, is selected because it contains all the elements required for this study. The test group receives a treatment at each experiment, the mean and standard deviation is taken after *n* experiments and is then compared to the control observation (benchmark).

$$
\begin{array}{llll}
 & X_1 & O_1 & \text{Experiment \#1} \\
 & X_2 & O_2 & \text{Experiment \#2} \\
R & X_3 & O_3 & \text{Experiment \#3} \\
 & \vdots & \vdots & \\
 & X_n & O_n & \text{Experiment } n \\
 & \mu RMI_{test} & \dfrac{\sum O_i}{n} & \text{Compare with the control } RMI
\end{array}
$$

Figure 5. Test design using multiple experiments.

Figure 5 is a graphical representation of this multiple-experiment design matrix. *R* represents that the economic conditions of the lattice (the object that varies randomly). The rows describe an experiment in which the asset allocation portfolio optimization treatment is applied and a resulting *RMI* is produced and recorded. At the termination of the experiments the μRMI_{test} is computed and compared to the $RMI_{control}$.

Sequence of Procedures

The sequence of procedures the experiments will follow mirrors the portfolio construction process depicted in Figure 1. This sequence was as follows.

1. The archival transaction data on 1.449 million households were summarized for each individual household, producing 1.449 million individual household records. A sequence number was issued to each household as a way to sort the households and to strip the records from any possible external identification. The data was placed into an SQL (structured query language) table so that manipulation of the data, sampling, and reporting was accelerated.

2. All 1.449 million records were utilized in the test group. The control observation had been derived utilizing the same record base, but applying the incumbent benchmark analytical methods. The benchmark method results were measured to reflect the incumbent *RMI* and to serve as a baseline to judge the asset allocation optimization performance. The test group was then subjected to a three step treatment: (a) segmentation; (b) exposure to the binomial lattice; and (c) investment allocation utilizing the numerical optimization methods.

3. A computer application was developed that clusters the members of the experimental group into distinct market segments across the multiple attribute dimensions contained in each household record. This clustering process consisted of the following: (a) an attribution and transformation of characteristics of each household record that

resulted in an *n*-dimensional clustering record (one for each household); (b) These attributes were then binned and a distance formula derived for each household from the binned values; (c) this distance value was then presented to the clustering algorithm from which separable partitions are developed; and (d) each of the 1.449 million households in the experimental group was then assigned to the *m* number of resulting clusters (partitions). This process follows Haydock (2006b) and has been found effective in partitioning marketing data.

The control observation utilized the incumbent segmentation that was derived from each record in the data. This segmentation can be described as a two dimensional description of customer types typical of the retail catalog industry. These dimensions represent the recency of purchase and the frequency of purchase.

4. A composite retail index was developed that served as a proxy for the market the firm participates in. A series of Bernoulli trials determined the probabilities of up and down ticks through the lattice. The index period began with the 2003 observation period and included monthly data up through March 2007. The index was forecasted six periods forward to determine the probable path through the binomial lattice that created the probabilities surrounding demands and customer counts. The index data were treated as a time series and various time series forecasting techniques were deployed in an effort to determine the best fit method.

5. Demands and customer counts were then determined for the test group by simulating the purchase behavior through the binomial lattice. Each node of the lattice simulated the uncertainty of a future value. One thousand Monte Carlo trials (rows) were conducted at each node that resulted in a stochastic path through the lattice traversing six

future time periods. The mean value of the Monte Carlo observations at each node is then multiplied by beginning period demands and customer counts and is adjusted either up or down depending on the node value in that part of the lattice. This continues by asset class for each node of the six period binomial lattice. The resulting matrix produces the necessary inputs for the asset allocation portfolio optimization. The demands and customer counts of the control observation were derived from the data in each household record and were not subjected to the economic conditions represented by the binomial lattice.

6. A computer application was developed utilizing extreme value theory to determine the value at risk (VaR) of the experimental portfolio given a probability that an adverse condition could dominate a scenario. This information was used as an early warning trigger that there is an increased probability that a revenue shortfall could occur in a future time period. The control portfolio was not exposed to this treatment.

7. Goals and constraints were set for the test portfolio and a computer application was developed that ingests all the available data and executes the linear goal program with stochastic extensions. The control observation was not exposed to this treatment. The linear goal program solved for the optimal diversified investment allocation across six quarterly time periods in order to maximize terminal wealth.

8. The resulting portfolio outcomes were measured and reported on for the return on marketing investment (μRMI_{test}) in the test group in order to contrast the $RMI_{control}$ measure of the control observation. Appropriate measurements also detailed the performance of each of the market segments for each experiment.

9. The experiment was conducted fifty times reflecting possible states of the economy and portfolio investment behavior as a result of exposure to extreme volatility. The inputs for the *t*-test were then made available in the form of a tableau. The results of each of the tests will be accumulated and contrasted in the overall hypothesis comparison for the decision to either accept or reject the null hypothesis. The *t*-test will describe accept or reject regions and the probability for both Type I and Type II errors.

Summary

This chapter began with the recognition that there is an important difference in the marketing science knowledge concerning the behavior of individual customers and the investment behavior of efficient portfolios of customers. The study of individual customer behavior is rich in the marketing science literature, while the study of the investment behavior of efficient customer portfolios is generally void. This understanding requires that any research methods deployed in this study begin with a grounded theory articulating portfolio construction methods and includes a scientific test of a hypothesis concerning the performance improvement possible from the proposed grounded theory of efficient allocation of resources.

Prior to articulating the research design, a knowledge acquisition strategy was determined so that claims to knowledge can be properly justified. The post positivism strategy was selected from four alternatives since its procedures lead directly to a study utilizing the scientific method. This in turn led directly to a hypothesis that must be tested and either accepted or rejected based on the quantitative results of the test.

The hypothesis requires a one-tailed *t*-test. The null hypothesis (H_0) stated that the performance of the portfolio optimization test group is less than or equal to that of the performance of the control benchmark observation with respect to the return on marketing investment ($\mu RMI_{test} \leq RMI_{control}$). The alternative hypothesis (H_{α}) stated that the optimal portfolio treatment delivers more *RMI* than the incumbent benchmark methods ($\mu RMI_{test} > RMI_{control}$).

Since the portfolio construction concept is a new concept and one that should be generalized, multiple experiments are warranted; each reflecting expected economic conditions and scenarios of extreme volatility. The drawback of this strategy is the physical time required for multiple tests, this is offset by the accuracy provided in the procedure. The time to construct the computer models, especially the complex binomial lattice Monte Carlo simulation engine and the numerical optimization codes are of practical concern, again offset by the insight gained by understanding portfolio behavior under uncertainty and extreme economic conditions.

Chapter 4 is designed to develop and articulate the grounded theory of asset allocation portfolio construction as it relates to direct marketing investment. The computer applications developed, the data accumulated, and the overall digital system that was constructed will be presented in chapter 4 as well. The experimental design concepts discussed in this chapter will be executed through the digital system that was built so that results can be recorded and reported on in chapter 4.

CHAPTER 4: RESULTS

Quantitative Grounded Theory of Portfolio Construction

This chapter describes the results observed from the experiments utilizing the optimal strategic asset allocation investment procedure. The hypothesis, posed in chapter 3, is that the strategic asset allocation method will improve the financial results of marketing investment in direct customer contact. This grounded theory will only detail the strategic aspects of this procedure.

The problem space can be bifurcated into two distinct problems: (a) the strategic investment allocation; and (b) the tactical treatment of a customer. The tactical treatment of customers is a well documented problem with as many approaches as there are practitioners. The strategy aspect of this problem has been widely ignored and is gaining importance as a potential source of new corporate performance (Kotler, 1994). The combination of the two techniques should actually provide very powerful results.

Figure 1 in chapter 2 illustrated the set of recommended procedures in developing a strategic asset allocation portfolio optimization solution. Each of these procedures will be detailed in this chapter. Where results are available, these will be illustrated within tables that show actual outputs from computer simulations. Most of the outputs have been posted to a Microsoft® Excel spreadsheet so the results can be easily presented in tables.

The components of the asset allocation procedure illustrated in Figure 1 that will not be dealt with in much depth in this chapter are primarily the market research aspects of attaining customer knowledge. In Figure 1 a process referred to as hedge attributes will be dealt with in chapter 5 on future research. The lifetime value study is briefly described in this study but is considered a separate body of work, sufficiently large enough as an individual effort that its detail would distract from this research. Information on specific details on lifetime value can be found in Faherty (2004).

The retail information warehouse identified in Figure 1 is again a study whose detail would distract from describing the optimal asset allocation strategy. The information warehouse procedure is the process of building an adequate time dimensioned data repository and is clearly of importance. The details of this construction are primarily concerned with mapping sources of data to the core target systems, and in the cleansing, house-holding, and efficient storage of this resource. Without dealing with these operational issues, this chapter starts out with a description of the data.

Description of the Behavioral Customer Data

The data collection methods are those appropriate for the use of archival data. A large customer sample was acquired that is comprised of the detailed purchase transactions of 1,449,001 households. These purchase observations were over the period 2003-2005. These purchases were made in the retail apparel and home furnishings merchandise categories from a large retail catalog company. The identification of any single household is not possible from the data as customer name and location have been removed for privacy and security purposes.

Table 2 describes some of the characteristics of the sample utilized in the research. Slightly over 3.8 million individual transactions were consolidated into 1.449 million households that was itself a sample randomly selected from over 32 million individual households in the retailer’s house file. Selection was based on at least one household purchase transaction occurring in the years 2002 through 2005.

It is possible, for instance, to have a purchase in the fiscal year 2002 and no purchases throughout the fiscal years 2003-2005 and be included in the sample. Records have been eliminated in a data cleansing effort if there were conflicting attributes in consequent years that would corrupt the overall household observation. A series of computer programs was developed in the Speakeasy (Cohen, 2000) programming language to cleanse the data and household the transactions. A random household number was assigned to each record to uniquely identify the household data.

Table 2

Characteristics of the Sample

Total Purchase Events - 2003	1,393,209
Total Purchase Events - 2004	1,167,827
Total Purchase Events - 2005	1,249,306
Total Purchase Events	3,810,342
Average Order Value - 2003	$ 39.95
Average Order Value - 2004	$ 37.00
Average Order Value - 2005	$ 35.79
Total Demand - 2003	$133,872,326.59
Total Demand - 2004	$121,865,400.95
Total Demand - 2005	$116,522,945.15
Total Advertising Spend - 2003	$ 14,386,634.03
Total Advertising Spend - 2004	$ 14,485,377.11
Total Advertising Spend - 2005	$ 14,715,604.05
Total Customer Records	1,449,001

The 479 fields of information on each household include categories such as the following:

1. Demographic information derived from the Acxiom® (Acxiom, 2006) database. These demographic data also included information on cluster group memberships produced by Acxiom based solely on demographic and buying behavior external to purchase observations related to the subject catalog company.

2. Total numbers of order transactions, total spend, and average order value for each household from 2003-2005 by year and broken down by quarter.

3. An indicator of whether that household has purchased products at full retail price, has purchased products at liquidation prices, the total number of full price and liquidation products, and total demand dollars for full price and liquidation spend from 2003-2005 by year and broken down by quarter.

4. Catalog and Internet channel demand summaries in terms of order value in dollars for each household from 2003-2005 by year and broken down by quarter.

5. There are seven merchandise categories from which a household can purchase: women's casual, women's tailored, men's casual, men's tailored, home furnishings, kid's merchandise, and other (these may include luggage and notional items). Observations include the demand for each merchandise category from 2003-2005 by year and broken down by quarter.

6. Information captured on offers (advertisements) to each household include the total number of offers, the number of core books (main catalog mailings), the number of prospectors (the best selling products from the main catalog used primarily to entice new customers), the total number of liquidation offers made, the total number of specialty

offers for each merchandise category (a men's book, a kids book, etc.), the number of advertising pages a household has seen, and lastly, the amount of dollars spent on that household for direct advertising. All observations are from 2003-2005 by year and broken down by quarter.

These data have been placed into relational tables in a Microsoft® Access database for ease of manipulation in reporting and for use by the other computer programs developed to perform the data cleaning, analytical data mining, and numerical optimization functions. The data are considered high quality from an accuracy perspective and household records that could not be completely matched such that all 479 fields could be integrated into the record were eliminated. The eliminations were less than 1% of the overall active records.

External Demographic Data

The demographic data utilized originated as demographic estimates from Acxiom Corporation (2006). Acxiom's consumer database contains over 1,600 items of information on most of the households in the United States. These data are well known to marketers and are primarily used to prospect for new customers where the information on buying behavior is unknown to the firm. The data selected were appended to the records of each household in the experimental database prior to removing the household identifiers. This process results in very high match rates. This served to augment the behavioral data and provide a better understanding of the customer household.

Not all 1,600 fields of information were required in this research. The data that proved most valuable in the development of customer understanding were those data related to: (a) age; (b) net worth; and (c) purchase estimates related to men's, women's, and kids clothing. These data are updated on a monthly basis by the Acxiom Corp. These data were used in the scoring models, the clustering models, and for other types of transforms and data preparation. The combination of the customer behavioral data and the external data from Acxiom® make up the contents of each household record.

Utility Concepts and Lexicographic Choices

Chapter 2 described the nature of portfolio problems in marketing as being inherently multiattribute decision-making models. Desired attributes were described for outcomes of marketing program investment in terms of goals that have lexicographic order properties in line with preferences. Multiattribute utility theory was also determined to be an ideal way of defining these preferences and priorities.

Alternative scenarios can be comprised of sets of these utility bundles (preferences and priorities) differentiated by assigning different weights to each of the attributes. For each alternative, a utility value was also assigned in such a way as to differentiate and order weighted schemes. The maximization of these expected utilities provides the appropriate criterion for the marketing decision-maker's optimal portfolio strategy.

The importance of this step in the asset allocation optimization process was to clearly determine which preferences should be declared goals, and in which priority order those goals should appear in the optimization. This was not a trivial task; asking any manager in an organization what the goals were and their priority order would probably net as many different answers as the number of people asked. In the multicriteria optimization area, these goals and their priorities need to be crisp. Having a method for taking preferences and converting them to choices is illustrated with the case that follows.

Allocating resources within a direct marketing firm would start with the various customer types. There are three major types of customer groups when classifying this aspect of a firm's assets. These may be describes as: (a) the retention group; (b) the re-activation group; and (c) the acquisition group. These designations relate primarily to recency attributes describing the time from the last purchase. The expression surrounding priorities would therefore begin with these customer types.

The retention group may be defined as those customers who have made a purchase between 0 and 12 months from today. These are the most valuable customers the firm currently has. Investment in these customers would be considered less risky based on their lifetime value, depicted in Table 3.

The re-activation group would be characterized as being previous retention customers, who have since lapsed. These customers are characterized in Table 3 as being between the recency bounds of 13 to 60 months. The firm would like to have these customers back, especially since they have indicated by their previous purchase relationship that the firm's products and services met a prior need. These customers are not as valuable to the firm as the retention customers, and consequently from a resource constrained investment pool, less would be desired to be spent to re-activate these customers than on retaining the more current group. Lifetime value (LTV) deviations are identified in Table 3.

The last recency group representing acquisitions has either aged off the house-file (greater than 60 months since the last purchase) or have never purchased from the firm. These prospects would be considered more risky, and therefore less likely to respond to promotional investment. Value to the firm, relative to the lifetime value metric, are illustrated in Table 3.

The risk-to-revenue ratio number in Table 3 is another metric with which to look at the risk of these individual recency groups. This number is derived from the ratio of standard deviation to mean revenues and is the proportion of risk relative to revenue. The acquisition group is by far the riskiest group, followed by the retention group.

Table 3

Historical Revenues and Portfolio Investment of the Population

Year	Totals	Retention	Re-Activation	Acquisition
2003 Revenues	$1,181,193,351	$862,875,025	$165,343,279	$152,975,047
2003 LTV	$34.63	$60.70	$17.92	$14.76
2004 Revenues	$1,078,229,125	$793,814,029	$163,978,626	$120,436,470
2005 Revenues	$1,016,333,862	$721,104,921	$176,364,482	$118,864,459
2006 Revenues	$925,080,261	$656,007,732	$172,685,406	$96,387,123
2007 (Forecast)	$839,906,452	$592,288,486	$168,769,571	$78,848,395
Mean of series	$1,008,148,610	$725,218,039	$169,428,273	$113,502,299
Standard deviation	$118,430,177	$107,391,929	$5,136,624	$27,967,641
Risk/Revenue ratio	11.75	14.81	3.03	24.64
Mean HH investment	$10.73	$13.72	$9.21	$5.48
Standard deviation	$0.67	$0.61	$0.76	$0.42

Revenues of each group from the population with their means and standard deviations are illustrated in Table 3. Mean investment amounts are also detailed and it is evident that the firm is mailing everyone within these groups essentially alike. The average variable promotional instrument costs $0.67, which is close to the one standard deviation mark for all groups. In essence, all member of a group are treated alike. An opportunity emerges to differentiate the investment for customers within the groups.

Each of these customer types was desirable. The perfect portfolio would have allocations going to each group in the proportions appropriate for their risk and return characteristics. Table 3 illustrates a year-to-year revenue attrition loss experienced by the retention group from 2003 through 2005 with 2006 and 2007 expectations. This revenue loss must be replenished from both the re-activation and acquisition groups, in addition to the core retention group, if the firm is expected to grow. Investment in these groups could therefore be prioritized where each has a goal, represented by a revenue target, and investment boundaries.

Based on the LTV metric the preference for the investment in the groups can be represented as follows: Retention > Re-activation > Acquisition. The retention group is preferred over the re-activation group, which is preferred over the acquisition group. The interesting observation is that a decrease in revenues from the retention group provides a greater disutility than that which would be provided from an equal amount of increase in revenues from the retention group.

Relative to risk aversion, the retention group is by far the most attractive investment and in this case the firm demonstrated a strong preference for retention investment over re-activation or acquisition (Table 3). The risk to revenue ratio clearly shows a priority preference. The core metric that best describes utility turns out to be the lifetime value measure. The lifetime value metric can be described as a measure of customer value over time. It is typically used to define a payback period for a customer that can then be used as a way to determine how much to pay for a customer. The typical payback period is within a 12 month investment horizon (Faherty, 2004).

Lifetime value also serves as an ideal upper-bound on the investment activity for any particular asset class. For instance, the marketing executive would never want to invest greater than $20.00 per re-activation household if this amount was the lifetime value quantity. This amount is the cost to acquire any single customer on average for that group. The upper-bound rule should be carefully followed for re-activation and acquisition customer groups. Use of the retention lifetime value would comprise the profit estimate for that group, and investment would be substantially lower in order to preserve profit.

The computation elements of lifetime value include the amount of dollars required in order to initiate and fulfill the original sale, the demand dollars generated on the on the initial sale, and demand dollars in the subsequent period on additional order activity. Table 3 identifies the lifetime values for the various groups based on a study conducted utilizing the 2003 data contained in this study. Lifetime value estimates will be required for each of the market segments generated from the clustering exercise and will be described in a later section. Each market segment can be decomposed into the three customer types (retention, re-activation, and acquisition).

Complexity, Indexing, and the Constrained Binomial Lattice

This section will introduce a method to simulate the anticipated movements of the economy used in forecasting a firm's demands and customer counts at the aggregate firm-wide level. The importance of this process in the asset allocation optimization is that demands and customer counts comprise one set of critical inputs into the portfolio optimization program and are not known in advance of the investment decision with certainty. These future customer behaviors in response to economic conditions are therefore stochastic in nature with uncertainties related to their financial risk and return characteristics.

Simulation may help clarify these uncertainties and parameters of interest can be represented by distributions at each time period, with probability P of increasing in value from the previous period, and probability 1-P of decreasing in value from the previous time period. The increase in value, or up movement, or the decrease in value or down movement, can be best represented as Brownian motion in continuous time models, and a binomial lattice in discrete time models. The Brownian motion model is useful for explaining random walks across time where a terminal value at the last time horizon is desirable.

Cox et al. (1979) argued that the binomial lattice model is useful where a discrete decision is required at each time step. The binomial lattice was selected in this research because a discrete marketing investment decision is required at each time period. The outputs from the binomial model form the financial returns required for the numerical asset allocation optimization model. The distributions generated by modeling uncertainties at each time period will represent the risk characteristics.

The binomial lattice incorporates one level of overall uncertainty. Figure 6 is a good representation of how the spread of uncertainty increases as time progresses through the model. In each time step, another node is added to the system. Time period four has five nodes while time period five has six nodes. The number of possible paths through the lattice also doubles with each time step representing an additional description of uncertainty. For instance, there are 32 possible paths at time period five (2^5) and 64 possible paths at time period six (2^6).

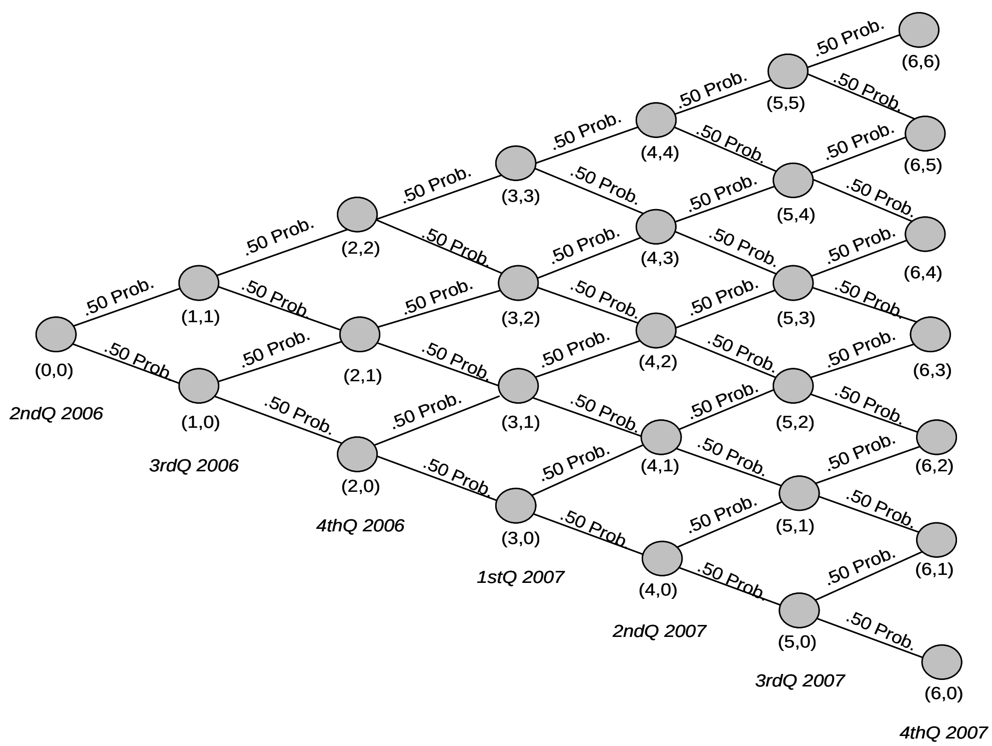


Figure 6. Six time period binomial lattice with transition probabilities.

The lattice represents the path-dependent movement of demands and customer counts through time. A trinomial lattice provides the possibility of a state where one time period to the next is represented by no change in values. This state was rejected as the data provide no evidence that this possibility occurs with any frequency, and would be an extremely rare event.

Windas (1996) described the binomial process as being the expected payout of a coin toss. Expressed mathematically, this payout is represented by weighing the payout of each possible outcome by the probability that the outcome will occur.

$$E(w) = \sum_{i=1}^{M} (w_i * p_i),$$

Where:

$E(w)$ = the expected payout w from one coin toss,

w_i = the payout received from an outcome i,

p_i = the probability that an outcome i will occur,

M = the number of possible outcomes, and

$i = 1,2,3,\ldots,M.$

Consider that at each movement in time, a coin is tossed and there is an equal probability for an up or down movement. The possible outcomes grow more complicated as time moves forward. In the first time period, only two outcomes are possible, either up or down.

In the second time period, the paths increase to where one of four possible outcomes is possible. The third time period presents a state where one of eight possible outcomes is possible. This progression continues in a geometric series through time, expanding the spread of the lattice at each time period simulating a Bernoulli distribution. The probability function for the Bernoulli distribution is (Berk & Carey, 2004, p. 202):

P(Y = Up) = *p;*

P(Y = Down) = 1 – *p*.

Where *p* is a value between 0 and 1.

An additional level of complexity comes with the requirement to understand the uncertainty of the values possible at each node of the lattice. These values are the demands and customer counts (as opposed to their paths). Since these values are themselves stochastic, the need arises to incorporate randomness into the mathematical model by formulating the values at each node as the result of a probabilistic process. This is opposed to assigning the values as rates in a deterministic model.

This stochastic model of the binomial lattice (representing the uncertainty across time) and the nodal values (representing the uncertainty in a state of time) has the property of two levels of complexity. One level, that will be referred to as the index level, is concerned with the uncertainty in the path-dependent march through time. The second level, referred to as the state level, will leverage Monte Carlo simulation to capture the dispersion around the state uncertainties at each node in time.

Cao, Gillespie, and Petzold (2005) argued that it was important in the study of populations or groups that the index space and state space be understood individually. They referred to these models as discrete stochastic systems. They differentiated these types of models from models where deterministic individual behaviors are the target of understanding. The understanding of individuals is not a priority of this research, but the understanding and investment strategy of groups are of immediate interest.

Turning to the binomial lattice, a concern arises in the amount of dispersion available in the lattice as it expands and moves from one time period to the next into the future. Figure 6 illustrates the actual binomial lattice that was used in this research. This six-period model represents the possible index states attainable, but perhaps not necessarily observed. This is an important point, since there may be no real value or requirement to compute the paths that have virtually no chance of occurring.

Windas (1996) described an interest rate model that has an equal probability of either an up or down movement occurring. These values, across time, can be considered a time series that can be forecasted. If the monthly data representing the time series were aggregated by quarters, then the data, over time, can be represented as a series of Bernoulli trials where the number of times interest rates went up or down can be recorded and a mean and standard deviation for each quarterly time period represented.

If an index could be built from these data to represent the most likely path through the lattice, then it is possible to narrow the range of possible values to those most likely to occur, and therefore, those of interest. This index could be used to center the lattice and could be forecasted forward to match the time periods of the model. The values at each node of the index could be simulated using the Monte Carlo method to capture the uncertainty of the future state of these discrete events numerically describing the risk inherent in making an investment in an asset class during that time period. This is in fact the strategy that was followed. Construction of the index is the focus of the next section.

Construction of the Retail Index

Aczel and Sounderpandian (2002) described an index as a number that measures the relative change of a set of values over time. Portfolio managers in the financial services industry, for instance, utilize indexes to gauge the performance of their strategies against a broad measure of securities in a peer portfolio (Sharpe & Alexander, 1990). It is possible to track a retail firm's performance against that of its peers by developing a tracking index closely matched to the firm's products and services. This index would include the total sales performance of all companies that participate (and report to the government) in the sales of certain products and service lines (Gephard & Zhu, 2006).

The importance of this step in the asset allocation optimization process is the ability to replicate the performance of the peer group from one economic time period to the next. The optimal portfolio would utilize the way the index travels through the binomial lattice, the up and down movements for the group that it is most alike, to determine the most likely path through the lattice. The use of Monte Carlo simulation adds an understanding of the dimension of risk, as the firm is unlikely to know for certain the exact path.

The U.S. Census Bureau collects data on sales for each industry at the six digit NAICS (North American Industrial Classification System) level (Census, 2006). One of the more recent industries added to this census is the retail trade sector. The retail trade sector comprises establishments, both store and non-store entities, engaged in retail merchandising (NAICS sectors 44-45). A retail apparel merchandiser for instance would want to compare their performance with the performance of their peer group using NAICS number 448 representing clothing and clothing accessories stores.

Table 4 describes product and service demand splits for the retail apparel merchant in this study that are averaged over the three-year period (2003-2005) for which observations exist. These splits would approximate the percentage of each product category representing total demand utilized in the composite index. A composite index, formed in this way, is therefore a market value weighted index of the revenue from sales of products and services of a firm.

These revenue ratios can be applied to the overall NAICS relevant categories in the exact proportions of the firms revenue splits to form an index of all participants trading in their customized category. Tracking this index over time should provide an accurate peer group comparison. Forecasting this composite index forward would also provide a fairly accurate indication of the demands for the firm at an aggregate level.

Table 4

Revenue Demand Splits and the NAICS Elements of a Composite Index

Product category	Demand	NAICS number and category
Men's	36.1%	44811: Men's clothing stores
Women's	39.2%	44812: Women's clothing stores
Kid's	16.9%	44813: Children's and infants stores
Home furnishings	7.8%	442: Home furnishing stores

Data for each of the NAICS categories is presented in a monthly format. The updates are done monthly as well by the Census Bureau. The index base year selected for this study is based on a 2003 fiscal year and accumulated quarterly in the following manner depicted in Table 5. These assignments represent the retails firm's fiscal quarters matching the data. NAICS data was accumulated by quarter for the calendar years 2003, 2004, and 2005. Table 5 shows how the months would accumulate into fiscal quarters for the trading year 2003.

Table 5

Monthly Data Accumulated by Quarter to Mirror the Case Fiscal Year

Quarter 1	02/28/2003	03/31/2003	04/30/2003
Quarter 2	05/30/2003	06/30/2003	07/31/2003
Quarter 3	08/29/2003	09/30/2003	10/31/2003
Quarter 4	11/28/2003	12/31/2003	1/30/2004

The index value for any period would be as follows (Aczel & Sounderpandian, 2002): Index number for period i = $100 * \frac{index_i}{index_b}$,

Where:

$index_i$ = the value of composite retail sales in period i, and

$index_b$ = the value of composite retail sales in the base period.

As an example, the base period for the composite index is the 1st quarter 2003. The value of the composite index for the first quarter is = \$8.548B (billion U.S. Dollars). The value of the 2nd quarter 2003 composite is = \$9.079B. The index value is $= 100(\frac{\$9.079B}{\$8.548B}) = 106.2$. This could be viewed as a 6.2% increase from the prior period index value. These values were in fact computed for each of the time periods from 1st quarter 2003 through 2nd quarter 2006 are represented in Table 6.

The values in Table 6 represent the growth from the prior period. The 4th quarter provides the largest growth rate from the previous quarter and that the 1st quarter experiences a large drop from the performance of the 4th quarter. This would represent seasonality in the retail apparel business relative to the products being sold, where the

Christmas season (4th quarter) would be by far the most active quarter. The values in Table 6 were derived by subtracting the current period index value from the prior period's index value. Representing the number in this manner allows for a quick way to spot a trend in growth (or loss) from period to period.

Table 6

Index Values Represented as Percentage Growth from Period to Period

Period	1st Quarter	2nd Quarter	3rd Quarter	4th Quarter
2003		6.2	4.6	13.9
2004	-14.3	2.0	2.6	14.8
2005	-15.0	3.7	4.3	16.3
2006	-19.3	4.0	4.2	15.7
2007	-19.6	4.1	4.2	16.4
Mean	-17.1	4.0	4.0	15.4
St. Dev	2.8	1.3	0.7	1.0

Table 6 also displays the mean and standard deviation of the series of numbers. These measures will be very helpful in the formulation of demand and customer count distributions utilizing Monte Carlo simulation. The values from 1st quarter 2006 through the 4th quarter 2007 were, in fact, forecasted. These forecasts were derived by treating the monthly sales results of the composite index as a time series.

The mathematical method used to produce the forecast is a Multiplicative Winters Seasonal Smoothing procedure. This procedure is a member of a family of advanced exponential smoothing methods. The forecast is based on a weighted average of current and past series values (Aczel & Sounderpandian, 2002). In this case 10 years of monthly

NAICS data was used in the forecast. These data are developed into the composite index using the rules described in Table 4.

The concept behind exponential smoothing is that the largest weight is provided to the most recent observation, less weight to the preceding observation, and even less weight to the observation prior to that, and so on throughout the time series. The weights decline geometrically as the data goes backwards in time. The method used requires at least two years of observational data to construct a forecast. Formally named the Holt-Winters method, this procedure constructs three statistically related series that are used to make the actual forecast (Berk & Carey, 2004). These series are: (a) the smoothed data series; (b) the trend index; and (c) the seasonal index.

The equations representing the series are as follows (Berk & Carey, 2004, p. 454):

$$a_t = \alpha \frac{y_t}{c_{t-s}} + (1-\alpha)(a_{t-1} + b_{t-1})$$
$$b_t = \beta(a_t - a_{t-1}) + (1-\beta)b_{t-1}$$
$$c_t = \gamma \frac{y_t}{a_t} + (1-\gamma)c_{t-s}$$

Where:

a_t = the smoothed data at time period t,

b_t = the trend index at time period t,

c_t = the seasonal index at time period t,

s = the number of time periods in a year (four in this case), and

α, β, γ = three smoothing constants with values between 0 and 1.

The six time period forecast provides the remainder of the values utilized in Table 5 to complete the requirements for the next step. This next step involves subtracting the quarterly index value from the mean. This process provides insight into the direction of the increase or decrease relative to the average movement of the index. The standard deviation provides a measure of the strength of the movement, relative to the mean. From this computation, the values in Table 7 can be derived.

Table 7

Retail Apparel Composite Index Values Used in the Lattice

Time Period	3rd Q 2006	4th Q 2006	1st Q 2007	2nd Q 2007	3rd Q 2007	4th Q 2007
Tick Value	0.2	0.3	-2.5	0.1	0.2	1.4
Relative Value	0.0500	0.0194	-0.1419	0.0250	0.0500	0.0649
Tick direction	Tick up	Tick up	Tick down	Tick up	Tick up	Tick up

In Table 7 the derivatives of the forecasted values are presented. For each time period, a distance from the mean is depicted by the tick value. The relative distance from the mean (the tick value / the mean) is also given. This turns out to be an extremely valuable number because the quarterly data in this particular business under study are represented by different consumer buying seasons. To put all seasons on the same scale, the relative tick value was used.

The tick value was deployed in the computation of the actual econometric effect on consumer buying behavior, explained in the next section. Table 7 also shows the direction of the tick from the mean, up or down. This up-down feature permits us to count the number of times in a period between 2003 and 2007 that the values in a season have ticked up or have ticked down.

These Bernoulli trials also provide us with the probabilities that the index is likely to tick up or likely to tick down. For instance, in the third quarter the number of times the index has ticked up relative to the mean is four times. The number of times it has ticked down below the mean is one time. So, the probability that in the third quarter the index will tick up is 80% with a 20% probability (1 – p) of a tick down.

Table 8 illustrates the results of these Bernoulli trials using the actual index data. The sum of the tick values probabilities in any time period is equal to 100%. The probability of the tick direction, combined with the relative tick value, provides the econometric inputs to the binomial model. These probabilities will be used to construct movements through the binomial lattice.

Table 8

Probabilities Indicating Index Ticks Up and Down

Time period	3rd Q 2006	4th Q 2006	1st Q 2007	2nd Q 2007	3rd Q 2007	4th Q 2007
Tick up	.80	.60	.50	.60	.80	.60
Tick down	.20	.40	.50	.40	.20	.40
Node location	(1,1)	(2,2)	(3,2)	(4,3)	(5,4)	(6,5)

What has been constructed is an accurate description of the probabilities of a movement through the binomial lattice. In effect, this phenomenon is based on the forecast methodology without regards to the possibilities that instead of a single value to be forecasted perhaps it is more intuitive to forecast simulating a distribution. The forecasting method used provides a good starting point, but the randomness of the economic event is not well captured. The question that should be asked is more related to the possible range of values the statistic can take on and the probabilities of these values, or its distribution.

Monte Carlo simulation provides an alternative understanding of a statistic's sampling distribution. The Monte Carlo method does this empirically using random samples from known populations in order to track the behavior of a statistic (Mooney, 1997). By simulating the mean values by quarter, the tick values, and the relative tick values with 1,000 trials, a frequency distribution of those values can be constructed and properties of the statistic of interest can begin to be known.

The random variable in this case is the quantity of the index value illustrated in Table 6 as the percent change in the index from period to period. The realization is that these events can take on a range of values and that the probability of each of these values occurring is determined by the distribution function of the quarterly index values. Since the index values are based on the performance of thousands of retail firms collected and reported by the NAICS function of the U.S. Census Bureau, the determination was made to utilize a normal random distribution.

What is of concern in a Monte Carlo study is the behavior of the statistic of interest over many trials. In this case 1,000 trials were used to establish the values of the index as it moves through the binomial lattice. This concept fits well with the problem domain in this research as the forward-looking forecast of demand is uncertain but is a key input into the investment optimization process.

A computer program was developed for this research to specifically determine the values across all lattice points using 1,000 Monte Carlo simulations. The mean index values were simulated for each time period, (six columns) in total, and the tick value and relative tick values are estimated for each trial. This process can be repeated for each experiment to determine the asset allocation range of decision-making capability.

Each experiment builds a new set of values. The experiment results were captured in a Microsoft® Excel spreadsheet for archival purposes. The asset allocation portfolio optimization was run for each experiment as a result of simulating the stochastic nature of demand, determined through the Monte Carlo trials. Scenarios were generated through this process.

The key outputs from the trials were the mean values of the index at each time period and the corresponding standard deviations, developed by utilizing 1,000 pseudo-observations from the simulations. The resulting values were binned and the histogram is presented in Figure 7. The bins were determined by measuring the counts around the mean of the series and at each standard deviation (+/- 1,2, and 3 standard deviations). The shape of the histogram suggests a normal distribution.

There is no apparent guideline as to the number of trials necessary to converge on the correct value of the stochastic variable. Mooney (1997) recommended that trials be composed of anywhere between 1,000 and 25,000 simulations. Mooney argued that since sample size is inversely related to the standard deviation that observing the stability of the standard deviation over *n* number of trials is a good gauge.

Another suggestion by Mooney was, if the statistic of interest is in the tails of the distribution, then more trials in an experiment are recommended. The 1,000 trials used in this research had very stable standard deviations when compared to doubling and tripling the number of trials and comparing the standard deviations of each. Working with 1,000 trials proved convenient to manage the archive of each experiment, which is a secondary benefit but nonetheless important in this research. The computer application built required only a function key to be depressed to change and recalculate every number in the resulting matrix (18,000 values) and took about two seconds to process on the computer (HP 8440 laptop).

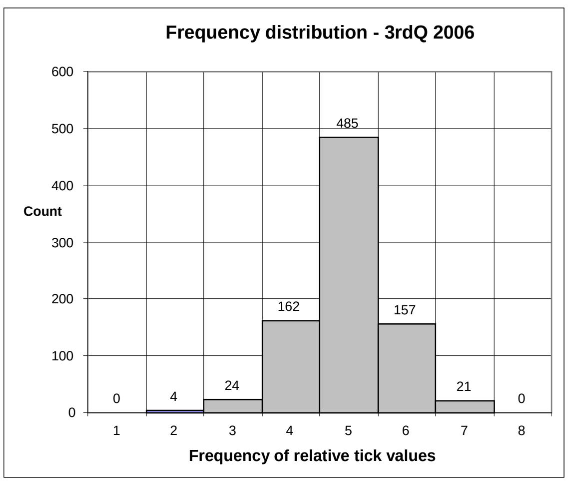


Figure 7. Histogram from 1,000 Monte Carlo trials – 3rd Q 2006.

With the ability of the index to traverse a likely path through the binomial lattice there is some knowledge of reactions of the composite index to various economic situations. The next step that would logically follow would be a keen understanding of how groups of customers will react to economic situations. The creation of asset class groupings is the topic of the next section and is of paramount interest in developing optimal portfolios.

Asset Class Determination

Most direct marketing enterprises segment their markets in order to understand the most effective ways to apply advertising treatments to the customers of the firm. Shepard (2003) argued that most direct firms utilize low dimensional segments primarily comprised of recency, frequency, and monetary value which are typically heuristically defined. This approach has the advantage of simplicity and the disadvantage of avoiding a more thorough interrogation of the data across many attributes and time periods.

This section will provide a more rigorous thought process surrounding the formulation of investable asset classes in an effort to improve investment performance in the asset allocation process. One argument of this research is that new and insightful consumer behaviors can be mined from a data driven process versus the typical heuristic process where the marketing manager determines the separable partitions. The issue is can data driven methods be used to provide more performance for the investment process by mining the data for previously unseen behaviors.

To precisely articulate the clustering problem to be solved in mathematical terms let $X_1, X_2, X_3, \ldots X_n$ represent a set of column attributes from an *n*-sample data set of customer purchasing and behavioral records from some unknown distribution with density *f* with respect to a line segment $(a_i \to b_i)$ (Haydock, 2006b). This line segment would constitute a closed interval corresponding to a finite portion of an infinite line (continuous data). The histogram estimator *f* is based on a set of partitions with *M* hyperplane segments (Birge & Rozenholc, 2002). The density of each histogram could be represented by: $f^{opt} = f_M(X_1, X_2, X_3, \ldots X_n)$.

Where:

f^{opt} = the optimal histogram density estimator,

M = the set of hyper plane segments, and

X_i = the attribute from a multidimensional attribute set.

Once the optimal bin set for each attribute has been computationally determined, the next step evaluates each customer's attribute set and assigns a numerical value representing the position of the bin attribute pair. This process continues for each attribute. A number is then created for each customer representing the bin locations for each attribute and is treated as a long digit composite number.

This composite number constitutes the mining base that the pattern detection and clustering algorithms use as input. In this case a 13-dimensional composite number is created and may look something like this: 6365121133179. Each of these 13 digit numbers (one per customer) is compared to every other customer for their similarity in each digit position. Similar long digit numbers are grouped together and eventually form clusters.

One may consider the task of clustering as binning the bins. The objective of the clustering is to create separable partitions such that customers are grouped together on their similarities, minimizing the differences of these attribute sets. The measure of optimality of fit will be a minimization of the intra-cluster distances between all customers in a particular cluster, and a maximization of the inter-cluster distances between all other clusters. These measures turn out to be statements of proximity.

This idea of proximity comes from the development of the binned data. One can visualize a histogram that is comprised of vertical bins (such as that illustrated in Figure 9). The original data values contained in the bins are on average increasing in value from left to right with the minimum value being contained in the left most bin and the maximum value being a member of the right most bin. The distance between these two numbers constitutes the basis for a proximity measure.

A new proximity measure was proposed in Haydock (2006b) and was designed to measure the distances between the bins. This new measure was referred to as the modified Hamming distance formula. The long digit number previously described would be an example of the modified Hamming distance.

Customer *n* attribute set: 4 3 3 3 4 1 2 1 4 4 6 4 2

Customer *m* attribute set: 1 4 1 6 9 1 3 1 7 6 6 2 3

Mod. Hamming difference: 3 1 2 3 5 0 1 0 3 2 0 2 1 $\Big\}\ abs\sum_{1}^{13} differences = 23$

Figure 8. Modified Hamming differences form the core of the mining base.

The logic of the formula concerns the number of absolute differences it takes to corrupt or mutate one binned value into another and by turning one composite string into another. This modified Hamming distance is the measure used to determine the cluster sets in this research. Figure 8 is an illustration of how this complex number is constructed and how proximity is considered.

Cluster analysis is the process of grouping a set of observations. Given a symmetrical data matrix of Modified Hamming distances composed of *m* rows representing customers and *n* columns representing attribute distances. The objective is to group the observations in such a way that they are internally homogeneous intra-cluster, and externally heterogeneous inter-cluster. Good cluster formation takes these two measures into consideration.

The observation matrix would be in the form (Giudici, 2003):

$$\Re = \begin{matrix} 0 & \cdots & d_{1n} & \cdots & d_{1N} \\ \vdots & \ddots & \vdots & & \vdots \\ d_{m1} & \cdots & 0 & \cdots & d_{mN} \\ \vdots & & \vdots & \ddots & \vdots \\ d_{M1} & \cdots & d_{Mn} & \cdots & 0 \end{matrix}$$

Where:

m = the row vector, one row per customer, M = maximum row,

n = the column vector of distance measures, N = maximum column,

$\Re$ = the modified Hamming distance matrix.

Details of the specific clustering techniques utilized to produce the asset classes can be found in Haydock (2006b) and will not be further articulated here. The techniques described were designed to offer a way to outperform some of the shortcomings of the k-means procedure, that was considered by Shmueli, Patel, and Bruce (2007) as the leading clustering technique used by business intelligence analysts. The major shortcoming of the k-means procedure is that it will allow two customers with identical attribute sets to be placed into different clusters.

Michaud (1997) stated that similarity is generally difficult to describe. The more complicated the pattern to be matched, the more difficult the attempts to describe similarity become.   Arrow (1951) gave clarity to the issue of similarity with his thoughts about paired unanimity. This idea of paired unanimity relative to the clustering problem states that a set of identical pairs, that will be called twins, shall always be placed into the same cluster. Haydock (2006b) proposed a clustering procedure that leverages this very constraint.

The intent of the grounded theory portion of this research is not to limit the data mining techniques available to other researchers in this area, but instead to identify the importance of constructing unique asset classes utilizing multiattribute methods. Researchers and practitioners may have their preferred method for producing clusters and market segments, and continuation with familiar and well understood analytical methods is encouraged. In Haydock (2006a) a general framework and process for evaluating social systems is presented from which the specific clustering technique utilized in Haydock (2006b) could be substituted.

The following are the steps, in sequence, that were taken to evaluate the data and prepare for the clustering exercise, resulting in unique investable asset classes:

1. The clustering application described in Haydock (2006b) was tuned to provide a specific analytical approach and reporting result desired for this research. The clustering application code was written in the Speakeasy Computing programming language (Cohen, 2000) that provides a powerful utility that leverages data analysis and matrix mathematics. The application code also utilizes various Open Source routines found in the public domain. These routines are primarily related to linear programming codes (lp_solve http://lpsolve.sourceforge.net/5.5/) and are used to produce cutting planes through multiple attribute space. These codes can be made available to interested

researchers upon request. The computations were done on a HP 8440 laptop (configured for scientific computing).

2. A random mining sample was selected from the sample population of 1.449 million records. This 1% random mining sample resulted in 14,607 records used in the clustering exercise. In Haydock (2006b) the 1% statistical sample was recommended as there would not be enough computing resources to process the entire data set in a reasonable amount of time. Also, the statistical sample provides enough variety of the data as tested by an analysis of variance on several fields (described later). The random mining sample selection was performed using a Speakeasy application developed for this research.

3. A metadata strategy was conducted to determine the types of data most likely desired across multiple attributes (479 fields to investigate). Missing values were analyzed in the mining sample and business rules were developed to handle the missing values. Outliers in certain attribute fields were also identified and dealt with in the data.

4. The next step was to construct the mining attribute set. A factor analysis was conducted to select the data attributes whose properties had the most explanatory value. Synthetic variables were created that produce strong signals that can serve to separate clusters. These applications were developed in the Speakeasy language and serve as the front end of the application program as a data creation step. The variables selected are in the following categories: (a) Demographics: age, income/net worth, gender, region (big city membership or not); (b) Behavioral: purchasing patterns, recency of purchase, frequency of purchase, monetary average order value across all purchases, cross merchandise frequencies (how many times did the customer buy from multiple categories

on a shopping visit), women's product demand, men's product demand, home product demand, kids' product demand; (c) Customer preferences: product categories where purchases occurred, seasonality preferences, channel preferences, and price point observations; and (d) Other: including lifetime value metric (computed for every record) and sales productivity (the ratio of promotional spend to purchase performance). This resulted in 13 clustering variables, or dimensions, that will determine the asset class designations. One example of these variables will be illustrated below in Figure 9.

5. A correlation analysis was performed on the variable list in order to determine if variables were containing duplicate or redundant information. Highly correlated variables could possibly skew cluster development. Table 9 illustrates a portion of the correlation matrix. The correlation analysis was performed utilizing the Speakeasy software.

6. The next step in the process was to develop categorical data from continuous data for each field that was accomplished in the binning process. The binning process is described in detail in Haydock (2006b). The bins were developed using a cutting plane technique driven by a genetic algorithm created for this research.

7. Clustering trials were then conducted. These trials were comprised of observing the clustering outputs and tuning some of the variable attributes in order to create clean separable partitions. Three iterations or trials were needed in order to derive the final segments. As a result of converging on the right set of separable partitions the corner attributes are then determined. These corner attributes are the *n* dimensional cut values used to classify all customers into asset classes, those in the clustering exercise and eventually those in the sample population. Once the corner attributes are known the

classification task is relatively simple and is referred to as a gating exercise (Haydock, 2006b).

8. An analysis of variance test (ANOVA) was conducted on all mining variables to determine the differences among several population means. Random mining samples were taken against the sample population (1% samples) for the ANOVA test. Variable means are compared to insure that both the number selected in the random mining sample is representative of the population mean for that variable and that projecting the corner attributes from the mining sample to the sample population will capture the correct classification and asset class determination.

9. The asset classes were then profiled. The dual use of this procedure is to describe the marketing characteristics of each asset class, and to spot the opportunities for investment differentiation. The benefit is a new insight into customer preferences and tendencies from a marketing treatment perspective. From an investment standpoint the objective would be to fund the asset class with enough dollars to never miss a sale, while simultaneously never saturating the customer base. The investment optimization application seeks to meet this objective.

Figure 9 illustrates the seasonal preference variable and its distribution. The chart shows that the majority of the customers buy in all seasons or quarters (bin 15). The next most popular season for purchase activity is the combination of the 3rd and 4th quarter season, which would be the height of the holiday season. The third most prominent purchase season is just in the 4th quarter (Christmas time). All 13 variables in the clustering experiment were detailed in a similar manner.

From a business standpoint, Table 9 shows that the variables selected for the clustering exercise are not highly correlated. Aczel and Sounderpandian (2002) argue that the relationship between any two variables that exceed correlation values of 0.50 would be a cause for concern pointing to the possibility of duplication of effect. Relationships greater than 0.80 would most likely necessitate removing a variable from the pair.

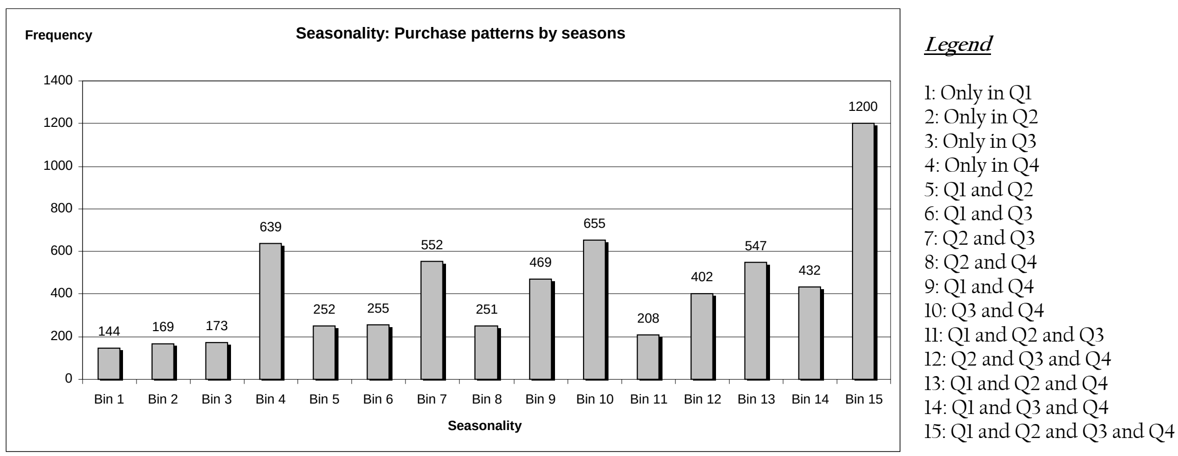


Figure 9. Binned results of preferences illustrating seasonal trends.

Independence of the variables is highly preferred. In this particular case Table 9 shows that the highest correlated pair is between seasonality and multiple merchandise category purchases, which could actually prove to be a valuable pairing. The preference would be to keep this particular pairing. While the correlation value is below the 0.50 concern threshold (0.48) the information provided in this pair outweighs the possibility of duplicity or undue emphasis.

The analysis of variance (ANOVA) is a statistical method for determining the existence of differences among several population means. The central questions that led to this test were those regarding removing concerns about correct mining sample size and the confidence of projecting results gained from clustering using a mining sample to the application and classification of the sample population. The hypothesis test is as follows:

$$H_0 : \mu_1 = \mu_2 = \mu_3 = \cdots = \mu_n ,$$

H_a : $Not\_all\_\mu_i (i = 1,2,3,..., n)$ are equal.

Table 9

Results of Correlation Analysis Show no Duplicate Effects in the Variables

Variables	Recency	Seasonality	Cross merchandise	Age	Ave. order value
Recency	1	-0.39	-0.29	0.01	-0.07
Seasonality		1	0.48	0.02	0.07
Cross merchandise			1	0.01	0.27
Age				1	-0.04
Ave. order value					1

In this case five new random mining trials each of size 14-15 thousand were drawn from the sample population of 1.449 million customers to compare variables utilized in the market segmentation, so, $n_{trials} = 6$ (five comparison mining samples and the original random mining sample) in this test. Each of the 13 attributes was tested in an effort to look for anomalies, that is, for a difference in means for a particular attribute. The null hypothesis states that all attributes have equal means and the alternative hypothesis states that they are not all equal.

Table 10 illustrates the results of the thirteen ANOVA tests and shows the counts of the mining trials that were drawn. Since the *p*-value is > .50 for most attributes, the means may be equal. This also implies that it is safe to project the results of the clustering corner attribute values to the sample population of 1.449 million.

Table 10

ANOVA Results Show the Means are Equivalent

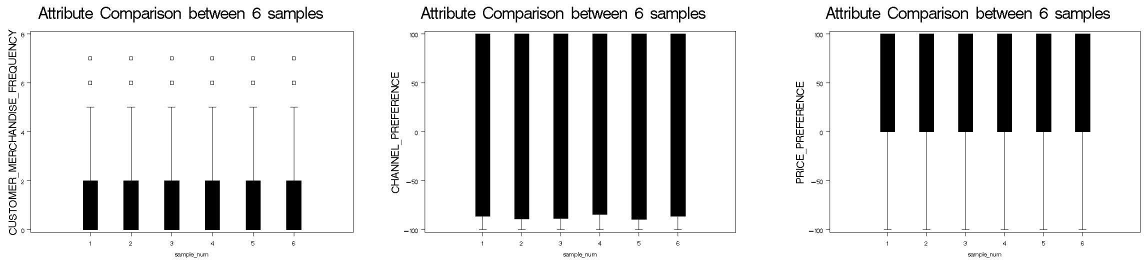
ANOVA Output

Attribute	DF	F Value	P Value
AGE_CD	5	0.66	0.66
CUSTOMER_RECENCY	5	0.29	0.92
CUSTOMER_SEASONALITY	5	0.57	0.72
CUSTOMER_MERCHANDISE_FREQUENCY	5	1.06	0.55
AVERAGE_ORDER_VALUE	5	1.02	0.40
SALES_PRODUCTIVITY	5	0.84	0.52
WOMENS_DEMAND	5	0.92	0.47
MENS_DEMAND	5	0.69	0.63
HOME_DEMAND	5	1.93	0.08
KIDS_DEMAND	5	0.62	0.68
CHANNEL_PREFERENCE	5	0.64	0.67
PRICE_PREFERENCE	5	1.22	0.30
NETWORTH	5	1.35	0.24
CUSTOMER_ORDER_FREQUENCY	5	0.28	0.92
BIG_CITY	5	1.99	0.28

Sample ID	N	
1	14677	
2	14476	
3	14544	
4	14445	
5	14585	
6	14607	Analysis Sample

Figure 10 shows a comparison of three of the variables used in the segmentation. The candlestick graphs in the figures represent the range of data found in the test for each of the six random mining trials. Each of the 13 attributes was compared across the six trials. Figure 10 highlights the similarity in merchandise frequency, channel preference, and price preference as examples. This graphic provides good visual evidence that the attribute values are equal within the tolerance afforded in the ANOVA test.

Marketing profiling of clusters provides the facility to understand the customer, plan for possible marketing treatments that are relevant to that segment, and to invest up to the point of saturation. This study was focused on the efficient allocation of assets and not necessarily on detailing methods for improved customer understanding in a general sense. With that focus in mind, only a select few profiles will be detailed so the reader can get a feel for the richness of information provided by the clustering activity.



Merchandise Frequency **Channel Preference** **Price Preference**

Figure 10. Results of the ANOVA test comparing six samples in three variables.

The nine segments, or asset classes, that appear from the clustering exercise were labeled Elite Families, Dress-ups, Busy Families, Older Traditionalists, Young Budgets, Older Budgets, Green Segment, Blue Segment, and Red Segment. Each of these groups can be described by its corner attribute values that define where they fall on each of the 13 dimensions in the clustering procedure. For instance, the Elite Families group can be defined as a high net worth group; with the average age of 54 years, they purchase the highest amount of men’s and women’s clothing, they typically buy at full price versus shopping for discounts, and they have a low average order value relative to other segments.

To detail this group further, they purchase 14% more women’s wear, 2% more men’s wear, and 10.6% less kid’s wear than other market segment results in the sample. This may be attributed to their age (54 years on average). This group appears to be dressing up to go out, as they live an urban lifestyle (indicator from the big city variable). Looking at the products that they purchased, they are seeking versatility in apparel and not necessarily trying to coordinate pieces.

This group may be purchasing kid's merchandise as gifts for possibly grandchildren (information leading to gift giving like wrapping, gift card insertion, etc. serve as indicators). The data show that when members of this group were mailed a kid's catalog they responded well above average. If this customer group could be enticed to purchase one more kid's item in a year, based on their spending patterns, this would be worth an additional $33.70 bringing their total kid's purchases in a year to $350.00 on average.

This group comprises nine percent of the 1.449 million customer sample. If 76,000 of these customers would place one more item in their shopping basket in a calendar year at $33.70, this would add an additional $2.6 million in additional demand dollars. Each of the asset classes has its own unique profile. Finding the previously unseen opportunity in the data is the distinct advantage of the clustering method over the heuristic segmentation process where the marketing manager determines the segment cut values.

A brief description profiling the individual asset class attributes follows:

1. Elite Families: High net worth, average age of 54 years, primarily men's and women's product buyers, and paying full price, with a low average order value.

2. Dress-ups: High net worth, average age of 53 years, and strong buying behavior in all merchandise categories.

3. Busy Families: Medium income, average age of 38 years, women's merchandise focus, and demonstrating a preference for shopping using the Internet channel.

4. Older traditionalists: High net worth, average age is 51 years, strong women's and men's product purchases, good frequency of purchases, and they prefer the catalog channel for purchases.

5. Young Budgets: Low to medium net worth, average age less than 41 years, largest buyers of kid's merchandise, and prefers to shop the Internet channel.

6. Older Budgets: Medium net worth, average age of 53 years, primarily women's product focused, low average order value, and demonstrating winter and spring seasonal buying preferences.

7. Blue Segment: Higher incomes, average age of 41 years, buying primarily from the women's product line, and shops in the spring and holiday seasons.

8. Green Segment: Medium incomes, average age of 48 years, men's product focused.

9. Red Segment: Medium income, average age of 35 years, women's and kid's product focus, and prefers buying on the Internet channel.

The following additional revenue gains were mined from the data studying all asset class opportunities: Elite Families, $2.60 million; Dress-ups, $6.98 million; Busy Families, $2.66 million; Older Traditionalists, $3.55 million; Young Budgets, $4.15 million; Older Budgets, $2.24 million; Green Segment, $4.4 million; Blue Segment, $2.22 million; and Red Segment, $3.90 million dollars. The total previously unseen revenue gains found by developing the asset classes properly is $32.7 million dollars. The cost of additional advertising was estimated to be $3.23 million dollars. The ratio of revenues to costs was approximately 10:1 meaning for every one dollar in advertising cost a ten dollar revenue gain is achieved.

The investment optimization process seeks to maximize revenues, subject to constraints. This process leverages the additional information on opportunities derived from the development of asset classes. The marketing descriptions help a lot regarding product and advertising message strategies, but an understanding of the investment behavior of the asset classes must include the risk and return characteristics necessary to fuel the investment optimization applications. The next section on the asset allocation process begins with a description of the procedure and then articulates the asset class inputs into the optimization process describing investment risk and financial return of these customer sets.

Asset Allocation Optimization

When constructing decision-making models a key consideration is the aspect of uncertainty when making projections in future time periods. Representing these uncertainties in a form that is suitable to practical decision-makers is at the heart of marketing executives' effective use of advanced mathematical techniques in their businesses (Hoyland & Wallace, 2001). If the uncertainties are represented as a discrete time model with too many possible outcomes, the executive may defer to a simpler, more heuristic approach.

These simpler approaches may not adequately capture the inherent risks in a forward-looking set of decisions. The core importance of the optimization process to the overall asset allocation portfolio construction is the ability to formulate the best outcome in a highly stochastic, forward looking environment. The optimization process brings together all aspects of the data preparation, customer studies, the binomial lattice, the retail index, and the asset class development as inputs into the decisioning process all focused on providing insight to the best course of action to take.

This section will develop the grounded theory for the asset allocation optimization as well as describe the inputs into the model and some results. A subsequent section will provide results derived from several experiments by varying components of the overall unified model. Two strategic tasks that must be accomplished to make the new market segments relevant are assigning financial asset return values to each marketing segment and then correctly allocating marketing spend to each of these segments to maximize the return potential.

Since the marketer is interested in the future value of the customer base, usually expressed in terms of demand or return on a form of customer equity, having a reasonable way of handling future events is a necessity. The stochastic binomial lattice will provide external economic expectations as inputs into the asset allocation model. Other inputs are the financial return expectations, previous allocation decisions, how changes in product mix attributes affect certain customer segments, the objectives of the marketing executive, and the constraints that the firm must operate under. All these will be described in detail beginning with the marketing objectives of the allocation.

Because the strategic asset allocation function is normally not a consideration in the marketing investment process, a great deal of care was taken in this research to articulate the inputs and outputs of the model. The optimal portfolio in this study made a set of 27 independent investment choices (nine asset classes within each of three recency categories) for each time period. There are six forward-looking time periods, so the total number of strategic decisions made for each model run equals 162 (27 decisions for each time period times six time periods).

These choices will be made to maximize the revenue component of purchases for each of nine market segments within the three recency groups. The hypothesis is that there is more return on marketing investment by adding this set of processes than when they are not considered. The problem is complicated by having multiple objectives, sometime conflicting, under constraints, with many of the inputs being uncertain as today's decisions depend on events that may or may not happen in the future.

The asset allocation process is centered on the amount of dollars that each market segment should receive within any one of recency groups (Table 10). The problem is formulated as a multi-objective linear goal program following Schniederjans (1984):

Minimize: $Z = \sum_{j=1}^{m} P_k (d_i^- + d_i^+)$ (for k = 1,2,3,…,K)

Subject to: $\sum_{j=1}^{n} a_{ij} x_j + d_i^- - d_i^+ = b_i$ (for I = 1,2,3,…,m);

and $x_j, d_i^-, d_i^+ \geq 0$.

Where:

Z = the objective function that serves as the minimized value of all negative deviations (d_i^-), and all positive deviations (d_i^+), in m goal constraints,

P_k = the set of preemptive objective function priorities, these are ranked as goal constraints such that $P_1 > P_2 > P_3 >>>> P_K$,

k = the index of the objective function priorities (goals) in their order,

K = the maximum number of objective function priorities (goals),

d_i^- = a negative deviational variables related to each goal,

d_i^+ = a positive deviational variables related to each goal,

i = the index of deviational variables,

a_{ij} = the technological coefficients in the problem,

x_j = the decision variables in the problem,

j = the index of decision variables, and

b_i = the right hand side goal values.

The decision variables for the linear goal program, x_j, represent the number of dollars that should be allocated to the *j*th asset category and recency group. As an example, the set of goal constraints that represent the investors' preference for total advertising program spend for the calendar year would be expressed by:

$$\sum_{j=1}^{n} a_{ij} x_j + d_i^- - d_i^+ = (boundary)_i \; .$$

In the contact economics context, this boundary would be the marketing budget limitation boundaries for total spend. Because the budget can not be exceeded, it is set as the highest priority or P_1. In this case, let us assume that the budget is equivalent to $100 million, which would substitute for the boundary variable.

The deviational variable d_1^- serves as the negative deviational variable for this priority and d_1^+ will serve as the positive deviational variable. The deviational variables allow a type of fuzziness in the answer that closely mirrors the actual marketing decision process of allowing some slack in selected constraints. Due to the use of deviational variables throughout the priority set, the constraints are not so tightly described that the problem goes infeasible using this goal programming approach. The decision variables and their relationship to recency categories are detailed in Table 11.

The second highest priority P_2, was determined by the need to add new customers (the acquisition group) to a declining base (the retention group). Table 3 showed that the revenue from the customer base is declining year over year that could indicate that a continuous flow of new customers should be added to the base. The intent of this objective was to set aside a pool of dollars so that the optimal quantity of new customers could be acquired. The logic for developing this priority was to take the historical on-average cost of acquiring a new customer multiplied by the number of new acquisition customers to target for the year.

Table 11

Decision Variables: Asset Classes and Recency Groupings

Asset class	Retention	Re-activation	Acquisition
Asset class 1 – Elite Families	X1	X10	X19
Asset class 2 – Dress-ups	X2	X11	X20
Asset class 3 – Young Budgets	X3	X12	X21
Asset class 4 – Busy Families	X4	X13	X22
Asset class 5 – Older Traditionalists	X5	X14	X23
Asset class 6 – Older Budgets	X6	X15	X24
Asset class 7 – Blue Segment	X7	X16	X25
Asset class 8 – Green Segment	X8	X17	X26
Asset class 9 – Red Segment	X9	X18	X27

As an example, the marketing executive is willing to spend $15.00 on average to acquire a customer, and has a total investment pool of $100M, and is seeking to create the appropriate acquisition pool for the 3rd Q 2006. The total investment pool is split by quarters, and the quarterly split for the 3rd Q is 19.3% of the total budget. So, if the number of customer acquisitions is targeted at 309,740 the budget would be ($15.00 x 309,740) = $4,646,100. How the pool is spent between the asset classes for any time period is left to priority number five.

This priority (P_2) constraint would be described by

$$\sum_{j=2}^{n} X_j + d_2^- - d_2^+ = \$4{,}646{,}100\,,$$

Where: $X_{19} + X_{20} + X_{21} + X_{22} + X_{23} + X_{24} + X_{25} + X_{26} + X_{27}$ = the individual segment acquisition investment decision amounts, and d_2^-, d_2^+ are the deviational amounts to be minimized in the objective function.

Priorities 3, 4, and 5 (P_3, P_4, P_5) follow the logic that the lifetime value of a retention customer is greater than the lifetime value of a re-activation customer, which is greater that the lifetime value of an acquisition customer. These values are expressed in Table 3 for each of the recency groups. Lifetime value is a way to express the investment amount in prospecting for a customer (Faherty, 2004). Each of the recency groups would have different lifetime value logic rules. Most direct marketing firms would prefer a 12 month return on their investment decision.

The lifetime value amounts of the retention group are considered to be the on-average profits from purchases within a 12 month period. The consideration for advertising expense would be to invest only a fraction of this profit amount, depending on the payback duration preferred. The lifetime value metric is developed from a study on the sales of merchandise, less fulfillment costs, shipping and other costs for each market segment (see also the details in Appendix A on lifetime value computation).

The re-activation and acquisition recency groups would use similar logic, but have very different values. The logic for these groups (Faherty, 2004) is to invest no more in any individual customer than the lifetime value amount in each segment to re-activate older customers who have not bought in some time, or to acquire new customers to the file. As an example, the lower-bound for these groups would be the lifetime value amount times the number of customers expected in the base case.

The upper-bound would be the lifetime value amount times the number of customers as treated by the product mix changes and economic effects described by the lattice. If there is no product mix or economic impacts on the base case, then the boundary is set as an equivalency where the lower-bound is equal to the upper-bound. Besides aligning the lexicographic order of the priorities, the lifetime value metric can also guide in setting boundaries.

The application keeps track of the customer counts for each phase of the process so the marketing executive can track the effects of each step individually. An example of the lifetime values for each of the segments are illustrated in Table 12. The goal priorities are easily sorted by these values such that $P_3 > P_4 > P_5$. The investment strategy is to insure that the advertising dollars go to the group that will provide the most expected return, subject to the constraints.

The procedure the linear goal program uses is to solve for each priority in their order and take the solution for that priority and set it as a constraint row in the next priority linear goal program. The next priority is then solved, with the prior priority as a constraint (so it can do no worse in minimizing the deviations). This continues for each priority (six in this case) until all have completed. This in effect produces six individual linear programs. The proposed model uses this technique and solves as described through each of the six time periods.

Within each time period, the retention decisions compete with the re-activation and acquisition decisions trading off of each other until the optimal mix is found. The retention goals are solved prior to the re-activation goals, which are solved prior to the acquisition goals. The mathematical formulation of these goals and their constraint set follows Schniederjans (1984) and Ehrgott (2005).

Table 12

Lifetime Values for the Nine Asset Classes and Three Recency Groups

Asset classes	Retention	Re-activation	Acquisition
Asset class 1: Elite Families	$66.60	$18.73	$17.23
Asset class 2: Dress-ups	$73.26	$22.05	$19.72
Asset class 3: Young Budgets	$50.54	$17.41	$12.77
Asset class 4: Busy Families	$57.50	$14.32	$15.56
Asset class 5: Older Traditionalists	$47.25	$18.13	$12.59
Asset class 6: Older Budgets	$55.72	$18.25	$14.85
Asset class 7: Blue Segment	$54.55	$13.01	$14.00
Asset class 8: Green Segment	$47.35	$17.95	$12.20
Asset class 9: Red Segment	$62.73	$17.11	$13.22

The final goal constraint (P_6) is to maximize wealth. This constraint also uses the lifetime value numbers, but instead of using the numbers as constraints as described for each of the recency groups (P_3, P_4, P_5), the lifetime value numbers are used in the constraint coefficients with a very large number as the right hand side value (can not get enough of this goal, make it as large as possible). The constraint is formulated as follows:

$$\sum_{j=6}^{n} X_j + d_{57}^- - d_{57}^+ = \$3B;$$

Where: $X_1 + X_2 + X_3 + \cdots X_{27}$ = the individual segment investment decision amounts with lifetime values as constraint coefficients (whose values appear in Table 12).

Data inputs to the asset allocation optimization

Table 13 describes the inputs required for the retention group computations. Each of these inputs is either derived or estimated for each quarter (the time units in the asset allocation optimization). Queries are made against the database to derive each of the historical values needed as well as other items that require forward-looking computations that are estimated from the data. The queries are done in Microsoft® Access, a relational database tool. The forecasts or other estimates are done using the Speakeasy programming language with models developed for each forecast or estimate. Each query or model produces a vector of numbers by quarter.

Each of the nine defined asset classes would have this set of values as the nine asset classes have membership in all three customer recency groupings. This information would also be developed for each asset class for each of the six time periods in the problem. The major difference in the retention group versus the re-activation or acquisition groups is that the current active customer base resides 100% in the retention group. All firm profits are generated from this group, as sales in the re-activation and acquisition groups would normally balance a purchase profit with the cost of advertising to create that sale, breaking even on average.

Table 13

Inputs Required for the Retention Group and Brief Description of Each

Retention group inputs	Description of the inputs
Historical advertising $	Household investment observed by segment and time period
Customer lifetime value	Lifetime value metric for each customer by segment
Sales per advertising $	Demand per advertising dollar for each customer by segment
Lower bound on adv. $/customer	Historic average advertising spend for each customer by segment
Upper bound on adv. $/customer	Lifetime value with payback for each customer and segment
Lower bound on mail depth	Minimum mail depth for the retention group in any time period
Upper bound on mail depth	Maximum mail depth for the retention group in any time period
Transition matrix	Matrix describing transitions between asset classes
Retention estimates	The rate that the retention group persists as customers in the base
Average demand per customer	Demand for the previous, current, and future periods by customer
Base customer inflows/outflows	Beginning count + gains – losses for each market segment by time period
Product improvement retention count	Product mix improvement estimates by segment
Expected retention count (lattice)	Customer counts for each market segment resulting from economic factors
Average base customer demand	Average demand for each segment based on historical trends
Product improvement demand values	Average demand for each segment from product mix improvements
Expected demand values (lattice)	Average demand for each segment resulting from economic factors (lattice)

Table 14 is an example of the inputs related to retention demand. This matrix of values is generated in an application that considers all previous purchases from the various asset classes and the economic prediction of the binomial lattice for each quarter to derive the values. The 3rd quarter 2006 values would be the first quarter prediction continuing for six quarters through the 4th quarter 2007 estimated performance (only 2007 results shown in Table 14). The total column in the table only sums across the four quarters of 2007.

Table 14

Retention Group Demand by Quarter for Each Asset Class

Total customer retention demand	1st Quarter 2007	2nd Quarter 2007	3rd Quarter 2007	4th Quarter 2007	2007 Totals
Elite Families	$35,559,124	$33,752,852	$37,084,105	$79,749,130	$186,190,211
Dress-ups	$24,749,519	$23,463,451	$25,757,983	$55,3331,886	$129,302,839
Busy Families	$5,985,868	$5,557,192	$5,746,356	$12,508,228	$29,797,644
Older Traditionalists	$13,974,353	$13,138,631	$14,438,872	$30,250,349	$71,802,205
Young Budgets	$11,055,757	$10,386,529	$11,294,220	$23,840,589	$56,577,097
Older Budgets	$6,332,651	$5,865,585	$6,059,210	$13,105,994	$31,363,440
Green Segment	$13,821,132	$12,849,739	$13,288,555	$28,910,802	$68,870,229
Blue Segment	$6,128,497	$5,684,546	$5,866,860	$12,700,876	$30,380,778
Red Segment	$17,700,086	$16,251,631	$16,633,684	$35,395,762	$85,981,163
Total customer spend	$135,306,988	$126,950,156	$136,169,845	$291,838,616	$690,265,606

Each input category described in Table 13 would look somewhat like the data described in Table 14, but a few categories may need some additional explanation. The lower and upper-bounds for advertising are derived from historical spend parameters. It makes no real statement on how effective the mailings were and may or may not impact decisions about the values of a lower and upper bound surrounding allocations.

Mail depth is a parameter that determines for the retention group how many households across any asset class on average should receive some sort of advertising contact. This value is expressed as a percent of the total (for instance in any one quarter, 65% of the asset class membership should receive some type of advertising stimulus). The mail depth parameter makes no statement on any individual customer or household, but about all customers in the aggregate. Most every direct marketing decision-maker would know how deep into the file they would like to reach.

Table 15

Transition Matrix of Movements Between Asset Classes

Retention transition matrix	Elite Families	Dress-ups	Busy Families	Older Traditionalist	Young Budgets
Elite Families	0.816	0.055	0.025	0.027	0.027
Dress-ups	0.045	0.833	0.002	0.056	0.002
Busy Families	0.032	0.003	0.667	0.019	0.066
Older Traditionalists	0.016	0.058	0.009	0.682	0.004
Young Budgets	0.042	0.002	0.071	0.005	0.747
2005 retention estimates	0.562	0.566	0.495	0.536	0.501
2006 retention estimates	0.548	0.553	0.475	0.519	0.484
2007 retention estimates	0.538	0.543	0.460	0.506	0.474
Retention averages	0.549	0.554	0.477	0.520	0.486
Average demand/customer-2005	$289.07	$296.07	$243.36	$241.17	$227.42
Average demand/customer-2006	$291.65	$296.22	$233.55	$239.26	$229.88
Average demand/customer-2007	$293.49	$296.15	$232.28	$236.86	$232.70
Average demand/customer	$291.40	$296.15	$233.39	$239.09	$230.00

The transition matrix comprises a very useful piece of information that describes the expected movement between the asset classes as customers' transit from one asset class to another in any time period. This matrix is illustrated in Table 15 and is set up as an *m* x *m* square matrix with the asset class membership retention rate running along the diagonal of the matrix. The importance of this matrix is that household movements can greatly affect the investment process. If not taken into account, an asset class could possibly receive too few, or too much investment funding, assuming its current state is projected forward for every time period, without change. Table 15 shows that this is not true and in some cases a considerable amount of movement will take place.

Table 16

Re-activation Group Inputs and a Brief Description of Each

Re-activation group inputs	Description of the inputs
Historical advertising $	Household investment observed by segment and time period
Customer lifetime value	Lifetime value metric for each customer by segment
Sales per advertising $	Demand per advertising dollar for each customer by segment
Lower bound on adv. $/customer	Historic average advertising spend for each customer by segment
Upper bound on adv. $/customer	Lifetime value with payback for each customer and segment
Lower bound on mail depth	Minimum mail depth for the re-activation group in any time period
Upper bound on mail depth	Maximum mail depth for the re-activation group in any time period
Re-activation estimates	The rate the re-activation group persists as customers in the base
Average demand per customer	Demand for the previous, current, and future periods by customer
Base customer inflows/outflows	Beginning count + gains – losses for each market segment by time period
Product improvement for re-activation	Product mix improvement estimates by segment
Expected re-activation count (lattice)	Customer counts for each market segment resulting from economic factors
Average base customer demand	Average demand for each segment based on historical trends
Product improvement demand values	Average demand for each segment from product mix improvements
Expected demand values (lattice)	Average demand for each segment resulting from economic factors (lattice)

Table 16 illustrates the model inputs from the re-activation group. These inputs are not exactly identical to the retention group, but are similar enough where describing them beyond that provided in the table would be somewhat repetitive. Similar to the retention group, each of the asset classes would have an entry for each data element, for each quarter in the problem. All data to construct the tableaus were derived from direct queries to the population database.

The inputs in Table 17 were used in a study for this research that was done on the re-activation group relative to conversion rates (from inactive to active customers) by asset class for this research. Since the investment decisions are made by asset class within recency group, these conversion rates comprise a key input. Results are consistent with the observation that most advertising spend was previously being funneled into the retention group and leaving somewhat unbalanced the investments made in re-activation and acquisition groups. There is a distinct pattern, first identified in Table 3, in each of the recency categories of lower conversion rates from 2005 actual to 2007 forecasted. The conversion study was based on trends from 2003 to 2005.

Table 17

Conversion Rates and Demands for the Re-activation Group

Re-activation conversion rates and demands	Elite Families	Dress-ups	Busy Families	Older Traditions	Young Budgets
2005 conversion rates	19.9%	19.6%	16.1%	17.6%	17.2%
2006 conversion rates	17.8%	17.7%	14.3%	15.3%	15.5%
2007 conversion rates	16.1%	16.1%	12.8%	13.5%	14.1%
Average conversion rates	17.9%	17.8%	14.4%	15.5%	15.6%
2005 demands / customer	$160.38	$163.56	$138.91	$139.31	$135.53
2006 demands / customer	$162.23	$163.42	$140.08	$137.27	$137.93
2007 demands / customer	$163.87	$162.65	$140.22	$135.37	$140.87
Average demands / customer	$162.19	$163.21	$139.74	$137.72	$138.11

The last group of inputs from the recency categories is represented in Table 18 and is made up of those required from the acquisition group. The acquisition group is comprised of new customers to the firm and consequently not much is known about these customers prior to purchase transactions. The balancing act the asset allocation optimization has to achieve is to insure that there is enough inflow of new customers that can replace the defection of retention customers.

This acquisition case presents an acute problem as the firm’s current strategy is to over-fund retention customers and starve re-activation and acquisition customers. The concern in that decision is that it leaves a gap in the balance of customer flows. A high retention group defection rate and overall downward trending revenues from year to year opens up the opportunity for a new optimal strategy. The asset allocation investment role is to attempt to stop the retention defections and increase the new customer counts and purchases while maintaining the profitability of the firm through optimal financial allocations.

Table 18

Acquisition Group Inputs and a Brief Description of Each

Acquisition group inputs	Description of the inputs
Historical advertising $	Household investment observed by segment and time period
Customer lifetime value	Lifetime value metric for each customer by segment
Sales per advertising $	Demand per advertising dollar for each customer by segment
Acquisition estimates	The rate at which the acquisition group purchases and converts to active status
Minimum base number to acquire	Target for each segment of the number of customers to acquire
Average demand per customer	Demand for the previous, current, and future periods by customer
Base customer inflows/outflows	Beginning count + gains - losses for each market segment by time period
Product improvement for acquisition	Product mix improvement estimates by segment
Expected acquisition count (lattice)	Customer counts for each market segment resulting from economic factors
Average base customer demand	Average demand for each segment based on historical trends
Product improvement demand values	Average demand for each segment from product mix improvements
Expected demand values (lattice)	Average demand for each segment resulting from economic factors (lattice)

Table 19 highlights the difference in the acquisition rates by asset class. The firm previously had utilized a heuristic rule for all acquisition conversions of 1.5% in 2006 and an estimated 1.6% conversions in 2007. The value of the acquisition study conducted in this research is to determine the opportunities where the firm's rule was outperformed by the actual data. This is another advantage to the understanding that can take place as a result of the asset class segmentation.

There are sometimes dramatic differences in how the asset classes responded to promotions. In some cases, like Elite Families and Dress-ups, the conversion rate is slightly greater than twice that of the standard heuristic rule. In the case of the Red

Segment for instance, the standard rate is too much advertising spend for the amount of return. The asset allocation optimization will consider each number in the matrix in Table 19 to optimally allocate resource to the various asset classes for the acquisition recency group.

Table 19

Conversion Rates for the Acquisition Group by Asset Class

Acquisition conversion rates and demands	Elite Families	Dress-ups	Busy Families	Older Traditions	Young Budgets
2006 acquisition rates	3.2%	3.1%	1.3%	2.6%	1.8%
2005 demands / customer	$128.56	$130.67	$112.32	$114.38	$112.03
2006 demands / customer	$129.71	$131.21	$111.31	$113.09	$113.16
2007 demands / customer	$131.04	$132.18	$111.59	$112.53	$115.80
Average demands / customer	$129.77	$131.35	$111.74	$113.33	$113.66

Table 20 illustrates the final set of inputs from the database which is a matrix of product mix factors determined by a study, performed in this research that resulted in an index of the most popular items sold for each of the nine asset classes. The concept is that one of the opportunities a retail firm has to improve sales is to make product mix changes that have a positive impact on sales. Prior to this research, the firm would make a product mix change and speculate how it would affect the entire buying population.

The results of the study pointed out how different segments will respond in different ways, depending on their propensity to purchase from that particular product family. The forecast of response comes from counting the number of advertising pages that household has seen with the product mix most favorable and looking at the purchase behavior over time. This is one of the few controllable variables the firm has to tune its offering to the customer base. Understanding what works with what asset classes could prove to be a new source of performance simulation.

Table 20

Receptivity Rates Show Asset Class Response to Product Mix Changes

Segments	Receptivity
Elite Families	0.101
Dress-Ups	0.083
Busy Families	0.000
Older Traditionalists	0.048
Young Budgets	0.072
Older Budgets	0.000
Green	0.000
Blue	0.000
Red	0.000

For example, Table 20 illustrates that a particular product mix change proposed will increase sales to the Elite Families group by 10.1%. The experiments described in a later section will have two primary components that vary in the model: (a) proposed product mix changes (a controllable variable); and (b) the effects of the economy (a non-controllable stochastic variable). The Older Budgets, Green Segment, Blue Segment, and Red Segment groups are not affected by the proposed change in product features. Consequently, their revenue performance under this scenario will not be affected either positively or negatively.

Matrix Construction for the Asset Allocation Optimization

The next item to construct in the process is the goal matrix for the portfolio optimization procedure. This matrix is important to point out because it replaces the decision vector normally represented in a linear programming solution where there is only one criterion to be minimized or maximized. The multicriteria optimization approach constructs a decision matrix that identifies the relationship between the goals, the decisions, lower and upper-bound constraints and the deviational values (Schniederjans, 1984). This is a unique feature of this derivative of linear programming that makes for an extremely powerful solution technique.

This matrix also sorts out priority preferences and sets up the logic to balance conflicting objectives. A brief description of each section of the matrix will follow. This matrix can be thought of as a series of carefully placed one’s and zero’s that turn on (with a one) or turn off (with a zero) certain relationships between the goals, decision variables, the lower and upper-bound constraints, and the deviational variables.

The goal matrix constructed has three groupings for the row entries. The first group is comprised of a row entry for each of the six goals in their priority order. The second group is comprised of a row entry of differential weights that are applied to the prioritized goals if desired. The third group is the weighted value of those priorities. For instance, not all priorities have the same impact on the firm, one priority may carry twice the weight in the optimal decision. A ‘1’ is placed at the intersection of the goal priority and the accompanying deviational variable representing a lower or upper-bound on that particular goal priority.

The formulation of this weighted feature is as follows (Schniederjans, 1984):

$w_{kl}P_k$ = an *l* row vector of differential weights attached to their respective *k* preemptive priorities, and

w_{kl} = a row vector of differential weights.

In this particular model weights are all set to 1.0, which in effect neutralizes them for these experiments. In constructing the computer programs for this research, it was determined that having a feature to utilize a weighted goal scheme was desirable. The third grouping is the row product of the prioritized goals multiplied by their respective weights. A '1' is placed at the intersection of the weighted goal priorities and their respective deviational variables.

The column vectors of the matrix are in the following format:

1. A vector of the 27 decision variables (X_1 through X_{27}), these are the asset classes within each of the recency groups (retention, re-activation, and acquisition),

2. An entry for the first priority, which is an entry being referred to as a portfolio entry that affects all asset classes at once. In this case it is the sum of the investment expenditures across all asset classes and represented as a not to exceed number. The two entries associated with this constraint are the deviational variables related to the first priority (d_1^- and d_1^+) the matrix entry is a '1' for each of the deviational positions. In an *m* x *n* matrix this would be at positions $d_1^- = m_1n_{28}$ and $d_1^+ = m_1n_{29}$.

3. The second priority is also a portfolio entry and is related to insuring there is a minimum acquisition pool available for spending on enticing new customers to the firm. The two entries associated with this constraint are the deviational variables related to the

first priority (d_2^- and d_2^+) the matrix entry is a ‘1’ for each of the deviational positions. In an *m* x *n* matrix this would be at positions $d_2^- = m_2 n_{30}$ and $d_2^+ = m_2 n_{31}$.

4. The third priority concerns the retention group. Constraints are determined for both lower and upper-bounds. Surrounding each lower and upper-bound is a set of deviational variables (d_3^- and d_3^+ as an example). There is one set of boundary conditions for each asset class regarding retention constraints. As an example: the lower-bound for Elite Families regarding the retention investment would be represented by d_3^- and d_3^+, these would be in the matrix positions $d_3^- = m_3 n_{32}$ and $d_3^+ = m_3 n_{33}$ with a ‘1’ as its entry. The upper-bound for Elite Families regarding retention investment would be represented by d_4^- and d_4^+, these would be in the matrix positions $d_4^- = m_3 n_{34}$ and $d_4^+ = m_3 n_{35}$ with a ‘1’ as its entry. This series repeats itself for all nine asset classes incrementing the deviational variable index and the row/column index up through d_{20}^{-+} and $m_3 n_{67}$.

5. The fourth priority is concerning the re-activation group. Constraints are determined for both lower and upper-bounds. Surrounding each lower and upper-bound is a set of deviational variables (d_{21}^- and d_{21}^+ as an example). There is one set of boundary conditions for each asset class regarding re-activation constraints. As an example, the lower-bound for Dress-ups regarding the re-activation investment would be represented by d_{23}^- and d_{23}^+, these would be in the matrix positions $d_{23}^- = m_4 n_{72}$ and $d_{23}^+ = m_4 n_{73}$ with a ‘1’ as its entry. The upper-bound for Dress-ups regarding the re-activation investment would be represented by d_{24}^- and d_{24}^+, these would be in the matrix positions $d_{24}^- = m_4 n_{74}$ and $d_{24}^+ = m_4 n_{75}$ with a ‘1’ as its entry. This series repeats itself for all nine asset classes

incrementing the deviational variable index and the row/column index up through d_{38}^{-+} and $m_4 n_{103}$.

6. The fifth priority is concerning the acquisition group. Constraints are determined for both lower and upper-bounds. Surrounding each lower and upper-bound is a set of deviational variables (d_{43}^{-} and d_{43}^{+} as an example). There is one set of boundary conditions for each asset class regarding acquisition constraints. As an example, the lower-bound for Busy Families regarding the acquisition investment would be represented by d_{43}^{-} and d_{43}^{+}, these would be in the matrix positions $d_{43}^{-} = m_5 n_{112}$ and $d_{43}^{+} = m_5 n_{113}$ with a '1' as its entry. The upper-bound for Busy Families regarding the acquisition investment would be represented by d_{44}^{-} and d_{44}^{+}, these would be in the matrix positions $d_{44}^{-} = m_5 n_{114}$ and $d_{44}^{+} = m_5 n_{115}$ with a '1' as its entry. This series repeats itself for all nine asset classes incrementing the deviational variable index and the row/column index up through d_{56}^{-+} and $m_5 n_{139}$.

7. The last entries comprise the total portfolio constraints. The sixth priority is regarding maximizing total wealth of the portfolio. The two entries associated with this constraint are the deviational variables related to the sixth priority (d_{57}^{-} and d_{57}^{+}) the matrix entry is a '1' for each the deviational positions. In an *m* x *n* matrix this would be at positions $d_{57}^{-} = m_6 n_{140}$ and $d_{57}^{+} = m_6 n_{141}$.

Table 21 illustrates how the actual constraint values appear, their associated relationship with the decision variables, and their accompanying deviational variables. The table describes the re-activation upper and lower-bounds for the first three time periods (3rd and 4th quarter 2006 and 1st quarter 2007). Each of the upper and lower-bounds for the whole problem is derived through a study that was done for this research on each decision variable with data originating from the sample population in the database.

Table 21

Re-activation Group Upper and Lower-Bounds for Three Time Periods

Customer segment	Goal priority #4	Time = 1	Time = 2	Time = 3
Elite Families	X10 + d21(-) – d21(+)=	$1,628,805	$1,431,373	$1,221,604
Dress-ups	X11 + d23(-) – d23(+)=	$1,114,966	$979,818	$836,224
Busy Families	X12 + d25(-) – d25(+)=	$534,471	$509,559	$440,965
Older Traditionalists	X13 + d27(-) – d27(+)=	$1,063,494	$963,792	$822,546
Young Budgets	X14 + d29(-) – d29(+)=	$730,010	$648,898	$547,507
Older Budgets	X15 + d31(-) – d31(+)=	$611,608	$530,060	$458,706
Green Segment	X16 + d33(-) – d33(+)=	$1,054,400	$1,065,987	$886,391
Blue Segment	X17 + d35(-) – d35(+)=	$466,377	$616,894	$526,487
Red Segment	X18 + d37(-) – d37(+)=	$1,998,312	$2,020,271	$1,778,717
Total minimum spend	Lower-bound on #4 =	$9,202,442	$8,766,653	$7,519,147
Elite Families	X10 + d22(-) – d22(+)=	$2,003,019	$3,937,558	$2,491,146
Dress-ups	X11 + d24(-) – d24(+)=	$1,614,166	$3,173,147	$1,992,881
Busy Families	X12 + d26(-) – d26(+)=	$601,280	$1,034,253	$751,166
Older Traditionalists	X13 + d28(-) – d28(+)=	$1,253,649	$2,156,384	$1,548,693
Young Budgets	X14 + d30(-) – d30(+)=	$836,880	$1,442,946	$1,068,563
Older Budgets	X15 + d32(-) – d32(+)=	$800,832	$1,377,500	$1,001,460
Green Segment	X16 + d34(-) – d34(+)=	$1,629,020	$2,701,980	$2,312,803
Blue Segment	X17 + d36(-) – d36(+)=	$533,003	$884,067	$734,421
Red Segment	X18 + d38(-) – d38(+)=	$3,306,588	$5,036,648	$4,253,987
Total maximum spend	Upper-bound on #4 =	$12,310,437	$21,744,483	$16,155,120

In the case of re-activation, the lifetime value study for this recency group was conducted as a part of this research. The study utilized data in the sample population over the historical period of 2003-2005. The derived values are forecasted forward for the periods in which the portfolio is trying to make forward decisions (six quarters beginning with 3rd quarter 2006). All of the constraint values for each of the decision variables are derived in a similar manner, with individual studies conducted for this research for each constraint set being utilized.

The constraint or 'A' matrix is developed next. This matrix forms the relationships between the goal priorities and their respective constraints. Table 22 illustrates a small portion of this matrix related to the first (total spend constraint) and second (establishing an adequate acquisition pool) priorities and a portion of the third priority (related to retention decisions).

Table 22

Constraint Matrix Showing Goal Constraints and Decision Variables

Constraint label	Elite Families retention	Dress-ups retention	Busy Families retention	Older Traditionalists retention	Young Budgets retention
Decision variable	X(1)	X(2)	X(3)	X(4)	X(5)
Budget total	1	1	1	1	1
Total acquisitions	0	0	0	0	0
Lower bound on Elite Families ret.	1	0	0	0	0
Upper bound on Elite Families ret.	1	0	0	0	0
Lower bound on Dress-ups retention	0	1	0	0	0
Upper bound on Dress-ups retention	0	1	0	0	0

The overall construction of this matrix is very similar in concept to the goal matrix previously described, therefore only differences in this matrix will be briefly highlighted. The initial set of rows describes the goal constraints and their relationship to both the decision variables and deviation variables. For instance, the first constraint is a portfolio constraint that affects all asset classes. A '1' would be placed in the cell for all 27 decision variables because they are all affected by this constraint (first row of Table 22).

The next constraint creates the investment pool for acquisitions. This constraint only affects the decision variables related to the acquisition group, so there would be a '1' entry for that constraint in the cell intersections of the acquisition group. The deviational variables are also turned on with a '1' which are related to this constraint. Again, this process and the deviational variable location in the matrix are identical to those described in the goal matrix and will not be repeated here.

The next area of the matrix details the retention group upper and lower-bound relationship with the decision and deviational variables. This begins the articulation of the third goal priority which is to optimize the investment of the retention group. This constraint affects each of the asset categories so consequently each has an upper and lower-bound in the problem. These are represented by constraint rows 3 thru 20. A '1' is placed in the appropriate cells turning on the relationship of the constraint, the decision variables, and the deviational variables. This sequence continues for the fourth and fifth goal constraint related to re-activation and acquisition investments.

The sixth goal constraint describing the maximization of total wealth is a total portfolio constraint. The coefficient utilized for this constraint is the lifetime value of each of the asset class groupings. This number, derived from the lifetime value study of the data, will appear in each of the decision variables matrix locations (a vector of 27 decisions). A '1' appears in the cell locations for the respective deviational variables in the matrix (d_{57}^{-} and d_{57}^{+}).

The last series of entries describe the non-negativity requirements. These are represented in the form of an entry ('1') along a diagonal where the row location and column location are in the equivalent position in the matrix. An example representing the decision variables would be that the retention decision for Elite Families (X_1) would be a non-negative value, or $X_1 \geq 0$. Each decision variable receives this constraint. Each of the deviational variables receives the non-negativity constraint as well. An example representing the deviational variables would be $d_1^{-} \geq 0$.

The last matrix utilized is a table of right hand side constraint values. This matrix is a table that is developed for each of the six quarters, a separate matrix for each quarter. The lower and upper-bound values are derived from a study on each asset class as a part of this research. Table 23 illustrates the layout of this vector of right hand side values for the first three goal constraints. These constraints are for the 3rd quarter 2006 time period.

The boundary for the first goal constraint is an equality. This sets the budget limit for total advertising spend in the quarter. The second goal constraint shown in table 23 is also an equality and sets the value of the pool of acquisition dollars. The next set of constraints is the upper and lower-bounds for the retention group spend for each of the asset classes. This sequence repeats itself looping through all asset classes for each of the recency groups. The return maximization goal constraint value is set to some very large number with the logic that you can't have enough wealth. This table also contains positions for the zero entries representing the non-negativity constraints.

Table 23

Constraint Matrix Showing the Right Hand Side Values

Constraint label	Constraint number	Right hand side value
Budget total	1	$31,200,000
Total acquisitions	2	$4,540,514
Lower bound on Elite Families ret.	3	$2,630,128
Upper bound on Elite Families ret.	4	$3,986,955
Lower bound on Dress-ups retention	5	$1,792,057
Upper bound on Dress-ups retention	6	$3,056,109

At this point all of the inputs into the asset allocation optimization model have been described and the mathematical formulation articulated. The inputs were all derived from extensive studies conducted on the data. The process exactly follows the process illustration proposed in Figure 1 of this study. The models are now available to run and achieve results, which is the focus of the next section.

Asset Allocation Results

The asset allocation models were run in two stages. Stage one was comprised of a series of Speakeasy applications that performs the computations preparing all input values to the optimization. Once the data have been prepared, the Speakeasy application loads all the tables necessary for each of the time periods. Included in this process is the determination of product mix changes where product factors and their probable effect on each of the asset classes are simulated. The index values were computed using the Monte

Carlo application and any assumptions on the state of the economy and its effect on the revenues and customer counts were undertaken resulting in a random walk through the stochastic binomial lattice application.

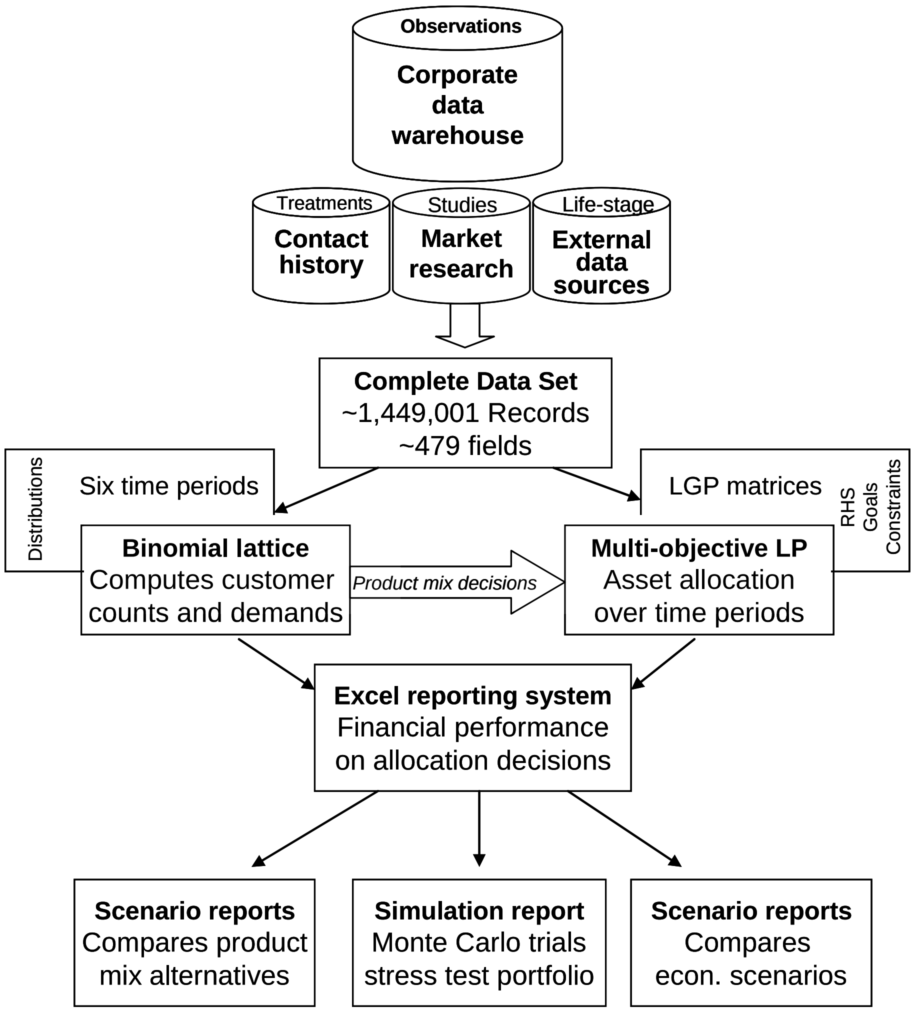


Figure 11. The asset allocation system: Data, computation, and reporting.

The second stage of the application was driven by a set of Speakeasy applications designed to perform the asset allocation optimization. The linear goal programs were invoked through Speakeasy that accesses the lp_solve libraries (lp_solve http://lpsolve.sourceforge.net/5.5/). The output of the application was posted to a Microsoft® Excel spreadsheet in order for further analysis to take place. The system stages are illustrated in Figure 11.

Some elements in the spreadsheet have been programmed as a part of this research, edit checking on constraint values to insure, for instance, that the lower-bound values are never higher than the upper-bound values. Other elements of the spreadsheet have been programmed in such a way that colors identify certain constraint boundary values such as grey colored cells indicating having met an upper or lower-bound limit on a constraint.

These features, built into the computer programs, allow for multiple experiments to be conducted by varying product mix factors and economic conditions with the output being an optimal allocation of advertising assets across each of the asset classes. The objective is to simultaneously never miss a sale without ever saturating the customer base. One scenario output will be described next in an effort to detail the richness of the information contained in the optimization output and illustrate the decision trade-offs made by the model, and how the marketing executive could interpret the results.

Each simulation is considered an experiment. In this particular experiment which will be referred to as Go-feminine, the product mix improvement scenario developed was favorable relative to purchases in the Elite Families (10.1% increase), Dress-ups (8.3% increase), Older Traditionalists (4.8% increase), and Young Budgets (7.2% increase). This experiment favored a more feminine-oriented product mix that would have a positive appeal to these particular asset classes. The product improvements had no economic effect on the other asset classes.

This type of overall product mix simulation is one of the few ways a company has to create an effect on its marketplace. Another method is to fuel the advertising budget with more money. This particular experiment found evidence of overall budget saturation, so increasing the advertising spend pool would not be among the optimal choices. An approach that optimizes what is known in the data is preferred.

The economic scenario was generated from the stochastic binomial tree and followed the expectations derived from the normal binomial process based on prior history. Monte Carlo simulations are used to generate distributions at each node of the lattice for each time period. Six time periods are simulated and the economic consequences are applied to the buying expectations of all asset classes impacting customer counts and revenue amounts.

The optimization model solves for each time period individually. The march through the binomial lattice allows asset class valuations to be modeled as path-dependent in time. The investment strategy shifts as the portfolio ingests economic information from the lattice and rebalances at every time step. The lattice also captures the seasonality of the business and varies decisions to meet volatile conditions.

Table 24 illustrates the 3rd quarter 2006 model result. The first column lists each asset class within recency grouping. The second column lists the optimal amount of advertising investment for each of the asset classes within recency grouping. The third column sums the asset class investments for each recency group. This particular number is noteworthy because the marketing executive would easily relate to this value and would most likely use it as a comparison to the heuristic systems in place today.

The fourth column represents the allocation percentages, which also provides a comparison to the heuristic systems in place today. The fifth and sixth columns are the lower and upper-bound constraint values in the solution for that time period. The grey shaded areas in Table 24, for instance, show that the optimal investment value went to one of these extremes. Where there is no shading, then the optimal value fell inside the basis for that time period.

It is easy to see that the first goal priority and constraint set was met. Table 23 identifies the first constraint for the same time period and sets the upper-bound on advertising spend at no more than $31,200,000. Table 24 shows that the sum across the recency groups indeed meets that constraint. The second goal priority goal was to create a pool of investment funds with a lower-bound not less than $4,540,514 that was illustrated in Table 23. Table 24 shows this constraint being satisfied as well.

Table 24 shows that no lower or upper-bound constraints were violated, so the third, fourth and fifth constraints have been met. These goal priorities were stated such that the value of the retention group > the value of the re-activation group > the value of the acquisition group. Table 24 shows that the optimal investment solution indeed funds these recency groups in the desired way.

Note that within the recency groupings the investments vary from asset class to asset class. This follows the logic that in some time periods, some asset classes outperform other asset classes and they should be funded when the model sees these opportunities. This data driven approach is very different from the current firm's rule that has recency groups being funded at roughly the same percentage throughout the year, all time periods being treated similarly.

Table 24

The Optimal Asset Allocation Solution for the 3rd Quarter 2006

Recency category	Optimal allocation	3rd Q 2006 $ allocation	3rd Q 2006 % allocation	Lower bound constraint	Upper bound constraint
Elite Families - retention	$3,986,955	Total	Percent	$2,630,128	$3,986,955
Dress-ups - retention	$3,056,109	adv. $ spend	allocations	$1,792,057	$3,056,109
Busy Families - retention	$844,044	$31,200,000	100%	$701,126	$844,044
Older Traditions - retention	$1,924,789			$1,405,339	$1,924,789
Young Budgets - retention	$1,496,421			$1,224,460	$1,496,421
Older Budgets - retention	$1,024,139			$753,693	$1,024,139
Green Segment - retention	$1,436,316	Retention	Percent	$1,401,327	$1,436,316
Blue Segment - retention	$768,492	adv. $ spend	allocation	$707,879	$768,492
Red Segment - retention	$2,696,384	$17,233,649	55.24%	$2,231,860	$2,696,384
Elite Families – re-activation	$1,628,805			$1,628,805	$2,003,805
Dress-ups – re-activation	$1,338,360			$1,114,966	$1,614,166
Busy Families – re-activation	$534,471			$534,471	$601,280
Older Traditions – re-activation	$1,063,494			$1,063,494	$1,253,649
Young Budgets – re-activation	$730,010			$730,010	$838,832
Older Budgets – re-activation	$611,608			$611,608	$800,832
Green Segment – re-activation	$1,054,400	Re-activation	Percent	$1,054,400	$1,629,020
Blue Segment – re-activation	$466,377	adv. $ spend	allocation	$466,377	$533,003
Red Segment – re-activation	$1,998,312	$9,425,837	30.21%	$1,998,312	$3,036,588
Elite Families – acquisition	$1,016,046			$895,960	$1,016,046
Dress-ups – acquisition	$857,901			$769,080	$857,901
Busy Families – acquisition	$242,630			$242,630	$242,630
Older Traditions – acquisition	$459,794			$451,240	$487,087
Young Budgets – acquisition	$352,520			$352,520	$389,238
Older Budgets – acquisition	$282,150			$282,150	$282,150
Green Segment – acquisition	$462,000	Acquisition	Percent	$462,000	$462,000
Blue Segment – acquisition	$219,600	adv. $ spend	allocation	$219,600	$219,600
Red Segment – acquisition	$647,873	$4,540,514	14.55%	$647,873	$647,873

The last goal priority is to maximize the wealth of the portfolio at each time period. The test of this goal would be the amount of revenue expectation received in any time period. The optimization method will look in numerous places in order to seek maximum revenues. The model will trade off within the 27 decisions it is making for each time period seeking to maximize wealth.

Table 25

The Optimal Asset Allocation Solution for the 4th Quarter 2006

Recency category	Optimal allocation	4th Q 2006 $ allocation	4th Q 2006 % allocation	Lower bound constraint	Upper bound constraint
Elite Families - retention	$9,432,905	Total	Percent	$4,156,686	$9,432,905
Dress-ups - retention	$7,220,380	adv. $ spend	allocations	$2,820,160	$7,220,380
Busy Families - retention	$1,624,551	$69,000,000	100%	$ 797,807	$1,624,551
Older Traditions - retention	$3,664,737			$1,624,637	$3,664,737
Young Budgets - retention	$2,536,361			$1,368,330	$2,536,361
Older Budgets - retention	$1,962,962			$ 874,380	$1,962,962
Green Segment - retention	$2,677,482	Retention	Percent	$1,185,311	$2,677,482
Blue Segment - retention	$1,157,822	adv. $ spend	allocation	$ 606,906	$1,157,822
Red Segment - retention	$4,905,038	$35,182,238	50.99%	$1,835,832	$4,905,038
Elite Families – re-activation	$3,937,558	Possible		$1,431,374	$3,937,558
Dress-ups – re-activation	$3,173,147	saturation of:		$ 979,818	$3,173,147
Busy Families – re-activation	$1,034,253	$4,198,133		$ 509,559	$1,034,253
Older Traditions – re-activation	$2,156,384			$ 963,792	$2,156,384
Young Budgets – re-activation	$1,442,946			$ 648,898	$1,442,946
Older Budgets – re-activation	$1,377,500			$ 530,060	$1,377,500
Green Segment – re-activation	$2,701,980	Re-activation	Percent	$1,065,987	$2,701,980
Blue Segment – re-activation	$5,082,200	adv. $ spend	allocation	$ 616,894	$ 884,067
Red Segment – re-activation	$5,036,648	$25,942,616	37.60%	$2,020,271	$5,036,648
Elite Families – acquisition	$1,713,945			$1,550,700	$1,713,945
Dress-ups – acquisition	$1,301,829			$1,262,080	$1,372,136
Busy Families – acquisition	$ 351,175			$ 351,175	$ 351,175
Older Traditions – acquisition	$ 818,508			$ 778,000	$ 818,508
Young Budgets – acquisition	$ 596,149			$ 553,960	$ 596,149
Older Budgets – acquisition	$ 430,650			$ 430,650	$ 430,650
Green Segment – acquisition	$ 952,000	Acquisition	Percent	$ 952,000	$ 952,000
Blue Segment – acquisition	$ 329,400	adv. $ spend	allocation	$ 329,400	$ 329,400
Red Segment – acquisition	$1,381,490	$7,875,146	11.41%	$1,381,490	$1,381,490

Table 25 is an illustration of the 4th quarter 2006 optimal solution. The 4th quarter is the holiday season and represents the heaviest buying season. The amount of promotion tends to be the heaviest in this period. The table is read identically to Table 24, except there is an additional concern with the investment values.

This study determined that the upper-bound on investment for the period would not exceed $69,000,000. Since this is the highest priority, the optimization seeks to satisfy this goal first. The Blue Segment asset class in the re-activation group has violated the investment upper-bound for this particular time period by $4,198,133.

This violation was allowed as the deviational variable for this constraint would open up to the point where it would make a choice to fund the next best place to make an investment once the optimal solution determined that there was money left over to spend. The goal priority for the re-activation group is the fourth goal priority, well down into the lexicographic priorities where the optimization program seeks to make some trade-offs if there are slack funds available. These slack funds, in this case, are caused by advertising saturation.

Figure 12 illustrates a way to consider saturation. Saturation has been defined as too many dollars chasing too few customers. The heuristic investment rules would have a low probability of guessing into the optimal region at point *B*. The most likely outcome of the heuristic investment rules is to under-invest (missing a sale at point *A*) or to over invest (saturation at point *C*) with a low probability of being anywhere on the efficient investment frontier.

At point *A*, there is more investment required as it moves up the notional curve (efficient frontier) to the optimal point (*B*). There is more return available, so consequently spend the dollars to achieve more rapid return. At point *C* the upward slope of the curve has fatigued exhibiting diminishing return properties. At this point there is no more return at any level of investment (indiscriminant risk taking).

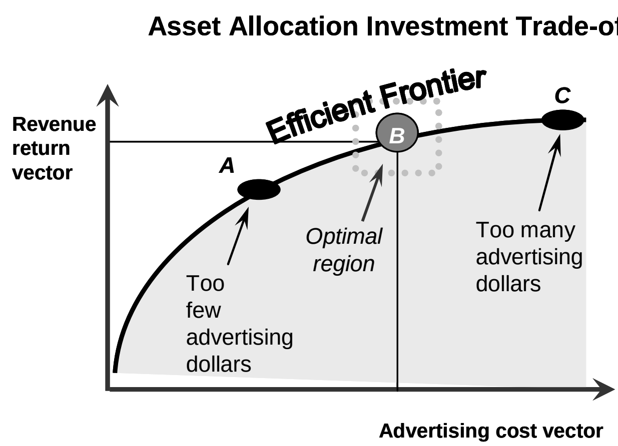


Figure 12. Efficient investment frontier trading off cost and revenues.

The asset allocation investment optimization process seeks the optimal region avoiding saturation. Each of the asset classes, in each time period, is judged for their saturative behavior. The heuristic method would have spent the money on advertising as it represents a rule and not a trade-off. The $4.2 million dollar saturation amount (point *C* in Figure 12) can be utilized in the investment pool to fund periods that may be under-funded where the system finds the buying opportunities, or can be reserved as an additional un-expected source of profit.

The recommended procedure would be to respect the upper-bound of the Blue Segment asset class within the re-activation group. These boundaries were determined through a thorough study of the data. The optimization application looks for another time period where the upper-bound on investment may not be enough for the revenue opportunity. In this case it will allocate the required amount from the pool into the needs of the other segments. This is in fact what the optimization application achieves, the recommended asset allocation rationalizes decisions surrounding the saturative quantity providing a new investment solution.

Finding the saturative investment opportunities and knowing exactly how to handle them was clearly one of the motivations for utilizing the mathematical optimization techniques described in this research. Cutting the cost of advertising by leveraging this feature of saturation identification and resolution, that is embedded in the logic of the application program, is highly desirable for use in direct marketing investment situations. Add to this the feature of the optimization application program that seeks the best revenue opportunities and a new source of corporate performance may emerge as a result of having these operations research tools.

Table 26 compares the results of the 3rd quarter 2006 with the results of the 4th quarter 2006. The point to be made here is the subtle way the asset allocation optimization will pick up revenue opportunities. The difference in the amount invested from 3rd quarter to 4th quarter is more a function of the 4th quarter being the heaviest buying season. The percentage differences in the investment behavior of the model are noteworthy.

The benchmark model made the same repetitive choices from quarter to quarter, and these choices were pre-determined at the time the plan was generated and rarely modified despite changing circumstances. The saturation decision made by the model would not have been determined heuristically. The firm may have launched a saturation study, but that activity would be well after the season had completed with the study taking up to a year to conduct (Haydock & Bibelnieks, 1999). Tuned to accept the data interactively, the proposed models could make these decisions in real time if necessary.

Table 26

A Comparison of 3rd and 4th Quarter 2006 Model Investment Choices

Recency groupings	3rd quarter 2006	4th quarter 2006	Variance
Retention group investment	$17,233,649 55.24%	$35,182,238 54.29%	$17,948,589 (0.95)%
Re-activation group investment	$9,425,837 30.21%	$21,744,843 33.56%	$12,319,006 3.35%
Acquisition group investment	$4,540,514 14.55%	$7,875,146 12.15%	$3,334,632 (2.40)%
Total investment	31,200,000 100.00%	$64,801,867 100.00%	$33,601,867

The processing of the goal priorities is based on the concept of satisficing. Schniederjans (1984) argued that linear goal programming seeks a solution that fully satisfies as many goals as possible rather than optimize around a single goal. The application processes follows Ehrgott (2005) beginning with the highest goal priority. The linear program is solved for this first priority attempting to minimize the deviations surrounding the constraints. Once this solution is formed, the solution elements are transformed into a new constraint row of the problem. The next priority is selected, the linear program solved, and the solution elements set as the next constraint row. This procedure continues through all goal priorities (six in this case).

The benchmark model will in no way make these types of trade-offs easily. The benchmark model is more the collection of valuable experiences from the management team that has operated inside the business. Though the experiences can be used as highly valuable inputs into the optimization model, this process mimics the formulation of a set of rules more than an attempt to mathematically optimize the portfolio. A comparison of the best efforts of the heuristic model and the asset allocation optimization model will follow next.

In order to make a fair comparison a base case should be established. The base case was identified as the best performance the firm could achieve utilizing the benchmark model. Table 27 is representative of a profit and loss statement of a base case to which the portfolio optimization efforts can be compared. This base case was in fact the firm's forecast of what it thought it could do for the calendar year 2007. The firm utilized the recency groups as a proxy for asset classes, but did not use the clustering techniques to uncover a deeper multidimensional organization of the data.

The firm executed its planning process using these recency groupings. This research utilized the same recency groupings in order to compare and additionally placed the asset class designations within the recency groupings as a way to provide a deeper level of detail to the optimization process. This design is highly recommended based on the results of this grounded theory exploration.

The totals column identifies the demand expected from the total investment as well as the resulting profit. The revenue achieved with the best efforts benchmark method is $956.7 million dollars. The total investment (treatment amount) was the same for both the control observation (benchmark method) and the test group (asset allocation optimization).

Table 27

The Base Case Benchmark Solution for all Time Periods for 2007

Base case heuristic model	Totals	Allocations
Beginning customer count	5,158,439	
Total demand	$956,743,125	
- Retention demand	$636,004,260	
- Re-activation demand	$168,876,469	
- Acquisition demand	$151,862,397	
Total investment	$165,000,001	100.0%
- Retention investment	$97,350,000	59.0%
- Re-activation investment	$41,250,000	25.0%
- Acquisition investment	$26,400,000	16.0%
Ave. investment per household	$31.56	
Ave. HH demand (retention)	$242.76	
Ave. HH demand (re-activation)	$140.87	
Ave. HH demand (acquisition)	$114.92	
Number of re-activations	1,176,470	
Number of acquisitions	1,295,345	
Ave. lifetime value per customer	$57.28	
Ave. profit % per customer	23.6%	
Total profit	$230,509,493	
Ending customer count	5,013,542	

The overall profit was estimated at $230.5 million dollars. Also note the beginning and ending customer counts show a loss in retained customers over the year from 5.158 million to 5.012 million, a loss of 144,897 customers. The following revenues were estimated: (a) the retention customer group billed $636.0 million dollars; (b) the re-activation group billed $168.9 million dollars; and (c) the acquisition group billed $151.8 million. The investment allocation followed the benchmark rule that had been in place for many years: 59.0% went to the retention group of current customers, 25.0% went to re-activate previous customers, and 16.0% went to new acquisitions.

Table 28

Asset Allocation Optimization Solution for all Time Periods for 2007

Go feminine scenario	Totals	+/- Base
Beginning customer count	5,158,439	No change
Total demand	$1,065,713,278	11.4%
- Retention demand	$710,976,294	11.8%
- Re-activation demand	$187,099,652	10.8%
- Acquisition demand	$167,637,332	10.4%
Total investment	$164,056,838	100.0%
- Retention investment	$91,786,810	55.9%
- Re-activation investment	$51,537,103	31.4%
- Acquisition investment	$20,732,925	12.6%
Ave. investment per household	$29.79	-5.1%
Ave. HH demand (retention)	$253.46	4.4%
Ave. HH demand (re-activation)	$146.94	4.3%
Ave. HH demand (acquisition)	$119.86	4.3%
Number of re-activations	1,232,103	4.7%
Number of acquisitions	1,354,755	4.6%
Ave. lifetime value per customer	$59.74	4.3%
Ave. profit $ per customer	$48.81	6.2%
Total profit	$256,669,532	11.3%
Ending customer count	5,258,020	4.9%

Table 28 represents an experiment from the asset allocation optimization model. The optimization model produced a superior ending customer count by gaining customers, spent less of the advertising budget (found saturative activities and did not fund them), and outperformed the benchmark model in the delivery of both revenue and profit. A key determinant in the performance difference of the optimization model was the number of re-activations and acquisitions achieved. This can be attributed to the goal priorities of setting up enough budget allocation to move these important customer metrics.

Comparisons of the base case utilizing the benchmark model with the results of the asset allocation optimization model are seen in Table 29. Only the totals column can be compared since the optimization model has the additional feature of the asset classes, which the benchmark model does not. The results show that the additional layer of asset class designations allows a much deeper targeting accuracy and made a significant difference in the performance of the optimization model over the benchmark model.

In Table 29, the beginning customer count was the same for both models since that is the starting position for both the control and the test groups. The revenue difference is the first observation of interest. The optimization model found $108.97 million dollars (11.39%) of opportunities in the data.

This performance is attributable to the use of the entire suite of techniques: (a) the various studies conducted on the data to uncover customer lifetime value; (b) the development of attributes with the data that contribute to the understanding of upper and lower-boundaries on spending; (c) appending the data with Acxiom® data to enhance the original purchase behavior observations; (d) the careful development of asset classes which allow for much finer grained targeting; (e) the development of the binomial lattice that allows the optimization model to look-forward to an expected economy so that opportunities can be identified and decisions can be taken; and (f) the utilization of the asset allocation optimization so that multiple goals can be considered and the proper trade-offs made for each time period based on conditions, providing the optimal answer.

The portfolio optimization revenue results for each of the recency groups were as follows: (a) the retention group performance was 11.79% above the benchmark method; (b) the re-activation group performance was 10.79% above the benchmark method; and (c) the acquisition group outperformed the benchmark method by a 10.39% margin.

Table 29

A Comparison of the Optimization Model with the Benchmark Model

Base case vs. go feminine scenario	Heuristic model	Asset allocation	Model difference	+/- Base
Beginning customer count	5,158439	5,158,439	No change	No change
Total demand	$956,743,125	$1,065,713,278	$10,8970,153	11.4%
- Retention demand	$636,004,260	$710,976,294	$74,972,035	11.8%
- Re-activation demand	$168,876,469	$187,099,652	$18,223,183	10.8%
- Acquisition demand	$151,862,397	$167,637,332	$15,774,935	10.4%
Total investment	$165,000,000	$164,056,838	($943,162)	100.0%
- Retention investment	$97,350,000	$91,786,810	($5,563,190)	55.9%
- Re-activation investment	$41,250,000	$51,537,103	($10,287,103)	31.4%
- Acquisition investment	$26,400,000	$20,732,925	($5,667,075)	12.6%
Ave. investment per household	$31.56	$29.97	$1.60	-5.1%
Ave. HH demand (retention)	$242.76	$253.46	$10.71	4.4%
Ave. HH demand (re-activation)	$140.87	$146.94	$6.07	4.3%
Ave. HH demand (acquisition)	$114.92	$119.86	$119.85	4.3%
Number of re-activations	1,176,470	1,232,103	55,633	4.7%
Number of acquisitions	1,295,340	1,354,755	59,410	4.6%
Ave. lifetime value per customer	$57.38	$59.74	$2.47	4.3%
Ave. profit $ per customer	$45.98	$48.81	$2.84	6.2%
Total profit	$230,509,493	$256,669,532	$27,103,201	11.8%
Ending customer count	5,013,542	5,258,020	244,478	4.9%

Note: Full P&L report for each market segment is included in the Appendix (Table B2).

Both the control observation and test groups started with the same amount of advertising investment capital ($165.0 million dollars). The experimental group using the portfolio optimization methods spent 0.57% less ($943,162 less). This was because the asset allocation methods were tuned to seek out saturative situations and to pull back spending when it found these conditions. The saturation is found primarily in the retention group, as would be expected since the instinct of the direct marketer is to over-promote to their known customer base. These saturative dollars can now be placed into profit as they are not needed in order to maximize the revenue potential.

A total of $7.2 million dollars less was spent by the optimization model in the retention group than the spend recommendation of the benchmark model. Even though less was spent relative to retention spend, the optimization model found an additional $74.9 million dollars in revenue. This increased the average customer spend in the retention group to $253.46 for the experimental group versus $242.76 for the control observation. This is an increase of $10.71 on average or 4.41%. Kotler (1994) argued that this can be likened to adding another item into the shopping cart, a key objective of all retailers.

Advertising spend in the re-activation group was increased as a result of the portfolio optimization application ($51.5 million vs. $49.5 million dollars). This can be attributed to the priority that the goal constraints set in insuring the proper spend trade-offs, and the opportunity uncovered in the asset class development for this recency group. The prescription for increased spend brought an additional increase in revenue results for the re-activation group totaling $18.2 million dollars (an increase of 10.8%).

Re-activation counts were increased by 55,633 customers as a direct result of the asset allocation optimization method. This increased the average spending by $6.07 per customer (4.31%) to $146.94 dollars versus $140.87 for the benchmark method. Equally as important is the long term effect of adding new customers to the firm's base.

Without adding new customers to the base, the firm would begin to see revenues fatigue and experience eroding income over time. This infusion of new customers will prove to be of high value in future time periods, and can be measured in the lifetime value metric. This is reflected in the increase in the lifetime value of the customers in the test group by an additional $2.47 per customer. When multiplied by the number of customers in the population (5.28 million) this would result in a net revenue increase of $12,987,309 dollars in additional product spend in future time periods.

The asset allocation optimization method added an additional 59,410 acquisition customers above the best efforts of the benchmark method. The strategy of the firm was to heavily treat the retention group, which are their best customers at the expense of the acquisition group. Similar to the re-activation situation, where known file fatigue over time will erode the overall revenue returns of the customer base.

Unless new customers are added, there is no way to stop the file erosion demonstrated in Table 3. The asset allocation optimization method had as its second goal priority the objective of insuring a pool of investment dollars is available for each time period specifically for new acquisitions. These additional acquisition customers are forecasted to spend an additional $4.2 million dollars above the benchmark method. This group will spend $119.86 per household on average in the first year after being added to the house file. This is an additional \$4.93 per customer (4.29%) more than the control observation.

The final result of interest is the ending balance of customers. The asset allocation optimization method produced an increase of 99,581 net new customers. This is after the effect of attrition has been balanced by new additions. The benchmark method had a net loss of customers totaling 144,897. Given the lifetime value of a customer, the impact on the revenue performance of the customer base in future time periods could be very significantly impacted. The deviation between the two groups is 244,478 customers. Since customers are the life blood of the firm, this is a very significant metric.

The results of using the asset allocation optimization method may provide a significant performance gain over the benchmark method. Changing investment behavior from an experience base gained over years of observing consumer behavior from some very bright people in the firm to a numerical method with a considerable bit of complexity is a daunting task. The hypothesis test was designed to be a way to traverse benchmark experience in favor of the numerical method if the test proves significant enough from a business standpoint. The results of the hypothesis test are described next.

Hypothesis Test Results

The return on marketing investment *(RMI)* was selected as a measure of effectiveness to compare the incumbent benchmark method to the asset allocation optimization method. The core question is, does the asset allocation optimization method outperform the benchmark method using this measure of effectiveness? This leads to the following hypothesis set.

H_0: The performance of the proposed asset allocation optimization test procedure does not perform as well as, or is equal to, the performance of the current control benchmark investment procedure ($\mu RMI_{test} \leq RMI_{control}$).

H_α: The proposed asset allocation optimization test procedure provides a reward over the control observation using the incumbent investment procedure ($\mu RMI_{test} > RMI_{control}$).

The return on marketing investment is defined as:

$$RMI = \frac{\sum_{i=1}^{N} Demands_i}{Investment - Saturation}$$

Where:

i = a customer asset class, and

N = the number of customer asset classes.

The examination of this hypothesis will utilize a one-tailed test since an acceptance of the null hypothesis (H_0) could occur if the return on marketing investment of the test group was either less than or equal to the return on marketing investment of the control observation. A *t*-test for the equality of the mean was utilized to determine actual rejection or non-rejection of the null hypothesis. The *t*-distribution was used because the population standard deviation (σ) is unknown and it is not known whether the population is normally distributed. Observations must be simulated in order to produce the sample statistic to test the hypothesis.

The *t*-test response allows for a measurement of the significance of the difference between the test and control results. The procedure also assumes that the population is normally distributed (Singleton & Straits, 2005). The level of significance, α, will be set to .05 in testing the hypothesis. The *t*-test can be represented by (Aczel & Sounderpandian, 2002):

$$t = \frac{\bar{x} - \mu}{s / \sqrt{n}}.$$

Where:

$\bar{x}$ = the sample mean *RMI* observed as a result of applying the treatment,

n = the sample size of observations (number of portfolio simulations),

μ = the mean *RMI* of the population under the null hypothesis, and

s = the sample standard deviation of the *RMI* metric.

Banks and Carson (1984) identified that a simulation is the imitation of the operation of a real world phenomena or process over time. The behavior of that system may not be known ahead of time, but through the use of simulation models important parameters may be understood. In this case the mean and standard deviation of the performance measure RMI_{test} needed to be estimated using observations generated through simulation of the asset allocation optimization procedure.

Each run of the model provides one observation of the population of *RMI's.* To estimate the measure of effectiveness, a sample was drawn from the population. The underlying assumption of the test is that the population *RMI* is normally distributed and the population standard deviation, σ, is unknown, but the sample standard deviation *s* is known.

This leads to three questions:

1. How large a sample is required; that is, how many runs of the simulation are necessary?
2. Is it reasonable to assume that the population is normally distributed?
3. How do we determine the sample standard deviation?

To address the number of required simulation runs, a series of asset allocation optimization simulation trials was executed (Banks & Carson, 1984). The standard deviation parameter *s* was taken at the completion of the fifth trial (Trials 1 through 5 inclusive) which yielded a value of s = 0.0160. Using the minimum required sample size in estimating the population mean Aczel and Sounderpandian (2002) articulated that:

$$n = \left(\frac{t_{.025}s}{B}\right)^2 = \left(\frac{2.776 * 0.0160}{.01}\right)^2 = 19.673 \approx 20.0 \text{ runs.}$$

Where:

n = the minimum sample size satisfying precision requirements,

$t_{.025}$ = the critical value of the *t* distribution $\left(\frac{\alpha}{2}\right), \alpha = .05$,

s = the sample standard deviation, and

B = the allowable margin of error (.01).

The second set of trials was set to 30 runs and a measurement taken. Following the formula directly above the new parameters are:

s = 0.0178, $t_{.025}$ = 2.045, B = .01, n = 13.292 $\approx$ 14 runs.

The determination was made to execute the simulation at 50 runs as a safety measure to insure validity of the results. The resulting mean and standard deviations are:

$$\mu RMI_{test} = \frac{\$1,069,573,914}{\$165,000,000 - \$975,683} = 6.521,\ s = .0205.$$

The next test is to confirm the normality assumption. The Kolmogorov-Smirnov test was used to compare the distribution of the data to a normal distribution. The SPSS® statistical software package was used to perform this test. The results of the test are illustrated in Table 30.

Table 30

Results of the Kolmogorov-Smirnov Test #1

One-sample Kolmogorov-Smirnov test

		RMI
N		50
Normal parameters[a,b]	Mean	6.520780
	Std. deviation	.205304
Most extreme differences	Absolute	.425
	Positive	.357
	Negative	-.425
Kolmogorov-Smirnov Z		3.009
Asymp. sig. (2-tailed)		.000

a. Test distribution is normal.

b. Calculated from data.

The results in Table 30 show a *p*-value (Asymp. Sig. 2-tailed) of less than α (.05) so H_0 (the distribution is normal) would be rejected. Further evidence of non-normality can be seen in Figure 13 which shows the P-P plot of the data to the expected cumulative probability of a normal distribution to the observed cumulative probability of the data. Ideally the data of the observed probability would lie close to the expected probability line and would be approximately linear if the specified distribution is the correct model. The chart in Figure 13 shows that it is not and in fact is somewhat orthogonal to it.

Further analysis of the P-P plot in Figure 13 identifies evidence that there may be several outliers in the data, most likely as a result of the random number generation process that provides the variability in economic scenarios. To identify the outliers it is necessary to compute a z-score for each RMI. This is done by taking the RMI score for a trial, subtracting the μRMI_{test} of the series (50 observations) and dividing by the standard deviation of the sample (s). The resulting z-scores can be ranked and outliers identified.

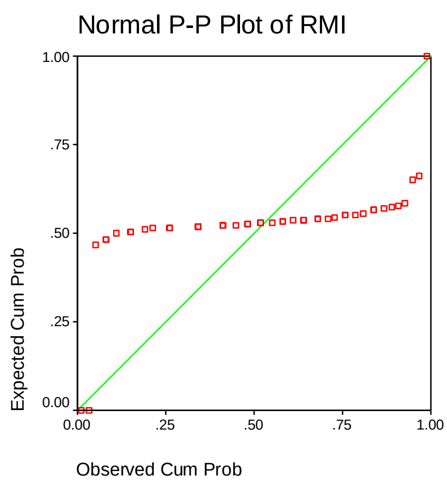


Figure 13. P-P plot #1 of the data to test for normality.

When inspecting the possible outlier values the RMI's from experiment numbers 34, 39, and 44 had the largest absolute value z-scores. The experiment data was kept for each binomial lattice Monte Carlo simulation trial so it was easy to go back to the original data to inspect why the results appeared as they did. The root cause were economic scenarios that were either extremely good (Trial 34) or extremely poor (Trials

39 and 44). The simulated economic scenarios were either much better or much worse than observed in the real data for those time periods.

Table 31

Results of the Kolmogorov-Smirnov Test #2

One-sample Kolmogorov-Smirnov test

		RMI	RMI2
N		50	47
Normal parameters [a,b]	Mean	6.520780	6.538723
	Std. deviation	.205304	1.88E-02
Most extreme differences	Absolute	.425	.154
	Positive	.357	.154
	Negative	-.425	-.117
Kolmogorov-Smirnov Z		3.009	1.057
Asymp. sig. (2-tailed)		.000	.214

a. Test distribution is Normal.

b. Calculated from data.

The determination was made to eliminate those outlier data and re-run the Kolmogorov-Smirnov test. Table 31 shows the second test resulting in a *p*-value of .214 > .05 so the null hypothesis of normality can not be rejected (the data are normally distributed). Looking at Figure 14, it is evident that the data plots quite close to the cumulative normal distribution line. There still appears to be some outliers, but the p-value statistic on the second run is large enough to allow for the procedure to stop.

The next step was to re-compute the sample mean and standard deviation with those outliers removed. This new μRMI_{test} was used in the hypothesis test. The previous measures of central tendency with all 50 simulation trials was μRMI_{test} = 6.521 and s =

0.205. The new value using a sample size of n = 47 after removing the outliers is

$$\mu RMI_{test} = \frac{\$1{,}072{,}497{,}863}{\$165{,}000{,}000 - \$978{,}636} = 6.539;\ s = 0.019.$$

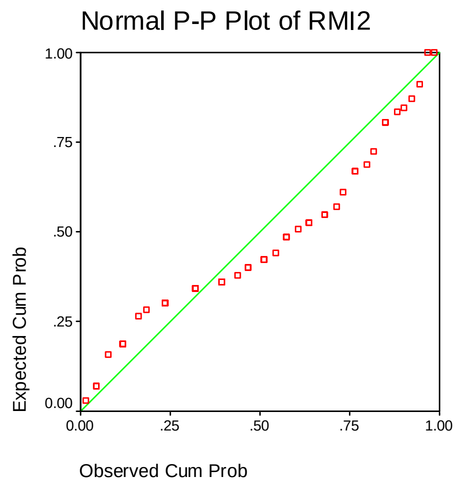


Figure 14. P-P plot #2 of the data to test for normality.

The third question on determination of the sample standard deviation can now be answered with s = 0.019. Removing the outliers provides a slight increase in the μRMI_{test} = 0.018, but reduced the sample standard deviation by .186 (0.205 – 0.019) decreasing variability. From Table 29 the

$$RMI_{control} = \frac{\$956{,}743{,}125}{\$165{,}000{,}000} = 5.798$$

The t-test can now be computed.

$$\frac{6.539 - 5.798}{0.018/\sqrt{46}} = \frac{0.740}{0.002773} = 269.871 = t_{calculated}.$$

The alpha value is $\alpha = .05$, n = 47, the critical value of the t distribution is = 1.679 (.05 with 46 degrees of freedom). Since 269.871 > 1.679, reject the null hypothesis and accept the alternative hypothesis that the RMI_{test} of the asset allocation optimization method provides a reward above that of the $RMI_{control}$ of the benchmark method ($RMI_{test} > RMI_{control}$). The calculated *p*-value = 1.48337E-75, which says there is virtually no chance of H_0 being true.

Scenario Experiments

The flexibility of the optimization model allows for the changing of conditions in both the product mix factors and the economic conditions that may impact the firm. Changing product mix factors provides one of the controllable variables for the firm. This is one of the few ways a direct marketing firm can experiment in the marketplace to test offerings and various bundled configurations. A product mix factor experiment can be conducted by manipulating several product offerings and simulate what their effects are on the various asset classes. Table 32 summarizes such an experiment and details the inputs.

Changing economic conditions are helpful in understanding how the asset allocation optimization methods can be stress tested with various economic scenarios. Marketing executives would like to know under what economic conditions the business does poorly and under what conditions might the business do unusually well. The firm has no influence over the economy and must instead react to these conditions.

One advantage of the binomial lattice method is that economic events could be surmised from the random walk paths which the lattice provides. Scenarios can be simulated and portfolio results inspected. Management may be able to identify an economic situation unfolding and take positive action prior to the event actually taking place. In this case, knowing what to spend, on which segments, in what time frame may make the difference between a profitable year and a year of losses.

Table 32 illustrates the results of several experiments manipulating either the product mix factors, the economic factors on the binomial lattice, or a combination of both. Each of the experiments has been compared to the benchmark base case. Included in the Appendix in Table B3 are the simulated scenario effects of the nine asset classes, so some level of detail can be seen on how sensitive one asset class is over another relative to conditions imposed in the scenario experiment. In all, 18 experiments were conducted in order to stress test the asset allocation methods.

As an example, experiment two titled Everybody's Happy – Great Economy was achieved by setting product mix factors in such a way that they positively affected each of the asset classes. Inspecting the differences between the asset class details in Table 32 of this scenario as compared with the base case, it is evident that all asset classes advanced in revenue, some significantly. Not all asset classes advance the same, or at the same rate, which may be attributed to the careful construction and detail of the model.

The economic simulation that creates the lattice values in this particular scenario is also easily manipulated by changing the mean values of the Monte Carlo inputs, having the simulation re-run, and providing new lattice values. In this case the values ticked up in the third and fourth quarters of 2007 and provided a positive portfolio shock. A full profit and loss report is developed for each of these scenarios similar to that illustrated in Table 28. This particular scenario achieved a revenue performance increase across all asset classes of 20.3% relative to the base case.

Table 32

Scenarios Comparing the Optimization Model with the Base Case

Scenario	Scenario name	Total revenues	Change from base
1	Base case	$956,743,125	N/C
2	Everybody's happy – great economy	$1,151,231,328	20.3%
3	Fashion forward – more fancy products	$912,958,629	-4.6%
4	Fashion forward II – targeted	$1,031,298,290	7.8%
5	More elegant to make a statement	$907,018,314	-5.2%
6	More elegant II – targeted	$1,025,357,975	7.2%
7	Not too fussy – versatile	$867,674,073	-9.3%
8	Not too fussy too II – targeted	$980,744,386	2.5%
9	More conservative – fair economy	$999,489,720	4.5%
10	More conservative II – targeted	$1,044,978,443	9.2%
11	More sporty, youthful oriented products	$1,003,286,280	4.9%
12	More sporty, targeted, good economy	$1,054,911,692	10.3%
13	Inexpensive basic, poor economy	$892,926,176	-6.7%
14	Inexpensive basic II, targeted	$1,023,600,915	7.0%
15	More upscale, combination of 3 & 4	$907,018,314	-5.2%
16	More upscale II, targeted	$1,025,357,975	7.2%
17	Go basics, combination of 7 & 8	$941,776,506	-1.6%
18	Go basic II, targeted	$1,015,937,218	6.2%
19	Go feminine, economy as expected	$1,065,713,278	11.4%

Note: Full scenario report for each market segment is included in the Appendix (Table B3).

Experiment 13 in Table 32 shows an example where both the product mix factors and the economic conditions were not favorable to the firm. This results in a loss of 6.7% relative to the base case. The conditions in this scenario are characterized by an opposite product mix scenario from that input in experiment two. Also the economy worked against the firm in exactly the opposite direction of the magnitude of that in scenario two. While scenario two had a 20.3% gain from these simulated values, the drop in values of equal magnitude, just in the opposite direction, only brought a loss of 6.7%, where -20.3% may have been expected.

The ease of making changes in the model using the Microsoft® Excel spreadsheet as the user interface should allow for the curious marketing executive to have a highly responsive, easy to use system for improved investment planning and customer targeting. This research does not attempt to provide insight into the change management challenges of implementing a complex system like the asset allocation optimization method into the firm's everyday business processes. The model is complex, only because it reflects a very complex decision process, operating in a complex business environment.

Summary

This chapter detailed the procedures in developing an asset allocation optimization solution and the results achieved. The target problem was focused on improving advertising investment performance above that of the incumbent methods used in the direct marketing industry. Marketing executives currently deploy experienced-based benchmark methods when developing market segments and in allocating financial resources to those segments.

The hypothesis of this research is that the asset allocation optimization procedure can significantly outperform the benchmark procedure. The hypothesis test proved that using μRMI_{test} as the measure of portfolio performance, that the asset allocation optimization procedure did in fact significantly outperform the $RMI_{control}$ which represented the best efforts benchmark method. The test also showed that there was an extremely small chance that the benchmark method would consistently outperform the asset allocation optimization method (type I error).

There are multiple steps in the asset allocation optimization procedure, some complex, some of which have not been previously documented in the marketing science literature. The complexity of the investment procedures may have restricted previous acceptance to using operations research methods to improve customer investment performance to those applications treating individual households. Part of the grounded theory states that the investment process utilized should mirror those deployed in the financial services industry. Financial economics theory begins with the allocation of resources into asset classes and concludes with the selection of investable instruments.

The direct marketing industry is no stranger to using complex numerical methods in attempts to predict aspects of consumer behavior, but the link between detecting an individual buying signal and making efficient marketing investments across the enterprise consumer base had not been previously made. The contribution of this research is adding this strategy dimension of the efficient allocation of resources, prior to selecting customers for the portfolio. To invest directly in customers without prior understanding of the clusters they belong to may prove financially inefficient. This is due to the infrequency of purchase behavior of any single consumer or household.

For this reason, the industry relies on recency, frequency, and monetary value heuristics in making investment decisions. This low dimensional view of the customer allows for easy explanation and rule development, but does not consider the high dimensionality central tendencies of the data, in which lie unseen opportunities. This chapter on the results of the study therefore opened with a description of the data.

A random sample of the population (5,684,000 customers in the active population) was taken with 1,449,001 customer household records being selected for the sample. These data are comprised of just over 3.8 million purchasing transactions that were consolidated into aggregates for each household. The purchasing observations are for the years beginning in 1st quarter 2003 through the end of 4th quarter 2005 (three complete years). The file includes 479 fields of information on various product preferences, pricing preferences, channel preferences, seasonal preferences, demographic data, as well as appended third party observations. These data were highly cleansed by the application programs developed for this research eliminating any incomplete records from the file during the observation period.

Certain external observations were appended to the data from the Acxiom® database of over 1,600 demographic and behavioral indicators. Certain key fields required for the allocation decision-making process and numerical clustering tasks were appended to the customer file and are inclusive in the 479 fields in the data. These extra observations, external to the behavioral data of the firm, attempt to give a marketing executive a 360 degree view of a household.

An important input to the asset allocation optimization is the formulation of goals and their respective priorities. This procedure more closely mirrors the actual decisioning environment of the marketing executive who deals with issues such as simultaneously maximizing revenues, not exceeding the overall advertising budget, gaining new customers, and the prevention of attrition from the current customer base. This is a more complicated formulation than the single objective of maximizing marketing profit.

Multicriteria optimization is a powerful mathematical technique that leverages the fact that multiple goals, sometimes conflicting, need to be resolved and optimized providing insights into complex real circumstances. The use of utility theory provides insight into the process of lexicographic goal prioritization. The lifetime value metric developed for this research ends up providing a very useful set of values in which to determine priorities and assists in setting up goal constraint boundaries.

This chapter introduced the use of a binomial lattice to determine the forward probabilistic buying behavior of the customer base relative to an uncertain economy. The lattice proves to be a very useful and practical forecasting tool. Through the use of Monte Carlo simulation the risk and perturbations of the lattice mirror a random walk process.

Rather than traversing every node of the lattice, a centering technique was developed that resulted in the construction of a retail index of peers who participate in the same marketplace as the firm. The index is built on available government data from the U.S. Census Bureau and can be forecasted forward using exponential smoothing techniques to determine the relationship between economic events and the growth of purchases and customer counts. This aspect of the asset allocation process also provides the capability to perturb economic scenarios for the development of experiments that can stress test the performance of the portfolio.

The firm in the study had extensive experience in the use of course grained market segments referred to as recency groups. Mostly created on the three dimensions of recency of purchase, frequency of purchase, and the monetary value of the purchase. A more aggressive segmentation scheme is proposed with the resulting asset classes having unique properties across 13 dimensions. The concept was to provide a much richer target marketing environment and to invest aggressively where previously unseen opportunities existed in certain time periods. This method clearly outperformed the benchmark segmentation method and was a large contributor to the results of the asset allocation optimization method.

The asset allocation optimization was explained in detail from the concept to the formulation of the matrices. Examples were given of outputs of the allocation experiments and performance comparisons with a benchmark base case were developed. The results were very significant in the aggregate where the asset allocation optimization method profit, revenue, and customer counts all outperformed the benchmark best efforts base case. Details of the performance of the individual asset classes were also demonstrated such that it was easy to see how the aggregate results were achieved.

The hypothesis test proved that the asset allocation optimization provides superior results, statistically significant enough to accept the optimization model over the benchmark model. Scenario experiments resulted in the ability to stress test the asset allocation methods across a wide range of product mix and economic scenarios. This capability should provide the marketing executive the flexibility to explore the most reasonable courses of action in their planning and investment environment.

The optimal portfolio method helps pinpoint the opportunities and funds them enough to never miss a sale, and to avoid saturating the customer base with extensive and wasteful advertising costs. The concept of saturation was highlighted and evidence that the asset allocation optimization application could spot saturative portfolio decisions and correct them was demonstrated. In the 2007 forecasted period, the optimization decisions found $943 thousand dollars of saturation that was converted into profit from planned advertising spend. Saturation is a consistent problem in direct marketing advertising that is not well documented in the marketing literature, and this research has hopefully provided some insight into how to spot it and solve for it at the aggregate level.

During the construction and operation of the asset allocation optimization models, there were several areas of additional research identified that were out of scope in this particular study, but may be of extreme interest to researchers, academicians, and marketing practitioners. These areas, once understood, could be incorporated into the computer programs and applications developed for this research. The next chapter details some of these areas of future importance.

CHAPTER 5: SUMMARY, CONCLUSIONS, AND FURTHER RESEARCH

Introduction

Efforts in the marketing sciences can be distinguished between the analysis of individual customers and the examination of portfolios of customers. The demarcation between tactical customer analysis and strategic portfolio construction is the exploitation of investment science and operations research as guiding principles for optimizing advertising expenditures within a direct marketing environment. While much of the marketing science literature has been devoted to the treatment of individual customers, the efficient diversification of marketing investments at the enterprise strategy level has been widely ignored.

Practitioners of financial economics have considered the investment process to foundationally begin with strategic asset allocation, later moving into instrument selection. Marketing practitioners, on the other hand, currently do not consider this foundational step and instead prefer to detect an individual’s buying signal and invest up to the point of saturation, hoping for a response. This point of saturation is not known in advance, nor is the buyer’s response to the promotion, both being stochastic.

The strategic asset allocation procedure was included as a cornerstone of financial economics because proof emerged, beginning with the work of Markowitz (1952), that showed that the efficient investment in instruments can only be optimally diversified through the aggregate balancing of co-variances between asset classes at the strategy level. The real key, then, was accumulating enough individual instrument performance so that strategic and statistical properties of groups of like asset types can be adequately measured. No individual financial instrument would show enough stability to insure the desired return of a portfolio, maximization of the expected return of the portfolio being the objective and not the maximization of any particular instrument.

In a similar manner, no individual customer generates enough purchase observations to form meaningful distributions, but placed in groups, buying behavior and saturation decisions can begin to be understood, managed, and acted upon. Without a portfolio strategy, the best performing customers continually receive promotional investment, surpassing their point of saturation. This consequently makes these good performing customers also the most expensive to treat. The accumulation of each saturative activity across an entire customer base over the period of a calendar year is considered an undesired expense to be eliminated, and a promising new source of enterprise profitability.

Saturation has been defined as a type of advertising inflation, too many dollars chasing too few customers. At the individual customer level, the benchmark approach can not comprehend that there are too many dollars in the budget. In fact, just the opposite would be true; there would never be enough dollars in the budget. Saturation therefore must be addressed first at the strategic budgeting level, prior to individual customer analysis.

The purpose of this quantitative grounded theory research was to develop an optimal strategic asset allocation investment procedure in order to improve the financial results of marketing investment in direct customer contact. This research has shown a detailed step by step procedure on how to construct an optimal portfolio based on a unified asset allocation strategy, weaving together multiple complex quantitative processes. The framework and algorithms developed were extensively tested using computer simulation experiments on representative data and measuring the portfolio performance against incumbent benchmark methods.

Interpretation of the Findings

The findings of this research show that the asset allocation optimization procedure provides a potentially significant return on marketing investment reward over the benchmark method of investment. The grounded theory component of this research has also articulated the discrete steps necessary in the construction of optimal marketing portfolios. The core research questions that were investigated in this study were:

1. How should a marketing executive consider risk and how do these risks affect utilities which the marketing investor seeks to optimize? This research showed that a persistent risk concern surrounds the issue of saturation. The advantage of the asset allocation optimization method was the identification of this risk in each time period and insuring that the next saturative dollar was not applied to the customer base. Those saturative dollars may now go unspent and contribute to profit instead of contributing to cost. The aspect of utility is addressed by the lifetime value calculation that also sets an upper-bound on advertising expense, reducing saturation risk.

2. What role does an understanding of promotional saturation play in the dissipation of risk when investing in discrete customer market segments? There were 27 independent investment decisions made in each time period in the asset allocation optimization procedure. Each of those decisions considered the investment pool available for that period and the ability for the customer segments (asset classes) to

absorb any more advertising expense in making the optimal allocation decision. The methodology used in the formulation of the market segments also allowed for a more precise understanding of saturative conditions, customer readiness to buy, as well as other behavioral tendencies.

3. What are the portfolio construction components and investment procedures appropriate for the marketing function, which simultaneously maximizes the profit potential of investable market segments and minimizes any waste in saturating customers with ineffective promotions? The grounded theory portion of chapter 4 articulated each step in the asset allocation optimization process. Figure 1, which appeared in chapter 2, provides a process flow which mirrors the set of procedures necessary to construct the efficient portfolio. The use of multi-objective linear programming allows for the simultaneous solution to maximize profits while minimizing saturation effect.

4. In what ways can quantitative models be used by the marketing function to efficiently allocate customer contact investments in order to maximize marketing program return on investment? The grounded theory articulated in chapter 4 is a series of interconnected quantitative models beginning with the transformation of the raw transaction data into a structural buying signal which varies over time. This signal is enhanced through the clustering exercise and leveraged by the multi-objective linear program to insure that investment gets to the right market segments, in exactly the right quantities, at exactly the right time period.

5. Which risk management metrics can be engaged in measuring marketing program profitability in order to compare competing investment procedures? The metric chosen to measure the effectiveness of the portfolio was the return on marketing

investment. This metric proved to be a reliable aggregate measurement of the performance of investment decisions. The metric considers: (a) revenue performance; (b) advertising dollars available; and (c) saturation. This metric as described would be ideal for those firms who deal with large direct advertising environments and seek a constant way of measuring advertising investment efficiency.

One interesting result reported in the chapter 4 findings was the extremely low probability that statistically the incumbent benchmark method would outperform the asset allocation optimization procedure. The simulation experiment described in chapter 4 also revealed that the portfolio method was sensitive to various economic scenarios which were randomly presented to it. Allocations were adjusted for the circumstances encountered subject to the investment rules and desired outcomes for revenue and profit.

Another interesting derivative of the research was the collection, cleansing, and attribution of the data. Approximately 3.8 million transactions were reduced to 1.449 million aggregate household records. The data were analyzed and each record was appended to accumulate 479 fields of information required for the studies that were conducted (like lifetime value), or specific analytical tasks like the market segmentation procedure or the portfolio optimization process.

The value of having collected a large amount of clean, accurate, and recent data was evident while constructing each of the applications and in conducting the studies. The data needed was always available and contained in the original observation set. The data model described in the development of chapter 4 would be appropriate for most firms dealing with direct marketing strategies. Knowing up front which data to collect and how it will be used may be considered a direct contribution to practitioners and chief information officers of direct firms as a result of this research.

Implications for Social Change

Advertising today is considered a corporate expense and not a source of investment. The contribution to social change derived from this research is to make the business firm more efficient in the allocation of advertising resources to acquire, re-activate, and retain their customer base. Customers are the lifeblood of any firm and the relationship built with that customer should be treated as an asset of the company. The understanding and management of saturative advertising expenditures opens up a new way of thinking about the investment options available.

This research addresses the when of investing as well as the how much issue. Knowing the optimal time period to promote and the precise amount of the investment from a strategic standpoint insures that the marketing executive can begin to shape business outcomes. Senior management is requiring more accountability on the effectiveness of the advertising expenditure. The asset allocation optimization capability described in this research could be the foundation of a solution for a new source of corporate performance not considered today.

Recommendations for Action

This research is of interest not only to corporate practitioners, but to marketing scientists as well. Corporate practitioners will benefit from the immediate reduction in advertising saturation. In the case presented in chapter 4 the mean value of saturation found as a result of the 47 experiments was just over $975,000 in the calendar year under investigation.

These slack funds can be converted into operating profit from what was destined to be potentially wasted expense. To achieve these gains, at a minimum, firms should consider implementing the multi-objective linear programming application in order to begin to gain a competency in allocation and operations research techniques. The performance of the asset allocation optimization application is dramatically enhanced by the suite of applications described in this research, so they are encouraged, especially procedures to capture and store the data in the way prescribed in the research.

Customers may benefit from an improved sense of relevancy in their relationship with the firm. Individual customer relevancy was not within the research scope of this study, but the understanding of customer groups gained through numerical segmentation techniques can not be overemphasized. To achieve this understanding the numerical segmentation and clustering procedures should be deployed within the firm. The insight gained from clusters of customer behaviors due to market segment attribution can be used for both strategic investment decisions as well as the tactical treatment of customers for long term relationships.

Operations research professionals and marketing scientists will benefit from this research as it proposes a new and complete systems approach to the allocation decision. The process steps surrounding the stochastic binomial lattice and indexing are new to the marketing science literature and should require further exploration on practical applications. The multi-objective linear programming application has good potential for being a source of further research into decision-making under uncertainty.

Recommendations for Further Study

Building a large complex system such as that described in this research has exposed the author to many issues where there is opportunity for further study. Four areas of opportunity come to mind: (a) the development of a financial hedging strategy to lock in marketing program profits through financial engineering; (b) the requirement for sensitivity analysis to be incorporated into the multi-objective linear program; (c) the change management procedures needed for a firm to implement the asset allocation optimization and have it deliver promised results to the enterprise; and (d) additional application areas.

The development of a hedge framework has the potential to immunize the firm from adverse market conditions. These market conditions can be simulated through the use of the binomial lattice where scenarios can be contrasted for their immunization value to the enterprise. The concept would be to insure the profits of the firm related to direct marketing programs by holding an indexed instrument which moves in the opposite direction of the peer retail index (in this case) in every time period.

This framework would include the algorithms which comprise the hedge technologies and a description of the operational data required. The social and business consequences of such a development would allow for stabilization of the firm under adverse conditions. The use of the binomial lattice in this research as a way of mirroring the short term stochastic movements of the economy was clearly motivated by this thought. The foundations of financial option theory are built from similar principles, but none currently applied to the area of marketing sciences were found in the literature search as of this writing.

The dynamic hedging of portfolio investments would rely on a measure of the Value at Risk (VaR). VaR concerns itself with the maximum amount of loss that the firm can incur in any time period. The behavior of the tails of the distribution of losses may contain the information necessary to understand and leverage these extreme events (Khoury, 2003). The application of extreme event theory supports these types of distributions (Cruz, 2002) and would again be a new contribution to marketing science. Applying extreme value theory may allow for the computation of the probability of events which have not been previously observed by the firm, but could be simulated using the Monte Carlo routines developed for this research.

The second area of further research recommended is the sensitivity analysis surrounding the use of multi-objective linear programming. This seems like a fundamental area where computer applications could be built to understand the sensitivity of an optimal solution to the changes in row and column boundaries. Because of the complexity of managing multiple objectives the sensitivity analysis is not as straight forward as those applied to single objective linear programs.

During the research, finding the increase and/or decrease required in the bounds specified to force a significant basis to change was a manual process, not very intuitive, and required a great deal of experience with the model to understand how it makes decisions and where the flexibility was. A programming capability to ignore the bounds and drive a variable or row value up or down until an interesting basis change occurs does not exist. Having an automatic way of looking at the bounds to determine the treatment of upper and lower-boundaries would also be an interesting area of research. In the model described in chapter 4, the boundaries were either heuristically determined or determined by a business rule. Visualization of the effect of changing a bound would be an important addition to this research area.

The third area of further study may be the most important short term suggestion, which is to take the results of this research and to determine how it can be implemented in the complex environment of the firm. In chapter 4 the hypothesis test clearly showed a reward associated with the use of the asset allocation optimization program. Sometimes in industry, a reward is not good enough.

The processes of the firm may have been determined in such a way that it is very difficult to unseat an incumbent method. Reporting and financial systems would have to change, new skills would have to be deployed, and most likely an increased requirement for data collection and processing are likely needed. These changes must be thought through and professionally managed for technology implementation to occur and for processes like those described in this research to become the fabric of the firm.

The last area for further research is in new applications for the combination of strong data collection and management, clustering, stochastic random walk processes, and multi-objective linear programming. One particular area that looks especially promising and is high intensity modulated radiotherapy, an area completely unrelated to the business application described in this research. This area could have very important social consequences related to improved health treatment at lower costs.

High intensity modulated radiotherapy is used to treat cancer patients either pre-operative or post-operative to help shrink the area of a tumor. The advantage of using multi-objective linear programming technologies is that multiple objectives must be traded off simultaneously to achieve the best beam strategy solution for the patient. The radiotherapist for instance would describe the ability to maximize a radiation dose to the tumor object, minimize the radiation exposure to healthy organs, and capture the stochastic nature of where the tumor object could be at any point in time (think of a breathing patient with a lung tumor which is moving in a vertical manner while laying down on a treatment table during the radiation treatment). The output would be a set of optimal beam strategies for that patient meeting the objectives and constraints under stochastic conditions.

Conclusion

The marketing application of asset allocation optimization allows for the movement of financial investment resources to the customer segments with the greatest opportunity, while simultaneously detecting saturative circumstances and withholding funding to those undesirable investments. This set of optimal strategic activities pre-conditions the pursuit of individual customers so that the right amount of investment gets to the best customer groups, at the best time periods. Individual customers then compete for their fair share of the investment through the use of individual customer propensity scores.

The strategic asset allocation process filters the budget down through the asset classes, and finally into the individual customer level. The advantage of the strategic asset allocation optimization process is leveraging the massive amount of information the application considers in minimizing the risk in making poor strategic funding decisions. This allows the optimal portfolio to provide enough investment so as to never miss a financial return opportunity, while not providing too much investment so as to add additional saturation risk to the portfolio.

This research accomplished the goals and objectives described in chapter 1 introducing the study. The performance of the asset allocation optimization portfolio strongly supports the use of the portfolio as a foundational investment procedure. The optimal portfolio method clearly outperformed the benchmark incumbent method and there was statistical validation that it would continue to outperform in the future.

The problem statement of this research identifies that an increasingly large amount of advertising and promotional dollars are being spent by firms and yet the optimal allocation of this investment is an area not well understood by the practitioners in industry. This inefficiency is attracting the attention of chief marketing officers, chief financial officers, and chief executive officers looking for strategies, methods, and technologies to help with the solution to this concern. This inefficiency can be corrected by using the asset allocation optimization process detailed in this research.

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APPENDIX A: LIFETIME VALUE

The computation of lifetime value (LTV) was a core input to the asset allocation optimization application. The rigorous explanation of lifetime value was beyond the tight scope desired in the research study, but a brief explanation of how this important variable is derived from the data will be described here. Lifetime value was used as a proxy for utilities in preferences surrounding the lexicographic priority ordering of goals. This metric was also used as a way to set upper-bounds on expenditure constraints in the optimization.

Table A1

Lifetime Value Computation

LTV calculations: Assumes 1st order or trigger order in calendar year 2004 with subsequent LTV for the 12 months after that order.	**Calendar year 2004 (January 2004 – December 2004)** Acquisition or trigger order occurs in 2004. The LTV 12 month period starts, and because it runs 12 months it extends into 2005.	**Calendar year 2005 (January 2005 – December 2005)** LTV includes only sales and profits on orders after the first order or trigger order. This is tabulated for a rolling 12-month period for each customer.
Example 1: Acquisition customer	1st order on January 15, 2004. Acquisition activity costs include all promotional costs up to January 15, 2005, the sales from the order and all variable costs (cost of goods sold, fulfillment, marketing).	LTV = January 16, 2004 to January 15, 2005 and includes all promotional costs, cost of goods sold, fulfillment, and marketing costs. Includes sales from all orders in that 12 months.
Example 2: Re-activation customer	Last order was 12 or more months prior to the start of 2004 (they lapsed). Trigger order for re-activation was on June 30, 2004. Includes all promotions from January 1 to June 30, 2004, and all variable costs and sales of the re-activation order.	LTV = July 1, 2004 to June 30, 2005. Includes all sales from all orders, variable costs and promotional costs during the 12 month period.
Example 3: Retention customer	Last order was sometime in fiscal 2003, 12 or fewer months ago. Trigger order that retained them as an active customer was on December 1, 2004. Includes all promotions in 2004 and all variable costs and sales related to the retention order.	LTV = December 2, 2004 to December 1, 2005. Includes all sales from all orders, variable costs and promotional costs during the 12 month period.

APPENDIX B: ASSET CLASS PERFORMANCE REPORTS

Table B1

Development of the A Matrix Used in the Linear Goal Program

	198 Rows	1	2	3	4	5	6	7	8	9
"A"	141 Columns									
Matrix		Retention	Retention	Retention	Retention	Retention	Retention	Retention	Retention	Retention
Constraint	**Constraint**	**Elite Families**	**Dress Ups**	**Busy Families**	**Older Traditionalists**	**Young Budgets**	**Older Budgets**	**Green**	**Blue**	**Red**
Label	**Number**	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9
Budget Total	1	1	1	1	1	1	1	1	1	1
Total Acquisitions	2	0	0	0	0	0	0	0	0	0
LB EF Retention	3	1	0	0	0	0	0	0	0	0
UB EF Retention	4	1	0	0	0	0	0	0	0	0
LB DU Retention	5	0	1	0	0	0	0	0	0	0
UB DU Retention	6	0	1	0	0	0	0	0	0	0
LB BF Retention	7	0	0	1	0	0	0	0	0	0
UB BF Retention	8	0	0	1	0	0	0	0	0	0
LB OT Retention	9	0	0	0	1	0	0	0	0	0
UB OT Retention	10	0	0	0	1	0	0	0	0	0
LB YB Retention	11	0	0	0	0	1	0	0	0	0
UB YB Retention	12	0	0	0	0	1	0	0	0	0
LB OB Retention	13	0	0	0	0	0	1	0	0	0
UB OB Retention	14	0	0	0	0	0	1	0	0	0
LB Green Retention	15	0	0	0	0	0	0	1	0	0
UB Green Retention	16	0	0	0	0	0	0	1	0	0
LB Blue Retention	17	0	0	0	0	0	0	0	1	0
UB Blue Retention	18	0	0	0	0	0	0	0	1	0
LB Red Retention	19	0	0	0	0	0	0	0	0	1
UB Red Retention	20	0	0	0	0	0	0	0	0	1

Table B1 illustrates a broader view of the constraint matrix and how it is developed. The matrix was formed in Microsoft® Excel for ease of use by the marketing scientist and shows the relationship between the market segments, the decision variables, and the constraint numbers. The tableau is 198 rows and 141 columns in size, so it is not possible to illustrate the entire matrix. A ‘1’ indicates the intersection of the relationship.

This constraint matrix is passed to the linear goal programming application along with the goal priority matrix and the right-hand-side values matrix. The goal programming application processes this data and returns the 27 decisions in each time period illustrated in reports such as those in Table B2 and Table B3. All reports are posted to Microsoft® Excel.

Table B2

Asset Class Performance the Optimization Model with the Base Case

Scenario Label	**Totals**	**Change from Base Case**	**Elite Families**	**Dress Ups**	**Busy Families**	**Older Traditionalists**	**Young Budgets**	**Older Budgets**
Go Feminine Scenario								
Beginning Customer Count	5,158,439	N/C	943,451	666,341	284,494	539,124	442,952	310,830
Total Demand	$ 1,065,713,278	11.4%	$ 265,789,574	$183,139,707	$ 48,926,249	$ 108,706,103	$ 91,443,075	$ 50,510,883
- Retention	$ 710,976,294	11.8%	$ 183,619,423	$128,275,762	$ 31,332,946	$ 74,044,936	$ 58,858,648	$ 33,387,338
- Re-activation	$ 187,099,652	10.8%	$ 44,271,036	$ 28,890,029	$ 9,670,413	$ 18,581,067	$ 17,725,093	$ 8,992,360
- Acquisition	$ 167,637,332	10.4%	$ 37,899,116	$ 25,973,916	$ 7,922,890	$ 16,080,100	$ 14,859,334	$ 8,131,185
Total Investment	$ 164,056,838	100.0%	$ 38,007,841	$ 30,451,873	$ 7,397,704	$ 15,961,769	$ 11,267,606	$ 8,533,349
- Retention	$ 91,786,810	55.9%	$ 21,873,121	$ 17,191,651	$ 4,357,755	$ 9,824,926	$ 6,999,733	$ 5,131,261
- Re-activation	$ 51,537,103	31.4%	$ 11,654,878	$ 9,686,082	$ 2,120,509	$ 3,993,778	$ 2,764,361	$ 2,251,213
- Acquisition	$ 20,732,925	12.6%	$ 4,479,842	$ 3,574,140	$ 919,440	$ 2,143,065	$ 1,503,512	$ 1,150,875
Average Investment per Household	$ 29.97	-5.1%	$ 35.73	$ 41.35	$ 26.91	$ 28.59	$ 24.11	$ 28.69
Average Customer Demand (Retention)	$ 253.46	4.4%	$ 327.09	$ 324.66	$ 232.28	$ 251.73	$ 252.51	$ 220.61
Average Customer Demand (Re-activation)	$ 146.94	4.3%	$ 182.65	$ 178.31	$ 140.22	$ 143.60	$ 152.86	$ 129.26
Average Customer Demand (Acquisition)	$ 119.86	4.3%	$ 145.76	$ 144.91	$ 111.59	$ 119.37	$ 125.65	$ 106.29
Number of Re-activations	1,232,103	4.7%	242,386	162,017	68,966	129,390	115,959	69,568
Number of Acquisitions	1,354,755	4.6%	260,002	179,241	71,000	134,706	118,262	76,500
Average LifeTime Value per Customer	$ 59.74	4.3%	$ 74.23	$ 80.31	$ 50.54	$ 61.00	$ 51.27	$ 55.72
Average Profit % Per Customer	23.6%	N/C	22.7%	24.7%	21.8%	24.2%	20.3%	25.3%
Total Profit	$ 255,726,369	10.9%	$ 60,314,102	$ 45,304,119	$ 10,645,482	$ 26,341,526	$ 18,567,620	$ 12,757,656
Ending Customer Count	5,258,020	4.9%	1,063,759	736,364	274,859	558,241	467,314	297,409

Table B2 illustrates the Go-feminine scenario reported on in the main text in chapter 4 on results. Table 28 in chapter 4 did not show the full complement of segment profit and loss reports because of insufficient room in the main document. This report details six of the nine market segments. The individual performance of the segments in the asset allocation optimization is a key as to why the overall portfolio performed so well. Each market segment leveraged the information content discovered in the clustering task that was input into the portfolio optimization. The Green, Blue, and Red segments could not be reported on because of space. The total column would represent the sum over all nine asset classes. The column labeled ‘change from base case’ shows the overall performance of this trial over that of the benchmark. Significant gains in revenue, profit, and ending customer balances are achieved.

Table B3

Scenarios Comparing the Optimization Model with the Base Case

			Change from	Elite	Dress	Busy	Older	Young	Older
Scenario	**Scenario Label**	**Totals**	**Base Case**	**Families**	**Ups**	**Families**	**Traditionalists**	**Budgets**	**Budgets**
1	Base case	$ 956,743,125		$ 213,780,172	$152,241,475	$ 48,926,247	$ 96,502,641	$ 77,584,949	$ 50,510,845
2	Everybody's Happy - Great Economy	$ 1,151,231,328	20.3%	$ 265,789,574	$183,139,707	$ 60,715,331	$ 118,892,071	$103,954,554	$ 63,367,342
3	Fashion Forward - More Fancy Products	$ 912,958,629	-4.6%	$ 265,789,574	$174,787,626	$ 44,155,165	$ 96,502,430	$ 56,055,125	$ 36,494,602
4	Fashion Forward II - Targeted	$ 1,031,298,290	7.8%	$ 265,789,574	$174,787,626	$ 48,926,249	$ 96,502,430	$ 77,583,840	$ 50,510,883
5	More Elegant to Make a Statement	$ 907,018,314	-5.2%	$ 251,497,179	$183,139,707	$ 44,155,165	$ 96,502,430	$ 56,055,125	$ 36,494,602
6	More Elegant II - Targeted	$ 1,025,357,975	7.2%	$ 251,497,179	$183,139,707	$ 48,926,249	$ 96,502,430	$ 77,583,840	$ 50,510,883
7	Not Too Fussy - Versatile	$ 867,674,073	-9.3%	$ 213,782,376	$137,405,058	$ 60,715,331	$ 108,706,103	$ 62,845,403	$ 40,913,628
8	Not Too Fussy II - Targeted	$ 980,744,386	2.5%	$ 213,782,376	$152,248,166	$ 60,715,331	$ 108,706,103	$ 77,583,840	$ 50,510,883
9	More Conservative - Clothes - Fair Econ.	$ 999,489,720	4.5%	$ 242,193,157	$169,540,304	$ 44,155,165	$ 118,892,071	$ 91,443,075	$ 50,510,883
10	More Conservative II - Targeted	$ 1,044,978,443	9.2%	$ 242,193,157	$169,540,304	$ 48,926,249	$ 118,892,071	$ 91,443,075	$ 50,510,883
11	More Sporty - Youthful - Oriented Products	$ 1,003,286,280	4.9%	$ 242,193,157	$123,323,493	$ 57,449,468	$ 112,682,728	$103,954,554	$ 40,913,628
12	More Sporty II - Targeted - Good Economy	$ 1,054,911,692	10.3%	$ 242,193,157	$152,248,166	$ 57,449,468	$ 112,682,728	$103,954,554	$ 50,510,883
13	Inexpensive, Basic - Poor Economy	$ 892,926,176	-6.7%	$ 154,455,051	$ 97,438,332	$ 55,323,280	$ 96,502,430	$ 70,017,678	$ 63,367,342
14	Inexpensive, Basic II - Targeted	$ 1,023,600,915	7.0%	$ 213,782,376	$152,248,166	$ 55,323,280	$ 96,502,430	$ 77,583,840	$ 63,367,342
15	Move Upscale, Combination of 3 & 4	$ 907,018,314	-5.2%	$ 251,497,179	$183,139,707	$ 44,155,165	$ 96,502,430	$ 56,055,125	$ 36,494,602
16	Move Upscale II - Targeted	$ 1,025,357,975	7.2%	$ 251,497,179	$183,139,707	$ 48,926,249	$ 96,502,430	$ 77,583,840	$ 50,510,883
17	Go Basics - Combination of 7 & 8	$ 941,776,506	-1.6%	$ 192,936,544	$109,999,669	$ 56,380,303	$ 105,826,219	$ 85,404,690	$ 50,510,883
18	Go Basics II - Targeted	$ 1,015,937,218	6.2%	$ 213,782,376	$152,248,166	$ 56,380,303	$ 105,826,219	$ 85,404,690	$ 50,510,883
19	Go Feminine, Economy as Expected	$ 1,065,713,278	11.4%	$ 265,789,574	$183,139,707	$ 48,926,249	$ 108,706,103	$ 91,443,075	$ 50,510,883

Table B3 shows how the asset classes performed in scenario experiments. These scenario experiments are interesting in that they are designed to stress test the asset allocation optimization application. Both product mix and economic scenarios can be manipulated to understand how the optimal portfolio will allocate resources. Asset class scenario performance is visible in this report. There was not enough space available in the main text to insert a view of the individual asset class performance. The scenario reports are interesting as they represent a very efficient way to describe various states of the business. This could be a very powerful planning tool for an enterprise.

CURRICULUM VITAE

Educational History

Florida Atlantic University BS 1973 Education

Specialization: Marketing Science

Graduation Project: A Retail Analysis of Britt's Department Store

(in conjunction with an internship at Britt's)

Florida Atlantic University MS 1976 Education

Specialization: Marketing Science

Masters Thesis: *Economic Concepts in Distributive Education*

Professional Experience

2007 – Present Hewlett-Packard Corporation, Palo Alto, CA

Vice President, Business Optimization Solutions

2003 – 2007 Decision Intelligence Corporation, Eden Prairie, MN

Managing Partner, Principal Investigator, Board of Directors Member

2002 – 2003 Data & Optimization Sciences, Inc. / SAS Institute, Cary, NC

Vice President, Executive Consultant – Supply Chain Intelligence

2001 – 2002 Cray Research, Inc., Seattle, WA

President, Chief Executive Officer, Board of Directors Member

1989 – 2001 International Business Machines Corporation, Armonk, NY

Vice President, Sell & Support Solutions

Vice President, Business Intelligence Consulting & Services

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Application Development Representative

1977 – 1989 Control Data Corporation, Bloomington, MN

Director of Environmental Sciences and Emerging Technologies

Manager, Strategic Marketing, Supercomputer Services

National Accounts Sales Manager, Business Information Solutions

District Sales Manager, Supercomputer Services

Marketing Manager, Business Information Solutions

Assistant to the Southeast Area Vice President, Service Bureau Company

Marketing Representative, Service Bureau Company

Systems Marketing Representative, Service Bureau Company

1973 – 1977 School Board of Broward County, Ft. Lauderdale, FL

Instructor of Marketing and Economics

Professional Training and Certifications

Harvard University	Computational Fluid Dynamic	1985
Massachusetts Institute of Technology	Computational Fluid Dynamics	1985
Wharton School of Business	Advanced Banking School	1991
Harvard University	IBM Presidents Class	1992
University of Minnesota	Analytical Approaches to Mktg.	1994

M.I.T. Sloan School of Business Supply Chain Optimization 2003

Patents and Awards

2003 U.S. Patent Number: 6,567,786 issued for "Horizontal Marketing and the Improvement of Customer Contact Strategies"

2001 IBM Chairman's Award

2000 Informs Franz Edelman Award Finalist for "Horizontal Marketing at Fingerhut"

1996 IBM Scientific and Technical Computing Directors Award

1994 IBM Consulting Group, Engagement Excellence Award

1978 - 1984 Control Data Top Performer Sales Award at Service Bureau Company

1978 Control Data - #1 in Service Bureau Company Sales School

1972 Florida Atlantic University – President of Collegiate Distributive Education Clubs of America

1971 Broward Community College – Divisional Honors Scholarship, Science and Mathematics

1970 – 1973 Broward Community College and Florida Atlantic University – Deans List

Publications (published and unpublished)

Haydock, M., & Bibelnieks, E. (Eds.). (1999). *Horizontal marketing: Optimized one-to-one marketing*. London: Macmillan Press.

Campbell, D., Erdahl, R., Johnson, D., Bibelnieks, E., Haydock, M., Bullock, M., et al. (2001). Optimizing customer mail streams at Fingerhut. *Interfaces, 31*(1), 77-90.

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Haydock, M. P. (2005). Contact optimization: Marketing program volatilities. *The International Journal of Applied Management and Technology*, *3*(1), 141-158.

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"Behavior Modeling and Pricing Risk" – Presentation unpublished – 2005.

"Saturation as a Proxy for Consumer Situational Behavior" – Presentation unpublished – 2005.

Haydock, M. (2006). Contact optimization: Asset class determination and profile risk. *The International Journal of Applied Management and Technology, 4*(1), 101-124.

"A Game Theoretic Approach to Airline Repair Shops Scheduling" – Presentation unpublished – 2006.

"Spare Parts Optimization" – Presentation unpublished – 2006.

Haydock, M. (2006). Contact optimization: Social systems segmentation and analysis. *The Proceedings of The Second Annual Conference on Applied Management and Decision Sciences*, 300-320.

"Contact Economics: Asset Allocation and Investment Risk" – Presentation unpublished – 2006

"Contact Optimization: Pricing Under Uncertainty" – Presentation unpublished – 2006

"Contact Economics: Allocation Under Uncertainty" – Presentation unpublished – 2006

Haydock, M. (2007). Media Allocation Optimization. *International Journal of Applied Management and Technology, 5*(2), 146-164.

Professional Associations

Institute for Operations Research and Management Science (INFORMS)

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