



Marketing Science Institute Special Report 08-207

Strategic Allocation of Marketing Resources: Methods and Managerial Insights

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STRATEGIC ALLOCATION OF MARKETING RESOURCES: METHODS AND MANAGERIAL INSIGHTS

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MSI Report

September 2008

Acknowledgement: I thank Jeff Meyer for data collection assistance and Roger Kerin, Tarun Kushwaha, the *AMA* review team, and the *MSI* review team for helpful comments.

**STRATEGIC ALLOCATION OF RESOURCES:
METHODS AND INSIGHTS
(Venkatesh Shankar)**

This article discusses how firms strategically allocate their resources between marketing and non-marketing variables, across products, markets, channels, customers and over the product life cycle. It presents resource allocation processes, models, and insights with examples drawn from different companies and industries. It highlights emerging methods and research directions in strategic resource allocation and planning for both executives and researchers.

1. Introduction and Overview of Resource Allocation

Marketing resource allocation is a strategic priority for organizations worldwide. From the largest enterprise to the smallest start-up, marketing resource allocation continues to dominate the decision-making realm of the chief marketing officer (CMO) and other marketing executives. Many marketers live and die by the marketing allocation strategies they help formulate and execute. According to a recent CMO Council (2007) report, the number-one challenge for most CMOs is to quantify, measure, and improve the value of marketing investments and resource allocation. Therefore, a deep understanding of marketing resource allocation is critical for practitioners and academics alike.

Marketing executives are interested in marketing resource allocation methods and the associated substantive insights they can apply in practice. The key marketing resource allocation decisions include those between marketing and product-related variables such as research and development (R&D); across different products and brands, marketing mix elements, markets, countries, customers, and channels; and over the product life cycle. An overview of these types of decisions appears in Figure 1. To assist these decisions, marketing researchers have developed several resource allocation models. The applications of these models have led to several useful empirical findings and insights.

< Figure 1 about here >

Consider the marketing resource allocation problem at Samsung Electronics, one of the world's leading electronics companies. In 1999, Eric Kim, at the time Samsung's new executive vice president and CMO, was challenged to reallocate a corporate budget of \$1 billion across 14 products over 200 countries and to improve the return on marketing spending.¹ Before the reallocation exercise, the company had allocated resources to products and countries roughly in proportion to the sizes of the products and markets. Faced with the reallocation task, Samsung collected data on variables such as country population, population of target buyers, spending power per capita, per capita spending on product category, category penetration rate, category growth, category profitability, share of the company's brand, media costs, previous marketing expenditures, and competitor actions. Samsung

¹This example is drawn from Corstjens and Merrihue's (2003) work.

developed a resource allocation model based on these factors and simulated forecasts of future profits based on the revised model.

How did the new model change resource allocation at Samsung? It informed Samsung that the company had invested more in North America and Russia than the profit potentials in those regions justified. Following this analysis, Samsung reduced the total shares of the budget to these regions from 45% to 35%. Furthermore, the model pointed out that the firm had underinvested in Europe and China, so Samsung increased the combined shares of the budget for those regions from 31% to 42%.

With regard to products, the model suggested that three categories—mobile phones, vacuum cleaners, and air-conditioning units—were getting more than half the marketing budget, but other potentially profitable categories (i.e., camcorders, DVD players and recorders, televisions, PC monitors, refrigerators, and VCRs) were being starved of support. This finding convinced Samsung to reduce its spending on mobile phones, vacuum cleaners, and air-conditioning units by 22%.

What were the results of the resource reallocation in Samsung? In 2002, the company achieved significant market share gains in four categories in which it increased marketing spend: camcorders, flat-panel computer monitors, DVD players and recorders, and digital televisions. It catapulted from tenth to third in the digital music player market, from eighth to second in the LCD monitor market, and from an insignificant rank to eighth in the portable DVD player market. Furthermore, Samsung's brand value increased by 30% to \$8.3 billion, while the brand value of its closest rival, Sony, decreased by 7% to \$13.9 billion during the same period. Samsung's annual sales rose 25% from \$27.7 billion in 2001 to \$34.7 billion in 2002, while its net income grew from \$5.1 billion in 2001 to \$5.9 billion in 2002. These improved results could be attributed at least in part to marketing resource reallocation. As Samsung's resource reallocation experience suggests, effective allocation of resources can help spiral a company's performance and brand value upward.

1.1. Types and Principles of Resource Allocation Models

Regardless of the allocation context, normative models of resource allocation can be classified into four broad types: (1) a set of optimization rules applied to an econometrically estimated model, (2)

empirical models that offer norms for strategic decision making, (3) analytical models with or without empirical estimation of market-specific parameters, and (4) decision calculus models in which the parameters are assessed by managerial input (Gatignon 1993). The first two types of models are quite similar in approach. Herein, we primarily review the first three types of models.²

In all the types of models, optimal resource allocation is based on the fundamental microeconomic and mathematical principle that an optimal level of spending on an element of resource allocation is that at which the marginal return from an investment in that element equals the marginal costs of that investment. Many resource allocation decisions are based on elasticities or responsiveness and costs or margins associated with the variables involved in the allocation problem. Elasticity of a variable is the percentage change in the outcome variable (sales or profits) in response to a percentage change in that variable. A key decision rule is to allocate most resources to the variable with the highest elasticity.

2. Strategic Allocation of Marketing and Product-Related Resources

Whether at the corporate, business unit, or product line level, executives frequently make decisions on allocating resources to both marketing activities and nonmarketing activities, such as R&D. Although firms base such decisions on factors such as past decisions, the type of industry, whether the product is new or existing, market responsiveness, and the interrelation among the different variables, not much is known about the effectiveness of such decisions. Furthermore, there is a dearth of tools for such resource allocation decisions.

2.1. Allocation Between R&D and Marketing

Allocation between R&D and marketing is a strategic decision. Consider, for example, the pharmaceutical industry. In 2006, pharmaceutical companies in North America spent roughly \$55.2 billion on R&D, or 19.4% of sales (PhRMA 2007), and \$27.3 billion on marketing expenditures, or approximately 10% of sales, for a total outlay of \$83 billion, or approximately 30% of revenues, against

² We do not address decision calculus models (e.g., Little 1970; Lodish 1971) and the issue of overall optimal budget determination although the allocation and overall budget decisions may be related (Lodish, Curtis, Ness, and Simpson 1988; Mantrala, Sinha, and Zoltners 1992).

industry sales of \$274.9 billion. With such a large outlay on R&D and marketing, allocating resources between them has critical implications for the returns to the firm.

The development of models for allocating resources between R&D and marketing has been a subject of discussion and debate among academics and practitioners. Any effective model for allocation between these two (or more) strategic variables involves a deep understanding of the industry, the competitive context, the unique effects of each variable on firm profits, and the effects of interactions among the variables.

Two issues make the formulation of an allocation model for R&D and marketing challenging. First, although marketing expenditures have both short-term and long-term effects on firm sales and profits (Dekimpe and Hanssens 1999), R&D investments primarily have a long-term effect on firm profits (Erickson and Jacobson 1992). Second, the interactions between R&D and marketing investments and their impact on firm profits are complex. On the one hand, higher marketing expenditures can enhance the effectiveness of R&D spending, leading to increased R&D levels. On the other hand, greater marketing spending can lead to lower R&D spending, given that most firms have fixed resources.

Most models do not deal directly with this high level of strategic allocation. There are, however, descriptive models that study the effects of R&D and marketing variables on returns and profits (e.g., Bayus, Erickson, and Jacobson 2003; Erikson and Jacobson 1992) and offer implications for resource allocation between these variables. Erickson and Jacobson (1992) estimate an econometric model of the effects of R&D and advertising expenditures on stock market returns and return on investment and conclude that after controlling for unobservable firm-specific factors and the feedback between discretionary expenditures and profitability, the accounting and stock market returns to R&D and advertising expenditures are substantially lower than previously believed. These findings imply that companies should not allocate more expenditures to either R&D or marketing than required. Bayus, Erickson, and Jacobson (2003) analyze financial returns from new product introductions in the computer industry. They find that greater R&D spending and new product introduction is accompanied by a reduction in marketing spending and that these changes lead to higher profit rates.

In practice, however, many firms set their R&D and marketing budgets according to one of the following methods: objectives and task, percentage of sales revenues, percentage change from the previous period, or competitive parity. These methods do not address the optimality of allocation between R&D and marketing, so there is a strong need for optimal models of and insights into resource allocation between R&D and marketing expenditures.

Figures 2 and 3 capture the resource allocation trends among R&D; selling, general, and administrative (SG&A) expenses; and advertising during 2001–2005 for *Fortune* 500 companies. The firms are divided into the following categories of industries: consumer packaged goods (CPGs), consumer durables, services/retail, high-tech, and other.

< Figures 2 and 3 about here >

During 2001–2005, SG&A, advertising, and R&D expenses as a percentage of sales remained fairly stable. Across industries, R&D expenses as a percentage of sales were consistently higher (2%–3%) than advertising expenses as a percentage of sales. The high-tech and CPG sectors had the highest SG&A expenses as a percentage of sales. The high-tech sector had the highest R&D expenses as a percentage of sales, while the CPG sector had the highest advertising expenses as a percentage of sales.

During 2001–2005, in the consumer durables and CPG sectors, SG&A expenses as a percentage of sales fell by approximately 4%, while advertising and R&D expenses as a percentage of sales remained fairly stable. In the services/retail sector, SG&A expenses as a percentage of sales fell by approximately 3%, while advertising and R&D expenses as a percentage of sales rose by approximately 2% and 1%, respectively. The high-tech sector consistently had the highest R&D expenditures as a percentage of SG&A expenses, while the services/retail and CPG sectors had the lowest R&D expenditures. In the services/retail sector, both advertising and R&D expenses as a percentage of SG&A expenses rose by approximately 6% and 4%, respectively. Other than the consumer durables sector, which saw a jump of approximately 4% in 2005, all other sectors' advertising and R&D expenses as a percentage of SG&A expenses remained fairly stable.

In summary, allocation to R&D is higher for high-tech firms, while allocation to marketing is higher for consumer goods firms. During 2001–2005, expenditures on R&D and marketing remained stable for most industries except for service firms, which increased both R&D and marketing expenditures over this period. Firms should be careful not to overspend on R&D or marketing, and often, if they increase R&D expenditures, they also reduce marketing spending.

When firms decide how much of the budget to allocate to marketing, the next decision is how to spread those dollars across different marketing elements, such as advertising, sales force support, and sales promotion. Marketing mix allocation is widely practiced by many firms, though the marketing mix variables vary considerably across industries. In the pharmaceutical industry, for example, of the total industry marketing spending of \$27 billion in 2006, \$15.9 billion was spent on detailing and samples, \$7.2 billion was expended on other professional physician marketing efforts (e.g., journal advertising), and \$4.2 billion was spent on direct-to-consumer advertising (IMS Health 2006). Thus, a majority of allocation is toward sales force efforts.

In contrast, in the CPG industry, the bulk of the allocation is divided between advertising and sales promotion. For example, Procter & Gamble used a marketing mix model to move approximately \$400 million of its 2005 marketing budget of \$4.3 billion to advertising in new media, and Clorox used a marketing mix model to shift its allocation from advertising to sales promotion (Neff 2004).

2.2. Allocation Between Advertising and the Sales Force

Advertising and sales force expenditures form a big chunk of firms' marketing spending in many markets, including those for industrial, high-tech, and pharmaceutical products. Lilien (1979) analyzed marketing expenditure allocation data obtained during the 1970s on 131 diversified industrial products from 22 companies through the ADVISOR, a joint project of Massachusetts Institute of Technology and the Association of National Advertisers. The findings from Lilien's analysis show that firms' allocation toward the sales force relative to advertising depends on its size, the size of an average order, the stage in the product's life cycle, the complexity of the product, the fraction of the product's sales made-to-order, and the purchase frequency of the product.

Often, marketing mix variables, such as advertising and sales force, are correlated. Rangaswamy and Krishnamurthi (1991) propose an equity estimator for estimating regression models of sales response in which the marketing mix variables are typically multicollinear. Their application to pharmaceutical data shows that firms should spend more on the sales force than on advertising because sales force elasticities are much higher than those for advertising for ethical drugs.

Gatignon and Hanssens (1987) develop an econometric model of the effects of local advertising and sales force in the context of Navy recruitment. They estimate their model and show that sales force effectiveness in the hiring of Naval personnel increased with local advertising support, suggesting a synergy between advertising and personal selling efforts.

Gopalakrishna and Chatterjee (1992) develop and estimate a customer account level sales response model to capture the separate and joint effects of advertising and personal selling (sales force) on the sales of a mature industrial product in the presence of passive competitors. They conclude that the optimal marketing budget increases with the number of accounts and the business potential of the accounts. Although they do not directly address the allocation between advertising and personal selling, they suggest that if customer accounts are equally responsive to communication effort, then greater personal selling effort should be directed to the segment with the greater average business potential.

Shankar (1997) develops optimal allocation rules based on a decoupled multiplicative sales response model of allocation between advertising and the sales force. The model allows for the interaction between advertising and the sales force and is specified as follows:

$$(1) S_{it} = e^{a_{it}} A_{it}^{b_i} A_{jt}^{c_i} D_{it}^{d_i} D_{jt}^{f_i} P_{it}^{-g_i} P_{jt}^{h_i}, \text{ with } a_{it} = \alpha_i - \frac{\phi_i}{T_{it}},$$

where S_{it} is units sales, A_{it} is the advertising spending, D_{it} is the sales force spending, P_{it} is the unit price, and T_{it} is the “time in market” of brand i in period t . The terms a – h , α , and ϕ are parameters to be estimated, and j is the main competitor brand. Maximizing the profit function, Π , with respect to advertising, sales force spending, and price provides the following:

$$(2) \underset{A,D,P}{Max} \Pi_{it} = m_{it}S_{it} - A_{it} - D_{it} - F_{it},$$

where m_{it} denotes the contribution margin and F is other fixed costs. Shankar derives the following equilibrium levels of spending for advertising and the sales force, respectively:

$$(3) A_{it}^* = b_i m_{it} S_{it}, \text{ and } D_{it}^* = d_i m_{it} S_{it}.$$

This result is an extension of the Dorfman and Steiner (1954) theorem on price and advertising elasticities. This result holds (1) if both the competitors play a Nash game or make their marketing mix decisions simultaneously or (2) if the competitor is a Stackelberg follower or makes the decision after the focal brand in one or all of the marketing instruments. His results show that, in general, a follower (leader) role in a marketing mix variable, a static (growing) market, a decrease (increase) in own elasticity, and margin all lead to a reduction of spending in that variable. Shankar's model and results offer compelling insights into the allocation between advertising and the sales force. The allocation strategies proposed by his model are both theoretically and empirically driven, so they have important normative implications for managers. His empirical analysis, however, is based on one product category.

Collectively, these models offer some generalizable insights into allocation between advertising and the sales force. The spending level on a marketing variable, such as advertising or sales force, is typically directly proportional to the elasticity of the variable and contribution margin. Managers should allocate spending between advertising and the sales force according to their competitively relative elasticities. These elasticities may differ across industries, markets, and firms.

2.3. Allocation Between Advertising and Sales Promotion

In many markets, marketers need to decide the levels of expenditures for advertising and sales promotion. This decision is particularly important for consumer products and services. For CPGs, during the past two decades, the spending on advertising relative to sales promotion has steadily declined. For some of these products, sales promotion now constitutes two-thirds or more of marketing spending.

Many practitioners follow several rules of thumb, including spending 75% of the budget on proven media, message, and channels and at least 5% on well-designed marketing allocation experiments.

Several factors have contributed to the continuing dominance of sales promotion over advertising for CPGs. First, most consumers make purchase decisions at the point of purchase, compelling marketers to spend more on in-store features, display, and other merchandising activities. Second, retailers have become more powerful over the years, so trade promotions have increased considerably. Third, mass media advertising has become fragmented and less effective with the advent and growth of the Internet, digital video recorders, and more targeted communication vehicles.

A few studies have examined the allocation between advertising and trade promotions. Sethuraman and Tellis (1991) incorporate two facets of trade promotions (price cuts) into the Dorfman and Steiner (1954) model of allocation: the opportunity loss from buyers who would have bought at the regular price and the loss from retailers' fractional pass-through of promotions to consumers. They find that when both promotion and advertising are profitable, the allocation between them is determined by their relative elasticities. Specifically, they find that for consumer nondurable goods, price cut elasticity is approximately 20 times that of advertising elasticity, while for durable goods, the corresponding ratio is only five.

Neslin, Powell, and Stone (1995) analytically extend the substitutability of advertising and trade promotion in optimal allocation to a dynamic context that includes a retailer's forward-buying behavior and carryover effects of advertising. Such a lopsided ratio of promotion to advertising elasticities may explain the migration of marketing dollars toward sales promotion for CPGs during recent years. However, because advertising has long-term effects (Dekimpe and Hanssens 1999), companies may be myopic in overallocating to sales promotion on the basis of short-term effects.

Although there are rules of thumb and marketing mix models that guide the allocation of marketing spending between advertising and sales promotion, many of these are not based on optimization principles. A major challenge in developing optimal allocation models between advertising and sales promotion is that often these two variables have synergistic effects on sales and profits, making it difficult to disentangle their unique effects.

Naik and Raman (2003) develop a dynamic advertising model (with advertising carryover effects) that captures synergy between communications in multiple media, using the Kalman filtering methodology. They estimate their model on data from Dockers brand and show a synergistic effect between television and print advertisements. They conclude that as the synergistic effect increases, a firm should raise its advertising budget and also increase its allocation to the less effective medium. They generalize the model to include differential advertising carryover and asymmetric synergy among media elements.

Naik, Raman, and Winer (2005) propose a model for allocation between advertising and sales promotion when the two have interaction effects and when managers can incorporate strategic foresight about competitor behavior. They use an extended Lancaster model and develop a continuous-discrete estimation method to calibrate dynamic models of oligopoly using market data. In the Naik and colleagues (2005) optimization model, brand i decides its advertising (u) and promotional expenditures (v) to maximize its performance index given by:

$$(4) I(u_i, v_i) = \int_{t=0}^T e^{-\rho t} [(p_i(t) - v_i(t))m_i(t) - c(u_i(t))] dt$$

where ρ is the discount rate, p is the brand price, m is the market share, c is the cost of advertising, and t is time. Solving this dynamic optimization model using data on five detergent brands, Naik and colleagues (2005) find that large brands underadvertise and overpromote, while small brands underadvertise and underpromote and that competitor responses to advertising and promotion are asymmetric.

In summary, consumer goods companies increasingly allocate more toward sales promotion and nontraditional media relative to advertising in the mass media, mainly because short-term mass media advertising elasticities are much smaller than elasticities of promotion or targeted media advertising. When interactions between advertising and sales promotions are included, large brands tend to underadvertise and overpromote, while small brands appear to advertise less and promote more.

2.4. Other Marketing Mix Allocations

Several models of marketing mix allocation across other elements exist (Mantrala 2002). Others include those on media and communications mix (Montgomery and Silk 1972), sales territory allocation (Rangaswamy, Sinha, and Zoltners 1990), direct mail campaigns (Elsner, Krafft, and Huchzermeier 2004), and product and nonproduct marketing elements (Shankar 2006). The marketing mix involving nontraditional media is gaining ground in today's environment. According to A.G. Lafley, chief executive officer of Procter & Gamble, although the company still invests mostly in television, the media mix for major brands now includes a greater focus on in-store, Internet, and nonmeasured media (Tode 2007).

Insights on media and communication mix allocation are somewhat limited. Using a distributed lag model of market share response on expenditures related to journal advertising, direct mail, samples and brochures for a company's ethical drug, Montgomery and Silk (1972) find that market share elasticities are highest for journal advertising and lowest for direct mail. They, however, observe that the company's actual allocation was inversely proportional to the suggested allocation mix. Strictly speaking, their model is based on market share response and would need to be extended to sales and profits to determine optimal allocation. Nevertheless, the findings suggest that many firms are still in search of optimal communications mix. Given the expanded mix of communication vehicles available to marketers, optimal communication mix models are likely to be more complex than before.

Furthermore, managers need to make allocation decisions that are simultaneously related to product line length, channel coverage, and pricing. Shankar (2006) develops a simultaneous model of demand and supply with product line and other marketing actions, which can be used to identify reaction and anticipation elasticities through the rational expectations approach. He estimates the model using data from the computer printer market, which comprises the market leader, Hewlett-Packard, and followers, Epson, Canon, and Lexmark. The results show a firm is more likely to allocate more to expanding a product line when its competitors changed their product lines in the past, when the firm is large, and when its price is high.

3. Allocation Across Products

Marketers make decisions on the allocation of funds toward different products and brands in their product portfolio. Models on allocation across products range from product portfolio models to models for a specific industry context (e.g., Mantrala, Sinha, and Zoltners 1992). Among product portfolio models, the Boston Consulting Group (BCG) matrix (Henderson 1998) is the best-known tool. This matrix begins with identifying the positions of a firm's or a business unit's products along two dimensions: relative market share and market growth rate. Products can fall under four possible quadrants. (1) "Cash cows" are products that are characterized by high relative market share but low market growth rate, (2) "stars" are those that have both high growth rate and relative market share, (3) "question marks" or "problem children" refer to products that have low relative market share in high-growth markets, and (4) "dogs" are products that have low relative market share in low-growth markets. The main resource allocation guidelines are to use the surplus cash from "cash cows" and "stars" (if any) to fund "question marks" so as to help them become "stars" for the future and to divest "dogs" unless they are strategic complements to other products or have substantial exit barriers.

Many firms practice variants of this tool (Kerin, Mahajan, and Varadarajan 1990). The enhancements to the BCG model are based on the recognition that relative market share is a proxy for competitive strength, and market growth is a measure of market attractiveness. For example, General Electric uses a model that has these two broad dimensions, which are determined by multiple indicators that include relative market share and market growth.

Despite their widespread use, product portfolio models suffer from several limitations. First, they do not explicitly incorporate profits or margins as a major criterion. They implicitly assume that profits are correlated with relative market share. Second, the allocation rules from these models are based on a static view of the business universe. In reality, fast movement in markets and competitive dynamics may alter some product positions in the matrix, calling for changes in allocation rules that are difficult to make after investments are made on analysis of the original matrix. Third, the definitions of high- and low-growth rates or relative market shares are subjective, driving the categorization of products as "stars," "question marks," "cash cows," or "dogs" and the allocation rules. Therefore, although the portfolio

models provide a useful high-level basis for resource allocation across products, they should be supplemented with more granular resource allocation models that are more detailed and specific to the industry and the firm.

Richardson (2004) develops and applies a linear programming model to allocate marketing funds for Reckitt and Coleman's (now Reckitt and Benckiser's) products, including Lysol. His approach involves weighing several company-specific criteria such as market growth, brand share, brand sales, contribution, and market size against the budget constraints of the project, group, business unit, and firm levels. He claims that the model led to improved profits, simultaneous examination of alternatives, fast response to unexpected situations, and better utilization of the data at the firm.

Taken together, models and studies of allocation across products offer interesting insights. Firms should use the profits generated by "cash cows" to allocate more funds toward products with greater future potential. In deciding which products have greater future potential, firms should use multiple factors that reflect the attractiveness of the markets and the firm's competitive position.

4. Allocation Across Markets/Countries

Allocation across different markets or countries is an important but challenging task. It requires a deep understanding of the response behavior of customers in different regions. Differences in responses across markets and countries increase the complexity of decision making. As previously noted in the Samsung example, however, resource allocation based on a careful analysis of the factors that drive the differences across countries can result in substantial improvements in allocation decisions. These market- or country-specific factors include the population of target buyers, spending power per capita, per capita spending on product category, category penetration rate, category growth, category profitability, share of the company's brand, media costs, previous marketing expenditures, and competitor actions.

Lilien and Rao (1976) propose a model for allocating retail outlet building resources across different markets for a consumer product. Lilien and Rao maximize the net present value of expected returns from a construction plan, comprising different number of outlets in different markets subject to size constraints and determine the optimal plan. The model is based on an S-shaped relationship between

outlet share and market share. Lilien and Rao implemented their model in a consumer goods firm in which, it went on to become an integral part of the planning process.

In addition to market-specific factors, some cross-market factors such as diffusion, market learning, and multimarket competition may drive allocation rules. Chintagunta and Desiraju (2005) develop a structural model that incorporates both cross-market contact effects, in addition to interaction effects, across marketing instruments and within-market competitive interaction effects, consistent with the theory of multimarket contact competition. They estimate their model using data from multiple European countries for a blockbuster category of ethical drugs. They find that detailing elasticities are comparable across the United States, Germany, and Italy but are higher in the United Kingdom and France, suggesting a greater allocation of the detailing budget to the latter regions.

Fischer et al. (2005) propose a market response model for entry timing across countries. Although they do not explicitly address allocation of marketing expenditures across countries, their results on marketing expenditures have implications for such allocation decisions. They find that a waterfall international entry strategy (entering markets sequentially) enhances marketing spending effectiveness. The normative implication for a brand that sequentially enters multiple markets or countries is that it should allocate greater spending to the later countries of entry than what would be appropriate based on market response in those countries if there were no prior entries in other countries.

Thus, although allocation across market or countries is a critical task, little practical guidance is available. The allocation criteria should go beyond country-specific factors, such as target market population, category growth, and profitability, to include cross-country effects that may be due to diffusion, market learning, and multimarket competition.

5. Allocation Across Customers and Channels

As organizations become more customer-centric, the allocation of resources by customers and customer segments is gaining greater importance than ever before. As companies increasingly offer their products through multiple channels, such as retail stores, the Web, and catalog or direct mail, and as more

consumers buy them through different channels, the allocation of marketing efforts targeted at customers across channels is also becoming a critical issue for many marketers.

Models of marketing resource allocation across customers are primarily based on customer lifetime value (CLV). Venkatesan and Kumar (2004) identify low- and high-value customer segments on the basis of CLV and determine the optimal allocation of marketing resources to these segments.

Venkatesan and Kumar maximize the following expression for CLV to determine x_{iml} , the optimal number of communication contacts to customer i in channel m in year l .

$$(5) CLV_i = \sum_{y=1}^{T_i} \frac{CM_{iy}}{(1+r)^{y/f_i}} - \sum_{l=1}^n \frac{\sum_m c_{iml} x_{iml}}{(1+r)^{l-1}}$$

where CM is predicted contribution margin, y is purchase occasion, r is discount rate, c is unit marketing cost, f is predicted purchase frequency, n is number of years to forecast, and T is predicted number of purchases until the end of the planning period. Applying this model to data from a large multinational computer hardware and software company, Venkatesan and Kumar find that the effect of marketing communication on CLV is nonlinear across channels and that marketers can improve profits by maximizing CLV.

Prior research has also examined the allocation between customer acquisition and retention (Reinartz, Thomas, and Kumar 2005) and between retention and reacquisition of lost customers (Thomas, Blattberg, and Fox 2004).

As the practice of allocation by customer segment has evolved, allocation across customer-channel segments has become the next key development in resource allocation practice (Kushwaha and Shankar 2007, 2008). A study by McKinsey & Company calls for developing resource allocation metrics across channels (Myers, Pickersgill, and Van Metre 2004). Neslin and colleagues (2006) emphasize the need to develop models for the allocation of marketing resources across channels.

Anderson, Lodish, and Weitz (1987) study the impact of variables associated with a financial portfolio model and the channel relationship on the selling time allocated by 71 independent sales agencies to the principals they represent. They find that the time (and resource) allocated to principals is

consistent with an optimal microeconomic model, but channel relationship elements such as communication, participation, and feedback also influence resource allocation.

Kushwaha and Shankar (2008) propose an approach and model for optimal allocation of marketing efforts to each customer-channel segment. Their approach comprises marketing response models for each component of firm profit, purchase frequency, purchase quantity, product return propensity, and contribution margin. Their purchase frequency model is an extended beta geometric/negative binomial distribution model, purchase quantity and product return propensity is a conditional negative binomial distribution model, and contribution margin is a gamma–gamma model. The optimal marketing effort allocation to each customer-channel segment is a function of the model parameters for that segment. They estimate the models using customer-level purchase, cost, and promotional data from a large marketer of shoes and apparel accessories across the catalog, the store, and the Web and solve the optimization model in Excel using simulation. Their results show that consumer response to the company’s marketing efforts varies significantly across the customer-channel segments for the different profit components, purchase frequency, purchase quantity, and contribution margin. Figure 4 shows the differential responsiveness across segments. Using a holdout sample analysis, they show that firm profits can be substantially improved by optimally reallocating marketing efforts across the different customer-channel segments. In their revised allocation, the multichannel segment exhibits the highest percentage growth in budget and profit, highlighting the high profit potential of the multichannel segment.

< Figure 4 about here >

Overall, there are some useful insights into allocation by customers and channels. Firms should allocate more to customers and customer segments that have higher CLVs than others. Multichannel customer segments are most profitable, so an optimal allocation model based on the responsiveness of customer-channel segment by profit components, such as purchase frequency, quantity, contribution, and return propensity, can help marketers improve the returns to marketing efforts.

6. Allocation over the Product Life Cycle

As a product goes through different stages in the product life cycle, marketers' strategic allocation decisions heavily influence its growth. Prior empirical analyses offer conflicting evidence or guidelines on changes in advertising spending over the product life cycle. Lilien and Weinstein (1984) and Parsons (1975) suggest that firms should decrease advertising expenditures over the life cycle, while Winer (1979) suggests that companies should increase advertising spending over the life cycle. However, Farris and Buzzell (1979) find no evidence for the main effect of the product life cycle on advertising expenditures. These studies do not consider any interaction or moderating effects of the product life cycle, nor do they study the allocation between advertising and other marketing mix variables, such as sales force.

Shankar (2008) develops a model to examine the effects of the product life cycle stages on a brand's strategic marketing allocation between advertising and the sales force. He allows the parameters to be moderated by the stage in the product life cycle. He estimates his model on data obtained from 29 brands in eight leading pharmaceutical categories over their life cycles. The results show that a brand's strategic marketing (pull vs. push, or emphasis on advertising vs. sales force expenditures) is moderated by its market position and the stage it is in the product life cycle. The results also show that dominant brands significantly shift their resource allocation toward a push strategy or sales force while moving from the growth to the mature stages of the product life cycle; in contrast, weak brands shift their allocations toward a pull strategy or advertising from the growth to the mature stages. Shankar's (2008) data cover the largest therapeutic categories over long periods, making the analysis empirically generalizable to the pharmaceutical industry. Nevertheless, the data do not include R&D expenditures and do not cover other industries.

Taken together, the models offer some useful insights for effective resource allocation decisions over the product life cycle. A dominant (weak) brand shifts its strategic resource allocation toward a push (pull) strategy as it moves from the growth to the mature stages of the life cycle. Therefore, allocation to

advertising relative to the sales force may decrease (increase) for dominant (weak) brands over their life in markets that are more elastic to sales force than advertising.

A summary of selected resource allocation models, the associated data, key findings, and limitations appears in Table 1. The models range from econometric models to optimization models to game-theoretic or other analytic models. The data cover a broad spectrum of industries, including CPGs, durables, pharmaceutical drugs, and industrial products. The key insights include optimal allocation based on competitively relative elasticities and several factors such as target population, category profitability, and growth potential. A key limitation of most models is that competitor responses—particularly, anticipated competitor actions—are not captured well. Furthermore, interaction effects among allocation variables are not often explicitly incorporated into the optimization approach.

< Table 1 about here >

7. Allocation to New Media

With the emergence and rapid growth of unmeasured and new media, the allocation of marketing resources to these avenues is becoming a challenging task for marketers of all products (Shankar and Hollinger 2007). Spending on unmeasured media includes expenditures on search engine marketing, Internet search ads, mobile media, social networking media, events, contests, in-store ads, and product placement. Although the proportion of the marketing budget allocated to such media is still low for many products, it is rising. For example, Nike's allocation of its U.S. advertising budget to unmeasured media increased from 45% in 1996 to 67% in 2006 (Story 2007). Furthermore, although most CPG manufacturers still spend the vast majority of their marketing budgets on traditional media, their allocation to new media is steadily increasing. For example, Procter & Gamble, the leading consumer goods marketing spender, hiked its spending on unmeasured media in 2006 by roughly 15% over 2005 compared to an increase of only 3.9% in measured media in the same period (*Advertising Age* 2007).

A report based on a survey of 382 marketers reveals interesting patterns in marketing mix spending and allocation to the new media (DMA 2008). A summary of the use of the media types appears in Figure 5. According to the report, email is used by most marketers (79.1%), followed by direct mail

(75.4%); 75.8% of respondents use more email, 61.1% use more online video, and 62.9% use more search engine marketing, than they were using three years earlier. The survey found that for business-to-consumer (B2C) marketers, direct mail continues to be the most popular marketing avenue (32.2%), followed by email (11.3%) and that marketers attribute 29% of the revenue generated from a campaign to direct mail, followed by email with 21.6% . The return on investment (ROI), however, is greater for email than it is for other forms of communication (nearly twice the revenue share relative to its budget share), according to the report.

The study also reports interesting differences between B2C and business-to-business (B2B) companies and between small and big firms. It reports that B2B integrated campaigns use telephone (42.7% vs. 29.3%) and events (34.9% vs. 18%) more often than do B2C campaigns, which in turn use DR Newspaper/Magazine ads (29.4% vs. 18.2%) and DR TV/Radio (29.4% vs. 4.2%) ads more frequently than do B-2B campaigns. Furthermore, according to the study, B2C (B2B) marketers derive 8.2% (1.1%) of their responses from their direct marketing campaigns. Finally, the study found that more small companies (fewer than 100 employees) use new media than do large companies---17.9% vs. 11.4% use RSS feeds, 32.1% vs. 24.6% blog, and 28.4% vs. 23.2% have social networking sites.

Retailers are using different forms of the new media. Many retailers use email to alert shoppers about new products, promotions, and store openings. Some retailers like Kroger (<http://shortcuts.com/?promo=kroger>) even offer coupons for downloading at their websites onto her/his loyalty card, saving the need to identify and clip coupons. Consumers can automatically redeem these coupons at the store checkout when they present their loyalty card. Retailers like American Eagle has Facebook applications, while retailers like Wal-Mart and Target have Facebook sponsored groups, Urban outfitters has MySpace pages, 1-800-Flowers has second life e-stores, Buy.com, Radioshack, and Overstock.com have Youtube/Video podcasts, and Officemax, Burger King and Taco Bell have viral micro sites (Bustos 2008).

There is a dearth of formal models of allocation to new media. Effective allocation models in the context of the new media require a deep understanding of the effectiveness of these media. Although

improved data availability in the new media enables firms to measure their effectiveness more accurately than before, existing metrics are still in their infancy. For example, in the initial years of the Internet, marketing allocation to the Web was based primarily on “eyeballs” or site traffic. With the advent and growth of targeted search advertising pioneered by Google, click-through has become the key metric for allocating advertising dollars on the Web. Marketers, however, are still searching for a more appropriate measure because click-through still suffers from limitations, such as the inability to control for click-fraud.

The core principle of allocating resources in proportion to their competitively relative elasticities is no different in this context than it is in the context of traditional media, the only exception being that the key metrics used for measuring customer responsiveness to marketing in these media are different from those in traditional media. As these metrics evolve, the resource allocation models will become more specific to the media.

8. Future Research Issues

As we move forward, resource allocation contexts and elements will likely become more complex. Although the basic principles of resource allocation and fundamental underpinnings will likely stay the same, the actual allocation rules will be based more on simulation than before. In many cases, closed-form analytical expressions for optimal resource allocation decisions may not be available, so managers will need to rely more on simulations for deriving the optimal decisions. Such simulations will not be as onerous a task as in the past, given the availability of richer data and greater computing power than before. In the future, managers will be more likely to use simulators and decision support systems for resource allocation than they did in the past.

What should the future research priorities with regard to marketing resource allocation be? First, we need to develop resource allocation models that are based on the relationship between marketing spending and company or shareholder value rather than on the link between marketing expenditures and profits alone.

Second, future resource allocation models should incorporate different scenarios of anticipated competitor responses in deriving optimal allocation rules. This exercise calls for data from different contexts that involve different types of competitor responses.

Third, there should be greater research on allocation of resources to the new media. Both manufacturers and retailers need better models of relative allocation of marketing budget toward traditional and new media. Models should incorporate interaction effects between the two types of media and the different media vehicles that make up these media.

Fourth, additional research is needed on the linkages between different types and levels of allocation decisions. Existing research allocation models focus on a single allocation type or level or context (e.g., marketing vs. sales force allocation, allocation across products) in isolation. Because many resource allocation decisions are interdependent, we need models that simultaneously optimize across different types of decisions. For example, a model that simultaneously optimizes allocation between R&D and marketing and within the marketing mix could offer more effective and precise allocation rules. Such models would likely be complex and simulation based.

Finally, research on the convergence of insights from the different types of allocation models is desirable. The allocation rules resulting from a triangulation of insights from different models would offer greater confidence to the decision-makers.

9. Conclusion

As the allocation of marketing resources continues to be a critical strategic priority for CMOs and other marketing executives worldwide, the application of existing models of strategic allocation and the emergence of new models are gaining importance. Strategic allocation of resources includes those between marketing and nonmarketing (e.g., R&D) variables; across marketing mix, products, markets, countries, customers, and channels; and over the product life cycle. Different models are available for these decisions. The core principle of allocation in these models is based on the relative responsiveness or elasticity of the outcome variable (e.g., sales, profits) to change in the allocation elements (e.g., marketing

vs. R&D, products, and channels). The relative elasticity is driven by factors such as the industry, company size, strengths and weaknesses, and stage in the product life cycle.

Although these models offer important guidance to managers, considerable potential exists for improved models of resource allocation that can incorporate greater complexity, interactions among variables, and anticipated competitor responses. To offer improved managerial guidance, future models of resource allocation should address issues such as the relationship of spending with shareholder value, incorporation of future competitor responses, spending on new media, and linkages between different types and levels of allocation.

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Figure 1

An Overview of the Types of Resource Allocation Decisions

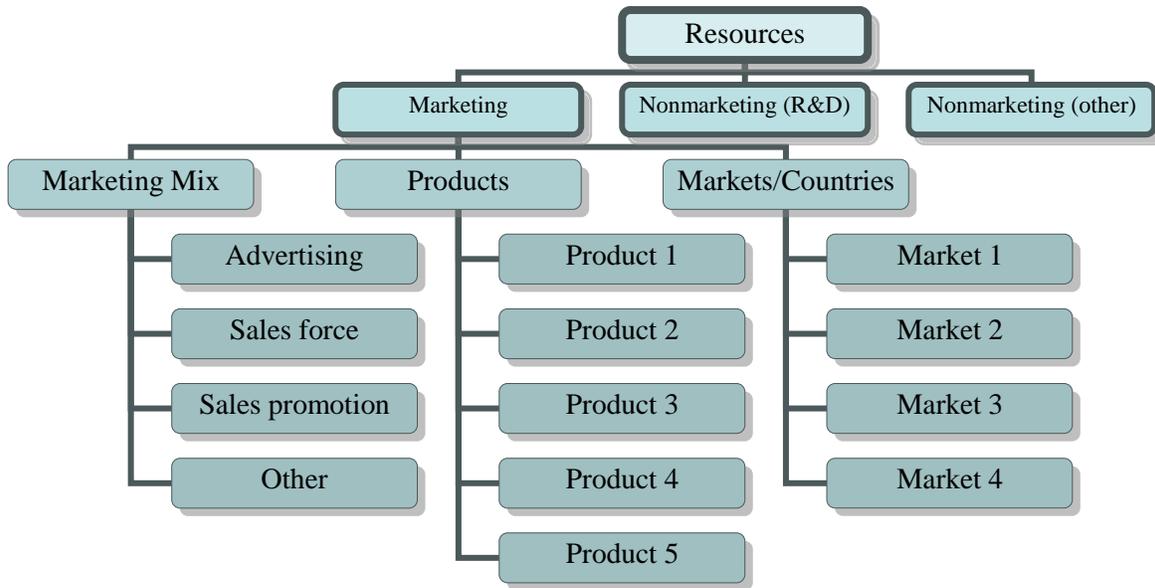


Figure 2
Annual Advertising and R&D Expenditures for *Fortune* 500 Firms

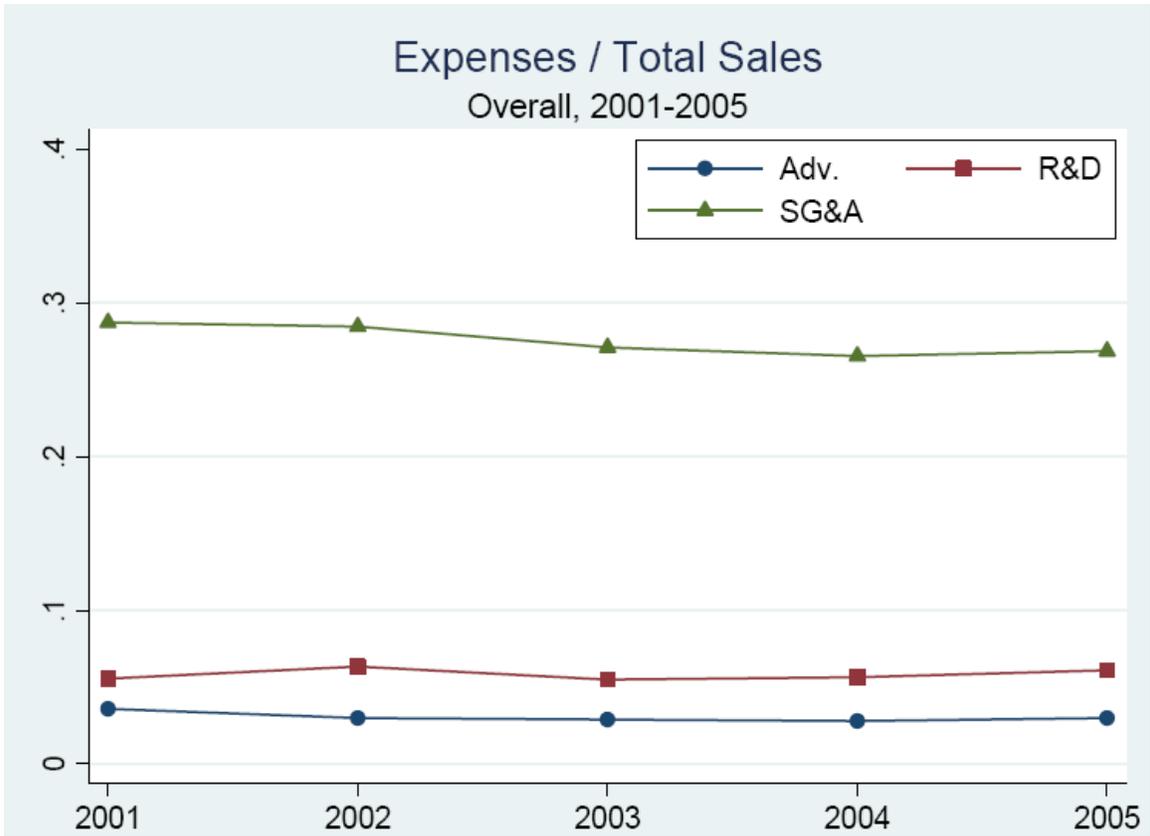
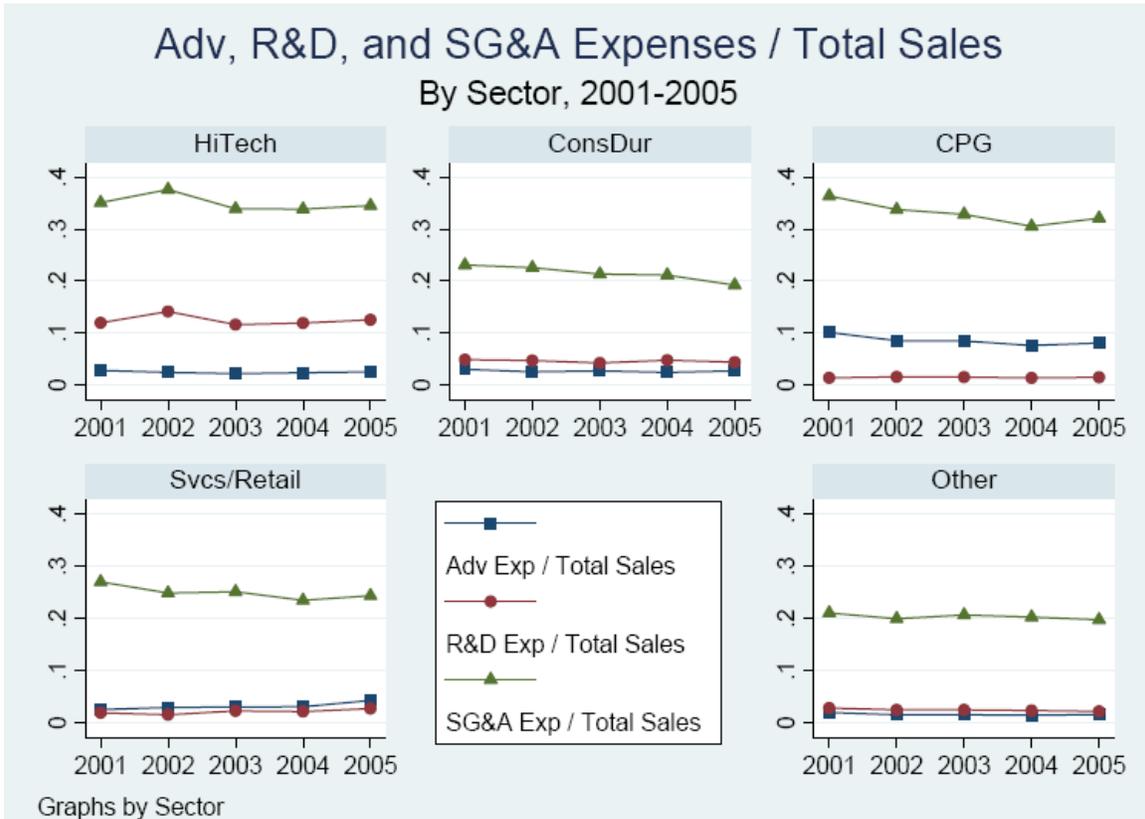
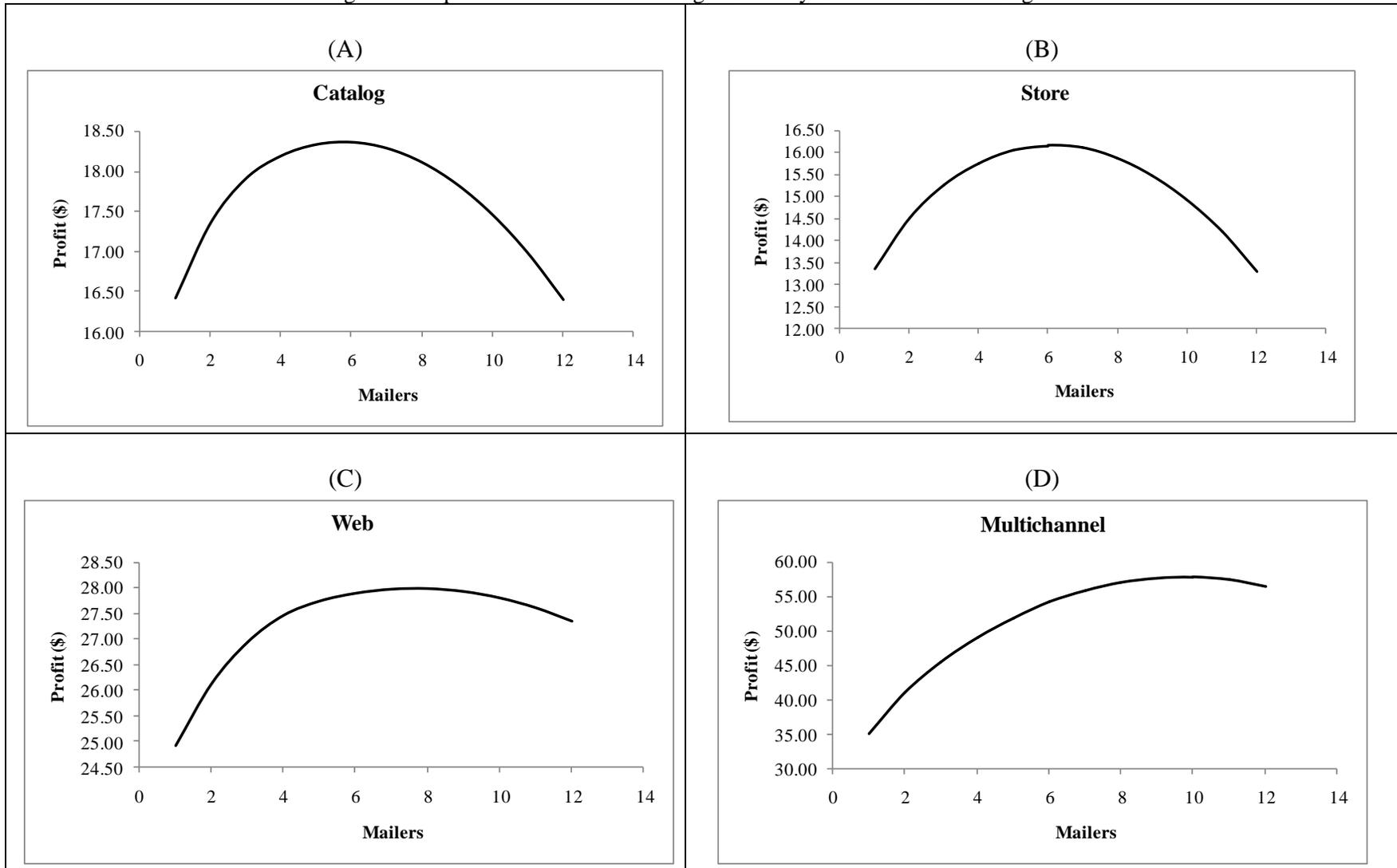


Figure 3
Annual Advertising and R&D Expenditures for *Fortune* 500 Firms by Sector



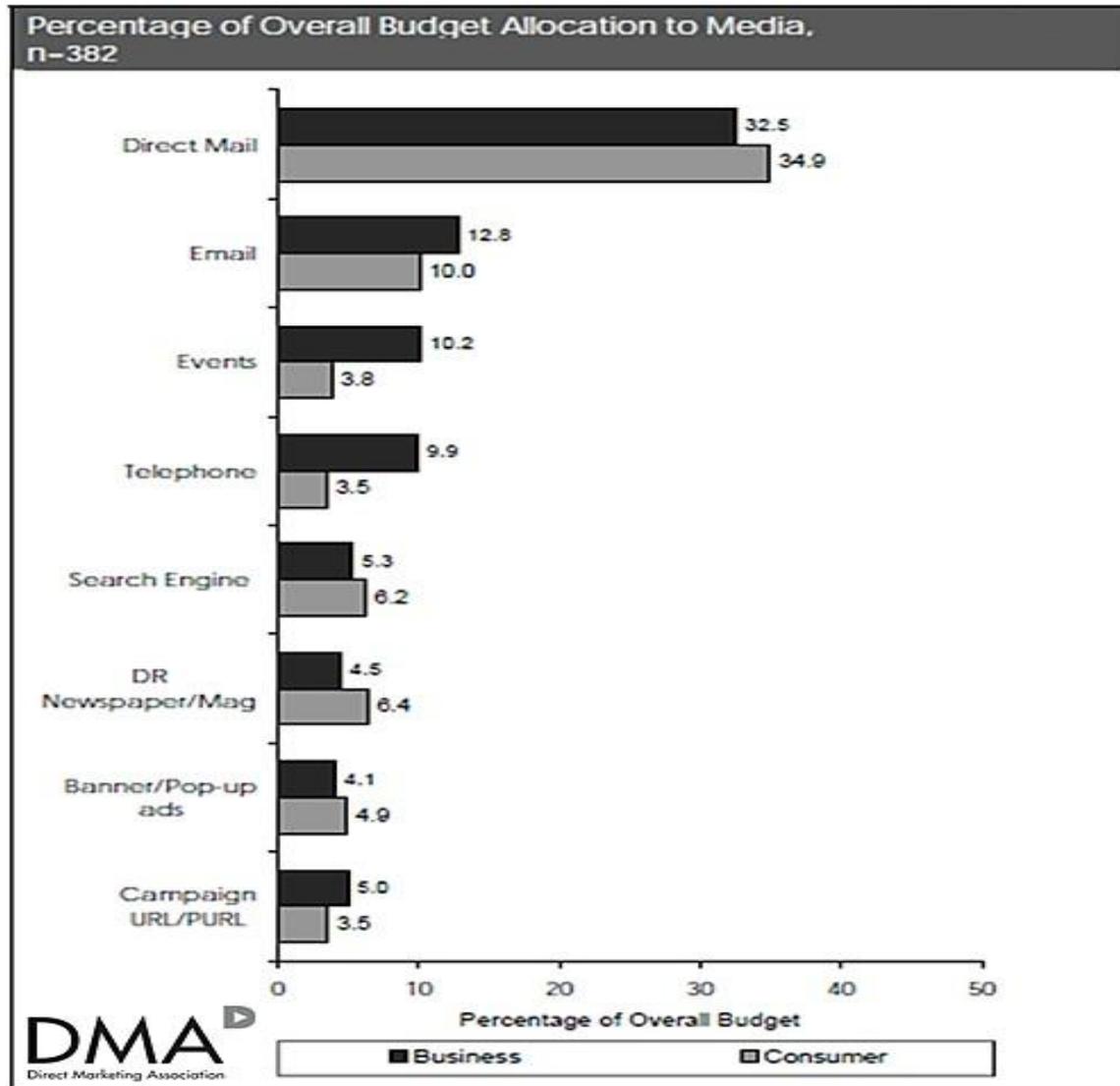
Notes: HiTech = high-technology, ConsDur = consumer durables, and Svcs/Retail = services/retail.

Figure 4 Shapes of Returns to Marketing Mailers by Customer-Channel Segment



Source: Kushwaha and Shankar (2008).

Figure 5 Summary of Budget Allocation to Different Media, Including New Media



Source: DMA (2008).

Table 1
Summary of Selected Marketing Resource Allocation Models

| Paper / Work | Model Type | Data | Key Findings / Guidelines | Key Limitations |
|--|--|---|---|--|
| Allocation across Marketing and Product-Related Resources | | | | |
| Erickson and Jacobson (1992) | Econometric model | 99 firms from S&P database during 1972-86 | After controlling for firm-specific factors and the feedback between discretionary spending and profitability, stock marketing spending are significantly lower, so firms should not overspend on R&D or marketing. | Residuals approximate unanticipated discretionary spending (R&D and marketing) |
| Bayus, Erickson, and Jacobson (2003) | Econometric model | PCs | Higher new product introductions and R&D spending are associated with lower marketing and advertising support. | Not generalizable to products in the mature and decline stages of the PLC. Results could be due to commoditization of product. |
| Allocation across Products and Markets/Countries | | | | |
| Lilien and Rao (1976) | Optimization model | Consumer product | The optimal number of outlets across geographic markets can be determined based on an underlying S-shaped relationship between outlet share and market share. | Simulation-based without a closed-form solution. Not validated on empirical data. |
| Henderson (1998) (The BCG matrix) | Conceptual model | NA | Milk the cash cows and feed question marks to upgrade them into stars and stars if needed. Stars self-finance themselves. Get rid of dogs unless they are strategic complements or have substantial exit barriers. | Too simplistic dimensions. Assumes profits correlated with relative market shares. Assumes a static view of the business universe. |
| Chintagunta and Desiraju (2005) | Econometric (Structural empirical industrial organization) model | Pharmaceuticals | Detailing elasticities are comparable across U.S., Germany, and Italy, but are higher in U.K. and France, suggesting greater allocation of detailing budget to U.K. and France. | Not an explicitly normative model of resource allocation across countries. |
| Fischer et al. (2005) | Econometric model | Pharmaceuticals | Marketing efficacy is higher in later countries of entry if firms follow a waterfall strategy, so firms should allocate more in later countries than that suggested by independent country response behavior. | Not an explicitly normative model of resource allocation across countries. |
| Marketing Mix Allocation and Allocation over the PLC | | | | |

| | | | | |
|-------------------------------------|---|---|--|---|
| Lilien (1979) | Econometric (Logit and linear regression) models | ADVISOR2 survey data from 22 companies for 131 products | Allocation to sales force determined by firm size, order size, stage in the product life cycle, product complexity, and purchase frequency. | Inappropriate for new products, narrow sample composition, US-centric data. |
| Montgomery and Silk (1972) | Econometric (Distributed lag) model | Time series data for an ethical product | Journal advertising has the highest and direct mail advertising has the lowest elasticities. The company's allocation is inversely related to these elasticities. | Market share model. Needs to be extended to sales and profits to make conclusions on resource allocation. |
| Gatignon and Hanssens (1987) | Econometric model | Time series data from US Navy | Sales force effectiveness in hiring of Naval personnel increased with local advertising support, suggesting a synergy between advertising and personal selling efforts. | Specialized context (Navy hiring). Potential multicollinearity between advertising and sales force may hinder estimation of true synergy. |
| Gopalakrishna and Chatterjee (1992) | Econometric model | Mature industrial product | Optimal marketing budget increases with number of accounts and the business potential of the accounts. Greater personal selling effort should be directed to the segment with the greater average potential. | Competitors assumed to be passive. Do not directly address relative allocation between advertising and personal selling. |
| Shankar (1997) | Analytical and Econometric (Game theoretic and empirical industrial organization) model | A large drug product category | Brands should allocate resources between advertising and sales force in the ratio of the competitive relative elasticities. | Decoupled response function. |
| Sethuraman and Tellis (1991) | Analytical and econometric model | Nondurable and durable goods | Promotions (price discounts) are more profitable than advertising for mature products, so allocate more to promotions. | Other marketing variables not considered. Interaction effect ignored. |
| Neslin, Powell, and Stone (1995) | Analytical model | NA | Advertising and trade promotion expenditures are substitutes and balance each other. | No empirical evidence. |

| | | | | |
|---|---|---|--|---|
| Naik and Raman (2003) | Optimization model | Apparel | Synergy between media elements can be estimated using a dynamic advertising model. As synergy increases, a firm should raise its advertising budget and allocate more funds to the less effective media element. | Results relevant for a monopoly; the role of temporal aggregation of data on optimal levels is unknown; potential multicollinearity between the media elements may hinder estimation of true synergy. |
| Naik, Raman, and Winer (2005) | Optimization (Differential game) model with continuous-discrete estimation method | Detergents | Advertising and promotion have significant interaction effects. Large brands under advertise and over promote. Small brands under advertise and over promote. | Model ignores category sales changes; ignores carryover effects; other mix variables omitted; role of retailer absent. |
| Shankar (2008) | Econometric (Market response) model | Pharmaceuticals | Marketing expenditures and moderated by the stage in the PLC. Dominant brands shift allocation of sales force over the PLC. | R&D decision not considered. |
| Allocation across Customers and Channels | | | | |
| Venkatesan and Kumar (2004) | Optimization model at customer-cohort level | B2B customer data from a multinational computer hardware and software firm | Optimization based on CLV yields improved profits relative to other optimization approaches. | Competitor responses not included in the model; indirectly relate costs and margins to CRM efforts. |
| Anderson, Lodish, and Weitz (1987) | Econometric (S-shaped effort allocation) model, Factor analysis of survey responses | Survey data from 95 firms belonging to Electronic Representatives Association (ERA) | Allocation of time by sales agencies to principal consistent with microeconomic model, but is also affected by communication, participation and feedback. | Self-reporting bias; common method variance; key informant bias; one industry view. |
| Kushwaha and Shankar (2008) | Optimization model decomposed into purchases frequency, quantity, and margin models | Shoes and accessories | The model produces a 32% increase in total profits in a holdout sample. Multichannel customers are most responsive to marketing mailers. | Models applied in only one industry. |