A Descriptive and Normative Analysis of Marketing Budgeting

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Dipl.-Kfm. und Dipl.-Vw. Nils Wagner

aus

Schleswig

Referent: Prof. Dr. Marc Fischer

Korreferent: Prof. Dr. Werner Reinartz

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CONTENTS

SYNOPSIS

Overview

The general topic of this cumulative dissertation and thus the linking theme for all papers is the analysis of the marketing budget process. In summary, this work contains four papers which allow for a comprehensive study of marketing budgeting, including a descriptive and normative analysis. The four papers are outlined in Table 1.

Table 1. Overview of Dissertation Projects

No.	Author(s)	Title	Journal	Ranking	Status
1	Nils Wagner	Determinanten der Marketingbudgetierung: Was wissen wir darüber?	Zeitschrift für Betriebs-wirtschaft	B * 3#	Revision completed; ready to submit for 2nd round
2	Nils Wagner and Marc Fischer	An Empirical Analysis of the Use of Practitioner Rules for Setting the Product Marketing Budget	Journal of Marketing Research	A+ * 1 #	Prepared to submit to journal
3	Marc Fischer, Sönke Albers, Nils Wagner and Monika Frie	Dynamic Marketing Budget Allocation across Countries, Products, and Marketing Activities	Marketing Science	A+ * 1 #	Published
4	Sönke Albers, Nils Wagner and Marc Fischer	Investigating the Performance of Budget Allocation Rules: A Monte Carlo Study	Marketing Science	A+ * 1 #	Prepared to submit to journal

* Ranking according to VHB-JOURQUAL 2.1 (2011)
\# Ranking according to the 'Kölner Liste der Fachzeitschriften':

1. 'Internationale Spitzenzeitschriften', 2. 'Hochrangige Zeitschriften', 3. 'Angesehene Zeitschriften'

Marketing budgeting is one of the most important aspects of management and of highly relevance for business success (Miles, White and Munilla 1997). Due to rising competitive pressure and a considerable increase in marketing investments the importance of this subject has additionally grown in the last years. For this reason, marketing budgeting receives a huge amount of attention by research and practitioners alike. Accordingly, it is stated in the CMO

Council Report of 2007: „The number-one challenge for most chief marketing officers is to quantify, measure, and improve the value of marketing investments and resource allocations“. The Marketing Science Institute (2010) set this issue as top research priority for the time period 2010-2012: „How should firms determine the absolute level of marketing spending and how should spending be allocated at the strategic level - that is, across products, customer groups, and geographies?”

The academic literature has been dealing with questions regarding the marketing budget process for a long time (Ramaseshan 1990) and therefore this issue has been discussed and analyzed in multiple ways (Leeflang and Wittink 2000). The focus of this literature has been on the allocation of budgets as previous research (Tull et al. 1986; Chintagunta 1993) has shown that profit improvement from better allocation is much higher than from improving the overall budget. To give an overview of the existing literature we may distinguish between two main research streams: (1) the descriptive and (2) the normative analysis of marketing budgeting.

Descriptive literature discusses the status quo of the marketing budgeting process in companies, i.e. it identifies how marketing budgets are actually determined and allocated by managers. Two types of descriptive studies have emerged in the literature. The first type covers a broad range of manager surveys about budgeting behavior. They indicate that budget decisions are mainly based on the application of some simple budgeting rules (Lilien 1979), such as the “Percentage of Sales” or “Competitive Parity” method, which are easy to apply and therefore be preferred by manager (Bigné 1995). But these studies ignore for the high complexity of the budgeting process and are exposed to several biases of survey studies. Therefore insights on the budgeting process based on survey results are quite limited (Armstrong and Overton 1973). The second type of descriptive studies try to explain budgeting behavior by estimating the impact of relevant factors on the observable size and allocation of the marketing budget to identify determinants of budget setting (e.g., Balasubramanian and Kumar 1990; Huskamp et al. 2008). But as all of these studies apply highly different approaches in model design results across studies about the impact of determinants on budgeting are characterized by high heterogeneity. So in summary, literature may only provide a fuzzy and fragmented picture on how manager determine their marketing budget.

Normative literature discusses how the marketing budget should be determined. A large body of work assists practitioners by developing diverse approaches for allocation optimization, covering several aspects of resource allocation (for an overview see Shankar 2008). All of these solutions offer important general insights into the budgeting problem but generally are not implemented in the marketing practice as they cover only some aspects of the budget allocation problem and/or give suggestions on budget allocation which are not understood and therefore are not accepted by manager. For this reason, researcher developed several heuristics (e.g., Albers 1998) or decision calculus models (e.g., Little 1970) which address the problem that optimization models cannot be well implemented in companies and offer easy to understand and close to optimum solutions for the complex allocation problem. But while all of the heuristics are focused on short-term profit maximization and thus ignore for dynamic effects which are highly important for budget allocation, the decision calculus models may only give imprecise implications for budget allocation. This explains why the application of scientific models for resource allocation by practitioners is quite rare (Bigné 1995).

The objective of this dissertation is to offer a comprehensive analysis of marketing budgeting. Therefore this work contributes to descriptive as well as normative research by addressing two main research gaps which exist in the literature. In terms of descriptive analysis the existing literature provides only a fragmented picture about influential factors in the budgeting process. In terms of normative literature no method has been developed which address the complexity of the budget allocation task for a multi-country, multi product-firm as well as the need of practitioners for simple allocation rules.

The first two papers of this dissertation address the descriptive analysis issues by (1) reviewing and structuring the fragmented literature of marketing budgeting behavior, and (2) developing an innovative approach to analyze empirically the application of budgeting methods in pharmaceutical companies. The last two papers of this dissertation address the normative analysis issues by (3) introducing and implementing an innovative solution to the dynamic marketing allocation budget problem for multi-product, multi-country firms, and (4) analyzing and comparing the performance of different allocation rules by simulation analysis. In summary, the dissertation's focus is to understand how marketing budgets are set by practitioners, and how the allocation decision process can be improved. Table 2 provides an overview of the classification and the contribution of the four dissertation projects. The next four sections present the research objectives, its contributions, and the main results of each research project of this dissertation.

Table 2. Overview of contribution and classification of dissertation projects

Paper	Perspective on budgeting process	Key research question	Type of main contribution
Determinanten der Marketingbudgetierung: Was wissen wir darüber?	Descriptive	What do we know on budgeting practices from the literature?	Literature review
An Empirical Analysis of the Use of Practitioner Rules for Setting the Product Marketing Budget	Descriptive	How do companies actually set their product budgets?	Empirical
Dynamic Marketing Budget Allocation across Countries, Products, and Marketing Activities	Normative	How can the budget allocation process in a multinational company be improved and implemented?	Theoretical-emprirical
Investigating the Performance of Budget Allocation Rules: A Monte Carlo Study	Normative	How well do budget setting rules perform?	Theoretical-simulation

1. Project: Determinanten der Marketingbudgetierung: Was wissen wir darüber?

The project "Determinanten der Marketingbudgetierung: Was wissen wir darüber?" ["Determinants of Marketing Budgeting: What do we know?"] reviews the large body of empirical studies which consider influential factors on marketing budgeting behavior.

As pointed out in the introductory discussion, the marketing budgeting process in companies has been analyzed extensively and in multiple ways. Empirical studies show that marketing budget decisions of managers are in general far from the optimal solution (Naik, Raman and Winer 2005; Manchanda, Rossi and Chintagunta 2004; Sinha and Zoltners 2001) which raise the question how manager determine their budget instead. But empirical studies on budgeting behavior provide highly heterogeneous results and are based on different concepts of how budgets are determined. This complicates a total view on the marketing budgeting practice and its influential factors. That motivates our project in which we review the fragmented literature regarding empirical results on determinants of marketing budgeting in order to derive empirical generalizations about factors which determine the size and allocation of marketing budgets in companies. Furthermore, we want to give suggestions for future research.

The review of the descriptive literature indicates that the determination of marketing budgets follows a complex decision process which is influenced by several factors. In particular, it is highly exposed to political influences within the company so that the measurement of the impact of influential factors is very complicated (Piercy 1986). Basically, surveys among managers identify simple budgeting methods, such as “Percentage of Sales”, which are applied for determining the marketing budget. They are preferred in practice as they are easy to understand and to implement. But these methods cannot explain fully the final budget decision. In addition, we see a significant impact on the level and the allocation of the marketing budget by several factors, such as company-, product-, or market-specific characteristics. Moreover, we observe that most of these factors have an indirect impact on budgeting behavior as well by influencing the choice of the applied budgeting method. This project aggregates all empirical results and therefore provides empirical generalizations about the impact of determinants on marketing budgeting.

Summarizing the key results, we find a higher marketing intensity for products of high quality, and product classes characterized by a low purchase frequency. Similarly, large companies which dominate the market and/or are characterized by a high involvement of top management into the budgeting process show a lower marketing intensity. We also find a strong competition orientation by managers resulting in more marketing spending due to intense competitive marketing spending. In terms of applied budgeting methods, large and profitable firms rather apply more sophisticated methods, such as “Objective and Task”.

But the reviewed empirical results should be considered with caution. Most studies on budgeting behavior ignore very often for theoretical contributions so that models are incomplete and results are not related to normative literature on marketing budgeting. Particularly, all studies are generally descriptive which does not allow the derivation of any managerial implications. In addition, the formalization of certain effects differs across studies which complicate a comparison of the results. With regard to methodology the studies vary further in terms of study design, analysis method and sample which may explain the heterogeneity in results across studies. Moreover, the studies are exposed to several biases, such as single source bias or simultaneity problems. Against this background, this project tries to examine the sources of heterogeneity in the results in order to provide empirical generalizations about the impact of determinants on marketing budgeting.

2. Project: An Empirical Analysis of the Use of Practitioner Rules for Setting the Product Marketing Budget

This paper is a joint research project with Marc Fischer (University of Cologne). In this project we analyze the application of rules in the marketing budget allocation process of companies by developing a conceptual framework that allows the estimation of the impact of practitioners' rules on the marketing outcome.

A review of 26 studies published since 1975 on actual budgeting behavior of firms from different countries and from diverse industries consistently shows that managers apply simple rules for allocation of marketing budgets. According to their focus these methods may be categorized into sales-oriented methods, such as “Percentage of Sales”, competition-oriented methods, such as “Competitive Parity”, and profit-oriented methods, such as “Objective and Task”. These rules are preferred by practitioners as they are easy to understand and to implement.

But almost all insights into application of budgeting rules are based on manager surveys. These studies offer a good first insight into the determination of budgets, but lack of validity because they are exposed to several biases and do not provide detailed information about how much and to what extent managers follow budgeting rules, or under which conditions they change applied rules (Mitchell 1993). We want to address these gaps in existing literature by providing answers to the following questions: (1) What is the influence of each of the three budgeting methods of sales-, competition-, and profit-oriented methods, on the budget decision?, (2) Are there differences in application across companies?, and (3) Which factors or conditions favor the use of some rules over others?

For this purpose, this project addresses the methodological problems of manager surveys by introducing an innovative analysis approach which may allow the identification of the impact of budgeting rules on the final budget decision. Building on previous research we develop a conceptual framework which relates the marketing budget of a product to the most frequently used practitioners' rules identified by survey literature research. As we formulate a random parameter model we are able to estimate the influence of each budgeting rule in each company simultaneously. Additionally, we integrate a comprehensive set of determinants as moderators to identify the conditions which favor the use of some rules over others. Our budgeting model is estimated with aggregate data at the brand level in the European pharmaceutical market which is an adequate dataset for our purpose due to its marketing-intensity.

Our analysis reveals important insights about budgeting behavior by analyzing the true application of budgeting rules. We find empirical support for the application of all three categories of budgeting rules. But the impact on the marketing budget varies significantly across brands which indicate that they are applied in different ways. More specifically, we find that for 81.2% of brands sales-oriented methods, for 53.2% of brands competition-oriented methods and for 40.5% of brands profit-oriented methods are applied. Our estimation results regarding the application of sales-oriented methods are in line with survey studies (e.g., Bigné 1995). But our study shows that the focus on competition is clearly underestimated by managers, while the focus on profit-oriented methods is overstated. So our study shows that the budgeting behavior of managers is much more influenced by competitors than expected, while budgeting methods derived from profit maximization are less applied. This finding contradicts one of the main assumptions of structural modeling.

Finally, our results indicate that the application of specific budgeting rules is affected by some moderating effects. Summarizing the main results of our moderator analysis, we find that sales- and profit-oriented methods are rather preferred by dominant firms. The application of profit-oriented methods particularly dominates in highly competitive markets when an expiring patent status enhances competitive intensity and therefore increases the need for sophisticated budgeting. On the contrary, competition-oriented methods are preferred in the early stages of the life cycle when it is important to create awareness and to obtain distribution in the market.

3. Project: Dynamic Marketing Budget Allocation across Countries, Products, and Marketing Activities

This paper is a joint research project with Marc Fischer (University of Cologne), Sönke Albers (Kühne Logistics University), and Monika Frie (Bayer Schering Pharma AG). In this project we develop a heuristic solution for the complex budget allocation problem which is easy to understand and gives close to optimal solutions. Further, we implement the proposed allocation rule in the company of Bayer to support management in the budgeting process and improve the allocation decision. Our paper was awarded with the “ISMS-MSI Marketing Science Practice Prize 2009-2010” for outstanding implementation of marketing science concepts and methods in practice.

The task of marketing budget allocation is characterized by high complexity. As companies generally offer a broad product portfolio to customers from various countries and use a variety of communication channels they have to allocate their fixed global annual marketing budget across countries, products, and communication activities. For many firms this task requires the determination of individual budgets for hundreds of allocation units. But to find the optimal allocation solution an evaluation of the impact of marketing investment decisions on future cash flows is necessary which is particularly complicated as the total impact of marketing on sales often fully unfolds in future periods.

To simplify the marketing budget allocation problem manager prefer to apply simple rules as shown in the descriptive analysis part of this dissertation. Unfortunately, these rules lead to suboptimal budget allocations as they ignore multiple information. Based on this background, we (1) introduce an innovative and feasible solution to the dynamic marketing budget allocation problem for multi-product, multi-country firms, (2) derive the heuristic allocation rule from optimal solution and explain it in detail, (3) implement the allocation rule in the company of Bayer, and (4) discuss the impact on the marketing budgeting practice at Bayer.

Our dynamic allocation rule proposes a budget allocation across the portfolio based on the three factors of (1) long-term effectiveness of marketing investments in the focal product, (2) profit contribution of the focal product, and (3) the focal product's growth expectations. It is suggested to be close to optimum while being easy to understand and to implement. For implementation into the company of Bayer, we developed a Decision Support Tool that integrates the proposed allocation heuristic into an Excel-based software program which produces a recommendation for the allocation of the total marketing budget.

Together with the management of Bayer, we implemented the heuristic for the product portfolio of Bayer's Primary Care business unit. This portfolio includes 36 products from four strategic therapeutic areas that are marketed worldwide including diabetes, hypertension, erectile dysfunction, and infectious diseases. The market positions of these products are quite diverse and determined by product age and competition. Depending on age and expected changes in the competitive and market environment, products offer different growth potentials. In addition, product managers can choose among six different types of marketing activities, such as detailing or print advertising. Hence, the challenge for the management was to find a balance in the allocation of marketing resources that trades off the size of the business, the growth expectations, and eventually the effectiveness of marketing expenditures. The main objective of this project was to improve the process and results of annual budget allocation in order to maximize discounted profits from the product portfolio over a planning horizon of five years.

The implementation of the heuristic at Bayer had various significant impacts on the organization that is reflected in several aspects. First, it initiated an important change in the understanding of the allocation task by providing structure and solution to a complex decision problem and giving information about product's contribution to profit, growth expectations of the product, and effectiveness of marketing expenditures across the portfolio. Second, the tool contributes to a reorganization of the bottom-up driven budget allocation process by adding an independent, top-down perspective that eventually resulted into the creation of a completely new marketing intelligence unit called Global Business Support. Third, the application of the tool initiated an important strategic discussion within the firm which affected a shift of more resources to older products and among several marketing activities. In summary, the empirical application revealed a profit improvement potential of more than 50% or nearly EUR 500 million of incremental discounted cash flows over the next five years.

4. Project: Investigating the Performance of Budget Allocation Rules: A Monte Carlo Study

This paper is a joint research project with Sönke Albers (Kühne Logistics University), and Marc Fischer (University of Cologne). In this project we analyze and compare the performance of different allocation rules by conducting a comprehensive simulation study.

The review of budgeting literature identifies a huge variety of different marketing budget allocation approaches which are characterized by different degrees of complexity. We find sophisticated optimization approaches provided by academics as well as simple 'rules of thumb' which are preferred by practitioners because they are easier to understand and to implement. Nevertheless, literature does not provide a systematic analysis how these rules perform in different market environments so that we cannot derive implications about which budgeting approach should be preferred in specific market scenarios.

This motivates our study in which we analyze under changing market conditions the performance of several allocation rules which are characterized by different complexity. Specifically, we apply the naïve solution of an equal distribution of the budget across the product portfolio, the common practitioners' rule of "Percentage of Sales" which proposes to allocate the budget proportional to the sales share of the product, the heuristic by Fischer et al. (2011) which has been developed by academics but still provides transparent solutions, and the numerical optimization approach. The evaluation of the performance of the four allocation rules is based on profit measures gained by application of these allocation rules compared to the optimal solution.

To test the near-optimality of the allocation rules as well as their convergence properties (if they converge to the optimal solution) we conduct a comprehensive simulation study by generating a multitude of different market scenarios in which we apply the four allocation approaches. In simulated experiments all parameter values are known a priori which allows us to analyze the performance of the heuristic exactly. We manipulate all factors which are contained in the dynamic profit maximization problem on which our simulation experiment is based in order to obtain generalizable results about the performance of the included allocation rules. Afterwards, we reconduct our simulation experiment by imposing an error on all parameters of interest which are unobservable in a realistic setting in order to analyze the sensitivity of the different rules to estimation error. Finally, we estimate some meta-models to identify the factors which influence the robustness and the convergence properties of the rules by regressing the performance outcomes on the simulation factors (Kleijnen and Groenendaal 1992, 149 et seq.).

We find that the “Percentage of Sales” rule outperforms a naïve solution of equal distribution, but that the solutions provided by the rule by Fischer et al. are far superior to the other rules and are robust to all changes in the simulation design. In the scenarios in which we assume that the unobservable parameters are not affected by estimation error the rule by Fischer et al. provides already after the first application solutions which deviate only 2% from the theoretical optimum on average and converges afterwards fast to optimality, while the solutions of “Percentage of Sales” diverge about 10%, and of the equal distribution about 20% from the optimal solution. Further, if we expose the unobservable demand parameter to estimation error the performance of the rule by Fischer et al. is only affected marginally. Compared to numerical optimization, we see that in most scenarios the rule may even outperform this mathematical optimization solution which is exposed to biased parameters as well, but appears to be much more sensitive to noisiness in the parameters. This finding also contradicts conventional wisdom which holds that, by using simpler heuristics than numerical optimization the allocation solution are achieved at the expense of poorer profit performance (Blackburn and Millen 1980). Similarly, the allocation solutions based on the rule by Fischer et al. are in all scenarios significantly better than the application of the simpler rules of equal distribution and “Percentage of Sales” which do not incorporate any unobservable demand parameters and therefore are not exposed to estimation error.

In summary, we find strong support for the application of the heuristic by Fischer et al. because it provides consistently far superior solutions in terms of profit maximization compared to simpler rules, such as equal distribution or “Percentage of Sales”, on the one side, and they are not as sensitive to estimation error as numerical optimization on the other side.

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Determinanten der Marketingbudgetierung: Was wissen wir darüber?

Autor: Nils Wagner

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Zusammenfassung

Das Marketingbudgetierungsverhalten von Unternehmen wurde in der Marketingforschung intensiv und breit untersucht. Empirische Untersuchungen weisen darauf hin, dass die Bestimmung des Marketingbudgets einem komplexen Entscheidungsprozess folgt und von einer Vielzahl von Determinanten beeinflusst wird. Grundsätzlich offenbaren Umfragen unter Managern, dass das Marketingbudget nach simplen Budgetierungsmethoden, wie z. B. Prozent-vom-Umsatz, bestimmt wird. Allerdings kann die Zusammensetzung von Marketingbudgets nur zum Teil auf diese Methoden zurückgeführt werden. So konnte für eine Vielzahl von Faktoren ein direkter Einfluss auf die Höhe und die Verteilung des Marketingbudgets nachgewiesen werden. Zusätzlich haben viele Determinanten auch einen indirekten Einfluss auf die Marketingbudgetierung, indem sie die Wahl der angewendeten Budgetierungsmethode beeinflussen. In dieser Studie werden die Ergebnisse der empirischen Forschung zum Marketingbudgetierungsverhalten zusammengeführt, systematisch dargestellt und kritisch betrachtet. Im Besonderen lässt sich an den existierenden Studien kritisieren, dass diese das Budgetierungsverhalten nicht strukturell, sondern nur über ad hoc formulierte Beziehungsgeflechte, abbilden und dabei wesentliche Aspekte der Budgetierung ignorieren.

Abstract

The marketing budgeting process in companies is analyzed extensively in marketing research. Empirical studies indicate that the determination of marketing budgets follows a complex decision process which is influenced by a multitude of different factors. Basically, surveys among managers identify simple budgeting methods, such as percentage-of-sales, which are applied for determining the marketing budget. But these methods cannot explain fully the final budget decisions. Instead, we see a significant impact on the level and the allocation of the marketing budget by multiple factors. Further, we observe that most of these factors have as well an indirect impact as they influence the choice of the applied budgeting method. But the empirical results with regard to marketing budgeting behavior are very fragmented which complicates a total view on what influences the determination of marketing budgets. Therefore, this study aggregates the results of empirical research to provide an overview of empirical findings regarding determinants in marketing budgeting behavior and gives suggestions for future research.

1 Einführung

Jedes Unternehmen steht vor der Herausforderung, sein Produktangebot mit einem geeigneten und optimal abgestimmten Marketingprogramm zu unterstützen. Die Frage der optimalen Höhe und Verteilung des Marketingbudgets ist dabei angesichts teilweise rapide wachsender Marketingbudgets von großer Bedeutung für den Unternehmenserfolg. Zusätzlich rücken steigende Marketingkosten, verschärfende Wettbewerbsbedingungen und ein besserer Zugang zu Daten den Fokus zunehmend auf ein effizientes und effektives Management der Werbeinvestitionen. Dennoch zeigt sich in den Ergebnissen der MAX Studie der American Association of Advertising Agencies, dass der Marketingbudgetierungsprozess von vielen Managern noch immer als ein komplexer, schlecht strukturierter und risikobehafteter Prozess angesehen wird (Farris, Shames und Reibstein 1998).

Empirische Untersuchungen bestätigen, dass die Höhe und Verteilung von Marketingbudgets in den meisten Unternehmen nach theoretischen Überlegungen suboptimal ist (z. B. Manchanda, Rossi und Chintagunta 2004). Gleichzeitig lässt sich beobachten, dass es zwischen Unternehmen, selbst innerhalb der gleichen Branche, große Variationen bei der Höhe des Marketingbudgets gibt (Balasubramanian und Kumar 1990). Es stellen sich daher die Fragen, wie Marketingbudgets in der Praxis bestimmt werden und welche Faktoren ihre Höhe determinieren.

Seit über 40 Jahren widmet sich die Forschung in deskriptiven Studien diesen Fragen (Ramaseshan 1990). In Abgrenzung zur normativen Literatur, die bestrebt ist, Marketingbudgetierung zu optimieren (z. B. Fischer et al. 2011), versucht die deskriptive Literatur nur das tatsächliche Budgetierungsverhalten, dass in Unternehmen beobachtet wird, zu beschreiben. Die Motivation dieser Studien basiert auf der Annahme, aus dem Budgetierungsverhalten erfahrener Manager generelle Implikationen für die Praxis ableiten zu können (Lilien und Little 1976). Manager lernen mit der Zeit die Bedeutung kritischer Determinanten und entwickeln daraus teilweise unbewusste Modelle, die es ihnen ermöglichen, auf Veränderungen im Markt, Unternehmen oder Produktportfolio zielführend zu reagieren. Im Besonderen schafft die Beschreibung gemeinhin genutzter Praktiken für

Manager eine gute Grundlage um das Marketingbudgetierungsverhalten ihrer Wettbewerber besser zu verstehen und das Budget der Wettbewerber zu schätzen (Stewart 1996). Gleichzeitig liefern diese Studien einen deutlichen Beitrag zur Entwicklung empirischer Modelle in der Forschung, da die Erkenntnisse dazu beitragen können, Marketingvariablen in Modellen zu identifizieren und auf diese Weise den Realitätsgehalt zu steigern und Verzerrungen von Parametern zu vermeiden (Manchanda, Rossi und Chintagunta 2004). Zusätzlich sehen wir eine vermehrte Anwendung von Strukturgleichungsmodellen in der empirischen Forschung, die auf teilweise sehr restriktiven Annahmen über Unternehmens- bzw. Managerverhalten basieren. Deskriptive Studien helfen dabei, die Rechtfertigung dieser Annahmen zu überprüfen.

Die Analyse des Budgetierungsverhaltens von Managern ist weit verbreitet und wurde mit vielschichtigen Methoden, wie z. B. Umfragen unter Managern oder ökonometrischen Studien zur Erklärung der beobachteten Verteilung von Marketingbudgets, untersucht. Allerdings hat dies die Entwicklung verschiedener Erklärungsmodelle des Budgetierungsprozesses begünstigt und zu sehr heterogenen empirischen Ergebnissen bezüglich der Determinanten des Marketingbudgetierungsverhaltens geführt. Versuche in der Literatur, den Budgetierungsprozess mithilfe eines einfachen Modells zu erklären (Balasubramanian und Kumar 1990), konnten in späteren Studien widerlegt werden (z. B. Ailawadi, Farris und Parry 1994). Es bleibt das Bild eines komplexen Budgetierungsprozesses, der in der Praxis durch eine Vielzahl von Entscheidungsträgern sowie exogener Faktoren beeinflusst wird, bestehen.

Aus diesem Grund führt dieser Beitrag die weitgehend fragmentierte empirische Forschung zum tatsächlichen Marketingbudgetierungsverhalten zusammen und systematisiert die empirisch nachgewiesene Wirkung von Determinanten auf die Marketingbudgetierung, mit dem Ziel die folgenden Fragen zu beantworten:

- Nach welchen Methoden und Verfahren werden Marketingbudgets in der Praxis verteilt?
- Welche Einflussfaktoren auf die Bestimmung der Höhe und Verteilung von Marketingbudgets sind empirisch validiert? Welche Wirkungsrichtung weisen sie auf und wie lassen sich Unterschiede in empirischen Befunden erklären?
- Wie sind die existierenden Arbeiten hinsichtlich ihrer Aussagefähigkeit zu beurteilen? In welchen Bereichen besteht weiterer Forschungsbedarf?

Einzelne Arbeiten thematisieren bereits den empirischen Forschungsstand zu Einzelaspekten des tatsächlichen Marketingbudgetierungsverhaltens. So liefern Farris und Albion (1981) einen frühen ersten, aber sehr eingeschränkten Einblick über Einflussfaktoren der Marketingbudgetierung. Bigné (1995) liefert einen systematischen Überblick über Studien zur Anwendung von Budgetierungsmethoden, nimmt jedoch keine Untersuchung der Determinanten der Wahl der Methode vor. Andere Artikel verfolgen das Ziel den Stand der empirischen Forschung darzustellen, weisen allerdings einen sehr starken Praxisbezug auf, so dass kaum allgemeingültige Erkenntnisse abgeleitet werden können (z. B. Reinecke und Fuchs 2003). Die hier vorliegende Untersuchung erweitert diesen Erkenntnisstand im Besonderen in zweierlei Hinsicht: Erstens schafft diese Arbeit erstmals einen systematischen Überblick über alle Aspekte der Marketingbudgetierung, die in der Marketingforschung untersucht wurden. Zweitens hat sich die Datengrundlage deutlich vergrößert. Während Farris und Albion (1981) nur auf 7 Beiträge zurückgreifen können, werden im Rahmen dieser Arbeit knapp 90 Studien der vergangenen 40 Jahre verarbeitet, so dass eine wesentlich breitere Perspektive auf die Einflussfaktoren der Marketingbudgetierung ermöglicht wird. Eine systematische Untersuchung empirischer Ergebnisse zu den Determinanten der Wahl der Budgetierungsmethode erfolgt im Rahmen dieser Arbeit sogar erstmalig.

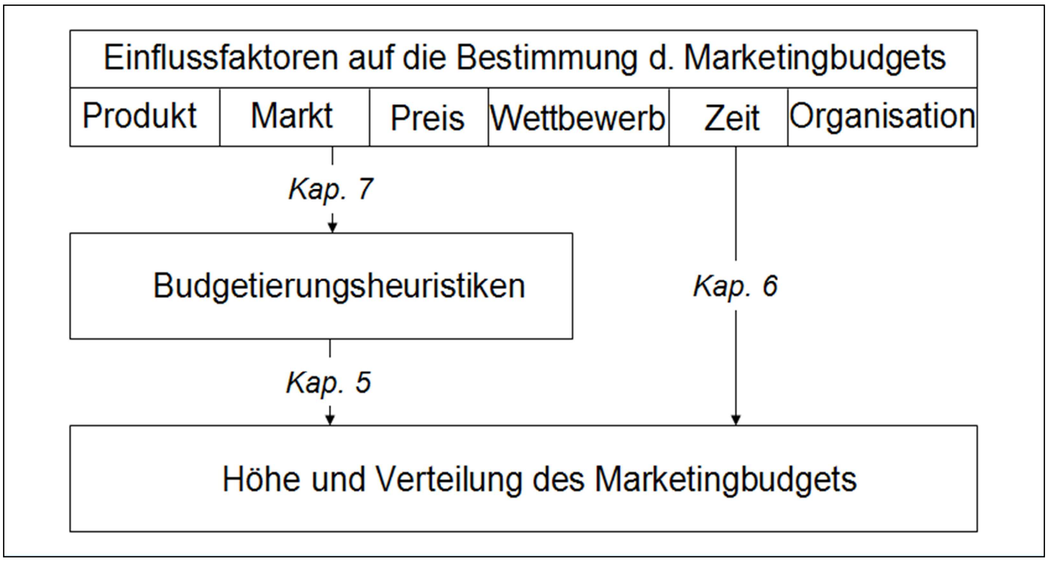
2 Untersuchungsmethode

2.1 Konzeptioneller Bezugsrahmen der Untersuchung

Basis für die Analyse der empirischen Forschung zur Marketingbudgetierung bildet ein konzeptioneller Bezugsrahmen. Bei der Untersuchung der verschiedenen empirischen Arbeiten wird auf diesen Bezugsrahmen zurückgegriffen mit dem Ziel einer systematischen Darstellung der Einflussfaktoren der Marketingbudgetierung.

Grundsätzlich ergibt sich im Rahmen der Bestimmung der Marketingbudgets ein komplexer Entscheidungsprozess zur Bestimmung der Marketingbudgets, der sich aus dem internen Wettbewerb der Manager eines Unternehmens um die verfügbaren Ressourcen ergibt (Piercy 1986). Gleichzeitig stehen Unternehmen vor der Herausforderung, ihr Marketingbudget im komplexen Umfeld dynamischer Märkte für ein breites Produktportfolio und einen vielfältigen Marketing-Mix möglichst optimal zu bestimmen und zu verteilen (Fischer et al. 2011). Es stellt sich daher die Frage, wie Unternehmen in der Praxis ihre Budgets letztlich bestimmen. Die Literatur identifiziert die Verwendung von einfachen Regeln, sogenannten Budgetierungsheuristiken, die von Managern zur Bestimmung ihrer Budgets angewendet werden, da sie das komplexe Optimierungsproblem deutlich vereinfachen (Bigné 1995).

Abbildung 1. Konzeptioneller Bezugsrahmen der Untersuchung



Darüber hinaus wird die Bestimmung der Höhe und Verteilung des Marketingbudgets durch eine Vielzahl weiterer Faktoren beeinflusst. In einer Managerumfrage identifiziert Mitchell (1993) neben den üblichen organisationalen und strukturellen Einflüssen die folgenden fünf Haupttreiber des Budgetierungsverhaltens: Produkt, Wettbewerb, Marktcharakteristika, Preis und zeitliche Effekte. Die empirische Forschung hat für eine Vielzahl dieser Faktoren einen direkten Einfluss auf das Marketingbudgetierungsverhaltens nachweisen können. Ebenso zeigt sich ein indirekter Einfluss vieler Faktoren auf die Bestimmung des Marketingbudgets über deren Wirkung auf die Wahl der angewendeten Budgetierungsheuristik.

2.2 Methodik der inhaltlichen Auswertung

Die Erarbeitung eines systematischen Überblicks über die Ergebnisse empirischer Studien und die sich daraus ergebende Ableitung von empirisch verallgemeinerbaren Erkenntnissen basiert auf der Auszählung signifikanter und insignifikanter Studienergebnisse. Ein empirisch verallgemeinerbarer Zusammenhang wurde identifiziert, wenn mindestens drei Studien einen Zusammenhang untersucht haben und bei mindestens 80% dieser Studien eine entsprechende Wirkrichtung festgestellt wurde, oder wenn zwei Studien einen Zusammenhang untersucht haben und bei beiden die gleiche Wirkrichtung festgestellt wurde. Sollte Heterogenität in den Ergebnissen vorliegen, werden im Rahmen dieser Studie mögliche Ursachen, z.B. durch Unterschiede in den Modellen, diskutiert. Eine genauere Auswertung mittels einer Meta-Analyse konnte aufgrund fehlender Informationen zu Datengrundlagen und

Modellspezifikation bei einer Vielzahl von Studien, die eine Vereinheitlichung empirischer Ergebnisse, z.B. über Elastizitäten, verhindern, nicht durchgeführt werden.[1]

2.3 Auswahl der empirischen Arbeiten

Der Fokus dieser Studie liegt in der systematischen Aufbereitung empirischer Studien, die den tatsächlichen Marketingbudgetierungsprozess analysieren. Dies umfasst Beiträge, die direkte oder indirekte Einflussfaktoren auf das Marketingbudgetierungsverhalten untersuchen. Gleichwohl finden auch Studien mit einem anderen Forschungsfokus, die ebenfalls bedeutsame empirische Ergebnisse zum Marketingbudgetierungsprozess beisteuern, Berücksichtigung, um ein möglichst breites Erkenntnisspektrum bieten zu können. Es sei aber darauf hingewiesen, dass im Rahmen dieser Studie ausschließlich Beiträge der Marketingforschung verarbeitet werden. Dies blendet im Besonderen weitestgehend verhaltenswissenschaftliche Ansätze der Erklärung des Budgetierungsprozesses in der Accountingliteratur aus. Gleichzeitig grenzt sich diese Studie von Beiträgen mit starkem Praxisbezug ab, da diese aufgrund ihrer Untersuchungsmethode meist keine verallgemeinerbaren Ergebnisse zulassen.

Für die Literaturrecherche wurde auf die drei führenden betriebswirtschaftlichen Datenbanken „ABI/INFORM Global (ProQuest)“, „Business Source Premier (Ebsco)“ und „Wiso Wissenschaften: Wirtschaftswissenschaften“ zurückgegriffen und zur Schaffung einer Ausgangsbasis Beiträge herausgefiltert, die im Titel, in der Zusammenfassung oder bei den Schlagwörtern die Begriffe „Budgetierungsmethoden“, „Budgetierungspraktiken“ sowie „Determinanten der Marketingbudgetierung“ bzw. „-intensität“ (bzw. in entsprechender englischer Übersetzung) aufweisen. Anschließend wurde mittels Querverweisen nach weiteren Beiträgen gesucht, so dass insgesamt knapp 90 empirische Studien identifiziert und in dieser Studie berücksichtigt wurden.

3 Grundlagen der Marketingbudgetierung

3.1 Definition der Marketingbudgetierung

Grundsätzlich bezeichnet die Budgetierung die systematische Planung, Koordination und Kontrolle der Unternehmensressourcen. Marketingbudgetierung im Speziellen umfasst die Formulierung quantifizierbarer Aktivitäts- und Leistungsniveaus der absatzpolitischen Entscheidungseinheiten eines Unternehmens, die in regelmäßigen Abständen neu festgelegt

[1] Aufgrund der teilweise sehr frühen Veröffentlichung einiger Artikel konnte auch keine Nacherhebung der fehlenden Daten bei den Autoren erfolgen.

werden (Barzen 1990, 90 f.). Der Begriff des Marketingbudgets umfasst damit alle regelmäßig neu festgelegten Kosten absatzpolitischer Maßnahmen, wie z.B. Verkaufsaußendienst, Werbung, Kundendienstkosten oder kundenspezifischer Produktmodifikationen. Infolge der wichtigen Bedeutung, den der Posten der kommunikationspolitischen Maßnahmen innerhalb des Marketingbudgets zukommt, legen einige Studien einen besonderen Fokus auf die Untersuchung abgegrenzter Anteile des Budgets. So findet sich eine abgegrenzte Untersuchung des Werbebudgets, d.h. alle Kosten von Werbemaßnahmen, die über Medien verbreitet werden, des Außendienstbudgets, in dem alle Kosten, die durch Außendiensttätigkeiten anfallen, zusammengefasst werden, sowie des Werbe- und Promotionsbudgets, das allgemein alle kommunikationspolitischen Maßnahmen umfasst.

Aufgrund der regelmäßigen Planungszyklen des Marketingbudgets ergibt sich ein besonderer Fokus auf den betriebswirtschaftlichen Planungsprozess der Budgetaufstellung im Marketing, der auch vornehmlicher Untersuchungsgegenstand der empirischen Forschung ist.

3.2 Prozess der Marketingbudgetierung

Der Marketingbudgetierungsprozess beschreibt den Entscheidungsprozess zur Bestimmung der Höhe und der Verteilung des Marketingbudgets. Lilien und Little (1976) sehen diesen Prozess als ein zweistufiges Verfahren, bei dem im ersten Schritt über die Höhe des Marketingbudgets und in einem zweiten Schritt über dessen Verteilung auf die Planungseinheiten der Organisation, d. h. Produkte, Länder, Marketinginstrumente, Zeitperioden usw., entschieden wird. Mitchell (1993) erweitert diesen Prozess um die vorgelagerte Entscheidung, ob überhaupt geworben werden soll. Obgleich die Forschung belegen konnte, dass die Allokation des Marketingbudgets auf den Unternehmenserfolg eine wesentlich stärkere Wirkung hat als die eigentliche Höhe (Chintagunta 1993), zeigt sich bei Managern ein anderes Meinungsbild. Daraus ergibt sich in der Praxis eine wesentlich höhere Bedeutung, die der Bestimmung des absoluten Marketingbudgets zugemessen wird (Mitchell 1993).

Grundsätzlich gilt in vielen Unternehmen, dass das Management zunächst eine übergeordnete allgemeine Strategie entwickelt und daraus Marketingziele abgeleitet werden. Anschließend wird auf der Basis von Prognosen und Zielen der finanzielle Spielraum für die nächste Planungsperiode abgesteckt und in diesem Rahmen die Budgets bestimmt, die nach Managementbeurteilung und analytischen Modellen zur Zielerreichung führen sollen. Der erste Budgetvorschlag wird dann dem Topmanagement präsentiert und in gegenseitiger

Absprache angepasst und beschlossen (Low und Mohr 1999). Die prozessuale Entscheidungsrichtung variiert jedoch nach Organisationsform und Philosophie eines Unternehmens. Eine Prozessstruktur, nach der die Entscheidung über Höhe und Verteilung des Marketingbudgets vor allem beim Topmanagement verbleibt und Manager von Untereinheiten (z. B. Produktmanager) nur noch ausführende Aufgaben übernehmen, wird als Top-Down-Prozess bezeichnet. Wenn die Produktmanager hingegen die Kompetenz besitzen über ihr Marketingbudget zu entscheiden, so liegt eine Bottom-Up-Prozessstruktur vor. Die Vorteile des Top-Down-Ansatzes liegen in der Möglichkeit, den unternehmensstrategischen Fokus bei der Budgetplanung zu berücksichtigen und auf diese Weise den Gesamtgewinn des Portfolios zu maximieren. Zusätzlich können zeitintensive Abstimmungsprozesse vermieden werden. Allerdings stoßen Vorgaben aus dem Topmanagement eher auf Akzeptanzschwierigkeiten bei den nachgeordneten Hierarchieebenen. Der Bottom-Up-Ansatz zieht vor allem Vorteile aus der Markt- und Kundennähe der Produktmanager, die ihnen eine bessere Schätzung des optimalen Budgets ermöglicht. Gleichzeitig fördert die Partizipation im Entscheidungsprozess die Mitarbeitermotivation. Allerdings lässt sich beobachten, dass Manager zu opportunistischem Verhalten in der Form zu hoher Budgetwünsche neigen und der Koordinationsaufwand deutlich zunimmt (Prendergast, West und Shi 2006).

Der Gedanke, die Vorteile beider Prozessformen zu kombinieren, hat in der Praxis zur Verbreitung von Mischformen geführt. Hanmer-Loyd und Kennedy (1981) zeigen, dass knapp 90% aller Unternehmen kombinierte Prozessformen anwenden, bei der in gegenseitiger Partizipation die Unternehmensziele und –strategien festgelegt und über das Budget entschieden wird. Dadurch ergibt sich in den meisten Unternehmen das Bild eines komplexen Verhandlungsprozess an dem eine Vielzahl von Abteilungen innerhalb eines Unternehmens beteiligt sind und der infolge unterschiedlicher Ziele und Perspektiven der einzelnen Abteilungen viele Reibungspunkte aufweist. Im Besonderen sind hier Kommunikationsschwierigkeiten zwischen Finanz- und der Marketingabteilung sowie zwischen oberen und unteren Hierarchieebenen zu nennen. Im ersten Fall bestehen unterschiedliche Auffassungen über Marketing als Kosten- oder als Investitionsfaktor, und im zweiten Fall stehen gesamtunternehmerische Interessen Abteilungsinteressen gegenüber (Low und Mohr 1999).

4 Normative ökonomische Theorie der optimalen Marketingbudgetierung

Erste Einblicke in die Marketingbudgetierung liefert die normative Literatur zur optimalen Bestimmung von Marketingbudgets, indem sie Aussagen trifft, wie das Marketingbudget optimalerweise gesetzt werden sollte. Die Grundlage hierfür liefert das Dorfman-Steiner-Theorem (Dorfman und Steiner 1954), das besagt, dass eine optimale Marketingbudgetierung erreicht ist, wenn sich Grenzertrag des Marketing und negative Preiselastizität entsprechen, d. h. je effektiver das Marketing, desto größer ist das optimale Marketingbudget. Fortführende Studien haben dieses Theorem weiterentwickelt, so dass sich auf der Basis normativer Aussagen die folgenden Ergebnisse bezüglich Determinanten zusammenfassen lassen, die verstärkte Marketinginvestitionen begründen:

- höhere Effektivität des Marketing (Dorfman und Steiner 1954).
- stärkerer Carry Over-Effekt in Bezug auf den Marketingstock (Nerlove und Arrow 1962)
- größere Profitabilität eines Produkts (Cable 1972).
- niedrige Kapitalkosten des Unternehmens (Nerlove und Arrow 1962).
- größerer Umsatz eines Produkts (Dorfman und Steiner 1954).
- hohes Wachstumspotenzial eines Produkts (Fischer et al. 2011).

Die normativen Aussagen bleiben damit insgesamt übersichtlich, geben aber einen ersten Einblick in die Bestimmung von Marketingbudgets. Inwieweit sich die normativen Aussagen im tatsächlichen Budgetierungsverhalten widerspiegeln, muss allerdings in empirischen Studien untersucht werden.

5 Budgetierungsmethoden

5.1 Konzept der Budgetierungsmethoden

Umfragen unter Managern zeigen, dass in der Praxis vor allem vereinfachende Methoden, sogenannte Budgetierungsheuristiken, für die Bestimmung von Marketingbudgets angewendet werden. Trotz der enormen Bedeutung der Budgetierung für den Unternehmenserfolg handelt es sich hierbei meist um einfache Regeln, die die komplexe Budgetierungsentscheidung auf der Basis weniger Kennzahlen festlegen und auf diese Weise übersichtlich und greifbar machen (Farris, Shames und Reibstein 1998).

Tabelle 1 fasst die nach Managerumfragen am weitesten verbreiteten Budgetierungsmethoden zusammen. Während in frühen Studien die Prozent-vom-Umsatz-Regel (Percentage of Sales) und der finanzkraftorientierte Ansatz (Affordable) am häufigsten genannt werden (z. B. San Augustine und Foley 1975), lässt sich über die Zeit eine wesentlich breitere Anwendung der differenzierteren Ziele-und-Aufgaben-Regel (Objective and Task) beobachten (z. B. Hung und West 1991). Diese Tendenz erfasst zunächst die größeren Unternehmen der Konsumgüterindustrie und breitet sich anschließend auch auf Unternehmen mittlerer Größe und anderer Branchen aus. Lynch und Hooley (1990) vergleichen dies mit einem Diffusionsprozess, der in der Literatur als Weiterentwicklung des Budgetierungsprozesses hin zu fortschrittlicher Budgetierungspraxis gewertet wird. Dennoch wecken einige Studien Zweifel an dieser Schlussfolgerung, da ein detaillierter Blick auf die Budgetbestimmung darauf hin deutet, dass die Ziele-und-Aufgaben-Regel nicht im eigentlichen Sinne Anwendung findet (Martenson 1989). Stattdessen ist anzunehmen, dass sie lediglich als ein Werkzeug zur Legitimierung und Rechtfertigung einflussreicher Akteure eingesetzt wird, um eigene Ziele durchzusetzen (Piercy 1987a). Bei kleineren Unternehmen wird die Entscheidung über das Marketingbudget hingegen meist direkt vom Topmanagement getroffen, die das Budget überwiegend auf der Basis ihrer eigenen Erfahrung (Arbitrary), d. h. nach subjektiven Kriterien, festlegen. Die anderen genannten Methoden haben schließlich einen eher ergänzenden Beitrag zur Bestimmung der Budgets. So handelt es sich bei dem Fortschreibungsansatz (Previous Budget) nicht um eine bewusst eingesetzte Regel, sondern sie ist vielmehr Ausdruck des politischen Einflusses der jeweiligen Manager (Piercy 1986). Nach dem wettbewerbsorientierten Ansatz (Competitive Parity) werden Anpassungen des Budgets als Reaktion auf Marketingausgaben der Konkurrenz vorgenommen. Wissenschaftliche Methoden der Allokationsoptimierung (für einen Überblick siehe Shankar 2008) werden schließlich auch in neueren Umfragen kaum genannt (Bigné 1995).

5.2 Kritik am Konzept der Budgetierungsmethoden

Die Ergebnisse dieser Umfragen müssen allerdings grundlegend hinterfragt werden, da sie auf der Annahme eines einfachen und direkten Budgetierungsprozesses beruhen, bei dem politische Prozesse innerhalb einer Organisation ausgeblendet werden (Mitchell 1993). Tatsächlich streben Manager allerdings ein Lösung an, die gegenüber den Vorgesetzten gerechtfertigt, den Gleichgestellten vermittelt und an die Untergebenen weitergeleitet werden kann, so dass diese die Lösung logisch und akzeptabel finden und nach ihr handeln (Piercy 1986). Daher haben Manager ihre Budgetentscheidung unter Berücksichtigung von Routinen, Präzedenzfällen sowie sozialen und politischen Druck zu treffen und entsprechend nur wenig

Tabelle 1. Übersicht über Budgetierungsmethoden

Budgetierungsmethode	Definition	Vorteile	Nachteile	Verbreitung[1]
Managementerfahrung	Willkürliche Entscheidung durch Manager, nur auf Basis ihrer Erfahrungswerte	• Einfach	• Keine theoretische od. empirische Validierung • Starke Politisierung	26,5 %
Finanzkraftorientierter Ansatz	Budgetentscheidung auf der Basis der zur Verfügung stehenden freien finanziellen Mittel	• Kostendeckung • Gute Kommunizierbarkeit ggü. Finanzabteilung	• Prozyklische Wirkung	33,1 %
Prozent-vom-Umsatz	Bestimmung des Budgets als relativer oder absoluter Anteil des erwarteten oder vergangenen Umsatzes	• Kostendeckung • Gute Kommunizierbarkeit ggü. Finanzabteilung • Zusammenhang zw. Umsatz und Marketing	• Kausalzusammenhang zwischen Umsatz und Marketing vertauscht • Zukunftspotenziale werden nicht ausgeschöpft	32,2 %
Wettbewerbs-orientierung	Festlegung des Budgets proportional zu den Marketingausgaben der Wettbewerber zur Verteidigung der eigenen Marktposition	• Abschreckende Wirkung auf Konkurrenz	• Starker Fokus auf Konkurrenz ineffizient bei großen Unterschieden	16,3 %
Fortschreibungsansatz	Marketingbudget wird auf der Basis der Budgets der Vorjahre fortgeschrieben	• Vereinfachung politischer Prozesse	• Dynamische Effekte werden nicht berücksichtigt	29,1 %
Ziele-und-Aufgaben	Aufstellung von Kommunikationszielen und Planung des Budgets, das für die Erreichung der Ziele benötigt wird	• Gibt die Natur des Marketing zur Erreichung von Absatzzielen wider • Basiert auf der Marginalanalyse der ökonomischen Theorie	• Erfordert hohen Grad an analytischen Fähigkeiten und eine genaue Kenntnis der Wirkung d. Marketing	42,7 %
Optimierungs-methoden	Budgetierungsmodelle, die sich direkt aus theoretischen Optimierungsmodellen ableiten lassen	• Optimale Bestimmung des Budgets zur Maximierung des Shareholder Values	• Kompliziert umzusetzen • Erfordert sehr gute Kenntnis aller Treiber	8,4 %

[1] Die Verbreitung gibt an, wie viele der Manager bei Umfragen unter der Möglichkeit von Mehrfachnennungen angaben, diese Methode anzuwenden (Gewichtetes arithmetisches Mittel über Studienergebnisse nach Anzahl befragter Manager).
Anmerkung: Nähere Informationen zu den einzelnen Studien finden sich in den Tabellen 1 und 2 im Appendix.

Möglichkeiten, *Best Practice* anzuwenden (Prendergast et al. 2006). Dementsprechend schätzen Manager die Bedeutung politischer Betrachtungen auch höher ein als finanzielle Betrachtungen (Farris, Shames und Reibstein 1998). Piercy (1987b) rechnet den politischen Faktoren sogar einen deutlich größeren Erklärungsbeitrag zur Ausgestaltung des Marketingbudgets zu als den Budgetierungsmethoden. Es ist daher anzunehmen, dass eine ausschließliche Erklärung durch Budgetierungsmethoden eine zu große Vereinfachung darstellt und die Bestimmung des Marketingbudgets von einer Vielzahl weiterer Faktoren erklärt wird.

6 Determinanten der Marketingbudgetierung

6.1 Untersuchungsrahmen

Grundsätzlich wird in der empirischen Forschung mittels regressionsanalytischer Methoden die Wirkung von Faktoren auf die Marketingbudgetierung über deren Einfluss auf die Höhe und Verteilung des Budgets untersucht. Allerdings variieren die Studien hinsichtlich Form und Definition der abhängigen Variablen sowie dem Aggregationsniveau.

Form der abhängigen Variablen: Die meisten Studien verwenden die relative Marketingintensität, d. h. das Verhältnis der Marketingausgaben zum Umsatz, als abhängige Variable in der Regressionsgleichung. Dies geht vermutlich auf die Nähe zu allgemeinen Budgetierungspraktiken (z. B. Prozent-vom-Umsatz-Regel) zurück, wonach Unternehmen ihr Budget als bestimmten Prozentsatz vom Umsatz planen (Farris und Albion 1981). Ailawadi, Farris und Parry (1994) ergänzen, dass bereits Nerlove und Arrow (1962) gezeigt haben, dass unter gewissen Annahmen ein bestimmter Prozentsatz vom Umsatz dem optimalen Marketingbudget entspricht, so dass sich auch normative Aussagen aus der deskriptiven Analyse der Einflussfaktoren auf die Höhe der Marketingintensität ableiten lassen könnten. Dennoch ist die Verwendung dieser Kennzahl keineswegs allgemein akzeptiert, da Prozent-vom-Umsatz als eine der am wenigsten differenzierten Methoden gilt und eine stärkere Rationalität in der Budgetierung gefordert wird. Entsprechend lässt sich insbesondere in neueren Studien die Betrachtung des absoluten Marketingbudgets beobachten (z. B. Shankar 2009). Dies erschwert einen übergreifenden Vergleich der Ergebnisse, da auftretende Skaleneffekte zu Verzerrungen in den Ergebnissen führen können (Farris und Albion 1981).

Einige Studien widmen sich zusätzlich der Untersuchung der zweiten Stufe des Budgetierungsprozess - der Budgetallokation. Die abhängige Variable wird hier analog zur ersten Stufe als relative oder als absolute Kennzahl definiert. Entweder gilt diese als Relation der Ausgaben eines Marketinginstruments zum gesamten Marketingbudget (z. B. Lilien und Little 1976) oder direkt als absolute Ausgaben dieses Instruments (z. B. Shankar 2009).

Definition der abhängigen Variablen: Gleichzeitig variieren die Studien hinsichtlich der Definition der abhängigen Variablen, d. h. des zu untersuchenden Budgets, da nur einige Studien alle absatzpolitischen Maßnahmen im Budget berücksichtigen. Stattdessen wird infolge der besonderen Bedeutung, der dem Posten absatzpolitischer Maßnahmen innerhalb des Marketingbudgets zukommt, in vielen Studien nur eine Untersuchung des Werbebudgets (z. B. Farris und Albion 1981), des Budgets für Außendiensttätigkeiten (z. B. Gönül et al. 2001), oder des Budgets aller kommunikationspolitischen Maßnahmen (z. B. Farris und Buzzell 1979) vorgenommen. Eine weitere Variation ergibt sich durch unterschiedliche Auffassungen über die Zusammensetzung der jeweiligen Ausgabengruppen. Blasko und Patti (1984) schätzen, dass bis zu einem Drittel des in den Daten erfassten Marketingbudgets falsch verbucht worden ist. Dementsprechend ist anzunehmen, dass die Rechnungslegungspraktiken der Unternehmen zu einem starken Grad Differenzen in den Marketingintensitäten erklären (Martenson 1989).

Aggregationsniveau: Bezüglich des Aggregationsniveaus des Untersuchungsgegenstands beziehen sich Studien meist auf die Ebene einer Unternehmung, d. h. es werden die Determinanten der Marketingbudgetierung eines Unternehmens analysiert. Der Zweig der Industrial-Organization-Forschung untersucht hingegen Einflussfaktoren ganzer Industrien.

6.2 Determinanten der Marketingbudgetierung

Ein Vergleich der Ergebnisse der empirischen Studien ermöglicht allgemeingültige Aussagen zu der Wirkung einer Vielzahl von Determinanten auf das Marketingbudget, die im folgenden Abschnitt dargestellt werden. Teilweise lässt sich allerdings auch eine große Heterogenität in den Ergebnissen beobachten, die jedoch meist auf methodische Variationen in den Studien zurückgeführt werden können und daher erklärbar sind. Tabelle 2 bietet hierzu einen zusammenfassenden Überblick zu den Aussagen empirischer Studien hinsichtlich der Wirkungsrichtung einzelner Determinanten auf die Höhe des Marketingbudgets.

6.2.1 Produktdeterminanten

Qualität: Ein Vergleich empirischer Studien zeigt, dass hochqualitative Produkte von einem umfangreicheren Marketingprogramm unterstützt werden. Dies ist vermutlich eine Folge der höheren Effektivität von Marketingmaßnahmen, wenn diese eine überlegene Qualität

Tabelle 2: Anzahl der Studien, die einen signifikanten Einfluss durch die Determinanten auf die Höhe des Marketingbudgets feststellen

		Einfluss auf die Höhe des Marketingbudgets				
		Linear		Nicht linear		
Determinante	Konzeptualisierung	Positiv	Negativ	U-förmig	Invertiert U-förmig	Nicht signifikant
Qualität		5 (80%)				1 (20%)
Einzigartigkeit	Produziert auf Bestellung		5 (100%)			
	„Hidden Values“	2 (33%)				4 (67%)
Kauffrequenz			5 (72%)		1 (14%)	1 (14%)
Preis	Absoluter Preis	1 (13%)	4 (50%)		1 (13%)	2 (25%)
	Relativer Preis	1 (100%)				
Profitabilität	Profitmarge (Firma)	4 (100%)				
	Profitmarge (Branche)	5 (63%)	2 (25%)			1 (13%)
	Höhe Free Cash Flow	2 (100%)				
Marktgröße	Gesamtumsatz		4 (80%)			1 (20%)
	Regionaler Marktbezug		1 (100%)			
Marktwachstum		5 (29%)	2 (12%)			10 (59%)
Anzahl Kunden		7 (88%)				1 (13%)
Marktdominanz		7 (44%)	8 (50%)			1 (6 %)
Marktkonzentration		5 (19%)	3 (12%)	2 (8%)	9 (35%)	7 (26%)
Anzahl Wett-bewerber	Auf gleichem Markt	8 (67%)	3 (25%)			1 (8%)
	Multimarktkontakte		2 (100%)			
Marketingausgaben Wettbewerb		5 (83%)	1 (17%)			
Produktlebens-zyklus	Zeit im Markt		8 (57%)			6 (43%)
Markteintritts-reihenfolge			2 (100%)			
Organisations-form	Entscheidungsrichtung („Top-Down“)		2 (100%)			
	Macht Marketingabteilung	1 (50%)				1 (50%)
Budgetierungs-methode	Komplexität der Methode	2 (50%)				2 (50%)
Partizipation am Geschäftserfolg	Höhe d. Besitzanteils		1 (33%)	2 (67%)		
	Langfristigkeit d. Belohnung	2 (100%)				

Anmerkung: Die Angaben in Klammern zeigen, wie viele der Studien, die diese Determinante untersucht haben, einen entsprechenden Effekt gemessen haben. Für Detailinformationen zu den empirischen Ergebnisse siehe die Tabellen 6 a-f und 7 a/b im Appendix.

kommunizieren können (Tellis und Fornell 1988). Entsprechend lässt sich im Besonderen eine Steigerung des Werbebudgets beobachten, um eine stärkere Verbreitung einer auf der hohen Qualität des Produkts basierenden Werbebotschaft sicherzustellen (Lilien und Little 1976).

Einzigartigkeit eines Produkts: Die Einzigartigkeit eines Produkts wurde in der empirischen Literatur mit zwei verschiedenen Konstrukten untersucht. Zum einen konnte bei Produkten, die auf Bestellung produziert werden, eine geringere Marketingintensität nachgewiesen werden. Begründet wird dies damit, dass diese Produkte meist eine künstlerische Komponente für den Kunden besitzen, so dass Marketing nur von nachrangiger Bedeutung ist und der direkte Kontakt zwischen Kunde und Anbieter wichtiger wird (Lilien 1979). Es kann daher vermutet werden, dass die Senkung der Werbeausgaben parallel mit einem Anstieg der Ausgaben für den Verkaufsaußendienst verbunden ist (Farris und Buzzel 1979). Hierfür gibt es aber keine empirische Validierung.
Das zweite Konstrukt basiert auf der Existenz von „Hidden Values“, d. h. Eigenschaften, die sich erst nach mehrmaligem Gebrauch des Produkts für den Konsumenten erschließen. Ein Vergleich der Studien zeigt grundsätzlich einen eher positiven, jedoch keinen einheitlich signifikanten Effekt auf die Marketingintensität, was offenbar auf die unterschiedlichen untersuchten Marketingmaßnahmen zurückzuführen ist. Insgesamt liegt die Vermutung nahe, dass bei Produkten mit „Hidden Values“ vor allem der Außendienst intensiviert wird, der Kunden direkt in die Besonderheiten des Produkts einführen kann (Farris und Buzzel 1979).

Kauffrequenz: Bei der Kauffrequenz eines Produkts zeigt sich über alle Studien ein negativer Zusammenhang mit der Marketingintensität, d. h. je häufiger ein Produkt gekauft wird, desto geringer ist das Marketingbudget. Ursache hierfür ist vermutlich, dass Produkte mit einer hohen Kauffrequenz meist standardisierte Produkte des Alltags sind, bei denen sich der Konsument eher auf seine Erfahrung verlässt, während bei selten gekauften Produkten zur besseren Werteinschätzung meist mehr Informationen benötigt werden (Zif, Young und Fenwick 1984). Ein differenzierteres Bild liefern jedoch Keown et al. (1989), die auch auf Nichtlinearität testen und einen invertiert U-förmigen Zusammenhang feststellen. Produkte mit mittlerer Kauffrequenz haben demnach die größten Marketingbudgets, gefolgt von selten gekauften Produkten. Die kleinsten Budgets zeigen sich bei Produkten mit hoher Kauffrequenz.

6.2.2 Preisdeterminanten

Preis: Bei der Untersuchung des Preises als Determinante der Marketingintensität stellt sich insgesamt ein uneinheitliches Bild dar, das auf gegenläufige Effekte zurückgeführt werden kann.

So stellen teure Produkte eher riskante Käufe dar, bei denen sich Kunden weniger auf das Marketing als primäre Informationsquelle verlassen und ihre Kaufentscheidung verstärkt auf Testergebnisse, Erfahrungen, Ratschläge von Freunden u.ä. stützen (Farris und Buzzel 1979). Andererseits besteht bei hochpreisigen Gütern die Notwendigkeit, mittels erhöhter Marketingaufwendungen ein Bild von hoher Qualität und Prestige aufrecht zu erhalten (Rizzo 1999). Gönül et al. (2001) erklären die widersprüchlichen Ergebnisse zusätzlich durch gegenläufige Interaktionseffekte zwischen Preis und Marketing. Höhere Marketinginvestitionen verhelfen auf der einen Seite zu einer besseren Produktdifferenzierung und damit geringerer Preiselastizität. Allerdings wird durch das verstärkte Marketing auch die Vergleichbarkeit zwischen den Produkten verbessert und auf diesem Weg die Preissensitivität der Konsumenten erhöht. Farris und Buzzell (1979) gelingt es, die gegenläufigen Effekte zu trennen, indem sie sowohl den relativen Preis (innerhalb einer Produktklasse) als auch den absoluten Preis im Modell berücksichtigen. Wie erwartet, zeigt sich beim relativen Preis ein positiver und beim absoluten Preis ein negativer Einfluss auf die Marketingintensität.
Eine Untersuchung der Budgetallokation bei hochpreisigen Produkten zeigt des Weiteren, dass hier vor allem markenaufbauende Werbung eingesetzt wird, die das überlegene Image des Produkts vermitteln soll, während Promotion-Maßnahmen, z. B. durch Preisreduktionen, den unerwünschten Effekt einer Senkung des Referenzpreises bei den Kunden herbeiführen (Low und Mohr 2000).

Profitabilität: Nach der mikroökonomischen Theorie hat die Profitabilität einen großen Einfluss auf die Bestimmung der Höhe der Marketingbudgets (Ailawadi, Farris und Parry 1994). Eine höhere Profitmarge führt demnach zu einer höheren optimalen Marketingintensität. Empirisch konnte dieser Zusammenhang sowohl für die Messung der Profitabilität als relative Größe (Profitmarge), wie auch als absolute Größe (Höhe des Free Cash Flows) bestätigt werden. Dieses Ergebnis deckt sich auch mit den Umfragen zu Budgetierungsheuristiken, nach der viele Manager ihr Budget auf der Basis der Höhe der frei verfügbaren finanziellen Mittel bestimmen. Es zeigt sich in diesem Sinne sogar, dass Firmen, die über viel freies Kapital verfügen, dazu neigen, mehr für Marketing aufzuwenden, als notwendig oder wünschenswert wäre (Tellis 1998). Die Kostendeckung der Marketingausgaben besitzt demnach eine hohe Priorität bei Managern (Wagner und Fischer 2011).
Eine Untersuchung der Profitabilität auf Industrieebene bestätigt grundsätzlich dieses Bild. Allerdings lässt sich hier eine größere Heterogenität in den Ergebnissen beobachten. Eine Ursache dieser unterschiedlichen Ergebnisse könnte in der Interaktion mit der Produktkategorie liegen. So zeigt sich bei Industriegütern eher ein negativer Effekt, d. h. je höhere Profitmargen

eine Industrie allgemein aufweist, desto weniger Marketing betreiben die Unternehmen, während im Konsumgüterbereich eher positive Effekte zu beobachten sind (Lee 2002). Eine Ursache hierfür könnte die traditionell wichtigere Rolle des Marketing im Konsumgüterbereich sein, die Unternehmen eher dazu verleitet, freies Kapital in Marketing zu investieren. Allerdings ist hier noch weiterer Forschungsbedarf notwendig.

6.2.3 Marktdeterminanten

Marktgröße: Bei der Untersuchung der Marktgröße zeigt sich das einheitliche Bild einer geringeren Marketingintensität in großen Märkten. Dieser Effekt ist vermutlich auf Skaleneffekte im Marketing zurückzuführen. Gleichzeitig findet sich in der Studie von Rundfelt (1973) ein positiver Einfluss auf die Höhe des Werbebudgets durch die Reichweite des Markts, d. h. Unternehmen, die nur einen regionalen und damit kleineren Markt bedienen, betreiben weniger Werbung. Ursache für diese widersprüchlichen Ergebnisse ist offenbar die größere Reichweite klassischer Werbeträger, so dass regionale Unternehmen eher auf andere Marketinginstrumente ausweichen. Um dies validieren zu können, sind allerdings weitere Studien notwendig, die auch andere Marketingausgaben mit einbeziehen.

Marktwachstum: Grundsätzlich ist anzunehmen, dass beständiges und systematisches Wachstum verstärktes Marketing rechtfertigt, da es auf einen noch weitestgehend unbedienten Markt hindeutet, der das Produkt bisher kaum wahrgenommen hat. Und tatsächlich werden die allgemeinen Marktbedingungen von Managern häufig als wichtige Determinante angegeben (Jobber 1980). Dennoch zeichnen die meisten empirischen Studien nur einen insignifikanten Effekt durch das Marktwachstum auf. Dies könnte eine Folge gegenläufiger negativer Effekte durch fehlende gewinnbringende Investitionsmöglichkeiten in niedrig wachsenden Märkten sein (Supanvanij 2005). Die Vermutung liegt allerdings näher, dass der Effekt des Marktwachstums generell eher gering auf das Marketingbudgetierungsverhalten ist, da die Variable schnell insignifikant wird, sobald andere Variablen, wie z. B. Produktlebenszyklus, im Modell berücksichtigt werden (Farris und Albion 1981).

Anzahl Kunden: Die Anzahl der Kunden im Markt hat einen eindeutig positiven Einfluss auf die Marketingintensität. Dies gilt im Besonderen bei Marketingmaßnahmen, die eine breite Kundenerreichung haben (Lilien 1983). Zurückführen lässt sich dieser Effekt vermutlich auf die höhere Marketingeffektivität bei größerem Publikum sowie auf ein höheres Marktpotenzial bei vielen Endkonsumenten (Farris und Buzzell 1979). Stewart (1996) identifiziert die Anzahl der Kunden, die angeben, das Produkt nochmals zu kaufen (Wiederkaufrate), sogar als bedeutsamste Variable zur Erklärung der Marketingintensität. Er vermutet, dass dies auf einen stärkeren Fokus des Marketings auf die Bindung der Kunden an das Unternehmen zurückzuführen ist. Übereinstimmend zeigt sich auch ein negativer Zusammenhang mit der Kundenkonzentration, d. h. dem Anteil des Umsatzes, der auf die größten Kunden entfällt (Lilien 1979).

6.2.4 Wettbewerbsdeterminanten

Marktdominanz: Die Marktdominanz eines Unternehmens, d. h. dessen relative Größe im Markt, meist gemessen als Marktanteil, gilt in der Literatur als einer der bedeutsamsten Treiber zur Erklärung der Marketingintensität. Dominante, umsatzstarke Produkte haben übereinstimmend größere Marketingbudgets; betrachtet man jedoch die relativen Kennzahlen zeigt sich einheitlich ein Rückgang der Marketingintensität mit zunehmender Marktdominanz (Lilien und Little 1976). Dies ist eine Folge von Skaleneffekten im Marketing. Der Wertbeitrag des Marketing nimmt mit zunehmenden Budget ab, so dass das Marketingbudget nicht proportional zum Umsatz bzw. Marktanteil mit ansteigt (Fischer et al. 2011).

Marktkonzentration: Obwohl das Meinungsbild zur Wirkung der Marktkonzentration in der Literatur sehr heterogen ist, scheint sich doch bei einem Vergleich der Studien ein invertiert U-förmiger Wirkungszusammenhang zu bestätigen. Die Ursache liegt offenbar in den gegenläufigen Effekten auf das Marketingbudgetierungsverhalten. So trägt nach der ökonomischen Theorie Marketing zur Abgrenzung von Konkurrenzprodukten bei und erhöht so Eintrittsbarrieren und damit auch die Marktkonzentration (Farris und Buzzell 1979). Zusätzlich lässt sich eine größere Marketingeffektivität in konzentrierten Märkten feststellen (Bowman und Gatignon 1996). Auf der anderen Seite kann in konzentrierten Märkten die Neigung zu kooperativen Marketingbudgetierungsverhalten beobachtet werden, die niedrigere Marketingintensitäten zur Folge haben (Ramaswamy, Gatignon und Reibstein 1994). Es ist daher anzunehmen, dass kooperatives Verhalten erst möglich wird, wenn sich nur sehr wenige Teilnehmer im Markt befinden (Willis und Rogers 1998) und sich der negative Effekt auf die Marketingintensität daher erst in hoch konzentrierten Märkten entfaltet. Insgesamt wurde allerdings in den bisherigen Studien zu selten auf Nicht-Linearität getestet, so dass dieser Befund noch nicht als empirisch gesichert angesehen werden kann. Zudem besteht in der Forschung die Überzeugung, dass es sich bei der Marktkonzentration um eine eher unwichtige Determinante des Marketingbudgetierungsverhaltens handelt, insbesondere wenn weitere Variablen im Modell berücksichtigt werden (Farris und Albion 1981).

Anzahl Wettbewerber: Nach der Wettbewerbstheorie steigt mit zunehmender Anzahl der Teilnehmer im Markt die Marketingintensität (Scherer und Ross 1990, 594 ff.). Dies scheint sich auch in empirischen Studien zu bestätigen, die mehrheitlich eine positive Korrelation der Anzahl an Wettbewerbern mit der Marketingintensität feststellen und damit auf eine starke Wettbewerbsorientierung der Manager hindeuten (Lilien 1979). Insgesamt bleibt allerdings ein heterogenes Bild über die Studien, das sich erst durch einen Blick auf die Budgetallokation aufklärt. Bei Marketinginstrumenten, die vor allem zu einer Erweiterung des Marktes beitragen, lässt sich mit zunehmender Anzahl an Wettbewerbern Free-Rider-Verhalten, d. h. reduzierte Marketinginvestitionen, beobachten. Die Ausgaben in Marketinginstrumenten mit Business-Stealing-Effekt nehmen hingegen zu (Iizuka 2004).

Eine weitere signifikante Wirkung auf die Marketingintensität haben die sogenannten Multimarktkontakte, d. h. die Anzahl der Märkte auf denen zwei Firmen mit ihrem Produktportfolio in Konkurrenz stehen. Es zeigt sich dabei, dass je mehr Multimarktkontakte existieren und je ähnlicher sich die Märkte sind, desto geringer ist das Marketingbudget, da die Angst vor Vergeltung zu höherer Rücksichtnahme führt (Chen 1996).

Marketingausgaben der Wettbewerber: Der Einfluss des Wettbewerbs auf die Marketingbudgetierung ist bereits durch die wettbewerbsorientierte Budgetierungsmethode offensichtlich und bestätigt sich auch in empirischen Studien. Unter der Annahme gewinnoptimalen Verhaltens lassen sich häufig deutliche Überreaktionen auf Marketingaktionen der Konkurrenz beobachten (Chintagunta und Desiraju 2005). Es scheint die Verbesserung der eigenen Position im Vordergrund zu stehen - auch wenn dies zu Lasten des Gewinns geht (Chintagunta, Kadiyali und Vilcassim 2006). Eine Ursache hierfür könnte in der Heranziehung von Erfolgsgrößen liegen, die in Relation zur Konkurrenz stehen. Ebenso können sie als Strafaktion gedacht sein, um die Konkurrenz abzuschrecken (Lynn 1987). Allerdings wurden auch Fälle von kooperativen Wettbewerbsverhalten beobachtet (Chintagunta und Desiraju 2005). In diesen Fällen steht die Absicht im Vordergrund, Marketingkriege vermeiden zu wollen, so dass eine angemessene Reaktion gescheut wird. Die unterschiedlichen Ergebnisse lassen sich vor allem auf zwei Interaktionseffekte zurückführen. Zum einen wird die Art der Reaktion wesentlich von der Unternehmensgröße beeinflusst. Dominantere Marken werden stärker als Bedrohung wahrgenommen, da sie über die notwendigen Ressourcen für einen Marketingkrieg verfügen. Die Reaktion auf Aktionen dominanter Marken fällt daher deutlich verhaltener aus (Dekimpe und Hanssens 1999). Zum anderen zeigt sich eine geringere Aggressivität in späteren Phasen des Produktlebenszyklus, da die Aussicht auf geringe Gewinne in der Reifephase Vergeltungsmaßnahmen nicht rechtfertigen (Chen 1996).

6.2.5 Zeitdeterminanten

Produktlebenszyklus: Nach der mikroökonomischen Theorie ist es bei einer Produktneueinführung zunächst notwendig, intensives Marketing zu betreiben, um mittels Carry-Over-Effekten einen hohen Bekanntheitsgrad für das Produkt aufzubauen (Ailawadi, Farris und Parry1994). Tatsächlich konnte in vielen empirischen Studien gezeigt werden, dass die Marketingintensität bei der Produkteinführung am höchsten ist und in den anschließenden Phasen des Produktlebenszyklus kontinuierlich abnimmt. Dementsprechend finden sich in den frühen Phasen des Lebenszyklus vor allem Werbemaßnahmen, die die Wahrnehmung der Marke erhöhen und auf diese Weise den Diffusionsverlauf beschleunigen sollen (Iizuka 2004). In den späteren Phasen wechseln Manager aufgrund zunehmenden Wettbewerbsdrucks auf Promotion-Maßnahmen (Shankar 2009). Gleichwohl werden in vielen Studien auch insignifikante Effekte gemessen, was eine Folge gegenläufiger Effekte sein kann. So gilt in der Wachstumsphase, dass Firmen sich zu Free-Riding ermuntert fühlen, während in der Reifephase, ein erhöhter Marketingaufwand nötig wird, um in dem wettbewerbsintensiven Markt seine Position verteidigen zu können.

Markteintrittsreihenfolge: Die Eintrittsreihenfolge der Produkte in den Markt wurde bisher nur selten empirisch getestet. Es zeigt sich dennoch, dass Pioniere und frühe Folger höhere Marketingbudgets aufweisen (Iizuka 2004), was sich vermutlich auf die höhere Effektivität des Marketing bei Pionieren zurückführen lässt (Shankar, Carpenter und Krishnamurthi 1998).

6.2.6 Organisationsdeterminanten

Organisationsform: Die Studien von Piercy (1987a,b) zeigen einen deutlichen Einfluss der Organisationsform auf das Budgetierungsverhalten. Insgesamt lässt sich bei Bottom-Up-Prozessen eine stärkere Marketingintensität beobachten, die wahrscheinlich auf die geringere Kontrolle durch das Topmanagement und die Finanzabteilung, die ein stärkeres Interesse an einer Begrenzung des Marketingbudgets haben, zurückzuführen ist. Zusätzlich zeigen verschiedene politische Faktoren einen Einfluss auf die Höhe des Budgets. Dieses ist desto höher, je politischer der Prozess insgesamt geprägt ist. Ein einheitlicher direkter Einfluss durch die Macht der Marketingabteilung konnte hingegen nicht bestätigt werden.

Budgetierungsmethode: Die Wahl der Budgetierungsmethode auf das Budgetierungsverhalten wurde in mehreren Studien untersucht, dennoch konnte sich kein einheitliches Bild durchsetzen. Grundsätzlich scheint allerdings die gewinnorientierte Ziele-und-Aufgaben-Methode eine stärkere Marketingintensität zu bewirken (Gilligan 1977), während die Budgets bei Anwendung kostenorientierter Ansätze deutlich kleiner sind (Piercy 1987a).

Partizipation am Geschäftserfolg: Die Effekte auf das Marketingbudgetierungsverhalten durch die Partizipation der Manager am Unternehmenserfolg wurde in der empirischen Forschung mit zwei unterschiedlichen Konstrukten untersucht. Zum einen wurde gezeigt, dass der Zusammenhang der Marketingintensität mit der Höhe des Besitzanteils der Manager am Unternehmen einem invertiert U-förmigen Zusammenhang folgt. Diese Beobachtung ist im Einklang mit der Agency-Theorie, nach der zwei gegenläufige Effekte auftreten. Zum einen konvergieren mit zusätzlichem Besitzanteil die Interessen von Management und Eigentümer und führen zu geringerer Marketingintensität, was unter der Annahme des häufig zu beobachteten ‚Overspendings' mit einem effizienteren Marketingeinsatz vergleichbar ist. Zum anderen treten allerdings nicht-lineare Entfremdungseffekte auf, die zu suboptimalen Effekten und zu hohen Ausgaben führen (z.B. Empire Building). Die Entfremdungseffekte sind bei sehr niedrigem Besitzanteil kaum vorhanden, da Marktdisziplin den Manager zu optimalem Verhalten nötigt. Mit wachsendem Einfluss der Manager neigen diese jedoch zu suboptimalem, ihren Interessen folgendem, Verhalten. Durch die Überlagerung überwiegen bei geringem Besitzanteil die positiven Effekte, bei mittlerem die negativen und bei hohem wieder die positiven Effekte.

Zum anderen wird anhand des Bonussystems der Managerbelohnung gezeigt, dass je mehr der Wohlstand eines Managers an den langfristigen Unternehmenserfolg anstatt den kurzfristigen Gewinn gebunden ist, desto mehr wird für Marketing ausgegeben (Corfman und Lehmann 1994). So führen kurzfristige Kompensationen, z. B. Gehalt und Bonus, zu einer Reduktion der Marketingintensität, während hingegen eine langfristige Kompensation durch Optionen die Marketingintensität erhöht, auch um die Volatilität des Aktienkurses des Unternehmens und damit den Wert der Option zu erhöhen (Supanvanij 2005).

6.3 Zusammenfassung

Zusammenfassend lassen sich damit die folgenden wichtigen empirischen Generalisierungen zu Einflussfaktoren der Marketingbudgetierung festhalten:

- Produkte von höherer Qualität weisen eine stärkere Marketingintensität auf, was eine bessere Kommunikation der Vorteile des Produkts ermöglicht.
- Häufig gekaufte Produkte werden weniger stark beworben, da es sich hier wohl meist um standardisierte Produkte des Alltags handelt, bei denen sich der Konsument in seiner Kaufentscheidung verstärkt auf seine eigene Erfahrung stützt.

- Freies verfügbares Kapital, z. B. infolge einer hohen Profitabilität, wird (teilweise) in verstärktes Marketing investiert.
- Bei Unternehmen, die einen großen Markt bedienen bzw. eine dominante Marktstellung besitzen, finden sich geringere Marketingintensitäten, während eine breite Kundenbasis gleichzeitig die Marketingintensität erhöht.
- Grundsätzlich lässt sich eine starke Wettbewerbsorientierung der Manager feststellen, die zu einer stärkeren Marketingintensität bei einer größeren Anzahl an Wettbewerbern bzw. bei größeren Marketinginvestitionen durch die Konkurrenz führt.
- Ein Unternehmen investiert desto weniger in das Marketing, je stärker der Einfluss des Topmanagements im Budgetierungsprozess ist und je kurzfristiger geplant wird.

7 Determinanten der Wahl der Budgetierungsmethode

7.1 Untersuchungsrahmen

Allgemein untersucht die empirische Literatur Determinanten der Wahl der Budgetierungsmethode über eine Analyse von Zusammenhängen zwischen Manageraussagen zu angewendeten Methoden sowie gleichzeitig erhobenen exogenen Faktoren, z. B. Markt- oder Unternehmenseigenschaften. Hier lassen sich zwei Untersuchungsansätze identifizieren. Der erste analysiert direkt Korrelationen zwischen Präferenzen für einzelne Regeln und exogenen Faktoren. Dabei existiert in vielen Studien ein Fokus auf der Ziele-und-Aufgaben-Regel, um Determinanten zu identifizieren, die die Anwendung differenzierter Budgetierungsmethoden fördern. Beim zweiten Ansatz werden Unternehmen auf der Basis ihrer Angaben zu verwendeten Methoden hinsichtlich ihres Komplexitätsgrads im Budgetierungsverhalten bewertet und dieses Maß in Relation zu exogenen Faktoren untersucht. Aus dem Ergebnis lassen sich ebenfalls Determinanten identifizieren, die eine bessere Budgetierungspraxis fördern. Einen anderen Weg gehen Wagner und Fischer (2011), die die Kritik aufgreifen, dass Managerumfragen infolge verschiedener Verzerrungseffekte und Ungenauigkeiten, wie z. B. dem K*ey Informant Bias*, nur begrenzt aussagefähig sind (Armstrong und Overton 1973). Aus diesem Grund untersuchen sie anstelle des in Umfragen geäußerten Willens von Managern das tatsächliche Budgetierungsverhalten. Dazu werden die Budgetierungsmethoden formalisiert, ihr Einfluss auf die Bestimmung der Marketingbudgets geschätzt und anschließend die Wirkung exogener Faktoren auf den Einfluss der einzelnen Methoden analysiert.

7.2 Determinanten der Wahl der Budgetierungsmethode

Die Anzahl der empirischen Studien, die Einflussfaktoren auf die Wahl der Budgetierungsmethode untersuchen, ist eher gering, so dass eine Ableitung allgemeingültiger Aussagen aus einem Vergleich dieser Studien mit Vorsicht zu betrachten ist. Dennoch lassen sich bei den meisten Determinanten deutliche Muster erkennen, die im Folgenden diskutiert werden. Tabelle 3 bietet dazu einen Überblick über Ergebnisse empirischer Studien hinsichtlich der Wirkung von Faktoren auf die Anwendung komplexer Budgetierungsmethoden, d. h. im Besonderen auf eine Anwendung der Ziele-und-Aufgaben-Regel.

Tabelle 3: Anzahl der Studien, die einen signifikanten Einfluss durch die Determinanten auf die Anwendung komplexer Budgetierungsmethoden feststellen

		Einfluss auf die Anwendung komplexer Budgetierungsmethoden				
		Linear		Nicht linear		
Determinante	Konzeptualisierung	Positiv	Negativ	Positiv	Negativ	Nicht signifikant
Produktkategorie	Konsumgüter	6 (55%)				5 (45%)
	Langlebigkeit des Produkts	1 (50 %)	1 (50 %)			
Profitabilität		6 (86%)				1 (14%)
Marktdominanz		7 (70%)				3 (30%)
Marktkonzentration		2 (100%)				
Marktwachstum		2 (67%)				1 (33%)
Produktlebens-zyklus	Zeit im Markt		1 (100%)			
Markteintritts-reihenfolge			1 (100%)			
Organisations-form	Macht Marketing-abteilung	7 (88%)				1 (13%)
Partizipation am Geschäftserfolg	Höhe des Besitz-anteils			1 (100%)		
	Langfristigkeit d. Belohnung	3 (100%)				

Anmerkung: Die Angaben in Klammern zeigen, wie viele der Studien, die diese Determinante untersucht haben, einen entsprechenden Effekt gemessen haben. Für Detailinformationen zu den empirischen Ergebnissen siehe die Tabellen 8a/b sowie 9 im Appendix.

7.2.1 Produktdeterminanten

Produktkategorie: Managerumfragen identifizieren die Produktkategorie als eine der wichtigsten Einflussfaktoren bei der Wahl der Budgetierungsmethode (Mitchell 1993). Konsumgüterhersteller haben dabei am schnellsten auf die Veränderungen eines stärkeren Wettbewerbs und sich wandelnder Marktbedingungen reagiert und bereits früh komplexere Budgetierungsmethoden übernommen. Industriegüterhersteller sowie Dienstleister wendeten hingegen länger einfache Regeln an, übernehmen aber nun verzögert ebenfalls zunehmend komplexere Budgetierungsmethoden (Miles, White und Munilla 1997); obgleich die finanzkraftorientierte Regel noch immer die stärkste Verbreitung findet. Dies mag an der traditionell wichtigeren Rolle des Marketing zur Stimulierung der Nachfrage bei Konsumgütern liegen. Der Trend zu komplexen Budgetierungsmethoden scheint bei langlebigen Konsumgütern besonders stark ausgeprägt zu sein (Ramaseshan 1990), während bei FMCG einfache Methoden, wie der finanzkraft- oder der wettbewerbsorientierte Ansatz stärker verwendet werden (West und Hung 1993). Insgesamt findet sich allerdings in zu vielen Studien ein insignifikanter Einfluss der Produktkategorie, als dass die beobachteten Effekte als empirisch generalisierbar angesehen werden könnten.

7.2.2 Preisdeterminanten

Profitabilität: Die Profitabilität eines Unternehmens gilt als ein Schlüsseltreiber der Anwendung komplexer Budgetierungsmethoden (Lynch und Hooley 1990). Insbesondere die Ziele-und-Aufgaben-Methode findet bei profitablen Unternehmen breite Anwendung (Parry, Parry und Farris 1991). Die Ursache mag in den größeren Ressourcen profitabler Firmen liegen, die ihnen die Anwendung differenzierter Methoden erleichtern (West und Crouch 2007). Angesichts höherer Profitmargen ist auch der Anreiz, komplexere Methoden anzuwenden, größer, da bei einer Ausweitung der Nachfrage der zu erwartende Gewinn umso stärker steigt.

7.2.3 Marktdeterminanten

Marktwachstum: In einer Umfrage von Prendergast, West und Shi (2006) gab die Mehrzahl der befragten Manager an, dass sie ihre Budgetierungsmethode wechseln, wenn sie im Angesicht von geringen Wachstums- bzw. Schrumpfungsraten des Marktes unter Profitabilitätsdruck geraten. Während bei hohem Wachstum der Strategiefokus auf Ausschöpfung der Möglichkeiten liegt, die eine vermehrte Anwendung der Ziele-und-Aufgaben-Regel zur Folge hat, konzentrieren sich Unternehmen bei niedrigem Wachstum oder Schrumpfung auf Kostenkontrolle bzw. Verteidigung der Marktposition durch z. B. die Prozent-vom-Umsatz-Regel bzw. den wettbewerbsorientierten Ansatz (Mitchell 1993). Auch wenn sich dies in empirischen Studien grundsätzlich bestätigt, ist hier noch weiterer Forschungsbedarf notwendig.

7.2.4 Wettbewerbsdeterminanten

Marktdominanz: Die empirische Literatur stimmt mehrheitlich darin überein, dass große und dominante Firmen mehrheitlich komplexere Budgetierungsmethoden anwenden, im Besonderen die Ziele-und-Aufgaben-Regel (Hung und West 1991). Dies würde die Prämisse unterstützen, dass größere Unternehmen ein stärkeres Interesse in *Best Practice* haben. Vermutlich lässt sich dies auf die breitere Verfügbarkeit umfangreicher Datensätze sowie die Existenz eines *Operations Department*, das zur Entwicklung und Schätzung von quantitativen Modellen benötigt wird, zurückführen (Parry, Parry und Farris 1991). Gleichzeitig besteht die Möglichkeit, dass eine in vielen größeren Unternehmen vorherrschende Produktvielfalt die Anwendung fortschrittlicher Budgetierungspraktiken ergibt. Dennoch finden sich in einigen Studien insignifikante Effekte, die eventuell darauf zurückzuführen sind, dass mit der Zeit vermehrt auch Unternehmen mittlerer Größe die Ziele-und-Aufgaben-Regel anwenden (Miles, White und Munilla 1997).

Marktkonzentration: Die empirische Literatur offenbart eine Präferenz für differenzierte Methoden in hoch konzentrierten Märkten, während bei vielen Wettbewerbern eher einfache Regeln angewendet werden. Aufgrund des offensichtlichen Zusammenhangs der Marktkonzentration mit der Größe der Unternehmen ist dies vermutlich auf die gleichen Effekte wie bei der Marktdominanz zurückzuführen, wonach große Unternehmen die notwendigen Ressourcen für die differenzierte Bestimmung von Budgets besitzen (Parry, Parry und Farris 1991).

7.2.5 Zeitdeterminanten

Produktlebenszyklus: Über die Hälfte der befragten Manager in der Studie von Mitchell (1993) bestätigen, dass sie bei neu eingeführten Produkten andere Budgetierungsmethoden anwenden als bei etablierten. Es zeigt sich dabei eine verstärkte Anwendung der Ziele-und-Aufgaben-Regel in den späteren Phasen des Lebenszyklus, die darauf hindeutet, dass Produkte während ihrer Reifephase mit einem differenzierten Marketingprogramm begleitet werden. Hintergrund ist vermutlich ein erhöhter Konkurrenzdruck infolge einer stagnierenden oder sinkenden Marktgröße (Wagner und Fischer 2011). Es bedarf hier jedoch noch weiterer empirischer Forschung um generalisierbare Ergebnisse ableiten zu können.

Markteintrittsreihenfolge: Die Anwendung differenzierter Budgetierungsmethoden findet sich eindeutig häufiger bei Pionieren. Dies wird auf die eher marktdominierende Position früher Markteintritte zurückgeführt, die infolge ihrer Größe auf die notwendigen Ressourcen eines komplexen Budgetierungsverfahrens zurückgreifen können (Wagner und Fischer 2011). Allerdings besteht hier ebenfalls noch weiterer Forschungsbedarf.

7.2.6 Organisationsdeterminanten

Organisationsform: Es zeigt sich deutlich, dass bei einem starken Einfluss durch das Topmanagement bei einem eher Top-Down geprägten Prozess einfache Methoden wie die managementerfahrungsbasierte oder die finanzkraftorientierte Regel den Budgetierungsprozess dominieren. Gleichzeitig findet sich bei einer Bottom-Up-Prozessstruktur und einem stärkeren Einfluss der Marketingabteilungen eine vermehrte Anwendung der Ziele-und-Aufgaben-Methode. Durch die verstärkte Interaktion mehrerer Abteilungen entsteht eine differenziertere Budgetallokation (Prendergast, West und Shi 2006). Parry, Parry und Farris (1991) weisen allerdings darauf hin, dass der Einfluss der Prozessstruktur insignifikant wird, sobald im Modell politische Faktoren berücksichtigt werden. Vermutlich ist daher der gemessene Effekt eher den bei diesen Organisationsformen typischen politischen Einflüssen zuzuschreiben. Daraus lässt sich auch ableiten, dass je stärker ein Prozess durch politische Einflussnahmen geprägt ist, desto eher wird die Ziele-und-Aufgaben-Regel angewendet. Dieses Ergebnis ist im Einklang mit der Vermutung, dass diese Methode vor allem als Instrument einflussreicher Akteure verwendet wird, um eigene Ziele durchzusetzen (Piercy 1987a).

Budgetierungsmethode: Korrelationsanalysen offenbaren, dass Methoden häufig in Kombination Anwendung finden. Sehr häufig zeigt sich dabei die Kombination der Anwendung von der Ziele-und-Aufgaben-Methode mit der finanzkraftorientierten Regel (Lynch und Hooley 1990) oder mit wissenschaftlichen Optimierungsmethoden (Parry, Parry und Farris 1991). Ebenso findet sich auch eine verstärkte gemeinsame Anwendung des wettbewerbsorientierten Ansatzes mit Optimierungsmethoden (Miles, White und Munilla 1997).

Partizipation am Geschäftserfolg: Empirisch wurde bestätigt, dass die Anwendung komplexer und differenzierter Budgetierungsmethoden verbreiteter ist, wenn das Management langfristiger orientiert ist, z. B. durch ein gesteigertes Bewusstsein für die langfristige Werbung des Marketing und die Orientierung am langfristigen Unternehmenserfolg (Low und Mohr 1999).

Zusätzlich zeigen Joseph und Richardson (2002) in ihrer Studie, dass die Annahmen der Agency-Theorie in Bezug auf die Wirkung des Grads des Besitzanteils von Managern am Unternehmen auch auf die Wahl der Budgetierungsmethode zutreffen. So finden sich gegenläufige Konvergenz- und Entfremdungseffekte, die dazu führen, dass die Neigung differenziertere Methoden anzuwenden, bei mittlerem Grad am Besitzanteil am höchsten ist, während bei niedrigem oder hohem Grad eher kostenorientiert budgetiert wird.

7.3 Zusammenfassung

Zusammenfassend lassen sich damit die folgenden wichtigen empirischen Generalisierungen zu Einflussfaktoren der Wahl der Budgetierungsmethode festhalten:

- Profitablere Unternehmen wenden mehrheitlich komplexere Budgetierungsmethoden an, was sich vermutlich auf die Verfügbarkeit einer breiteren Ressourcenbasis, die für eine komplexe Budgetierungspraxis notwendig ist, sowie höherer Anreize durch die größere Profitmarge zurückführen lässt.
- Bei (großen) Unternehmen in hochkonzentrierten Märkten findet sich eine breitere Anwendung komplexer Budgetierungsmethoden, was vermutlich ebenfalls auf die breitere Ressourcenbasis zurückgeführt werden kann.
- Je stärker ein Budgetierungsentscheidungsprozess Bottom-Up orientiert ist und je stärker dieser durch politische Einflussnahme geprägt ist, desto mehr findet die Ziele-und-Aufgaben-Regel Anwendung.

8 Kritische Würdigung der empirischen Forschung

8.1 Inhaltliche Kritik

Zusammenfassend lässt sich im Rahmen des zugrunde gelegten konzeptionellen Bezugsrahmens festhalten, dass ein umfangreicher Erkenntnisstand über die Einflussfaktoren der Marketingbudgetierung besteht. Dennoch lassen sich folgende Kritikpunkte festhalten, die Ansatzpunkte für die zukünftige Forschung liefern.

8.1.1 Budgetierungsmethoden

Berücksichtigung politischer Einflussfaktoren: Greift man das Ergebnis von Piercy (1987b) auf, wonach politische Faktoren einen deutlich größeren Erklärungsbeitrag zur Ausgestaltung des Marketingbudgets liefern als die reinen Budgetierungsmethoden, sind die Umfrageergebnisse zur Anwendung von Budgetierungsheuristiken nur begrenzt aussagefähig und unterliegen der Gefahr einer Verzerrung. Ein stärkerer Fokus auf politische und strukturelle Faktoren und dessen Berücksichtigung in Managementbefragungen könnten einen Beitrag zur Entwicklung eines umfassenden Erklärungskonzepts des Budgetierungsverhaltens liefern, aus dem sich auch der theoretische Unterbau eines Modells zur empirischen Analyse der Marketingintensität bzw. -allokation ableiten ließe.

Untersuchung der Wirkung des Einsatzes von Budgetierungsmethoden auf Erfolgskennzahlen: Die deskriptive Analyse des Marketingbudgetierungsverhaltens besitzt den

Anspruch aus dem beobachtbaren Verhalten von (erfolgreichen) Unternehmen Richtlinien und Implikationen für eine erfolgreiche Budgetierung ableiten zu können. Eine direkte Untersuchung des Budgetierungsverhaltens auf verschiedene Erfolgskennzahlen ist bisher allerdings noch nicht vorgenommen worden, obgleich sich hieraus wesentlich deutlicher Erfolgsfaktoren der Marketingbudgetierung identifizieren ließen. So ist zu beobachten, dass Marketingbudgetentscheidungen Kapitalmarktreaktionen auslösen (Srinivasan und Hanssens 2008). Daher könnte eine Untersuchung der kurz- und langfristigen Auswirkungen am Kapitalmarkt durch bestimmte Budgetierungspraktiken einen wesentlich tieferen Einblick liefern.

8.1.2 Determinanten der Marketingintensität

Unzureichende theoretische Fundierung: Die Modelle in den empirischen Untersuchungen sind selten mit einer theoretischen Basis verknüpft. Das ist im Besonderen verwunderlich, da die Theorie zur Marketingbudgetierung zahlreiche Anknüpfungspunkte liefert. In der Konsequenz unterbleiben damit meist eine Überprüfung theoretischer Ergebnisse sowie eine systematische Darstellung der empirischen Einzelbefunde.

Unvollständigkeit von Untersuchungsmodellen: Der konzeptionelle Bezugsrahmen stellt verschiedene mögliche Einflussfaktoren auf die Marketingbudgetierung dar. Eine auch nur annähernd vollständige Untersuchung zu den Erfolgsfaktoren, d. h. ein interdependentes Gesamtmodell, liegt jedoch bisher nicht vor. Daher muss kritisch hinterfragt werden, ob aufgezeigte Einflussfaktoren auf die Budgetierung nicht durch unberücksichtigte Variablen (*Omitted Variable Bias)* verzerrt dargestellt werden (Ailawadi, Farris und Parry 1994).

Generalisierbarkeit der empirischen Ergebnisse: Die meisten der diskutierten Determinanten der Marketingintensität können durch die Ergebnisse mehrerer empirischer Studien als generalisierbar angesehen werden. Dennoch lässt eine zu hohe Heterogenität in den Ergebnissen oder ein zu geringer Untersuchungsumfang Unsicherheiten über die Wirkung einiger Faktoren. Im Besonderen bei den Faktoren „Hidden Values“, Profitabilität auf Industrieebene sowie Marketingausgaben der Wettbewerber lassen sich heterogene Ergebnisse beobachten. Ursache könnten unterliegende moderierende Effekte oder nicht-lineare Wirkungszusammenhänge sein, die es zu erforschen gilt. Der Einfluss eines regionalen Marktbezugs sowie der Organisationsform ist hingegen noch sehr wenig erforscht worden, so dass mangels einer ausreichenden Anzahl empirischer Ergebnisse nur bedingt allgemeingültige Aussagen abgeleitet werden können.

Konzeptualisierung von Faktoren: Die Fähigkeit, die Wirkung exogener Einflüsse auf das Marketingbudgetierungsverhalten zu schätzen, ist immer begrenzt durch die Fähigkeit, diese zu konzeptualisieren. So zeigt ein Vergleich der einzelnen Studien, dass die Effekte, die im Rahmen der empirischen Untersuchungen abgebildet werden sollen, unterschiedlich operationalisiert werden. Bisweilen findet sich sogar eine weitere Aufgliederung der Effekte in Teilfaktoren, die verschiedene Aspekte des Effekts innerhalb eines Modells abbilden. Ebenso findet sich eine Mischung von Faktoren, bei der mehrere Effekte durch eine Variable dargestellt werden (Farris, Shames und Reibstein 1998). Wiederum bei anderen Einflüssen, z. B. der Marktstruktur, ist noch überhaupt kein Faktor gefunden worden, dem eine hinreichende Abbildung gelingen würde (Lee 2002). Aus diesem Grund bedarf das Modell einer gründlichen Spezifikation, um aus den mathematischen Ergebnissen die wahren empirischen Zusammenhänge und Beziehungen zu identifizieren.

Untersuchung nicht-linearer Kausalzusammenhänge: Einige frühere Studien haben nicht-lineare Wirkungszusammenhänge einzelner Determinanten auf die Bestimmung der Marketingbudgets festgestellt (z. B. Keown et al. 1989). Es ist überraschend, dass diese Ergebnisse mit Ausnahme der Marktkonzentration in späteren Studien nicht mehr aufgegriffen werden, obwohl sie teilweise einen sinnvollen Beitrag zur Erklärung von widersprüchlichen Ergebnissen liefern. Weiterführende Studien sollten daher auch nicht-lineare Zusammenhänge untersuchen, um bereits gefundene Ergebnisse zu validieren oder ähnliche Verläufe bei weiteren Determinanten festzustellen.

Aufgliederung der Preiseffekte auf die Marketingintensität: Die Ergebnisse zum Preis als Erklärungsfaktor der Marketingintensität sprechen dafür, in zukünftigen Modellen mit produktübergreifenden Datensätzen, ähnlich wie bei Farris und Buzzell (1979), sowohl den relativen Preis als auch den absoluten Preis des Produkts zu berücksichtigen um die widersprüchlichen Effekte separat abbilden zu können. Dies könnte mögliche Verzerrungseffekte vermeiden und die Ergebnisse von Farris und Buzzell (1979) validieren.

8.1.3 Determinanten der Wahl der Budgetierungsmethode

Generalisierbarkeit der empirischen Ergebnisse zu Determinanten der Wahl der Budgetierungsmethode: Insgesamt ist das Feld der Einflussfaktoren auf die Wahl der Budgetierungsmethode noch zu wenig erforscht. Einige der im Rahmen dieses Beitrags diskutierten Ergebnisse zu den einzelnen Determinanten lassen sich auf nur ein oder zwei Studien zurückführen. Dies gilt im Besonderen für die Aussagen zu den Effekten der

Langlebigkeit eines Produkts, dem Produktlebenszyklus, der Markteintrittsreihenfolge sowie der Partizipation des Managements am Unternehmenserfolg, bei denen nur eine geringe Anzahl empirischer Ergebnisse vorliegt. Hier besteht noch dringender weiterer Forschungsbedarf. Ebenso bleiben regionale Einflüsse auf die Wahl der Budgetierungsmethode undurchsichtig, da Studien widersprüchliche oder insignifikante Effekte feststellen. Bigné (1995) führt dies auf Fehler bei der Datengrundlage zurück, da zu viele multinationale Unternehmen die Effekte verzerren.

8.2 Methodische Kritik

Einheitlichkeit der Forschungsmethode bei Untersuchung der Budgetierungsmethoden: Studien zur Anwendung von Budgetierungsmethoden in Unternehmen sollten eine einheitlichere Forschungsmethode anwenden, um die Vergleichbarkeit zwischen den Studien zu erhöhen und Trends besser erkennen zu können. So lassen sich teilweise große Unterschiede hinsichtlich der Methodik der Datensammlung, dem Fragebogendesign, der befragten Grundgesamtheit und abgefragten Budgetierungsmethoden finden, was eine mögliche Erklärung für die Heterogenität in den Studienergebnissen sein könnte. Darüber hinaus ist es nicht möglich, den Einfluss der einzelnen angewendeten Regeln auf den Marketingbudgetierungsprozess zu identifizieren (Mitchell 1993). Dies impliziert auch eine Untersuchung der genauen Umsetzung einzelner Regeln, da insbesondere bei der Ziele-und-Aufgaben-Regel Unsicherheit über eine genaue Anwendung durch die Manager besteht.

Key Informant Bias: Die Umfrageergebnisse zum Budgetierungsverhalten eines Unternehmens basieren ausschließlich auf den Aussagen eines Unternehmensrepräsentanten, der meist dem Topmanagement angehört. Allerdings partizipieren unzählige Manager auf verschiedenen Hierarchieebenen und in verschiedenen Abteilungen am Budgetierungsprozess. Es kann daher davon ausgegangen werden, dass je nach Unternehmensposition und –funktion sowie je nach Kenntnisstand die Einstellung zur Marketingbudgetierung variiert. Diese unterschiedlichen Perspektiven innerhalb eines Unternehmens werden durch den *Key Informant Bias* nicht abgebildet.

Berücksichtigung des mehrstufigen Charakters des Budgetierungsprozesses: Studien zum Budgetierungsverhalten ignorieren mit wenigen Ausnahme (z. B. Iizuka 2004) den mehrstufigen Charakter des Budgetierungsprozesses. So wird die erste Stufe, d. h. ob das Produkt überhaupt beworben werden soll, nicht modelliert. Es wäre ratsam, diesem Wesenszug des Prozesses Rechnung zu tragen, indem z. B. die erste Stufe mittels eines Logit-Modells abgebildet wird.

Daraus ließen sich weitere Einsichten zu den Determinanten des Budgetierungsprozesses und ihren Einfluss in den einzelnen Schritten der Budgetbestimmung sammeln.

Berücksichtigung von Endogenität: Ein methodisches Problem stellt die Simultanität zwischen dem Marketingbudget und vielen Einflussfaktoren dar. So konnte bereits ein Endogenitätsproblem für den Zusammenhang von der Höhe des Marketingbudgets und der Profitabilität eines Unternehmens empirisch gezeigt werden (Amadi 2005). Eine Nicht-Berücksichtigung dieses Problems hat verzerrte Schätzergebnisse zur Folge. Da nur sehr wenige Studien sich diesem Problem angenommen haben, besteht daher die Gefahr, dass die im Rahmen dieses Beitrags diskutierten Ergebnisse der Verzerrung unterliegen. Weitere Studien müssten mögliche Simultanitäten identifizieren, so dass diese in zukünftigen Budgetierungsstudien berücksichtigt werden können (Moorthy und Zhao 2000).

Beschreibung der Datengrundlage: Die Ergebnisse von Blasko und Patti (1984) deuten auf einen hohen Grad der Ungenauigkeit bei der Abgrenzung von Marketingbudgets hin. Es ist anzunehmen, dass Widersprüche und Unterschiede in den Ergebnisse auch eine Folge von Ungenauigkeiten bei der Datenerfassung sein können. Es ist daher dringend anzuraten, dass die Datengrundlage von Studien genauer beschrieben wird, um Rückschlüsse und Erklärungen für mögliche Widersprüche in den Ergebnissen zu finden.

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Appendix

Tabelle 4. Umfrageergebnisse der Studien zur Anwendung von Budgetierungsmethoden

Studie	% der befragten Manager geben an, folgende Budgetierungsmethode zu verwenden								
	Optimierungsmethoden	Ziele und Aufgaben	% erwarteter Umsatz	% vergangener Umsatz	Fortschreibungsansatz	Wettbewerbsorientiert	Finanzkraftorientiert	Managementerfahrung	Sonstiges
San Augustine/Foley (1975)[a]	2	6	50	14	/	/	30	12	26
San Augustine/Foley (1975)[b]	4	10	28	16	/	/	26	34	10
Permut (1977)[a]	13	15	58	33	/	/	43	18	3
Permut (1977)[b]	0	10	20	5	/	/	63	50	15
Gilligan (1977)[a]	0	10	38	31	/	5	8	/	8
Gilligan (1977)[b]	4	4	52	28	/	2	4	/	6
Jobber (1980)	5	62	25	13	/	15	/	/	13
Patti/Blasko (1981)	51	63	53	20	/	24	20	4	/
Lancester/Stern (1983)	20	80	53	20	3	38	13	/	12
Blasko/Patti (1984)	3	74	16	23	/	21	33	13	/
Hooley/Lynch (1985)[a]	/	43	56	/	/	29	51	/	14
Hooley/Lynch (1985)[b]	/	36	29	/	/	19	42	/	7
Ortega (1986)	/	43	13	/	/	/	/	32	/
Piercy (1986)	1	41	25	11	/	/	34	/	8
Lynch/Hooley (1987)	/	40	33	/	/	10	54	/	7
Piercy (1987b)	1	39	23	6	/	2	31	/	5
Lynch/Hooley (1989)	/	51	21	/	/	6	49	/	17
Martenson (1989)	/	42	32	/	/	/	14	/	12
Synodinos/Keown/Jacobs (1989)[a]	/	73	38	/	11	22	24	46	5
Synodinos/Keown/Jacobs (1989)[b]	/	54	33	/	16	0	5	51	10
Synodinos/Keown/Jacobs (1989)[c]	/	68	38	/	13	8	3	8	0
Synodinos/Keown/Jacobs (1989)[d]	/	36	36	/	21	33	30	27	15
Synodinos/Keown/Jacobs (1989)[e]	/	69	31	/	6	33	25	8	0
Filiatrault/Chebat (1990)	/	58	69	/	80	17	49	/	/
Lynch/Hooley (1990)[a]	/	53	33	/	/	10	49	/	23
Lynch/Hooley (1990)[b]	/	44	22	/	/	10	53	/	23
Ramaseshan (1990)[a]	/	5	5	30	/	/	35	25	/
Ramaseshan (1990)[b]	/	42	30	6	/	/	2	20	/
Ramaseshan (1990)[c]	/	5	34	7	/	/	24	29	/
Parry/Parry/Farris(1991)	11	63	3	/	/	12	68	19	7
Hung/West (1991)[a]	/	61	31	14	/	33	47	/	/
Hung/West (1991)[b]	/	75	21	11	/	46	39	/	/
Hung/West (1991)[c]	/	50	42	6	/	36	36	/	/
Mitchell (1993)	/	40	27	8	/	/	/	/	19
Miles/White/Munilla (1997)	/	67	24	26	52	12	48	/	/
Reinecke/Reibstein (2002)[a]	/	/	33	27	47	7	/	53	18
Reinecke/Reibstein (2002)[b]	/	/	45	27	42	8	/	45	24
Francois (2003)	/	27	14	/	/	5	27	31	/
Prendergast/West/Shi (2006)	3	39	44	28	/	26	62	27	/
West/Crouch (2007)	0	24	21	4	/	7	18	4	18

Tabelle 5: Eigenschaften der Studien zur Anwendung von Budgetierungsmethoden

Studie	Produktkategorie[1]	Land	Unternehmens-größe[2]	Beobach-tungen
San Augustine/Foley (1975)[a]	Konsum	US	G	25
San Augustine/Foley (1975)[b]	Industrie	US	G	25
Permut (1977)[a]	Konsum	US/Europa	G/M	41
Permut (1977)[b]	Industrie	US/Europa	G/M	49
Gilligan (1977)[a]	Industrie	UK	G/M	39
Gilligan (1977)[b]	Konsum	UK	G/M	53
Jobber (1980)	Industrie	UK	G	55
Patti/Blasko (1981)	Kons./Dienstl.	US	G	54
Lancester/Stern (1983)	Konsum	US	G	60
Blasko/Patti (1984)	Industrie	US	G	64
Hooley/Lynch (1985)[a]	Konsum	UK	G/M/K	572
Hooley/Lynch (1985)[b]	Dienstl.	UK	G/M/K	558
Piercy (1986)	Allgemein	UK	M	130
Ortega (1986)	Kons./Ind./Dienstl.	E	G	168
Lynch/Hooley (1987)	Industrie	UK	G/M/K	560
Piercy (1987b)	Kons./Ind.	UK	G/M	141
Lynch/Hooley (1989)	Industrie	UK	G/M/K	536
Martenson (1989)	Allgemein	S	G/M/K	126
Synodinos/Keown/Jacobs (1989)[a]	Konsum	UK	G	37
Synodinos/Keown/Jacobs (1989)[b]	Konsum	DK	G	39
Synodinos/Keown/Jacobs (1989)[c]	Konsum	F	G	40
Synodinos/Keown/Jacobs (1989)[d]	Konsum	S	G	33
Synodinos/Keown/Jacobs (1989)[e]	Konsum	D	G	36
Filatrault/Chebat (1990)	Dienstl.	CDN	/	293
Lynch/Hooley (1990)[a]	Konsum	UK	G/M/K	399
Lynch/Hooley (1990)[b]	Dienstl.	UK	G/M/K	269
Ramaseshan (1990)[a]	Konsum[3]	/	/	126[5]
Ramaseshan (1990)[b]	Konsum[4]	/	/	126[5]
Ramaseshan (1990)[c]	Dienstl.	/	/	126[5]
Parry/Parry/Farris (1991)	Krankenhäuser	US	/	130
Hung/West (1991)[a]	Konsum	CDN	G/M	36
Hung/West (1991)[b]	Konsum	UK	G/M	28
Hung/West (1991)[c]	Konsum	US	G/M	36
Mitchell (1993)	Allgemein	UK	G/M	52
Miles/White/Munilla (1997)	Industrie	US	G/M	43
Reinecke/Reibstein (2002)[a]	Allgemein	US	G/M	234
Reinecke/Reibstein (2002)[b]	Allgemein	D/CH	G/M	418
Francois (2003)	Industrie	B	G/M/K	102
Prendergast/West/Shi (2006)	Allgemein	CHN	G/M/K	206
West/Crouch (2007)	Kons./Ind.	AUS/NZ	G	71

Anmerkungen:
[1] Kons.: Konsumgüter/Ind.: Industriegüter/Dienstl.: Dienstleistungen
[2] G: Groß/M: Mittel/K: Klein
[3] Langlebige Konsumgüter
[4] Kurzlebige Konsumgüter
[5] Die Studie von Ramaseshan (1990) umfasst über alle Produktkategorien insgesamt 126 Beobachtungen.

Tabelle 6a: Übersicht der Ergebnisse empirischer Studien zur Untersuchung der Marketingintensität–Produktdeterminanten

		Wirkung auf die Marketingintensität				
		Linear		Nicht-linear		
Determinante	Konzeptualisierung	Positiv	Negativ	U-förmig	Invertiert U-förmig	Keine Wirkung
Qualität		• Farris/Buzzell 1979 • Tellis/Fornell 1988 • Iizuka 2004 • Huskamp et al. 2008 • Shankar 2009				• Lilien/Little 1976
Einzigartigkeit	Auf Bestellung produziert		• Farris/Buzzell 1979 • Lilien 1979 • Zif/Young/Fenwick 1984 • Zellner 1989 • Francois 2003			
	„Hidden Values“	• Farris/Buzzell 1979 • Zif/Young/Fenwick 1984				• Lilien 1979 • Meisel 1979 • Lilien/Weinstein 1984 • Francois 2003
Kauffrequenz			• Albion 1976 • Farris/Buzzell 1979 • Zif/Young/Fenwick 1984 • Keown et al. 1989 • Francois 2003		• Keown et al. 1989	• Lilien/Little 1976

Tabelle 6b: Übersicht der Ergebnisse empirischer Studien zur Untersuchung der Marketingintensität–Preisdeterminanten

		Wirkung auf die Marketingintensität				
		Linear		Nicht-linear		
Determinante	Konzeptualisierung	Positiv	Negativ	U-förmig	Invertiert U-förmig	Keine Wirkung
Preis	Absoluter Preis	• Rizzo 1999	• Farris/Buzzell 1979 • Zif/Young/Fenwick 1984 • Gönül et al. 2001 • Narayanan/Desiraju/ Chintagunta 2004		• Keown et al. 1989	• Albion 1976 • Hurwitz/Caves 1988
	Relativer Preis	• Farris/Buzzell 1979				
Profitabilität	Profitmarge (Unternehmens-spezifisch)	• Rundfelt 1973 • Comanor/Wilson 1974 • Albion 1976 • Zif/Young/Fenwick 1984				
	Profitmarge (Branchen-spezifisch)	• Strickland/Weiss 1976 • Martin 1979 • Buxton/Davies/Lyons 1984 • Willis/Rogers 1998 • Lee 2002[K]	• Lee 2002 [I] • Misra 2010			• Zellner 1989
	Höhe Free Cash Flow	• Amadi 2005 • Supanvanij 2005				

Anmerkungen: K: Für Konsumgüterhersteller, I: Für Industriegüterhersteller

Tabelle 6c: Übersicht der Ergebnisse empirischer Studien zur Untersuchung der Marketingintensität–Marktdeterminanten

		Wirkung auf die Marketingintensität				
		Linear		Nicht-linear		
Determinante	Konzeptualisierung	Positiv	Negativ	U-förmig	Invertiert U-förmig	Keine Wirkung
Marktgröße	Gesamtumsatz		• Rundfelt 1973 • Albion 1976 • Brush 1976 • Misra 2010			• Willis/Rogers 1998
	Regionaler Markt		• Rundfelt 1973			
Markt-wachstum		• Lilien/Little 1976 • Strickland/Weiss 1976 • Zellner 1989 • Balasubramanian/ Kumar 1990 [I,D] • Ramaswamy/Gatignon/ Reibstein 1994	• Balasubramanian/ Kumar 1990 [K] • Supanvanij 2005			• Greer 1971 • Cable 1972 • Comanor /Wilson 1974 • Brush 1976 • Farris/Buzzell 1979 • Martin 1979 • Buxton/Davies /Lyons 1984 • Ailawadi/Farris/ Parry 1994 • Stewart 1996 • Willis/Rogers 1998
Anzahl Kunden		• Farris/Buzzell 1979 • Lilien 1979 • Martin 1979 • Meisel 1979 • Lilien 1983 • Lilien/Weinstein 1984 • Zif/Young/Fenwick 1984				• Francois 2003

*Anmerkungen:*K: Für Konsumgüterhersteller, I: Für Industriegüterhersteller, D: Für Dienstleister

Tabelle 6d: Übersicht der Ergebnisse empirischer Studien zur Untersuchung der Marketingintensität–Wettbewerbsdeterminanten I

		Wirkung auf die Marketingintensität				
		Linear		Nicht-linear		
Determinante	Konzeptualisierung	Positiv	Negativ	U-förmig	Invertiert U-förmig	Keine Wirkung
Markt-dominanz	Marktanteil	• Lilien 1979 • Lilien 1983 • Balasubramanian/ Kumar 1990 [K,I] • Corfman/Lehmann1994 • Metwally 1997 • Bhattacharyya 2005 • Supanvanji 2005	• Rundfelt 1973 • Lilien/Little 1976 • Farris/Buzzell 1979 • Zif/Young/Fenwick 1984 • Keown et al. 1989 • Balasubramanian/ Kumar 1990 [D] • Ailawadi/Farris/Parry 1994 • Francois 2003			• Stewart 1996
Marktkonzen-tration		• Mann/Henning/Meeham 1967 • Martin 1979 • Zellner 1989 • Lee 2002 [I] • Misra 2010	• Primeaux 1981 • Ramaswamy/Gatignon/ Reibstein 1994 • Shankar 2009	• Connor/Weimer 1976[W] • Willis/Rogers 1998	• Greer 1971 • Cable 1972 • Rundfelt 1973 • Sutton 1974 • Connor/Weimer1976[NW] • Strickland/Weiss 1976 • Buxton/Davies/Lyons 1984 • Esposito/Esposito /Hogan 1990[K] • Lee 2002 [K]	• Comanor /Wilson 1974 • Reekie 1975 • Albion 1976 • Brush 1976 • Ornstein 1976 • Farris/Buzzell 1979 • Esposito /Esposito/Hogan 1990[I]

Anmerkungen: K: Für Konsumgüterhersteller, I: Für Industriegüterhersteller, D: Für Dienstleister
W: Für Werbeausgaben, NW: Für Nicht-Werbeausgaben

Tabelle 6e: Übersicht der Ergebnisse empirischer Studien zur Untersuchung der Marketingintensität–Wettbewerbsdeterminanten II

		Wirkung auf die Marketingintensität				
		Linear		Nicht-linear		
Determinante	Konzeptualisierung	Positiv	Negativ	U-förmig	Invertiert U-förmig	Keine Wirkung
Anzahl Wettbewerber	Anzahl Wettbewerber auf gleichem Markt	• Cable 1972 • Albion 1976 • Lilien 1979 • Leffler 1981 • Connor/Weimer 1986 • Zellner 1989 • Azoulay 2002 • Shankar 2009	• Meisel 1979 • Iizuka 2004 • Bhattacharyya 2005			• Keown et al. 1989
	Anzahl Multi-marktkontakte		• Shankar 1999 • Shankar 2009			
Marketing-ausgaben Wettbewerber		• Corfman/Lehmann 1994 • Leeflang/Wittink 1996 • Marks/Albers 2001 • Azoulay 2002 • Chintagunta/Kadiyali/ Vilcassim 2006	• Chintagunta/Desiraju 2005			

Tabelle 6f: Übersicht der Ergebnisse empirischer Studien zur Untersuchung der Marketingintensität–Zeit- & Organisationsdeterminanten

		Wirkung auf die Marketingintensität				
		Linear		Nicht-linear		
Determinante	Konzeptualisierung	Positiv	Negativ	U-förmig	Invertiert U-förmig	Keine Wirkung
Produktlebens-zyklus	Zeit im Markt		• Lilien/Little 1976 • Farris/Buzzell 1979 • Lilien 1979 • Meisel 1979 • Lilien 1983 • Lilien/Weinstein 1984 • Iizuka 2004			• Zif/Young /Fenwick1984 • Caves/Whinston /Hurwitz 1991 • Stewart 1996 • Azoulay 2002 • Francois 2003 • Shankar 2009
Markteintritts-reihenfolge			• Iizuka 2004 • Huskamp et al. 2008			
Organisations-form	Entscheidungs-richtung („Top-Down“)		• Piercy 1987a • Piercy 1987b			
	Macht der Marketingabteilung	• Piercy 1987a				• Francois 2003
Budgetierungs-methode	Komplexität der Methode	• Piercy 1987a • Gilligan 1977				• San Augustine /Foley 1975 • Francois 2003
Partizipation am Geschäfts-erfolg	Höhe des Besitzanteils		• Supanvanij 2005	• Joseph/Richardson 2002 • Supanvanij 2005		
	Langfristigkeit der Manager-belohnung	• Corfman/Lehmann 1994 • Supanvanji 2005				

Anmerkungen: K: Für Konsumgüterhersteller, I: Für Industriegüterhersteller, D: Für Dienstleister

Tabelle 7a: Eigenschaften der Studien zur Untersuchung der Marketingintensität I

Studie	Branche	Land	Aggregations-niveau	Untersuchte Variable[1]
Ailawadi/Farris/Parry (1994)	Übergreifend	US	Unternehmen	W&P/U
Albion (1976)	Übergreifend	US	Industrie	W/U
Amadi (2005)	Haushaltsprod.	US	Unternehmen	W
Azoulay (2002)	Pharma	US	Unternehmen	W
Balasubramanian/Kumar (1990)	Übergreifend	US	Unternehmen	W&P/U
Bhattacharyya (2005)	Pharma	US	Unternehmen	W
Brush (1976)	Übergreifend	US	Industrie	W/U
Buxton/Davies/Lyons (1984)	Übergreifend	UK	Industrie	W/U
Cable (1972)	Übergreifend	UK	Industrie	W/U
Caves/Whinston/Hurwitz (1991)	Pharma	US	Unternehmen	M
Chintagunta/Desiraju (2005)	Pharma	US/UK/F/I/G	Unternehmen	A
Chintagunta/Kadiyali/Vilcassim (2006)	Übergreifend	US	Unternehmen	W
Comanor/Wilson (1974)	Übergreifend	US	Industrie	W/U
Connor/Weimer (1986)	Lebensmittel	US	Unternehmen	M/U
Corfman/Lehmann (1992)	Experiment	US	-	-
Esposito/Esposito/Hogan (1990)	Übergreifend	US	Industrie	W/U
Farris/Buzzell (1979)	Übergreifend	US	Unternehmen	W&P/U
Francois (2003)	Industriegüter	B	Unternehmen	M/U
Gilligan (1977)	Übergreifend	UK	Unternehmen	M
Gönül et al. (2001)	Pharma	US	Unternehmen	A
Greer (1971)	Übergreifend	US	Industrie	W/U
Hurwitz/Caves (1988)	Pharma	US	Unternehmen	A/U
Huskamp et al. (2008)	Pharma	US	Unternehmen	M
Iizuka (2004)	Pharma	US	Unternehmen	W
Joseph/Richardson (2002)	Übergreifend	US	Unternehmen	W
Keown et al. (1989)	Übergreifend	Global	Unternehmen	W/U
Lee (2002)	Bier	US	Unternehmen	W/U
Leeflang/Wittink (1996)	FMCG	NL	Unternehmen	M
Lilien (1979)	Industriegüter	US	Unternehmen	W, M
Lilien (1983)	Industriegüter	US	Unternehmen	A
Lilien/Little (1976)	Übergreifend	US	Unternehmen	W/U, M/U
Lilien/Weinstein (1984)	Übergreifend	US/Europa	Unternehmen	M
Mann/Henning/Meeham (1967)	Übergreifend	US	Industrie	W/U
Marks/Albers (2001)	Experiment	G	-	-
Martin (1979)	Übergreifend	US	Industrie	W/U
Meisel (1979)	Bedarfsartikel	US	Industrie	W/U
Metwally (1997)	Konsumgüter/ Dienstl.	AUS	Unternehmen	W
Misra (2010)	Konsumgüter/ Dienstl.	IND	Industrie	W/U
Narayanan/Desiraju/Chintagunta (2004)	Pharma	US	Unternehmen	W, A
Piercy (1987a)	Übergreifend	UK	Unternehmen	W/U
Piercy (1987b)	Übergreifend	UK	Unternehmen	W/U
Primeaux (1981)	Energie	US	Unternehmen	W&P/U

Anmerkungen:
[1] A: Außendienst/P: Promotion/U: Umsatz/W: Werbebudget

Tabelle 7b: Eigenschaften der Studien zur Untersuchung der Marketingintensität II

Studie	Branche	Land	Aggregations-niveau	Untersuchte Variable[1]
Ramaswamy/Gatignon/Reibstein (1994)	Übergreifend	US	Unternehmen	A
Reekie (1975)	Konsumgut	UK	Industrie	W/U
Rizzo (1999)	Pharma	US	Unternehmen	A
Rundfelt (1973)	Übergreifend	S	Industrie	W/U
San Augustine/Foley (1975)	Übergreifend	US	Unternehmen	M
Shankar (1999)	Pharma	US	Unternehmen	M
Shankar (2009)	Pharma	US	Unternehmen	W, A
Stewart (1996)	Automobilind.	CDN	Unternehmen	W&P/U
Strickland/Weiss (1976)	Übergreifend	US	Industrie	W/U
Supanvanji (2005)	Übergreifend	US	Unternehmen	W
Sutton (1974)	Übergreifend	UK	Industrie	W/U
Tellis/Fornell (1988)	Konsumgut	US	Unternehmen	W
Willis/Rogers (1998)	Lebensmittel	US	Industrie	W/U
Zellner (1989)	Lebensmittel	US	Industrie	W/U
Zif/Young/Fenwick (1984)	Übergreifend	US/CDN/Europa	Industrie	M/U, W/U, A/U

Anmerkungen:
[1] A: Außendienst/P: Promotion/U: Umsatz/W: Werbebudget

Tabelle 8a: Übersicht der Ergebnisse empirischer Studien zur Untersuchung der Anwendung von Budgetierungsmethoden I

		Wirkung auf die Wahrscheinlichkeit differenziertere Budgetierungsmethoden anzuwenden			
Determinante	Konzeptualisierung	Positiv	Negativ	Kein Zusammenhang	Sonstiges
Produkt-kategorie	Konsumgüter	• San Augustine/Foley 1975 • Gilligan 1977 • Permut 1977 • Blasko/Patti 1984 • Hooley/Lynch 1985 • Lynch/Hooley 1990		• Gilligan 1977 • Lynch/Hooley 1987 • Lynch/Hooley 1989 • Miles/White/Munilla 1997 • Francois 2003	
	Langlebigkeit des Produkts	• Ramaseshan 1990	• Synodinos/Keown/Jacobs 1989		• West/Hung 1993 (Wettbewerbsorientierter Ansatz -)
Profitabilität		• Hooley/Lynch 1985 • Lynch/Hooley 1989 • Lynch/Hooley 1990 • Parry/Parry/Farris 1991 • West/Crouch 2007 • Prendergast/West/Shi. 2006		• Hung/West 1991	• Prendergast/West/Shi 2006 (Competitive Parity +)
Markt-dominanz		• Patti/Blasko 1981 • Hooley/Lynch 1985 • Lynch/Hooley 1987 • Lynch/Hooley 1990 • Hung/West 1991 • Parry/Parry/Farris 1991 • Piercy 1987a		• Jobber 1980 • Lynch/Hooley 1989 • Miles/White/Munilla 1997	
Marktkonzen-tration		• Parry/Parry/Farris 1991 • Wagner/Fischer 2011			
Marktwachs-tum		• Hung/West 1991 • Mitchell 1993		• West/Crouch 2007	
Produktlebens-zyklus		• Wagner/Fischer 2011			• Wagner/Fischer 2011 (Wettbewerbsorientierter Ansatz +)

Tabelle 8b: Übersicht der Ergebnisse empirischer Studien zur Untersuchung der Anwendung von Budgetierungsmethoden II

		Wirkung auf die Wahrscheinlichkeit differenziertere Budgetierungsmethoden anzuwenden			
Determinante	Konzeptualisierung	Positiv	Negativ	Kein Zusammenhang	Sonstiges
Markteintritts-reihenfolge			• Wagner/ Fischer 2011		
Organisations-form	„Bottom-Up“/ Einfluss der Marketingabteilung	• Piercy 1986 • Piercy 1987a • Piercy 1987b • Parry/Parry/Farris1991 • West/Hung 1993 • Francois 2003 • Prendergast/West/Shi 2006		• Parry/Parry/Farris 1991	
Budgetierungs-methode					• Hung/West 1991, Lynch/ Hooley 1990 (Ziele & Aufgaben/ Finanzkraftorientiert +) • Parry/Parry/Farris 1991 (Wettbewerbsorientiert/ Optimierungsmethoden +)
Partizipation am Geschäfts-erfolg	Grad des Besitzanteils				• Joseph/Richardson 2002 (U-förmig)
	Langfristigkeit der Managerbelohnung	• Miles/White/Munilla 1997 • Low/Mohr 1999 • Prendergast/West/Shi 2006			

Tabelle 9: Eigenschaften der Studien zur Untersuchung der Anwendung von Budgetierungsmethoden

Studie	Branche	Land	Untersuchte Variable
Blasko/Patti (1984)	Industriegüter	US	Korrelation von Methoden
Wagner/Fischer (2011)	Pharma	Europa	Marketingbudget
Francois (2003)	Industriegüter	B	Korrelation von Methoden
Gilligan (1977)	Übergreifend	UK	Korrelation von Methoden
Hooley/Lynch (1985)	Übergreifend	UK	Korrelation von Methoden
Hung/West (1991)	Übergreifend	US/UK/CDN	Korrelation von Methoden
Jobber (1980)	Industriegüter	UK	Korrelation von Methoden
Joseph/Richardson (2002)	Übergreifend	US	Marketingbudget
Low/Mohr (1999)	Konsumgüter	US	Korrelation von Methoden
Lynch/Hooley (1987)	Industriegüter	UK	Korrelation von Methoden
Lynch/Hooley (1989)	Industriegüter	UK	Korrelation von Methoden
Lynch/Hooley (1990)	Übergreifend	UK	Korrelation von Methoden
Miles/White/Munilla (1997)	Landwirtschaft	US	Korrelation von Methoden
Mitchell (1993)	Übergreifend	UK	Manageraussagen (Umfrage)
Parry/Parry/Farris (1991)	Krankenhäuser	US	Korrelation von Methoden
Patti/Blasko (1981)	Übergreifend	US	Korrelation von Methoden
Permut (1977)	Übergreifend	Europa	Korrelation von Methoden
Piercy (1986)	Übergreifend	UK	Marketingbudget
Piercy (1987a)	Übergreifend	UK	Marketingintensität
Piercy (1987b)	Übergreifend	UK	Marketingintensität
Prendergast/West/Shi (2006)	Übergreifend	CHN	Komplexität
Ramaseshan (1990)	Einzelhandel	AUS	Korrelation von Methoden
San Augustine/Foley (1975)	Übergreifend	US	Korrelation von Methoden
Synodinos/Keown/Jacobs (1989)	Übergreifend	Global	Korrelation von Methoden
West/Crouch (2007)	Übergreifend	AUS	Komplexität
West/Hung (1993)	Übergreifend	US/UK/CDN	Korrelation von Methoden

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An Empirical Analysis of the Use of Practitioner Rules for Setting the Product Marketing Budget

Authors: Nils Wagner and Marc Fischer

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Abstract

The marketing budget allocation process receives great attention within a company. Surveys among managers identify that some budgeting rules, such as “Percentage of Sales” or “Objective and Task”, are predominantly used in companies for the determination of a product’s marketing budget. But due to some serious methodological flaws the insights into the budgeting process based on these survey results are limited. This study extends the knowledge about budgeting behavior by conducting a descriptive study in which we analyze the application of rules in the budgeting process of companies. Specifically, we develop a marketing budget model that relates three dominant budgeting rules to the observed marketing budget outcome. This allows the identification of each rule’s impact on the budget decision for each brand and company contained in our dataset. Additionally, we analyze moderating effects which influence the application of single budgeting rules. Our results show that the budgeting rules are indeed applied by practitioners, but the application differs across market and life-cycle conditions. Our results indicate that sales-oriented methods, such as “Percentage of Sales”, are more widely used. Contrary, sophisticated profit-oriented methods, such as “Objective and Task”, are less widespread than expected based on manager surveys. Finally, competition-oriented methods, such as “Competitive Parity”, have only a marginal impact in the budgeting process on average.

1 Introduction

The marketing budget allocation is one of the most critical but least understood aspects of the management process (Miles, White and Munilla 1997). Researchers and practitioners attach a high importance to this subject, as competitive pressure and marketing expenditures have increased substantially over the last years. The CMO Council Report (2007) underlines this relevance by emphasizing the quantification, measurement, and improvement of the value of marketing investments and resource allocation as the number-one challenge for most chief marketing officers. Due to this need to deeply understand the marketing resource allocation process and its drivers for practitioners and academics alike, the attention of marketing budget allocation in marketing literature has been extensive. Marketing research provided practitioners with various allocation optimization models based on the analysis of marginal returns to improve the budgeting process in companies (see Mantrala 2002). But interviews with managers show that practitioners do not accept these analytic approaches. Reasons include that they are too complex in implementation (Fischer et al. 2011), the database is insufficient for good parameterization (Little 1970) and the budget setting process is highly exposed to political influences (Piercy 1986).[2] Instead, manager surveys (e.g., Bigné 1995) indicate that marketing budgets are determined by the application of simple budgeting rules which base the budget decision on single key performance numbers, such as the “Percentage of Sales” or “Competitive Parity” method. These surveys offer a good first insight into the budgeting process of companies, but they lack validity as they ignore the high complexity of the budget setting process caused by organizational policy (Armstrong and Overton 1973). Hence, survey results are likely to be very subjective and fragmented. They do not provide detailed information about how much and to what extent managers follow budgeting rules and under which conditions they change these rules.

Besides manager interviews, another research stream emerged which tries to explain budget setting behavior by the empirical analysis of the impact of relevant factors on the observable size and allocation of the marketing budget in order to identify determinants of budget setting (e.g., Lilien and Little 1976; Balasubramanian and Kumar 1990). However, prior studies did not include practitioner budgeting rules, which were identified by manager surveys as predominant drivers of the budgeting process. Hence, the informational value of these studies remains limited as important structural variables may be missing from model specification. In summary, our knowledge about whether and how managers apply common budgeting methods is very limited based on prior research.

A comprehensive understanding of budgeting behavior is important for several reasons. First, it contributes to allocation practice. Studies have indicated that management decision makers come to good decisions on average, although they do not always take the optimal decision. Thus, a descriptive analysis may provide reasonable guidelines for budgeting practices (Lilien and Little 1976). In addition, it allows managers to understand competitor’s budgeting behavior and the prediction of the size of competitor’s marketing budgets (Stewart 1996). Second, it contributes to theory as a full knowledge of factors that influence budgeting

[2] This is confirmed by marketing response studies which show that budgets are determined suboptimal in most companies (Naik, Raman and Winer 2005; Manchanda, Rossi and Chintagunta 2004).

behavior may help to identify marketing variables in empirical models. This may increase model validity and avoid biases in parameter estimates. Third, we have been experiencing the rise of the structural modeling approach for several years, which seems to become the dominant modeling approach in marketing research. These models rely on sometimes very restrictive assumptions about firm behavior. Descriptive studies help to inform to what extent these assumptions are justified or not (Albers 2011).

This motivates our project in which we address the existing research gap by an explorative study of the application of rules in companies' budgeting process. In particular, we want to give some insights into the budgeting behavior by answering the following questions:

- Which budgeting rules are frequently used?
- How much do these rules explain in observed variance in product budgets?
- Are there differences in the application of rules across products?
- Under which conditions is a rule more preferred?

Building on previous research, we develop a conceptual framework, which relates the observed marketing budget of a brand to the most frequently used practitioner rules identified by the survey literature. Therefore, we formalize these rules and integrate them into our model in order to explain the determination of observed marketing budgets. This approach enables us to describe the real marketing budget setting behavior and to identify the degree to which the marketing budgeting rules are used by companies. In particular, for each product, we are able to identify which rules are applied and which impact the respective rules have on the final budget decision. Furthermore, we integrate a set of factors as moderators in order to identify the conditions which favor the use of a rule over other factors.

In this paper, we examine the impact of practitioner rules on the marketing budget with aggregate data at the brand level in the pharmaceutical market. As this market is very marketing-intense (Berndt 2001) and subject of many empirical studies, it is an appropriate dataset for our purpose. Our study is based on 518 prescription drugs in four different product segments covering 12 years from the five most important European markets: Germany, the United Kingdom, France, Italy, and Spain.

The remainder of this paper is organized as follows. In the next section, we review the relevant empirical research on application of budgeting methods. In section 3 we discuss possible moderator effects on the preference for the application of particular methods. We then present our model, estimation-related issues, and the data. The results of our analysis are displayed in the penultimate section, and the paper concludes with a discussion of the findings, implications, and the limitations of the study.

2 Budgeting practices

Surveys among managers indicate that the budgeting process is dominated by the application of simple budget decision rules. Many of these rules overlap with one another; however we may classify the methods into a few major groups (Martenson 1989). Specifically, we identify the following three major classes:

1. Sales-oriented methods,
2. Competition-oriented methods, and
3. Profit-oriented methods.

The sales-oriented methods are widely accepted in companies (e.g., Patti and Blasko 1981). According to these budgeting rules, the marketing budget is determined proportional to the (anticipated) sales volume of a product. The most common approach of sales-oriented methods is the "Percentage of Sales" rule which proposes to set the budget as a percentage of past or anticipated sales. Another popular approach is the "Affordable" rule, which limits the marketing budget to the disposable resources of a company. The most important limitation is the sales level of the product.

Several advantages of these methods may explain their acceptance by management. First of all, they provide budgeting solutions which are very easy to understand. Second, they help recovering marketing cost, because the marketing spending is linked to the amount of sales and associated profits. Hence, budget decisions are easy to communicate to financial executives by ensuring that a firm with limited resources is not spending too heavily. Third, they may lead to a certain stability of advertising within the industry, if it is also used by competitors (Aaker and Myers 1982, 65). Nevertheless, sales-oriented methods have some serious flaws. In particular, the marketing budget is determined by sales and therefore marketing receives less budget when the company is less successful, i.e. sales deteriorate, but more effort would be needed to stimulate demand. Further, the methods reveal some problems in dynamic situations, e.g., the introduction of new products, repositioning moves, or competitor's actions (Fischer et al. 2011). For example, they lead to exorbitant marketing budgets for large established brands or over-the-hill brands but only low budgets in the introductory stage of a product when it is necessary to generate awareness. Finally, competitive activities as well as exogenous effects are ignored by sales-oriented methods.

The competition-oriented methods focus on the preservation of the own market position by avoiding the loss of market share. Correspondingly, marketing budgets are adjusted according to past or expected competitive activities. The most common rule is the "Competitive Parity" rule, which proposes a budget allocation proportional to competitive marketing investments.

Another approach is the "Share of Voice" rule, which is similar as it focuses on keeping a fixed share of voice in the relevant market. In general, these methods are based on the assumption of a zero-sum competition, i.e. the gain of one company is the loss of the others in case of a stable market size (Yoo and Mandhachitra 2003). Hence, the objective of own marketing effort is to neutralize or to diminish the substitutive effect of competitive marketing activities.

One advantage of this rule is that it allows a company to react promptly on competitors' activities, so that retaliatory actions can be applied which may lead to the prevention of marketing wars (Lilien, Kotler and Moorthy 1992, 279). Nevertheless, it is not recommendable to orientate too strongly on competitive marketing budgeting because firm characteristics probably vary strongly across an industry. Bigné (1995) supposes that competition-oriented methods are rather applied complementary which may lead to the assumption that their impact on the final budget decision is lower than others, such as sales-oriented methods.

The profit-oriented methods are rather complex rules which allocate the budget according to managerial assumptions about marketing efficiency by focusing on the maximization of firm profit. The "Objective and Task" approach, which requires that either sales or communications objectives are established by management, is the most popular approach. According to this rule, the marketing budget is determined and allocated to effectively achieve the objectives defined by management (Lilien and Little 1976; Aaker and Myers 1982, 67). Previous studies identify a broad range of key numbers which are considered as marketing objectives by managers, e.g., sales, market share, awareness etc. (e.g., Reinecke and Reibstein 2002). But as all of these numbers can be considered to be sub-goals derived from the objective profit maximization, we may conclude that the application of "Objective and Task" results in an effective use of marketing in order to maximize the firm profit. Even more sophisticated but similar in approach is "Scientific Modeling" which gives optimal budget solutions based on mathematical derivation.

As profit-oriented methods are close to marginal analysis they have been advocated as the most theoretically sound and logical (Mitchell 1993). They provide great flexibility, but can be difficult to apply (Martenson 1989). In particular, a precise consideration of the effects of marketing on sales and therefore comprehensive abilities in measuring the marketing performance are needed (Riordan and Morgan 1979).

Other methods finally contain unsophisticated methods which mostly reflect political influences within an organization. Very popular in smaller companies is the "Arbitrary" rule which bases the marketing budget decision only on managerial experience. For this reason, budget decisions are highly exposed to the influence of the top management (Piercy 1986). Another approach is the “Previous Budget” rule which reflects political influences within the company as it sets the marketing budget according to the budget of previous planning periods and so exhibits the power of the corresponding department manager. This rule may be not formally recognized in many companies which explain why it is not mentioned in most survey studies. But as the budget of the previous period is mostly taken as starting point in the budget planning process it can be expected that the previous budget has a strong impact on the final budget decision (Low and Mohr 1999; Farris, Shames and Reibstein 1998).

A comparison of survey results, which are summarized in Table 1, indicates that the group of sales-oriented methods, such as “Percentage of Sales” and “Affordable”, is most often applied in the marketing budget process. In summary, it is applied by more than 80% of managers. But budget determination evolves towards more advanced techniques. “Objective and Task” becomes one of the dominant budgeting rules in most survey studies published since the 80’s. On average, approximately 50% of managers declare that they apply “Objective and Task”. In academic literature, this trend is interpreted as an increased degree of sophistication in budgeting (e.g., Ramaseshan 1990). But this is controversial as a detailed look on marketing budgeting behavior indicates that “Objective and Task” is not correctly applied by practitioners (Martenson 1989). Most companies seem to have fairly stable marketing budgets over time which supports the idea of a more comprehensive use of the percentage rules as these lead to a smoothed evolution of the marketing budget. In addition, recent surveys do not support the hypotheses of a more frequently use of the “Objective and Task” method (e.g., Francois 2003; West and Crouch 2007). Finally, competition-oriented methods are less widely-used as it is mentioned by only 20 % of managers and it appears that it is only applied complementary.

Insights into the application of budgeting rules based on survey studies should be considered with high caution for several reasons. First, survey results are highly exposed to key informant biases as they are based on information given by single managers that are to represent the whole company. Second, they may not be able to differentiate between “what people say and what they do” as budgets and allocation are considered sensitive by management and thus could be biased (Armstrong and Overton 1973). Third, all survey studies differ in the methodology of the data collection, survey design, and sample selection which makes the results hardly comparable. More specifically, all survey studies consider a

Table 1. Survey results about application of budgeting rules

Category	% of respondents applying the following budgeting rule						
	Sales -oriented			Competition -oriented		Profit -oriented	
Budgeting rule / Study	% anticipated sales	% past sales	Affordable	Competitive Parity	Share of Voice	Objective and Task	Scientific modeling
San Augustine/Foley (1975)	39	15	28	/	/	8	3
Permut (1977)	37	18	54	/	/	12	6
Gilligan (1977)	46	29	6	3	/	7	2
Jobber (1980)	25	13	/	15	/	62	5
Patti/Blasko (1981)	53	20	20	24	/	63	51
Lancester/Stern (1983)	53	20	13	33	5	80	20
Blasko/Patti (1984)	16	23	33	21	/	74	3
Hooley/Lynch (1985)	43	/	47	10	14	40	/
Ortega (1986)	13	/	/	/	/	43	/
Piercy (1986)	25	11	34	/	/	41	1
Lynch/Hooley (1987)	33	/	54	4	6	40	/
Piercy (1987b)	23	6	31	/	2	39	1
Lynch/Hooley (1989)	21	/	49	6	/	51	/
Martenson (1989)	32	/	14	/	/	42	/
Synodinos/Keown/Jacobs (1989)	35	/	17	18	/	60	/
Filiatrault/Chebat (1990)	69	/	49	17	/	58	/
Lynch/Hooley (1990)	29	/	51	10	/	49	/
Ramaseshan (1990)[a]	23	14	20	/	/	17	/
Parry/Parry/Farris (1991)	3	/	68	12	/	63	11
Hung/West (1991)	32	10	41	38	/	61	/
Mitchell (1993)	27	8	/	/	/	40	/
Miles/White/Munilla (1997)	24	26	48	12	/	67	/
Reinecke/Reibstein (2002)	41	27	/	8	/	/	/
Francois (2003)	14	/	27	5	/	27	/
Prendergast/West/Shi (2006)	44	28	62	26	/	39	3
West/Crouch (2007)	21	4	18	7	/	24	0
Average response (rule)[a]	31.6	17	35.6	14.9	6.8	44.3	8.8
Average response (category)[b]	84.2			21.7		53.1	

Notes: Multiple responses possible.
[a]) Average manager response of a rule across surveys (unweighted)
[b]) Average manager response of a category across surveys (Sum of average response across category-specific rules)

different scope of budgeting rules and lack a clear definition for the rules included. This may explain the considerable differences in the survey results and decreases the insights obtained by these surveys in general. Finally, the budget setting process is not as simple as implied by survey studies (Mitchell 1993). Marketing budgets are the result of an annually recurring budget meeting process in which several managers participate. These managers have different agendas and belong to different hierarchical levels of the company (Piercy 1987a). Thus, most firms are likely to use more than one method to determine the marketing budget which leads us to suppose a more complex pattern of decision-making, one that includes basic and complementary methods (Bigné 1995). This complicates the identification of the impact each rule has on the final budget decision (Bigné 1995).

Our analysis approach addresses these limitations of survey research and takes into account the complex pattern of decision-making by simultaneously analyzing more than one rule. This avoids biased estimation results due to single source bias or subjective management sensitivity for budgeting issues. Further, we take into consideration that budgeting rules may be applied differently across companies and may have a different impact on the final budget decision. By giving clear definitions of each budgeting method we are able to identify the influence of each rule on the marketing outcome for all products in our dataset.

3 Determinants Affecting the Use of Budgeting Rules

Survey results indicate that multiple rules are applied simultaneously in the budgeting process. But their application seems to vary across companies and over time (Mitchell 1993). Hence, we want to understand under which conditions the three major classes of budgeting methods are more preferred.

Empirical studies about budgeting methods choice behavior are scarce and thus the insights about factors which influence the application of budgeting rules are limited. In this study, we want to shed some light on this issue by studying the impact of four potential key drivers: (1) market concentration as a measure of competitive intensity, (2) the time in the market as a measure for life cycle, (3) the order of entry of a product, and the (4) patent status which is very important in pharmaceutical markets as a patent expiration changes the competitive situation dramatically (Fischer, Leeflang and Verhoef 2010).

3.1 Sales-oriented methods

Market concentration. Highly concentrated markets are dominated by only a few large companies. Previous studies (e.g., Lynch and Hooley 1990) indicate that these companies, which generally have to manage a broad portfolio, need some key indicators, such as sales, to make the complex allocation decision manageable. Instead, the allocation decision of companies in less concentrated markets, which are predominantly small companies, are highly influenced by top management decisions and therefore rely more on their managerial judgment. For this reason, we assume that sales-oriented methods are rather preferred by companies in highly concentrated markets.

Stage in life cycle. Due to lower expected profits in the future, products in the later stage of the life cycle are focused more on cost recovery than on claiming a market position which promises high future potential. Thus, we expect a higher preference for the application of sales-oriented budgeting methods in the later stages of the product life cycle.

Order of entry. As later entrants have to compensate brand disadvantages, they cannot focus as much on cost recovery as pioneers can. This may reduce the preference for the application of sales-oriented methods for later entrants. So we expect that the preference for the application of sales-oriented budgeting methods is higher for pioneers.

Patent status. A factor of particular importance in the pharmaceutical industry is the patent status. Patent protection avoids generic entry so that firms are less threatened by competition and may have a stronger focus on cost recovery. Therefore, we expect that the preference for the application of sales-oriented budgeting methods is higher when the product is patent protected.

3.2 Competition-oriented methods

Market concentration. Previous studies show a higher degree of relational behavior in more concentrated markets (e.g., Ramaswamy, Gatignon and Reibstein 1994). This effect has been explained by a higher threat of competitive moves for the few large firms competing in a highly concentrated market which results in a higher competition orientation in budgeting (Besanko et al. 2007). Consequently, we expect that competition-oriented budgeting methods are more preffered in concentrated markets.

Stage in life cycle. Pharmaceutical products follow a life cycle (e.g., Fischer, Leeflang, Verhoef 2010). In the early stages of the life cycle, it is of particular importance to create awareness and to obtain distribution channels (Ailawadi, Farris and Parry 1994). Companies need to get a fixed share of voice in the market to achieve market penetration which may result in a stronger competitive orientation. But in later stages of the life cycle the degree of competition increases due to slower market growth or downturn which complicates the defense of the own market position. This results in an increased focus on competition. Because of these contradicting effects we cannot predict the impact of life cycle effects on the preference for competition-oriented methods and consider it as an empirical issue.

Order of entry. Studies of pharmaceutical markets identified time advantages of pioneers as well as a higher return of marketing for early entrants due to habit persistence of doctors keeping them by the same drugs, which are most likely pioneer drugs (Coscelli 2000). This allows early entrants a stronger focus on their own business. In addition, due to these effects early entrants generally become dominant player with greater market shares and larger marketing budgets (Berndt et al. 1995) so that the threat due to marketing activities of later (and smaller) entrants is rather low. Contrary, late entrants face brand disadvantages compared to pioneers which they need to compensate in order to improve their position in a mature market. This demands an increased focus on competitors to be able to oppose competitive campaigns. Thus, we expect an increase in application of competition-oriented methods for later entrants.

Patent status. The loss of patent protection in pharmaceutical markets allows for generic entry which results in a significant increase of competition intensity. This threat of rising competition may strengthen the focus on competitive activities. Contrary, an increase in price elasticity due to generic entry decreases the threat of competitive marketing because in a market of highly comparable products the price becomes the most important driver. As a result of these opposite effects we cannot provide a prediction about the effect of patent status on the application of competition-oriented methods.

3.3 Profit-oriented methods

Market concentration. Profit-oriented methods need to solve a complex profit maximization problem which has to take account of several factors, such as competition. Due to less competitiveness in highly concentrated markets profit maximization is easier to achieve (e.g., Fischer et al. 2011) so that the allocation solution derived from profit-oriented methods is less complex and more reliable. Further, previous studies indicate that companies in highly concentrated rather fulfill the prerequisites for sophisticated budgeting because they are by definition, on average, larger. They obtain more data which is necessary for estimation of quantitative models, and they possess the operations departments, which are necessary for the development of analytic methods (Patti and Blasko 1981; Lynch and Hooley 1987; Hung and West 1991). Finally, as companies in concentrated markets are generally characterized by a larger variety in the product portfolio the need for sophisticated budgeting approaches like the profit-oriented methods increases. For all of these reasons, we expect a more intense application of profit-oriented methods in higher concentrated markets.

Stage in life cycle. While in the beginning of the product life cycle managers mainly focus on improving their market position, this focus changes to exploiting the product's profit potential, i.e. maximizing profits, in later stages of the life cycle (e.g., cash cows). Further, a reliable estimation of the marketing performance, which is a prerequisite for the application of profit-oriented methods, is rather possible when products stay in the market for a longer time period and a larger database is available. For these reasons, we expect that the preference for applying profit-oriented budgeting methods is higher in the later stages of the product life cycle.

Order of entry. Later entrants suffer from brand disadvantages when entering a market. To overcome these weaknesses in competition, they are not able to focus as much on profit maximization than pioneers. Contrary, early entrants benefit from time advantages leading to a larger marketing responsiveness and a superior market position (Coscelli 2000). Hence, pioneers are much more focused on profit maximization because they have a larger knowledge about own marketing performance and the resources necessary for sophisticated budgeting, such as "Objective and Task". Therefore, we expect that the preference for the application of profit-oriented budgeting methods is higher for pioneers.

Patent status. We see an increase in competition intensity due to patent expiration which may enhance the need for sophisticated budgeting methods, such as "Objective and Task". But simultaneously, lower profit margins after patent expiration reduce the market attractiveness significantly so that the benefit of the application of profit-oriented budgeting is decreasing. These opposite effects do not allow for a prediction on the effect of patent expiration on the application of profit-oriented methods.

3.5 Summary

We provide a summary of the expected effects of our included determinants on the choice of budgeting methods in Table 2. Herein we also report the operationalization of these variables which we discuss in the next section in more detail.

We do not expect that the preference for the different budgeting rules is stringent substitutive, i.e. there may be arguments which may provide reasons for the application of all three of the budgeting rules included in our study. Further keep in mind, that there are still some rules, in section 2 named as *other rules*, which are not considered in our empirical analysis.

4 Empirical model formulation and estimation

We first specify the marketing budgeting model that incorporates the most common budgeting practices, sales-oriented, competition-oriented, and profit-oriented rules. We then specify the demand model, which provides marketing budget elasticity estimates.

4.1 Marketing budgeting model

4.1.1 Formalization of budgeting methods

Sales-oriented methods. Let $\tilde{S}_{it}$ denote sales of product i that is anticipated in year t and M_{it} denote the marketing budget to be allocated to product i in t. The idea of the "Percentage of Sales" rule is to spend a specific percentage of expected product sales on marketing. If this percentage does not change from period to period the change in marketing budget is proportional to the change in expected sales. Hence, the method can be formalized as follows:

$$\frac{dM_{it}}{M_{it}} = \delta_i^{Sales} \cdot \frac{d\tilde{S}_{it}}{S_{it}}, \tag{1}$$

where δ_i^{Sales} is a proportionality factor that measures how "closely" the marketing budget follows expected sales. It is 1 if the rule is applied in its pure sense, i.e. the percentage does not change over time. However, due to diminishing returns to scale the marginal profit of marketing investments decreases with higher budgets, which suggests that managers rather adopt a disproportionate rule (Lilien and Little 1976). For this reason, we expect $0 \leq \bar{\delta}^{Sales} \leq 1$, where $\bar{\delta}^{Sales}$ is the average proportionality factor. Solving the differential equation (1), leads to the following relation between budget and expected sales:

$$\ln(M_{it}) = \delta_i^{Sales} \cdot \ln(\tilde{S}_{it}) + IC_i, \tag{2}$$

where *IC* represents the integration constant.

Competition-oriented methods. Competition-oriented methods are based on the principle that product i's marketing budget is set proportional to the expected budget for its competitors:

$$\frac{dM_{it}}{M_{it}} = \delta_i^{Comp} \cdot \frac{d\widetilde{MC}_{it}}{MC_{it}}, \tag{3}$$

Table 2.Variable definition and expected direction of effects

Variable	Definition	Expected Effect on the preference for…		
		Sales-oriented Methods	Competition-oriented Methods	Profit-oriented Methods
Market Concentration	Average Herfindahl index of the product category during our data interval	+	+	+
Stage in Life Cycle	Mean of the elapsed time since launch of the product during our data interval	+	+/-	+
Order of Entry	Count variable that counts the entry rank of a new chemical entity into the product market	-	+	-
Patent Status	Dummy variable: 1 = product was under patent protection in more than 50% of observed time periods; 0 otherwise.	+	+/-	+/-

where $\widetilde{MC}_{it}$ represents the expected expenditures by *i*'s competitors, δ_i^{Comp} is the associated proportionality factor, and all other terms are defined as earlier. If management has adopted a fully counteractive reaction behavior, it follows that $\delta_i^{Comp} = 1$. However, research (e.g., Leeflang and Wittink 1994) has shown that managers may overreact, i.e. $\delta_i^{Comp} > 1$, underreact, i.e. $0 < \delta_i^{Comp} < 1$, do not react at all, i.e. $\delta_i^{Comp} = 0$, or show an accommodating behavior, i.e. $\delta_i^{Comp} < 0$. The most frequent reaction seems to be no reaction, but since counteractive behavior appears to be more widespread (Leeflang and Wittink 1994), we expect that $0 \le \bar{\delta}^{Comp} \le 1$.

From the differential equation of (3), it follows:

$$\ln(M_{it}) = \delta_i^{Comp} \cdot \ln\left(\widetilde{MC}_{it}\right) + IC_i \tag{4}$$

Profit-oriented methods. Profit-oriented methods encompass scientific modeling approaches and the "Objective and Task" rule. Managers may set sales or communication objectives that determine the marketing agenda of the company and thereby the allocation of the marketing budget (Lilien and Little 1976). Consistent with economic theory, we assume that these objectives contribute to the ultimate goal of profit maximization.

Usually, the firm's overall marketing budget is limited. The allocation literature provides guidance on how to allocate a fixed marketing budget across products in an optimal way (Doyle and Saunders 1990; Fischer et al. 2011). Basically, these approaches suggest allocating the budget according to a proportionality rule:

$$M_{it}^* = \frac{A_{it}}{\sum_{j \epsilon I} A_{jt}} R, \qquad \forall\, i \in I$$

$$\text{with } A_{it}^* = \left(\textstyle\sum_m \varepsilon_{im}^*\right) \cdot p_i \cdot d_i \cdot MS_{it}^* \cdot PD_{it}\,, \tag{5}$$

where M^* denotes the optimal budget, A is an allocation weight that measures the attractiveness of a product for receiving more budget, and I is the index set of products. ε_m is the elasticity of marketing activity m, p is the product price, d is the contribution margin (in percent), MS is the market share, and PD is the primary demand. The star indicates that variable values correspond to the optimal solution for the marketing budget. Under a fixed total budget, an improvement in the allocation weight should increase the budget for product i:

$$\frac{dM_{it}}{M_{it}} = \delta_i^{Profit} \cdot \frac{d\tilde{A}_{it}}{A_{it}}, \tag{6}$$

where δ_i^{Profit} denotes the proportionality factor, $\tilde{A}$ measures the anticipated optimal allocation weight and all other terms are defined as earlier. But, it is difficult to predict the magnitude of the proportionality factor because the budget change not only depends on the allocation weight for *i* but also on the weights for the other products in the portfolio. Because the allocation is basically a zero sum game, we expect that $0 \leq \bar{\delta}^{Profit} \leq 1$.

We may simplify equation (6) as the primary demand is equal for products across the portfolio in the same product category The contribution margin for pharmaceutical products amounts to ca. 90% usually does not vary across products (Fischer et al. 2011). Therefore:

$$\frac{dM_{it}}{M_{it}} \approx \delta_i^{Profit} \cdot \left(\sum_m \varepsilon_{im}\right) \cdot p_i \cdot \frac{d(\widetilde{MS}_{it})}{MS_{it}} \tag{7}$$

Finally, we solve the differential equation (7) to obtain:

$$\ln(M_{it}) = \delta_i^{Profit} \cdot \left(\sum_m \varepsilon_{im}\right) \cdot p_i \cdot \ln\left(\widetilde{MS}_{it}\right) + IC_i \tag{8}$$

4.1.2 Specification of the marketing budget model

We use these formalized rules to explain the marketing budget for a product. The marketing budget allocation is a complex multi-step process which is influenced by several managers. All of them potentially prefer different budgeting practices. Therefore, we consider the final marketing budget decision as the result of application of different budgeting rules. Further, we apply yearly data to our model as budget decisions are made on an annually recurring budget process and therefore budget decisions made for a time period of one year (Albers 2011; Lilien 1979):

$$\begin{aligned} \ln(M_{ickzt}) = \theta_i + \delta_i^{Sales} \cdot \ln \tilde{S}_{it} + \delta_i^{Comp} \cdot \ln \widetilde{MC}_{ickt} \\ +\delta_i^{Profit} \cdot \ln\left(\sum_m \varepsilon_{im} \cdot p_{it} \cdot \ln \widetilde{MS}_{it}\right) + \eta_1 \cdot \ln M_{i,t-1} \\ +\eta_2 \cdot \ln LCT_{it} + \tau_z + \upsilon_k + u_{ickzt} \end{aligned} \tag{9}$$

with

$$\delta_i^l = \omega_l + \lambda_{l1} \cdot \ln(OOE_i) + \lambda_{l2} \cdot \ln(\overline{H_i}) + \lambda_{l3} \cdot \ln(\overline{LCT_i}) + \lambda_{l4} \cdot \overline{\mathrm{D\_PAT}_i} + \xi_{li} \tag{10}$$

$\tau_z \sim N(0, \sigma_\tau^2), \upsilon_k \sim N(0, \sigma_\upsilon^2), u_{ickzt} \sim N(0, \sigma_{ickzt}^2)$

$\xi_{li} \sim N(0, \sigma_{li}^2)$,

where

M_{ickzt}	: Marketing expenditures by brand i of company z in country c and category k and period t;
$\tilde{S}_{it}$	: EUR Sales of brand i in period t;
$\widetilde{MC}_{ickt}$	: Aggregated marketing expenditures by brand i's competitors in country c and category k in period t;
ε_{im}	: Elasticity of marketing activity m of brand i;
$\widetilde{MS}_{it}$	: Market share of brand i in period t;
LCT_{it}	: Elapsed time since launch of brand i in period t;
p_{it}	: Unit price of brand i in period t;
OOE_i	: Entry order of brand i;
H_i	: Herfindahl index of brand i;
D_PAT_i	: Patent status of brand i;
τ, υ, u, ξ	: Error terms;
σ^2	: Error variance;
$\theta, \delta, \eta, \omega, \lambda$	: Parameters to be estimated;
m	= 1,2,3 (number of marketing activities);
k	= 1,2,…, N_k (number of product categories);
c	= 1,2,…, N_c (number of countries);
z	= 1,2,…, N_z (number of companies);
i	= 1,2,…, N_i (number of brands);
t	= 1,2,…, T_i (number of periods per brand);
l	= Sales, Comp, Profit.

The heterogeneous random brand constant (θ_i) covers the sum of the integration constants in equations (2), (4), and (8), as well as an overall constant term. It controls for the influence of other unobserved variables that are time-invariant and brand-specific, such as the application for other budgeting rules which are not included in our model. The δ parameters indicate the degree to which the brand managers apply the corresponding budgeting rules as described above. The heterogeneous distribution of random parameters δ allows the estimation how each budgeting rule is applied by each product in our dataset.

Additionally, we contain the marketing budget of the previous year and the time since launch as control variables. As indicated by manager surveys, the marketing budget of the previous year has a significant impact on budgeting behavior because it is taken as starting point in the budget planning process due to inertia effects (Piercy 1986). By including the previous budget, measured as deviations from the group mean to account for heterogeneity, our model adjusts for this behavior. Since the transient and persistent effects of marketing decreases over time (Osinga, Leeflang and Wieringa 2010), marketing investments are more intense in the beginning of the life cycle and being reduced afterwards. We adjust for these effects by including the time variable *LCT*.

We analyze moderating effects of the application of budgeting rules by specifying a heterogeneous mean for the δ parameters which is influenced by the four factors of order of entry, market concentration, elapsed time since launch and patent status as shown in equation (10) and discussed in section 3. Since we assume a decreasing influence of the moderators on the preference of the budgeting rules, we always take the log of order of entry, Herfindahl index, and elapsed time since launch. Specification tests, which we report later, support this assumption.

Finally, the model shows a nested, multilevel error structure, which consists of error components that are company-specific, τ_z, as well as category-specific, υ_k. We assume these errors and the idiosyncratic error, u_{ickzt}, to be uncorrelated. As a result, the error variance is $Var(\tau_z + \upsilon_k + u_{ickzt})$. While the brand constant control for the influence of other unobserved brand-specific variables, this error structure further account for budgeting related firm-specific characteristics, e.g. unobservable firm-specific budgeting rules, as well as category-specific characteristics, e.g. changes in marketing regulations.

4.1.2 Estimation of the marketing budget model

We integrate equation (10) into equation (9) and estimate the resulting equation by using a two-step simulated maximum likelihood approach. In the first step, we first have to estimate the anticipated sales, market share, and competitor spending, respectively, for application of the budgeting rules. We obtain the expected values by OLS estimation of reduced-form models, i.e. the variables which need to be estimated are regressed on a set of explanatory variables. To avoid biased parameter estimates due to simultaneity the explanatory variables have to be exogenous (Franses 2005). We obtain the expected market share by regressing the log of the market share on the exogenous but related variables of log of number of products in the market, the log of order of entry and the log of the average product price in all countries except for the focal country as well as the time since launch and the log of time since launch representing the life cycle. The corresponding F-value accounts to 382.6. To obtain expected sales we regress the log of sales on the log of the average product price in all countries except for the focal country and the aggregated category primary demand in the other four countries as well as the time since launch and the log of time since launch to represent life cycle effects. The corresponding F-value accounts to 154.8. Finally, we regress the marketing spending of competitors on the number of products in the market, the Herfindahl index and the aggregated category primary demand in the other four countries to obtain the expected competitive marketing. The corresponding F-value accounts to 1879.9.

In the second step, we have to account for the heterogeneity in parameters as the θ and δ parameter from equation (9) are specified as random parameters with the heterogeneity structure of $\theta_i = \theta_{0i} + \vartheta_i$, respectively $\delta_{li} = \delta_l + \vartheta_{li}$ for budgeting method *l*, with $\vartheta \sim N(0, \Gamma)$, while η is specified as fixed parameter. ϑ, Γ are error terms, respectively the variance-covariance matrix, of the brand-specific parameters. Therefore, we estimate the resulting equation of (9) and (10) by simulated maximum likelihood. In terms of its econometric properties, the two-step estimator is unbiased and consistent (Greene 2006).

4.2 Brand sales model

4.2.1 Specification of the brand sales model

To estimate model (10) we need to know the elasticities of marketing activities. For this purpose, we estimate a parsimonious sales model that relates brand unit sales to relevant variables to obtain brand-specific estimates of marketing responsiveness. We apply quarterly data to the *brand sales model*. Following Fischer et al. (2011), we define unit sales of brand *i* and period *w* as follows:

$$\begin{aligned}\ln q_{ickw} = {} & \alpha_{0i} + \alpha_{1i} \cdot \ln DET_{iw} + \alpha_{2i} \cdot \ln PJA_{iw} + \alpha_{3i} \cdot \ln OME_{iw} + \alpha_{4i} \cdot \ln q_{ick,w-1} \\ & + \alpha_{5i} \cdot LCT_{iw} + \alpha_{6i} \cdot \ln LCT_{iw} + \beta_{1i} \cdot \ln MC_{ickw} + \beta_{2i} \cdot \ln p_{iw} \qquad (11) \\ & + \sum_{k=1}^{K-1} \gamma_{0+k} \cdot \ln D\_CAT_k + \sum_{se=1}^{SE-1} \ln \gamma_{3+s} \cdot SD_{se,w} + \varsigma_{ickw}\end{aligned}$$

with

$\varsigma_{ickw} \sim N(0, \sigma^2_{ickw})$, with $Cov(\varsigma, \xi) = 0$

where

q_{ickw}	: Unit sales of brand i in country *c* and category *k* in period *w*;
DET_{iw}	: Expenditures on detailing by brand i in period *w*;
PJA_{iw}	: Expenditures on professional journal advertising by brand *i* in period *w*;
OME_{iw}	: Expenditures on other marketing activities by brand *i* in period *w*;
LCT_{iw}	: Elapsed time since launch of brand *i* in period *w*;
MC_{ickw}	: Aggregated marketing expenditures by brand *i*’s competitors in country *c* and category *k* in period *w*;
p_{iw}	: Unit price of brand *i* in period *w*;
D_CAT_k	: Category dummy variable for category *k*;
$SD_{se,w}$	: Seasonal dummy variable for quarter *se* and period *w*;
ς, σ^2	: Error term and error variance;
α, β, γ	: Parameters to be estimated;
k	= 1,2,…, N_k (number of product categories);

c = 1,2,…, N_c (number of countries);
i = 1,2,…, N_i (number of brands);
se = 1,2,…, SE (four quarters); and
w = 1,2,…, W_i (number of periods per brand).

We apply the multiplicative interaction model, a standard response model, to explain brand unit sales. This functional form has received large empirical support, has been found useful in normative applications, and incorporates interaction effects in a parsimonious way (e.g., Hanssens, Parsons and Schultz 2001, 100). We later test for the functional form and find that the multiplicative model is indeed best representing our data (see also Fischer and Albers 2010; Fischer et al. 2011).

The parameters $\alpha_1 - \alpha_3$ can be directly interpreted as elasticities. We categorize the marketing expenditures in detailing expenditures, professional journal advertising and other marketing expenditures. To allow for dynamics, we include a carryover effect, as it is common in the time-series literature on advertising effects (Leone 1995). Again, to account for heterogeneity the previous sales units are measured as deviations from the group mean. The parameter α_{4i} allows us to obtain brand-specific marketing carry-over coefficients. We include the elapsed time and the log of the elapsed time since launch of the brand to control for brand-life-cycle effects (Brockhoff 1967).

In equation (11), we account for brand heterogeneity in demand responsiveness (e.g., quality, brand equity) via brand-specific slope parameters (Greene 2006). An analysis of data shows that product life cycles differ in trend and length. Therefore, we account for heterogeneity in the trend variables as well. Finally, we specify a heterogeneous random brand constant (α_{0i}) for influences of other unobserved, time-invariant variables, such as management luck or brand equity (e.g., Berndt et al. 1995; Fischer, Shankar and Clement 2005).

In addition, the model includes the price of the considered brand as control variable. Distribution is less an issue in the response model as all pharmacies are required to list every drug in the countries covered by our data. Due to the inclusion of various categories that are likely to differ in terms of market size, we include category dummies as non-random variables to correct for market-size differences. Dummy variables that represent one of the four quarters of the year control for seasonal variation in demand.

The long-term marketing elasticity ε for brand i which we need for estimation of equation (9) is derived from the estimation results by (Fischer et al. 2011):

$$\varepsilon_i = \frac{\hat{\alpha}_{1i}+\hat{\alpha}_{2i}+\hat{\alpha}_{3i}}{1-\hat{\alpha}_{4i}} \tag{12}$$

4.2.2 Estimation of the brand sales model

The specification of the brand sales model accounts for brand heterogeneity. From equation (11) the random parameters are $\alpha_0 - \alpha_6$ with a heterogeneity structure on these parameters of $\alpha_i = \alpha + \varphi_i$, with $\varphi_i \sim N(0, \Omega)$. φ_i denote the error terms, and Ω the variance-covariance matrix of the brand-specific parameter α_i. We account for the heterogeneity in the parameters by estimating equation (11) by simulated maximum likelihood.

Our marketing budget model in equation (9) indicates an endogenous relationship between marketing expenditures and sales on a yearly basis. So we have to check whether our marketing expenditure variables in equation (11) in which we use quarterly data are as well subject to endogeneity. Since potential cross-sectional correlation is controlled by including a random brand constant, we only have to test for an error correlation of expenditure variables over time. Therefore, we apply the Hausman-test to the model in first differences (Greene 2006) using the variables that are two periods lagged as instruments (Anderson and Hsiao 1982). We do not find evidence that marketing decision variables are endogenous (p>.5). The F-value of the first-stage regression accounts to 363.5 which indicate that we have valid instruments. This finding indicates that quarterly changes in marketing expenditures are not the result of budgeting methods which is in line with the results of prior studies (e.g., Fischer and Albers 2010).

5 Data

We estimate our models using data from four prescription drug categories, Hypertension, Antidiabetics, Erectile Dysfunction and Antiinfectives. We are provided with data on unit sales counted in standard units, revenues (all in EUR), and the date of product launch, which we use to obtain order-of-entry and life-cycle information, by IMS Health, Inc. for a time period of 12 years (1996-2007). This allows us to account for time variation by using panel data (Farris and Buzzel 1979). In addition, we may reduce the level of multicollinearity due to more degrees of freedom (Brobst and Gates 1977) and increase the generalizability of our results (Balasubramanian and Kumar 1990). We computed prices from revenues and unit sales. Via their CAM database, CEGEDIM, S.A. provided information on detailing expenditures targeted at general practitioners, specialists, and pharmacists. In addition, we possess information on professional journal advertising expenditures (including direct mailing), and other expenditures. The subcategories for the classification of the order-of-entry are defined according to the corresponding ATC-Class (Coscelli 2000).

Table 3 shows mean values and standard deviations for the variables used in estimation. In total, 18,391 observations are available. The dataset comprises 518 products in the four product categories. Note, that we transformed the quarterly data to annual data for estimation of the *marketing budget model* as the budget decision is made in an annually recurring budgeting process. This reduces the number of observations to 4,908.

6 Estimation results

6.1 Brand sales model

We present the estimation results for the *brand sales model* in Table 4. As our main objective is to obtain brand-specific estimates of marketing responsiveness, we focus on the estimation of marketing elasticities.

Consistent with prior research (e.g., Albers, Mantrala and Sridhar 2010; Fischer and Albers 2010), we find the strongest impact for detailing showing short-term elasticities of about .07 and long-term elasticities of about .20. Journal advertising and other marketing expenditures are considerably less effective with short-term elasticities of about .04 and .02, respectively, and long-term elasticities about .10 and .05, respectively.

In terms of control variables, we find typical life cycle shapes (Fischer, Leeflang and Verhoef 2010), a negative price impact and an average carry-over effect of about .63. Only the impact of competitive marketing expenditures is slightly surprising as it is positive. This indicates a market-expansive character on average.

6.2 Marketing budget model

We present the estimation results for the *marketing budget model* of equation (9) in Table 5 and of equation (10) in Table 7. The estimation results in Table 5 indicate how the budgeting rules are applied across companies, while the moderating effects as shown in Table 7 give insights about which factors have an impact on the preference for the corresponding rules.

6.2.1 Analysis of “rule-parameter” values

The estimated coefficients of the “rule-parameters” in Table 5 indicate how the budgeting rules are applied on average. For the coefficient of sales-oriented methods, we find a value of about .45 on average which is in the range of our expectations. As we have a double-log model, the coefficient value corresponds to the elasticity, i.e. budgets do not increase to the same amount as expected sales. The coefficient of competition-oriented methods is positive

Table 3. Descriptive statistics

	Mean	SD
Sales in thousand EUR	4,083.6	5,534.6
Market share in standard units	8.2 %	17.3 %
Detailing expenditures in thousand EUR	6,993.9	235.1
Professional journal advertising expenditures in thousand EUR	27.8	90.6
Other marketing expenditures in thousand EUR	235.05	792.4
Price in EUR per standard unit	1.1	4.1
Elapsed time since launch in quarters	50.2	39.4
Proportion of drugs under patent-protection	43.0 %	
Order of entry	3.9	2.6
Herfindahl-Index	.12	.23
# of countries	5	
# of products	518	
# of companies	79	
# of observations (quarterly/yearly)	18,391/4,908	

Table 4. Estimation results of the brand sales model

Dependent variable	*Ln(Unit Sales)*			
	Est. Parameter	Standard error	Est. Parameter SD	Standard error
Constant	6.150	(.017)**	.036	(.001)**
Ln(Lagged Unit Sales)	.639	(.002)**	.127	(.002)**
Ln(Competitive Marketing Expenditures)	.044	(.001)**		
Ln(Price)	-.381	(.002)**		
Elapsed Time Since Launch	-.006	$(.7\times10^{-4})$**	.040	$(.5\times10^{-4})$**
Ln(Elapsed Time Since Launch)	.287	(.003)**	.078	$(.4\times10^{-3})$**
Marketing variables				
Ln(Detailing)	.073	(.001)**	.066	$(.2\times10^{-3})$**
Ln(Journal Advertising)	.037	(.001)**	.036	$(.7\times10^{-3})$**
Ln(Other Marketing Expenditures)	.017	(.001)**	.005	$(.5\times10^{-3})$**
Log Likelihood	-10,807.1			
Pseudo R^2	.922			
# of observations	17868			
# of products	518			

Notes: ** p<.01; * p<.05; ^{ns} = not significant and significant on average at a value about .185, i.e. increasing competitive spending results in an increase of the own budget size. This confirms that managers are competitor-oriented, which results in aggressive reactions (e.g., Leeflang and Wittink 1996). Previous research showed that this behavior is very often not driven by rational profit-oriented considerations. Instead, managers are more interested in improving their market position compared to their competitors (Azoulay 2002). Leeflang and Wittink (1996) argue that the affinity to aggressive reaction to competitors marketing spending can be explained by competitor-oriented objectives or the evaluation on relative performance measures of brand managers. Our study confirms that aggressive reactions can be explained as well by application of competition-oriented methods. Finally, the estimated coefficient of profit-oriented methods is on average significantly below the value of one, but within the expected range (=.717). An explanation of this result is that budget changes depend on the allocation weight for all products in the portfolio. As allocation is basically a zero sum game, changes in allocation weight generally cannot be fully followed (as discussed in section 4.1.1).

Table 5. Estimation results for the Marketing Budget Model

Dependent variable	*Ln(Marketing Expenditures)*			
	Est. Parameter	Standard error	Est. Parameter SD	Standard error
Constant	-.617	(.436) ns	.072	(.028)**
Lagged Marketing Budget	.185	(.058)**		
Elapsed Time Since Launch	-2.830	(.065)**		
Budgeting methods				
Sales-oriented Method	.450	(.112)**	.369	(.004)**
Competition-oriented Method	.185	(.058)**	.051	(.002)**
Profit-oriented Method	.717	(.100)**	.329	(.017)**
Moderators				
	Estimation results are shown in Table 7			
Error components	.296	(.026)**		
Firm-specific error component (standard deviation)	.512	(.026)**		
Category-specific error component (standard deviation)				
Log Likelihood	-9,737.5			
Pseudo-R^2	.777			
# of observations	4,390			
# of products	518			

Notes: Nested, multilevel error structure which consists of company- and category-specific error components. ** p<.01; * p<.05; ns = not significant

The covariates have the expected signs. The budget of the previous period has a positive impact, which indicates that previous budgets are adopted in the budgeting process, probably as they are taken as starting points in budget planning (Farris, Shames and Reibstein 1998). The elapsed time since launch has a negative impact on the marketing intensity. This is in line with prior studies (e.g., Osinga, Leeflang and Wieringa 2010; Lilien and Little 1976) as products first need to generate awareness when entering a market, while they benefit from built-up marketing stocks in the later stages of their life cycle (Ailawadi, Farris and Parry 1994; Farris and Buzzel 1979).

6.2.2 Analysis of "rule-parameter" distribution

To identify how many companies apply each of the three dominant budgeting methods we analyze the distribution of the "rule-parameters" across brands. Our estimation approach provides us with posterior standard deviations for the individual parameters. Therefore, we may apply a pseudo t-Test which tests for how many brands the individual parameter value is significantly different from zero ($p<.05$), i.e. has a statistically significant impact on the marketing budget decision, and for how many brands the individual parameter value is significantly not different from one ($p<.05$), i.e. the corresponding rule is fully applied. The distribution of the three "rule-parameters" is shown in Table 6.

Table 6. Application of budgeting methods across brands

	Applied ($\delta \neq 0$)*	Fully-applied ($\delta = 1$)*
Sales-oriented Methods	81.24%	11.53%
Competition-oriented Methods	53.18 %	0.34%
Profit-oriented Methods	40.54%	33.56%

Notes: * $p<.05$

The sales-oriented methods are applied most often as they have a significant impact on the marketing budget for 81.24% of all brands. This result is consistent with the average response across survey studies of 84.2%. that managers state that they apply sales-oriented methods (see Table 1). But we only find for 11.53% a statistically significant parameter value of one, i.e. a full proportional adjustment to sales, which indicates that most firms apply "Percentage of Sales" in a disproportional way. Further, we observe a widespread use of competition-oriented methods, which are applied to 53.18% of all brands. The mean parameter value of .185 (see Table 5) and the fact that only .34% apply this method fully, i.e. have a parameter of one, show that competition-oriented methods are rather used complementary. Nevertheless, this finding confirms that marketing budgets are widely influenced by competitive marketing budgets (Chintagunta und Desiraju 2005; Chintagunta, Kadiyali und Vilcassim 2006) and thereby contradicts the results of survey studies according to which only 21.7% of managers apply competition-oriented methods. Contrary, profit-oriented methods are applied for only 40.54% of brands according to our “rule-parameter” values. This points out that “Objective and Task” is less widespread than expected based on survey results. But we observe a wide range of parameter values close to one, as for 33.56% of products profit-oriented methods are fully applied, i.e. about 82% of brands which use profit-oriented methods apply it fully.

Summarizing our results, managers have a reliable picture of the influence of sales-oriented methods on the marketing outcome. But the focus on competition is clearly underestimated as changes are much more driven by competitive activities than stated in surveys. On the other hand, methods which are derived from profit maximization, i.e. profit-oriented methods, are less applied which confirms the assumption of prior studies that managers tend to overstate the application of profit-oriented methods (e.g., Martenson 1989).

6.2.3 Moderator analysis

The “rule-parameters” show significant variation across brands. Our estimation results of moderating effects are shown in Table 7. They provide information about the sources of this observed variation.

We find significant moderator effects for most of the determinants discussed in section 3. Our results support most of our expectations as summarized in Table 8. Further, we get insights about moderators where we could not hypothesize about their impact due to opposite effects. We compare the results of the moderator effects of application of budgeting methods for equation (10) in Table 8.

Table 7. Estimation results for the moderating effects of the Marketing Budget Model

Dependent variable	*Brand-specific rule parameter (proportionality factor δ) for…*					
	Sales-oriented Method		*Competition-oriented Method*		*Profit-oriented Method*	
	Est. Parameter	Standard error	Est. Parameter	Standard error	Est. Parameter	Standard error
Market Concentration	.0499	(.014)**	-.0083	(.009)^{ns}	.1573	(.010)**
Later stage in Life Cycle	.4883	(.030)**	-.0461	(.018)*	.3211	(.040)**
Order of Entry	-.0391	(.029)^{ns}	-.0090	(.017)^{ns}	-.2483	(.029)**
Off-patent Status	.5336	(.051)**	-.2223	(.030)**	-.9401	(.048)**

Notes: $^{**}p<.01$; $^{*}p<.05$; ^{ns} = not significant

Market Concentration is measured as Herfindahl index. Patent status is a dummy variable coding 0 if patent is expired and 1 otherwise. The stage in life cycle is measured as time since product launch.

Table 8. Comparison of expected and estimated results for moderating effects

	Preference for the application of…					
	Sales-oriented Methods		Competition-oriented Methods		Profit-oriented Methods	
	Expected	Estimated*	Expected	Estimated*	Expected	Estimated*
Market Concentration	+	+	+	NS	+	+
Later Stage in Life Cycle	+	+	+/-	-	+	+
Order of Entry	-	NS	+	NS	-	-
Off-patent Status	+	+	+/-	-	+/-	-

Notes: * p<.05; NS = not significant

The expected impacts are summarized in Table 2. The estimated results are presented in Table 6.

Sales-oriented methods. Our estimation results provide support for our expectations that sales-oriented methods are rather applied in highly concentrated markets, in the maturity stage of a product and under patent protection. But our results do not provide evidence that order of entry has an impact on the preference for sales-oriented methods. Nevertheless, summarizing our results the estimated effects confirm that sales-oriented methods are rather applied by dominant firms in the market, as indicated by previous studies (e.g., Lynch and Hooley 1990).

Competition-oriented methods. We do not find empirical support for our expectation that competition-oriented methods tend to be more applied in highly concentrated markets. This is surprising due to a higher threat of competitive marketing in oligopoly structured markets. A possible explanation for this insignificance could be that larger firms, which can be found in highly concentrated markets, generally prefer to apply rather sophisticated budgeting methods, such as “Objective and Task”, instead of unsophisticated competition-oriented methods (Parry, Parry and Farris 1991; Hung and West 1991). We could not provide a prediction on life cycle effects on the application of competition-oriented methods due to opposite effects. The estimated negative impact of elapsed time since launch indicates that the need for generating awareness in the market after product introduction outweighs the threat of competitors in declining markets which results in a higher preference of applying competition-oriented methods in the early stage. Our results do not provide evidence that order of entry has an impact on the preference for competition-oriented methods. The insignificance of competition-oriented methods may be explained by the fact that pioneers are focused on defending their market position and therefore react on any competitive activity. Finally, patent expiration leads to a decreased application of competition-oriented budgeting methods which indicates that the effect of loss in market attractiveness outweighs competition intensification after patent expiration, i.e. a more profitable market enhances the focus on competitive activities.

Profit-oriented methods. All of our expectations regarding profit-oriented methods are supported by the estimation results, i.e. the preference for applying profit-oriented budgeting methods is higher in concentrated markets, in the later stages of a product, and for pioneers. Further, we find that patent expiration leads to an increased application of profit-oriented budgeting methods which indicate that the effect of competition intensification outweigh the negative effect due to a loss in market attractiveness after patent expiration and, therefore, increases the need for sophisticated budgeting methods, such as "Objective and Task" (Huskamp et al. 2008).

6.2.4 Robustness Checks

The Pseudo-R^2 of the *marketing budget model* is .78 and .92 for the *brand sales model*, which is quite high and shows that our models provide an appropriate framework for budget setting behavior. Further, we checked whether our model specification and estimation is appropriate for the data in three ways. First, we checked multicollinearity by estimating the Variance Inflation Factor of each variable. As all Factors are close to one, we do not find an indication of multicollinearity (Greene 2006). Second, we tested alternative functional forms of the moderators in the *marketing budget model* and the *brand sales model* as well. In particular, we estimated equation (10) as linear model and equation (11) as semi-log and market share attraction model. The Davidson and MacKinnon (1981) test for unnested models suggests that the proposed specifications are superior to alternative specifications. Third, we tested an alternative specification of the "Objective and Task" formalization (see equation (5)) by including revenues instead of market share, i.e. $A_{it} = (\sum_m \varepsilon_{im}) \cdot d_i \cdot S_{it}$. Therefore, we executed a Davidson and MacKinnon (1981) test which is inconclusive for our data, i.e. the two formalizations are not superior to each other. But due to the business stealing character of the marketing activities in the European pharmaceutical market (e.g., Narayanan, Desiraju and Chintagunta 2004) we assume that practitioners rather focus on market share.

7 Conclusions, Limitations, and Future Research

Our analysis of 518 brands in the pharmaceutical market reveals important insights about budgeting behavior. By formalizing the existing budgeting rules, we developed a model to estimate their impact on the observed product marketing budget decision. This allows us to find empirical support for the application of all three categories of budgeting rules. But the impact on the marketing budget varies significantly across brands. We find that for 81.2% of the brands sales-oriented methods, for 53.2% of the brands competition-oriented methods and for 40.5% of the brands profit-oriented methods are applied. In summary, managers have a good feeling of the influence of sales on the marketing budget, but they underestimate the impact of competitive marketing spending, while the application of profit-oriented methods is overstated. This finding shows that marketing budgets are generally not based on profit maximization approaches, and therefore also contradicts one of the main assumptions of structural modeling.

To explain the variation in application, we further analyzed the moderating effects which affect the preference for specific budgeting methods. Our results indicate that sales-, as well as profit-oriented methods, are rather applied by dominant firms in the market. Profit-oriented methods additionally dominate in highly competitive markets when an expiring patent status allow for competition which increases the need for sophisticated budgeting. Contrary, competition-oriented methods are preferred in the early stages of the life cycle, i.e. at market entry, when a strong focus on competition may allow to generate awareness and to obtain distribution in the market.

In summary, this study offers a new approach for the analysis of the budgeting process in companies. Our results provide insights into the budgeting process by analyzing how budgeting rules are applied and which moderating effects may influence the application of the rules. This provides managers with a deeper understanding of how budgets are set in companies and they may help to predict the marketing budget of competitors. Further, our results also shed some further light on theory and model development. We find empirical evidence that marketing budget decisions are based on budgeting rules which provide some explanations for prior studies. This indicates that managers set their marketing budgets suboptimal (e.g., Albers, Mantrala and Sridhar 2010). For this reason, assumptions in models regarding budgeting behavior should take these results into account. Structural modeling approaches base on the assumption of profit maximization by practitioners. But our results indicate that this assumption does not hold in general so that the structural modeling approach has to change.

Our study is also subject to limitations. The *marketing budget model* probably does not include all factors which may have a significant impact on the determination of the marketing budget. But since we control for many factors by our random constant and the error terms and our focus is on the analysis of the application of budgeting rules, we ignore for an exhaustive discussion of determinants of marketing budgets. To identify the influence of these controlled factors may represent an interesting issue for ongoing research. Finally, the estimation results hold for pharmaceutical firms in European markets. It would be interesting to extend the analysis to other industries and other regions. This is of particular interest as regional impact on budgeting behavior is still unclear (Bigné 1995). Finally, although we analyze the effects of some important variables, such as order of entry, stage in life cycle, market concentration, and patent status, we do not claim they are the only important moderators for the application of budgeting methods. More research should investigate the role of other variables.

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Dynamic Marketing Budget Allocation across Countries, Products, and Marketing Activities

Authors: Marc Fischer, Sönke Albers, Nils Wagner and Monika Frie

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Abstract

Previous research on marketing budget decisions has shown that profit improvement from better allocation across products or regions is much higher than from improving the overall budget. However, despite its high managerial relevance contributions by marketing scholars are rare.

In this paper, we introduce an innovative and feasible solution to the dynamic marketing allocation budget problem for multi-product, multi-country firms. Specifically, our decision support model allows determining near-optimal marketing budgets at the country-product-marketing-activity level in an Excel-supported environment each year. The model accounts for marketing dynamics and a product's growth potential as well as for trade-offs with respect to marketing effectiveness and profit contribution. The model has been successfully implemented at Bayer, one the world's largest firms in the pharmaceutical and chemical business. The profit improvement potential is more than 50% and worth of nearly EUR 500 million in incremental discounted cash flows.

1 Introduction

Determining the marketing budget has been of paramount importance to marketers for many decades. Global players such as Procter & Gamble spend around US$ 8.5 billion on advertising per year (P&G 2008). Since marketing expenditures are immediately recognized as costs on the income statement but their total impact on sales often fully unfolds only in future periods they need to be evaluated in terms of an investment decision. In view of limited financial resources, the global annual marketing budget of a company is usually set in the previous year, i.e. it is fixed. If companies offer a broad product portfolio to customers from various countries and use a variety of communication channels they need to break down the fixed annual budget into expenditures across countries, products, and communication activities. For many firms this task requires determining individual budgets for hundreds of allocation units. As a result, firms face a complex decision problem: they need to allocate a fixed budget across a multitude of allocation units by evaluating the impact of these investment decisions on future cash flows. Technically, management needs to solve a dynamic optimization problem for an investment portfolio under a budget constraint. As marketing budgets are set on an annual basis this management challenge recurs on a regular basis.

1.1 State-of-the-art of Marketing Budget Allocation

Marketing practitioners frequently use heuristic methods when it comes to determining the marketing budget. Bigné (1995) reviews 16 studies published between 1975-1991 on actual budgeting behavior of North-American and European firms from diverse industries. He finds that by far the most often used budget rules are the “percentage-of-sales”, “objective-and-task”, and “affordability” method. These rules usually yield results that are rather far away from the optimal profit-maximizing budget. Analytic methods that are based on the principle of marginal returns analysis produce optimal budgets but are only considered by a minority of firms.

The academic literature has been dealing with budget questions for a long time. A large body of work focuses on optimizing the budget for a single product in a static environment (for an overview see Hanssens, Parsons and Schultz 2001). Among the earliest and most influential contributions is the work by Dorfman and Steiner (1954). They derive necessary conditions that must hold for static profit maximization when optimal levels for several marketing-mix variables are set simultaneously. The solution offers important general insights into the budgeting problem but does not offer guidance for implementation into marketing practice. In addition, it does not consider dynamics and the perspective of a multi-country, multi-product firm.

A large stream of papers takes a dynamic perspective (for an overview see Erickson 2003). The recent paper by Naik, Raman and Winer (2005), for example, considers interaction effects between advertising and promotion under dynamic oligopolistic competition. The focus of these studies, however, remains on single products. They do not inform on how budgets are simultaneously set for several products in view of limited financial resources.

This question can only be answered by an integrated *allocation* approach. Previous research (e.g., Tull et al. 1986) has shown that profit improvement from better allocation across products or regions is much higher than from improving the overall budget. However, despite its high managerial relevance and profit improvement potential contributions by marketing scholars are rare (Reibstein, Day and Wind 2009).[1] An important emerging literature stream (e.g., Kumar et al. 2008; Reinartz, Thomas and Kumar 2005) deals with the problem of resource allocation across customers. Typically, these approaches require data on individual customer behavior and focus on service industries. Other articles focus on problems of sales territory design and sales force size (e.g., Skiera and Albers 1998; Zoltners and Sinha 2005) but do not address allocation decisions for products in multi-product, multi-country businesses. Only a few approaches are based on aggregate market response models that can be calibrated with sales and marketing data at the product level, which is the primary data source in many industries. Lodish (1988) proposes an allocation algorithm for a specific type of market response that has been adopted by a pharmaceutical company. Doyle and Saunders (1990) derive a closed-form allocation solution under a budget constraint for the semi-log response model and apply it to a British retailer. Albers (1998) generalizes the solution to the case of an arbitrary response function and allocation unit. Since a closed-form solution in terms of response parameters no longer exists he proposes a heuristic rule and shows via simulation that it quickly converges to the optimal numerical solution. While these approaches consider trade-offs among products of a portfolio for budget decisions they are focused on short-term profit maximization. Marketing decisions, however, need to account for dynamics, as well. On the one side, dynamic considerations result from lagged effects that can be represented by a marketing stock variable. On the other side, dynamic considerations arise from the fact that a portfolio mixes products with different ages and growth opportunities. Requirements for marketing support change as the product evolves along its life cycle. To the best of our knowledge, a dynamic marketing budget allocation approach for a product portfolio has not been suggested so far.

1.2 Contribution to Allocation Theory and Practice

In this paper, we propose an allocation method for breaking down a global marketing budget into individual budgets at the country-product-marketing-activity level. We take the position of an international firm that offers a broad portfolio of products to customers from different countries. Products are promoted by various activities including classical advertising, below-the-line activities, personal selling, etc. Each year the firm sets a global marketing budget that is to be spent by the various allocation units in the year ahead. The portfolio is composed of products that differ in their life-cycle stage. The firm wishes to maximize the discounted total profits of its portfolio. While we propose a method that recommends how to allocate the

[1] We acknowledge other research traditions that deal with allocation problems. For example, international trade theory discusses issues of dynamic resource allocation across countries at a macro level (e.g., Wong 1995).

annual global budget across countries, products, and marketing activities, we do not address the tactical problem of inter-temporal allocation of an individual budget within the year (for a summary of this literature see Doganoglu and Klapper 2006).

We contribute to allocation *theory* by offering a solution to the dynamic portfolio-profit maximization problem. The theoretical solution provides important insights into how individual budgets should be set so that they account for differences in profit contribution, marketing effectiveness, and growth potential. The optimal budget describes an endogenous relationship where various variables need to be in their global optimum. This relationship also holds under Nash competition. Under both monopoly and Nash competition, however, it can only be solved with numerical methods. Numerical optimization often faces significant acceptance barriers in practice, which may be one reason for the frequent use of suboptimal budgeting heuristics (Bigné 1995). While the numerical method produces the optimal budget, the product manager cannot reproduce the result on its own. Therefore, s/he does not understand why the recommended budget level should be optimal for his/her product.

Hence, our second contribution is to allocation *practice*. We develop a near-optimal allocation rule that addresses the demand for simple allocation rules by practitioners. The rule is directly derived from the theoretical solution. It provides insights into the solution structure and can be used with a spreadsheet. In a simulation study, we demonstrate that the allocation heuristic quickly converges to the optimal solution under varying conditions. While easy to understand and to implement, the heuristic goes beyond widespread budgeting rules such as the "percentage-of-sales" method (size of the business). Specifically, it integrates and trades off information about

- the size of the business,
- the profit contribution margin,
- the (short-term) effectiveness of marketing investments,
- the carryover-effect of marketing investments,
- the growth potential,
- and the time value of money.

Together with the management of Bayer, we developed and implemented the heuristic for the product portfolio of Bayer's Primary Care business unit. This portfolio includes 36 products from four strategic therapeutic areas that are marketed worldwide. Product managers can choose among six different types of marketing activities such as detailing or print advertising. The project had significant impact on the marketing budgeting practice at Bayer. It initiated an important change in the understanding of the allocation task by providing structure and solution to a complex problem. The empirical application revealed a profit improvement potential of more than 50% or nearly EUR 500 million of incremental discounted cash flows over the next five years. Finally, the project significantly contributed to an organizational change that resulted into the creation of a new marketing intelligence unit. One of the main tasks of this unit is to support top management in evaluating the financial impact of marketing decisions.

The rest of the paper is organized as follows. In the next section, we describe our analytic approach to derive the proposed heuristic allocation rule and the associated simulation study. Section 3 provides information about Bayer and the market background. The fourth section focuses on the empirical application. We discuss the data, the estimation of the market response model and validation issues. Section 5 presents the implementation of the allocation heuristic in Excel. We further evaluate the empirical findings and the impact of the project on Bayer. We close with limitations and suggestions for future research.

2 A Heuristic Rule for Dynamic Marketing Budget Allocation

2.1 Theory

Assume an international firm that operates across the world and sells several products that may belong to the same or different categories. The number of products offered may differ across countries. Product management can choose among various marketing activities, such as print advertising, personal selling, direct mailing, etc. to enhance current and future sales. At the end of each year, marketing investment plans for the next year are developed. We assume that the firm wishes to maximize the net present value Π of its product portfolio over a planning period T, e.g., five years. We further assume that a total marketing budget R has already been set at the firm level. We do not model this process, i.e. R is exogenous. Additionally, the total budget is assumed to be constant over the planning horizon. Top management, however, may decide to adjust the level during next year's planning cycle.

2.1.1 Allocation Solution for an Arbitrary Growth Function. Denote $q(t, S, \mathbf{Z})$ as the sales of a product in period t that depends on S, the marketing stock, and other variables (e.g., competitive marketing stock) that are summarized in the row vector $\mathbf{Z}$. Without loss of generality, we focus on only one own stock variable. Let us decompose sales into two components

$$q\left(t,S,\mathbf{Z}\right)=g\left[t,S\left(t\right)\right]f\left[S\left(t\right),\mathbf{Z}\left(t\right)\right], \tag{1}$$

where $g[\cdot]$ is a growth function that represents a basic pattern of growth dynamics as known from diffusion and product life cycle research, and $f[\cdot]$ is a separate response function that measures the direct impact of S and $\mathbf{Z}$ on sales. Note that this decomposition is helpful for interpretation but does not limit the generality of our model development. The growth function describes the evolution of new product sales over the life cycle and is assumed to be influenced by investments into the marketing stock. Research on diffusion processes and product life cycles provides broad evidence for the dependence of growth dynamics on marketing-mix variables (e.g., Bass, Jain and Krishnan 2000; Fischer, Leeflang and Verhoef 2010). The marketing stock S follows a dynamic process that satisfies the differential equation (Nerlove and Arrow 1962)

$$\frac{dS}{dt} = -\delta S + x, \quad x \geq 0, \quad \text{and } S(0) \text{ known}, \tag{2}$$

where x denotes marketing expenditures and δ is the depreciation rate of the marketing stock. Let k denote the country with the index set K and i denote the product, whereas the set of products offered in country k may vary and is given by I_k. Let n denote the type of marketing activity or spending category, respectively, and N_i be the associated index set that may vary across products. We omit the time argument unless it is needed for an unambiguous understanding. $\mathbf{S}_{ki}$ is an N_i-dimensional row vector summarizing the activity-specific marketing stocks for product i. Let ET measure the elapsed time since launch of a product in $t = 0$, r be a discount rate, $0 < r < \infty$, p denote price, c be marginal cost, and x_n be activity-specific marketing expenditures. The constrained dynamic profit maximization problem of the firm is

$$\underset{\mathbf{S}_{ki}}{Max}\ \Pi = \underbrace{\int_{t=0}^{T} \underbrace{e^{-rt}}_{\text{Discounting}} \left\{ \left[\sum_{k\in K} \sum_{i\in I_k} \underbrace{(p_{ki} - c_{ki})}_{\text{Profit contribution}} \cdot \underbrace{q_{ki}(ET_{ki} + t, \mathbf{S}_{ki}, \mathbf{Z}_{ki})}_{\text{Unit sales}} \right] - \underbrace{\sum_{k\in K} \sum_{i\in I_k} \sum_{n\in N_i} x_{kin}}_{\text{Marketing expenditures}} \right\} dt}_{\text{Discounted net value of product portfolio}} \tag{3}$$

$$\text{subject to } R = \sum_{k\in K} \sum_{i\in I_k} \sum_{n\in N_i} x_{kin}, \text{ with } \frac{dR}{dt} = 0, \qquad \text{(Budget constraint)} \tag{3.1}$$

$$\frac{dS_{kin}}{dt} = -\delta_{kin} S_{kin} + x_{kin}, \text{ with } x_{kin} \geq 0, \qquad \text{(State variable equation)} \tag{3.2}$$

$$S_{kin} \geq 0, \quad S_{kin}(0) = S_{kin0}, \text{ and } S_{kin}(T) = S_{kinT}. \qquad \text{(Boundary conditions)} \tag{3.3}$$

S_{kinT} is free but must be nonnegative and satisfy the budget constraint. In the Appendix, we show how this problem can be solved by employing the calculus of variations together with the Lagrange approach (Kamien and Schwartz 1991). Specifically, the solution to the $1+\sum_{k\in K}\sum_{i\in I_k}|N_i|$ Euler-Lagrange equations is

$$\frac{x_{kin}^*}{R}=\frac{\dfrac{(p_{ki}-c_{ki})q_{ki}^*\left(\varepsilon_{f(x_{kin}^*)}+\varepsilon_{g(x_{kin}^*)}\right)}{(r+1-\gamma_{kin})}}{\sum_{l\in K}\sum_{j\in I_l}\sum_{m\in N_j}\dfrac{(p_{lj}-c_{lj})q_{lj}^*\left(\varepsilon_{f(x_{ljm}^*)}+\varepsilon_{g(x_{ljm}^*)}\right)}{(r+1-\gamma_{ljm})}+\lambda\sum_{l\in K}\sum_{j\in I_l}\sum_{m\in N_j}\dfrac{dS_{ljm}^*}{dt}} \tag{4}$$
$$+\frac{1}{R}\frac{dS_{kin}^*}{dt},\quad \forall\, k\in K,\ i\in I_k,\ n\in N_i,\ t\in[0,T],$$

where $\varepsilon_{f(x)}$ denotes the *current-period* elasticity of sales with respect to marketing expenditures, $\varepsilon_{g(x)}$ measures the sales growth elasticity, γ measures the marketing carryover (with $\gamma = 1 - \delta$), λ is the dynamic Lagrange multiplier, and all other terms are defined as earlier. The star indicates that variable values correspond to the optimal solution for the marketing budget, which is measured as the optimal share in the fixed total budget R in Equation (4). In a common product portfolio, the number of allocation units tends to be quite large. Since the total budget R to be allocated is fixed, some stocks increase and others decrease in the dynamic optimum. As a result, gains and losses tend to cancel each other out and the second summand in the denominator of Equation (4) is close to zero. Considering the restriction that optimal budget shares must sum to 1 (see the Appendix), we obtain the following general solution for the optimal budget that is close to solution (4)

$$x_{kin}^*(t)\cong\frac{Max\{w_{kin}^*(t),0\}}{\sum_{l\in K}\sum_{j\in I_l}\sum_{m\in N_j}Max\{w_{ljm}^*(t),0\}}R,\quad \forall\, k\in K,\ i\in I_k,\ n\in N_i,\ t\in[0,T], \tag{5}$$

with

$$w_{kin}^*(t)=\underbrace{(p_{ki}-c_{ki})}_{\substack{\text{Profit}\\ \text{contribution}}}\underbrace{q_{ki}^*(t)}_{\substack{\text{Unit}\\ \text{sales}}}\left(\underbrace{\varepsilon_{f[x_{kin}^*(t)]}}_{\substack{\text{Sales elasticity}\\ \text{w.r.t. marketing}}}+\underbrace{\varepsilon_{g[x_{kin}^*(t)]}}_{\substack{\text{Growth elasticity}\\ \text{w.r.t. marketing}}}\right)\Big/\underbrace{(r+1-\gamma_{kin})}_{\substack{\text{Discounted marketing}\\ \text{multiplier}}}, \tag{6}$$

where w is an allocation weight and all other terms are defined as earlier.

The optimal solution considers dynamics in two different ways. First, it incorporates the dynamic effects of building and leveraging the marketing stock, which is reflected in the marketing carryover coefficient γ. Second, it accounts for the growth potential of a product that is related to marketing investments as reflected in the growth elasticity $\varepsilon_{g(x)}$. Note that our sales response in Equation (1) includes a growth function, $g[\cdot]$, that describes the evolution of new product sales along its life cycle. The growth elasticity measures the power of marketing to shape the life cycle. Hence, we assume that the growth process is endogenous with respect to marketing expenditures. A recent empirical study on drugs by Fischer, Leeflang and Verhoef (2010) supports this premise. The authors find that the shape of the life cycle is indeed influenced by investments in the marketing stock. More importantly, their results suggest that marketing investments in the growth potential of a new product have a strong impact on future cumulative sales and discounted cash flows. On the basis of a parametric growth model, we show subsequently how the optimal solution favors shifting marketing resources to young products so that they can leverage their endogenous growth potential.

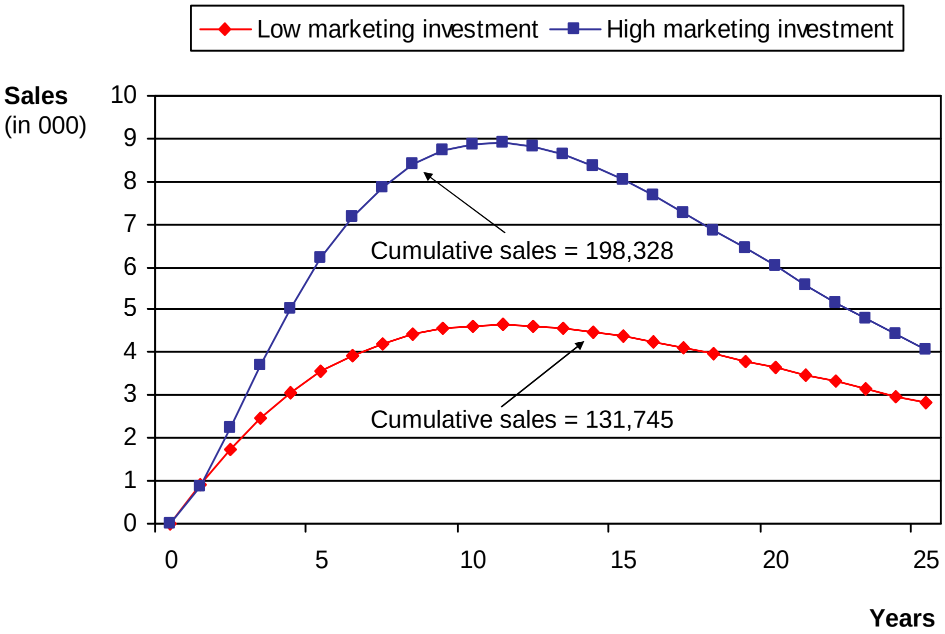
Equations (5) and (6) represent the first-order conditions of the constrained dynamic maximization problem. These conditions also need to be fulfilled by each firm under Nash competition. Here, each firm sets marketing budgets independently of its competitors by taking the competitor budgets as given. Equilibrium values may be obtained by numerically and simultaneously solving the budget equations for the portfolio of each competitor. Note that our general sales model in (1) assumes product sales being influenced by competitor variables such as competitive price and competitive marketing expenditures. Competitor actions thus have an impact on the optimal solution as they change q^*, $\varepsilon_{f(x^*)}$, and $\varepsilon_{g(x^*)}$ in Equation (6).

2.1.2 Allocation Solution for a Specific Growth Function. We now introduce a parametric growth function and derive the growth elasticity for this specific case. This enables us to demonstrate the effects of the growth potential on the allocation solution in more detail. Following the study on drug life cycles by Fischer, Leeflang and Verhoef (2010) and consistent with our empirical application at Bayer, we specify the growth function as follows

$$g_{ki}\left(t,\mathbf{S}_{ki}\right)=\alpha_{ki}t^{a_{ki}(\mathbf{S}_{ki})}e^{-b_{ki}(\mathbf{S}_{ki})t},\ \text{ with } \alpha_{ki},a_{ki},b_{ki}>0 \text{ and } t\in[0,\infty), \tag{7}$$

where α is a scaling constant, and a and b are growth parameters that depend on the marketing stock. The model describes an asymmetric growth path that leads to a single peak in the life cycle which occurs at $t^{Peak} = a/b$. Hence, the growth parameters determine the time-to-peak sales and, as Fischer, Leeflang and Verhoef (2010) also show, the height-of-peak sales. In addition, they define the shape of the life cycle. Equation (7) is equivalent to the gamma distribution, which has been frequently used by researchers because of their flexibility to capture many shapes (see the Appendix). For example, if a = 0 it reduces to the exponential distribution that is characteristic for many media products such as movies. Most importantly, we assume that marketing investments have a long-term impact on cumulative sales that is mediated by the growth parameters. Figure 1 compares two life cycles that peak around the same time. Cumulative sales are, however, quite different because of the differences in growth parameters that are assumed to arise from either low or high marketing investments. In the appendix, we show that cumulative sales are always higher for the life cycle whose difference between growth parameters a and b is larger.

Figure 1. Illustrative product life cycles for different marketing investment levels (see Equation 7)



Growth parameters in low investment case: a = 1.1, b = .10 (scale parameter α = 1)
Growth parameters in high investment case: a = 1.6, b = .15 (scale parameter α = 1)

From Equation (7), we obtain for the growth elasticity

$$\varepsilon_{g(x_{kin})} = \varepsilon_{a,kin} \ln(t)\, a_{ki} - \varepsilon_{b,kin}\, t\, b_{ki} \,,$$

which can be inserted into (6) to yield the optimal allocation weight in planning period t

$$w^*_{kin}(t) = (p_{ki} - c_{ki})\, q^*_{ki} \left[\varepsilon_{f(x^*_{kin})} + \varepsilon^*_{a,kin} \ln(ET_{ki} + t)\, a^*_{ki} - \varepsilon^*_{b,kin} (ET_{ki} + t)\, b^*_{ki} \right] \Big/ (r + 1 - \gamma_{kin}), \quad (8)$$

where $\varepsilon_{a,kin}$ and $\varepsilon_{b,kin}$ measure the elasticity of the growth parameters with respect to expenditures on marketing activity *n* and all other terms are defined as earlier. Note that *ET* (elapsed time since launch in $t = 0$) accounts for differences in launch times among products in the portfolio context.

2.1.3 Implications for Budget Allocation. The optimal solution provides a number of intuitive insights into the allocation problem. Equations (5) and (6) show that a fixed budget should be allocated according to a simple proportional rule. The optimal budget for a product relative to other products increases with its contribution margin *p-c* and its sales base *q*. Similarly, the larger product *i*'s long-term marketing effectiveness for activity *n* is the higher its budget. The long-term marketing effectiveness is composed of the short-term sales elasticity, the discount rate, and the marketing carryover: $\varepsilon_{f(x^*)}/(r+1-\gamma)$. Consequently, if long-term marketing effectiveness is larger across all of product *i*'s activities compared to other products the total budget for product *i* increases. Finally, Equations (5) and (6) reveal the importance of a product's growth potential for budget setting as reflected by the sales growth elasticity. This term varies over the life cycle. It is largest at the beginning when most of the sales is yet to come. Hence, the potential impact of marketing expenditures on future cash flows is greatest at this stage, which is why young products get a higher allocation weight and thus a larger share in total budget. Because of the growth potential the optimal marketing budget might even be higher than revenues of a new product at the beginning of its life, i.e. the solution may suggest to spend money on products that may a temporary loss.

The role of the growth potential term becomes more clear when we consider a specific growth function such as in Equation (7). Now, the optimal allocation weight is expressed in terms of growth parameters. From (8), it follows that the larger the difference $\varepsilon_a^* \ln\left(ET+t\right)a^* - \varepsilon_b^*\left(ET+t\right)b^*$ is the higher the budget for a product. For products that have been launched in the same year, we know that cumulative sales are higher for those products for which the distance between *a* and *b* is larger (see the Appendix). The distance may be enlarged by marketing investments to a certain extent as reflected in the elasticity parameters ε_a and ε_b. The growth expectations of a product also change over time. Since the growth potential term varies with *t* it accounts for this. To facilitate interpretation assume $\varepsilon_a^* = \varepsilon_b^* = 1$. Then, our measure simplifies to $\ln\left(ET+t\right)a^* - \left(ET+t\right)b^*$. For mature products, it gets smaller and may turn negative at some point in time. In the decline stage, the budget is likely to be zero as the sum of the short-term marketing elasticity and the growth potential measure in Equation (8) is eventually becoming smaller than zero.

2.2 Proposed Near-optimal Allocation Rule

The optimal budget for spending category *n* of product *i* in country *k* describes an endogenous relationship where various variables need to be in their optimum. To obtain the optimal values we need to solve the profit maximization problem (3) – (3.3) numerically. The use of numerical methods, however, has two disadvantages. First, it requires to explicitly specify the sales response function which limits the generalizability of the solution approach. Second, marketing managers are reluctant to accept results from numerical optimization because they do not understand how the budget recommendation is derived. While the optimization algorithm implicitly evaluates and trades-off factors such as marketing effectiveness, growth potential, or the size of the business, this process is not transparent for the manager.

Consistent with Little (1970), we believe that simplicity of the allocation rule is important as it enables the manager to understand the allocation solution. The wide distribution of heuristic budget rules among companies (see Bigné 1995 again) despite the advances in the analytical marketing literature seems to support the need for simplicity in allocation methods in practice. We derive an allocation heuristic directly from the theoretical solution that produces near-optimal budgets and is easy to understand for managers:

$$\tilde{x}_{kint} = \frac{\tilde{w}_{kint}}{\sum_{l\in K}\sum_{j\in I_l}\sum_{m\in N_j}\tilde{w}_{ljmt}} R_t, \quad \forall\, k\in K,\ i\in I_k,\ n\in N_i,\ t\in[0,T], \tag{9}$$

$$\text{with } \tilde{w}_{kint} = \underbrace{\varepsilon_{kin,t-1}\big/\left(r+1-\gamma_{kin}\right)}_{\text{Long-term marketing effectiveness}} \cdot \underbrace{d_{ki}\cdot RV_{ki,t-1}}_{\text{Profit contribution}} \cdot \underbrace{\rho_{kit}}_{\text{Growth potential}} \tag{10}$$

where

- $\tilde{x}_{kint}$: Near-optimal budget for marketing activity *n* and product *i* in country *k* and period *t*;
- $\tilde{w}_{kint}$: Heuristic allocation weight for marketing activity *n* and product *i* in country *k* and period *t*;
- R_t : Total budget to be allocated in period *t*;
- r : Discount rate (capital cost of firm, strategic business unit, etc.) ;
- γ_{kin} : Carryover coefficient of marketing activity *n* for product *i* in country *k*;
- $\varepsilon_{kin,t-1}$: Short-term sales elasticity with respect to product *i*'s marketing expenditures on activity *n* in country *k* and available from last year;
- d_{ki} : (Percentage) contribution margin for product *i* in country *k* [= $(p_{ki}-c_{ki})/p_{ki}$];
- $RV_{ki,t-1}$: Revenue level of product *i* in country *k* available from last year (= $p_{ki,t-1}\cdot q_{ki,t-1}$); and
- ρ_{kit} : Multiplier to measure the growth potential of product *i* in country *k* and period *t*.

The basic idea of the heuristic is to explicitly map Equations (5) and (6), the true optimum, to Equations (9) and (10), the heuristic approach. We do so by substituting currently available values for revenues and sales elasticity for their optimal values that are only endogenously determined by solving the equation system iteratively. We approximate the growth potential ρ by a multiplier that divides expected revenues in 5 years (planning horizon) by the current revenue level. By this heuristic approach, we assure that products get a greater share of the total budget as long as they are expected to grow. In contrast, when they are expected to turn into their decline stage their budget is reduced. Current values of revenues are available from last year and the contribution margin is a target figure decided by management. Data for the carryover coefficient, sales elasticity, and the growth multiplier are not readily available but must be estimated. In our empirical application, we specify a parametric response model to estimate these quantities econometrically. But we note that this is not a prerequisite of the allocation heuristic. The user may adopt other, non-parametric approaches to estimate the required data.

Basically, the proposed heuristic is a simple proportional rule that integrates relevant information from three areas

- the long-term effectiveness of marketing investments in the focal product,
- the profit contribution of the focal product,
- and the focal product's growth expectations.

The logic behind the selection and integration of information into a proportionality rule is well-founded in theory but at the same time easy to understand for practitioners.

2.3 Testing the Near-optimality of the Allocation Rule via Simulation

By definition, the heuristic solution is likely to differ from the optimal solution, but it should not deviate too much to be useful. Because the heuristic rule is a contraction mapping on the theoretical optimum, it exhibits a fixed point property. According to the Banach fixed-point theorem, an iterative sequence such as (9) and (10) where values are subsequently replaced by values closer to the fixed point will converge to the fixed point, which is in our case the true optimum (Granas and Gurundji 2003). Note that this holds also under Nash competition because the Nash equilibrium establishes the fixed point. The interesting question is how fast the convergence process is.

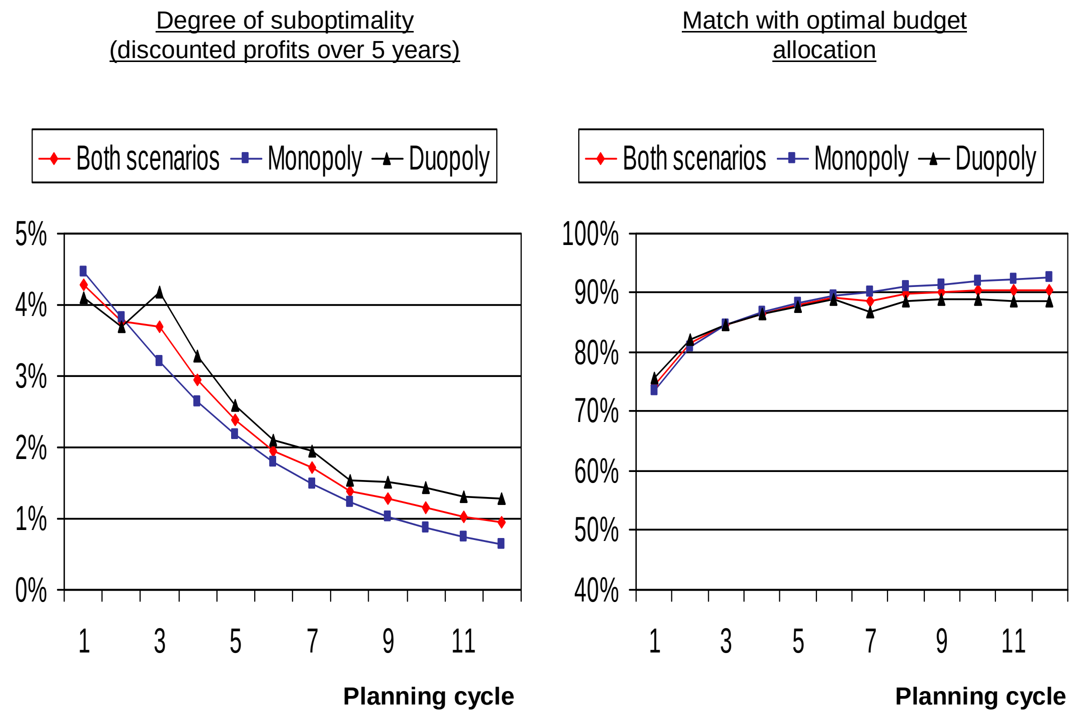
To analyze the performance of the heuristic we therefore conducted an experimental simulation study (for full details see the Web Appendix). In this study, we analyze a firm with a product portfolio of four products.[2] We consider two scenarios, a single-firm scenario and a competitive scenario including a second firm with a portfolio of four products. Sales is generated by a multiplicative market response function, the most frequent type of response in empirical studies (Hanssens, Parsons and Schultz 2001). The response function includes an asymmetric growth function, consistent with Equation (7), and two expenditure categories, whose stocks evolve according to Equation (2). Six factors that characterize the products in the portfolio were experimentally manipulated: current-period elasticities, carryover coefficients, size of the revenue bases, profit contribution margins, growth parameters, and launch dates as reflected in the elapsed times since launch. Each factor has two levels. The initial condition assumes equally distributed budgets across the two marketing activities and four products. We use a five year planning horizon, and the objective criterion is the discounted profit over the five years.

Optimal budgets are obtained by numerically solving the dynamic optimization problem as described by Equations (3)-(3.3). To reduce overall computation time, which is especially high in the competitive scenario, we construct an efficient Latin-square design that contains eight portfolio profiles. Profiles are randomly assigned to the two competitors. Consistent with practice, we simulate an annually recurring budget planning process and investigate 12 planning cycles. We compare the performance of the heuristic with the optimal solution in terms of (profit) suboptimality and match with the optimally allocated budget (for details, see the Web Appendix). Figure 2 shows how these two performance criteria develop over time (the number of planning cycles).

Values in Figure 2 represent mean values across the 16 experimental conditions. If we do not apply the heuristic rule to improve the initial naïve budget allocation the deviation from discounted profits of the optimal solution amounts to 19.2% on average. This suboptimality increases to 28.6% after 12 planning cycles (not shown in Figure 2). The match with the optimal budget allocation is 47.1% and remains around this level (50% after 12 planning cycles). As Figure 2 shows, we already achieve a dramatic improvement with our heuristic rule in the first planning cycle (4.3% profit suboptimality and 74.6% match with optimal budget allocation). Moreover, the rule quickly converges to the optimal solution when it is repeatedly used in the following planning cycles (0.95% profit suboptimality and 90.7% match with optimal budget allocation). This result holds under both the single-firm and the competitive scenario. Hence, the proposed rule appears to be a useful allocation heuristic.

[2] We also tried larger product portfolios, e.g., with eight products. Results do not change but computation time increases exponentially.

Figure 2. Performance of heuristic rule relative to optimal solution



Note: Data points represent averages from 16 experimental situations, 8 under monopoly and 8 under duopoly condition.

3 Background for Implementation in Practice

3.1 Company Background

Together with the management of Bayer, we implemented and adapted the proposed heuristic to the specifics of Bayer's Primary Care business unit in the period 2005-2006 and derived budget recommendations for 2007. Bayer belongs to the leading companies in the pharmaceuticals and chemicals business sector of the world. As of 2008, the company had EUR 32.9 billion sales and around 107,000 employees (Bayer 2009). Bayer consists of three major business areas: Bayer HealthCare, Bayer CropScience, and Bayer MaterialScience. Bayer Healthcare is the largest area in terms of sales contributing almost 50% to total sales. In 2008, the business area reported EUR 15.4 billion in sales positioning Bayer among the top 10 pharmaceutical firms worldwide. Bayer Healthcare is divided into a prescription drug business (Pharmaceuticals: EUR 10.7 billion) and an OTC drug business (Consumer Health: EUR 4.7 billion). The prescription drug business is composed of several business units. Primary Care is the largest unit (EUR 3.1 billion) and our focus for implementation of the allocation heuristic. Three business units, Women's Health, Diagnostic Imaging, and

Specialized Therapeutics, are rather new to the company as they mainly belong to Schering, a pharmaceutical competitor Bayer acquired in 2006.

3.2 Market Background

The Primary Care business unit of Bayer comprises prescription drugs that operate in four separate competitive market environments or therapeutic areas, respectively. These drugs treat diabetes, hypertension, erectile dysfunction, and infectious diseases. The hypertension segment is the largest one that includes several subcategories, such as beta blockers, calcium channel blockers, ACE inhibitors, and AII-antagonists. Bayer has several offerings in this segment. With EUR 626 m, the calcium channel blocker Adalat is its best-selling drug (Bayer 2009) which has already been in the market since the mid-1970s. Although the drug has lost patent protection more than 20 years ago and is facing increasing generic competition it contributes substantially to sales and profits of the Primary Care business unit. Avelox and Ciprobay are Bayer's drugs in the Antiinfectives business (EUR 445 m and 338 m). While Avelox is an innovative, young drug under patent protection, Ciprobay recently lost patent protection. In the antidiabetes segment, Glucobay is also off-patent and generated EUR 304 m in sales in 2008. All three mentioned therapeutic areas represent established areas which are in their saturation stage. Due to the aging of population in industrialized societies and innovative new product introductions they are, however, expected to continue to grow at moderate rates in the future. The biggest challenge for Bayer in these areas is to keep its market position. Innovative drugs by other global players are the main competitors for the Bayer drugs. In contrast, the market for the treatment of erectile dysfunction is a new category that was pioneered by Pfizer with its Viagra brand in 1998. Bayer and Eli Lilly followed in 2003 with the introduction of their brands Levitra and Cialis, respectively. Levitra achieved EUR 341 m in 2008. The market is still growing and does not face generic competitors yet.

To summarize, the Primary Care business unit of Bayer holds a broad portfolio of drugs that are at different stages in their life cycle, face varying conditions of competition, and differ in their contributions to sales/profits.Hence, the challenge for the management was to find a balance in the allocation of marketing resources that trades off the size of the business, the growth expectations, and eventually the effectiveness of marketing expenditures. The main objective was to improve the process and results of annual budget allocation in order to maximize discounted profits from the product portfolio over a planning horizon of five years.

Bayer invests substantial resources in marketing and sales activities. Total marketing and selling expenditures were EUR 7.1 billion (~21.5% of total sales) in 2008. For confidentiality reasons, we cannot report on exact figures for the Primary Care product portfolio. The lion's share is spent on detailing targeted at general practitioners and specialists. Competitors also spent a significant share of their budget on pharmacists detailing. In addition, Bayer invests in print advertisements, direct mailing activities, invitations of physicians to symposia, and other marketing activities. The implementation of the allocation tool is targeted at the five main European countries which contribute the largest share to total sales. The U.S. market provides also a substantial portion of sales. However, the Bayer products are marketed here by licensee firms. Hence, budget decisions are not under the control of the Bayer management.

4. Data and Model Estimation

4.1 Data

To calibrate the heuristic allocation tool for Bayer we need to estimate a number of input variables. Specifically, we require product-specific data on the short-term sales elasticity of different types of marketing investments, carryover coefficients, and information to compute the growth multiplier. For this purpose, we use 10 years (1996-2006) of quarterly marketing and sales data at the product level to estimate a market response model for each product market. IMS Health, Inc. provided data on unit sales counted in standard units, revenues (all in EUR), and the date of product launch, which we use to obtain order-of-entry and life-cycle information. We computed prices from revenues and unit sales. Via their CAM database, CEGEDIM, S.A. provided information on detailing expenditures targeted at general practitioners, specialists, and pharmacists. In addition, we have information available on professional journal advertising expenditures (including direct mailing), expenditures on physicians for invitations to symposia, meetings, etc. (hereafter denoted as meeting invitations), and other expenditures (hereafter denoted as OME).

The database covers the four strategic Bayer Primary Care prescription drug businesses Antidiabetes, Hypertension, Erectile Dysfunction, and Antiinfectives in five countries, Germany, France, the UK, Italy, and Spain. Bayer management helped us to identify the relevant subcategories and competitors within each therapeutic area by country. Subcategories vary from 12 for Antiinfectives to one for Erectile Dysfunction. Products vary from 15 for the Erectile Dysfunction area and 306 for the Hypertension area (see Table 1).

Table 1. Descriptive statistics

	Antidiabetes		*Hypertension*		*Erectile dysfunction*		*Antiinfectives*	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Unit sales in thousand standard units	16,319	20,674	11,891	16,649	1,008	649	5,291	8,004
Elapsed time since launch in years	14.50	12.69	10.00	7.42	2.75	1.91	12.25	10.45
Order of entry (Median)	3		4		2		3	
Price in EUR per standard unit	.16	.26	.50	2.96	7.00	.48	2.01	1.97
Marketing stock variables								
Detailing at general practitioners in thousand EUR	22,519	36,566	64,595	87,134	55,026	30,326	44,259	34,930
Detailing at specialists in thousand EUR	2,081	4,068	8,803	13,701	14,498	12,771	10,380	11,353
Detailing at pharmacies in thousand EUR	588	1,453	1,930	3,039	[1]		1,766	2,598
Professional journal advertising in thousand EUR	149	341	[1]		458	502	165	295
Meeting invitations in thousand EUR	730	2,030	1,361	3,062	3,884	2,481	471	837
Other marketing expenditures in thousand EUR	[1]		2,558	9,278	3,912	4,404	[1]	
# of countries	5		5		5		5	
# of subcategories	6		10		1		12	
# of products	104		306		15		100	
# of observations	2,398		7,908		233		2,916	

Notes: All units and EUR figures are on a quarterly basis. The marketing stock S_{kint} for activity n of drug i in country k and period t is defined as $S_{kint} = \sum_{\tau=0}^{t} (1-\delta_{TA})^{\tau} x_{kint}$, where δ_{TA} is the quarterly decay rate, specific for each therapeutic area *TA*, and x measures the marketing expenditures. We used a numerical search algorithm to estimate the decay coefficient in a first-stage non-linear regression of Equation (11) that minimizes the residual sum of squares. Due to the complexity of our model, we could only identify decay parameters at the level of the therapeutic area. With better data, a brand- and marketing-activity-specific parameter may be obtained. If we did not observe initial stocks we imputed the first quarter by dividing the average quarterly expenditures of the first observed year by the decay coefficient.

[1] Spending category was only rarely used by firms.

Table 1 also shows mean values and standard deviations for the variables used in estimation. The detailing stocks for general practitioners are highest, followed by the stocks for specialists. Stocks are computed consistent with Equation (2) (see also Berndt et al. 1994). Details on estimation are given in Table 1. The carryover is highest for Hypertension which is a chronic disease and lowest for Antiinfectives that are usually used for a one-time therapy (see also Tables 2a and 2b). Note that not all marketing spending categories are equally utilized across the different markets. For example, OME for antidiabetes and anitinfective drugs are rarely used, so that the data is not rich enough for estimating reliable marketing effects. Prices are highest in the youngest category, the Erectile Dysfunction category. Finally, we note that sample sizes differ to a great extent due to the number of brands. The Erectile Dysfunction category has only been launched in 1998, so that we have the smallest sample size here that limits model estimation to some extent. Finally, note that the samples are unbalanced, i.e. several drugs were launched after the start of the observation period and a few drugs left the market during that period. Thus, we observe 25.6 quarters per drugs on average.

4.2 Specification of Market Response Model

Following Fischer and Albers (2010), we specify a double-log sales response function for each therapeutic area. Let sales of drug *i* in country *k* and period *t* be defined as follows:

$$\begin{aligned}\ln q_{kit} = {} & \alpha_{0ki} + \alpha_{1ki} \ln gp\_sdet_{kit} + \alpha_{2ki} \ln sp\_sdet_{kit} + \alpha_{3ki} \ln ph\_sdet_{kit} + \alpha_{4ki} \ln sadv_{kit} \\ & + \alpha_{5ki} \ln smeet_{kit} + \alpha_{6ki} \ln sOME_{kit} + \beta_1 \ln scomp_{kit} + \beta_2 \ln prc_{kit} + \beta_3 \ln comprc_{kit} \\ & + \beta_4 \ln OE_{ki} + \beta_5 stot_{kit} \times \ln ET_{kit} + \beta_6 stot_{kit} \times ET_{kit} + \sum\nolimits_{l=1}^{M-1} \gamma_l CTY_{lk} \\ & + \sum\nolimits_{l=1}^{M} \sum\nolimits_{h=1}^{H-1} \gamma_{lh} SD_{ht} \times CTY_{lk} + \upsilon_{kit}, \quad \text{with } \upsilon_{kit} \sim N\left(0, \sigma_\upsilon^2\right),\end{aligned} \tag{11}$$

where

q_{kit}	:	Unit sales of drug *i* in country *k* and period *t*;
gp_sdet_{kit}	:	Stock of detailing expenditures at general practitioners of drug *i* in country *k* and period *t*;
sp_sdet_{kit}	:	Stock of detailing expenditures at specialists of drug *i* in country *k* and period *t*;
ph_sdet_{kit}	:	Stock of detailing expenditures at pharmacists of drug *i* in country *k* and period *t*;
$sadv_{kit}$	:	Stock of professional journal advertising expenditures of drug *i* in country *k* and period *t*;
$smeet_{kit}$	:	Stock of expenditures on meeting invitations of drug *i* in country *k* and period *t*;
$sOME_{kit}$	:	Stock of other marketing expenditures of drug *i* in country *k* and period *t*;
$scomp_{kit}$	:	Stock of cumulative marketing expenditures by drug *i*'s competitors in country *k* and period *t*;

prc_{kit}	:	Price of drug i in country k and period t;
$comprc_{kit}$	:	Average price by drug i's competitors in country k and period t;
OE_{ki}	:	Order of entry by subcategory of drug i in country k;
$stot_{kit}$	:	Stock of drug i's total marketing expenditures in country k and period t;
ET_{kit}	:	Elapsed time since launch of drug i in country k and period t;
CTY_k	:	Country dummy variable for country k (1 for $k = l$, 0 else);
SD_{ht}	:	Seasonal dummy variable for quarter h and period t (1/0);
$\alpha, \beta, \gamma, \gamma'$	:	(Unobserved) parameter vectors;
υ, σ^2	:	Error terms and error variances;
i	:	Index for drug that belongs to country-specific set I_k;
k	=	1, 2, …, l, …, M (number of countries);
t	=	1, 2, …, T_i (number of periods per drug); and
h	=	1, 2, …, H (quarters of the year).

The $\alpha_{1\text{-}6}$-parameters measure the effects of own marketing expenditure stock variables. β_1 captures the effect of competitive marketing expenditures which are observable to competitors. We combine all expenditure types in a cumulative stock variable. We could have specified a greater number of more differentiated competitor variables. Since our interest does not rest on competitive effects, we save degrees of freedom by using a composite variable. The same argument applies for the average competitor price that we include in addition to own price. The sales model does not incorporate a distribution variable. Since pharmacies in Europe are required to list every prescription drug there is no variation in this variable.

We include interactions of the stock of total marketing expenditures with elapsed time and the log of elapsed time to measure an asymmetric growth function that is consistent with Equation (7). By this specification, we assume that the growth parameters a and $b$are scaled by the stock whereas β_5 and β_6 measure the two scaling factors and are to be estimated. Note that the resulting growth parameters a and b are drug-specific since they are determined by a drug's total marketing stock.

Finally, our model incorporates a number of control variables that have been shown to impact sales of pharmaceuticals. With order of entry, we control for the disadvantage of a late market entry (e.g. Berndt et al. 1995). Since order of entry is defined at the subcategory level we may have more than one pioneer drug in a therapeutic area. We account for product quality, brand equity, and other unobserved time-invariant variables by specifying a *random* drug-specific constant (α_{0ki}). Since we include the randomness into the conditional mean function but not the error term we avoid potential *endogeneity* issues that arise from the correlation of unobserved product quality, brand equity, etc. with marketing-mix variables (Fischer and Albers 2010). Even though we do not model endogeneity in budget setting, e.g., allocating resources to more effective activities as represented by elasticities $\alpha_{1\text{-}6}$,we effectively control for it and obtain consistent parameter estimates. We account for market size differences by including country dummies. Seasonal dummy variables by country control for seasonal variation in demand.

4.3 Estimation and Results

4.3.1 Estimation. We estimate four models, one for each therapeutic area. The specification of the sales model accounts for heterogeneity in the constant term and marketing effectiveness. We impose the following heterogeneity structure on these parameters:

$$\alpha_{kiv} = \bar{\alpha}_v + \lambda_{v1}\eta_{1ki} + \lambda_{v2}\eta_{2ki}, \text{ whith } \eta_{1ki}, \eta_{2ki} \sim N(0,1) \text{ and } Cov(\eta_{1ki}, \eta_{2ki}) = 0, \quad (12)$$

whereα_{kiv} represents an unknown drug-specific parameter associated with predictor $v \in [0,6]$, $\bar{\alpha}_v, \lambda_{v1}$, and λ_{v2} are heterogeneity parameters to be estimated, and η_{1ki} and η_{2ki} denote variance components that vary by drug and country. The implied variance of α_{kiv} is ($\lambda_{v1}^2 + \lambda_{v2}^2$). The variance-covariance matrix for $\boldsymbol{\alpha}_{ki}$ is given by $\boldsymbol{\Sigma} = \boldsymbol{\Lambda\Lambda}'$.

We adopt the estimation approach used by Fischer and Albers (2010). Estimation also produces a set of posterior means of the drug-specific elasticity parameters (for details, see Fischer and Albers 2010).

4.3.2 Results. Tables 2a and 2b show the results of model estimations. Due to confidentiality reasons, we cannot show individual estimates for Bayer products. Reported estimates therefore reflect market averages. In-sample model fit is very good across all four therapeutic areas. Pseudo R^2, which is based on the squared correlation between predicted and observed values of the criterion variable, ranges from .933 (Hypertension) to .973 (Erectile dysfunction). Since we account for drug heterogeneity, it is quite high. In a few cases, a marketing spending category was used by only a very small number of firms leading to an inflation of zero-stock values (e.g., OME for Antidiabetes and Antiinfectives). Estimation of marketing effects was unreliable in such cases, so that we excluded this variable from the model. The relatively low number of 233 observations in the young Erectile Dysfunction category created collinearity issues for the interactions of total marketing stock with the elapsed-time variables and for the price variables. Since we could not separate the associated effects we estimated only main effects with respect to elapsed time since launch and the own price effect. In addition, we include a dummy variable for the pioneer Viagra, because only two competitors followed in the same quarter and the common order-of-entry variable lacks variation.

Table 2a.Estimation results for market response models (Equation 11): Antidiabetes and Hypertension categories

	Antidiabetes				*Hypertension*			
	Est. Parameter	Standard error	Est. Parameter SD	Standard error	Est. Parameter	Standard error	Est. Parameter SD	Standard error
Constant	5.32	(.202)	.904	(.019)	9.06	(.154)	1.98	(.021)
Ln(elapsed time since launch) × total marketing stock	$.225\times10^{-5}$	$(.155\times10^{-12})$			$.897\times10^{-8}$	$(.470\times10^{-9})$		
Elapsed time since launch × total marketing stock	$-.531\times10^{-9}$	$(.598\times10^{-14})$			$-.503\times10^{-9}$	$(.383\times10^{-10})$		
Ln(own price)	-.597	(.026)			-.911	(.013)		
Ln(average competitor price)	-.449	(.024)			-.049	(.018)		
Ln(order of entry)	-.256	(.016)			-.225	(.011)		
Marketing stock variables								
Category-specific carryover coefficient (annual level)	.57				.78			
Ln(detailing at general practitioners)	.103	(.005)	.046	(.004)	.193	(.004)	.100	(.003)
Ln(detailing at specialists)	.016	(.007)	.089	(.005)	.047	(.004)	.085	(.003)
Ln(detailing at pharmacies)	.035	(.005)	.034	(.003)	.035	(.003)	.070	(.003)
Ln(professional journal advertising)	.060	(.010)	.032	(.006)		1)		
Ln(meeting invitations)	.023	(.006)	.030	(.005)	.019	(.003)	.016	(.003)
Ln(other marketing expenditures)		1)			.001	(.003) NS	.033	(.002)
Ln(cumulative competitive marketing expenditures)	-.008	(.015) NS			-.224	(.011)		
Log Likelihood	-11,859.02				-52,608.69			
Pseudo R^2	.949				.933			
# of observations	2,398				7,908			
# of products	104				306			

Notes: NS = not significant ($p > .05$). Product-specific parameter estimates for Bayer brands cannot be shown for confidentiality reasons. Effects for country dummies and seasonal dummies are not shown but can be obtained from the authors upon request.

1) Spending category was only rarely used by firms.

Table 2b. Estimation results for market response models (Equation 11): Erectile dysfunction and Antiinfectives categories

	Antiinfectives				*Erectile dysfunction*			
	Est. Parameter	Standard error	Est. Parameter SD	Standard error	Est. Parameter	Standard error	Est. Parameter SD	Standard error
Constant	8.95	(.216)	1.50	(.054)	.138	(.626) NS	2.84	(.315)
Ln(elapsed time since launch) × total marketing stock	$.133\times10^{-7}$	$(.885\times10^{-13})$			.477	(.130) 1)		
Elapsed time since launch × total marketing stock	$-.299\times10^{-9}$	$(.516\times10^{-14})$			-.036	(.017) 1)		
Ln(own price)	-.803	(.070)			-.848	(.255)		
Ln(average competitor price)	-.023	(.068) NS			1)			
Ln(order of entry)	-.267	(.011)						
Pioneer dummy					.540	(.109)		
Marketing stock variables								
Category-specific carryover coefficient (annual level)	.33				.52			
Ln(detailing at general practitioners)	.254	(.009)	.107	(.007)	.464	(.042)	.201	(.049)
Ln(detailing at specialists)	.032	(.005)	.029	(.004)	.080	(.031)	.032	(.026) NS
Ln(detailing at pharmacies)	.035	(.004)	.021	(.003)	2)			
Ln(professional journal advertising)	.026	(.004)	.037	(.003)	.079	(.034)	.075	(.023)
Ln(meeting invitations)	.004	(.003) NS	.011	(.003)	.059	(.047) NS	.080	(.042) NS
Ln(other marketing expenditures)		2)			.034	(.014)	.032	(.012)
Ln(cumulative competitive marketing expenditures)	-.273	(.014)			-.007	(.008) NS		
Log Likelihood	-3,851.37				-50.63			
Pseudo R^2	.972				.973			
# of observations	2,916				233			
# of products	100				15			

Notes: NS = not significant ($p > .05$). Product-specific parameter estimates for Bayer brands cannot be shown for confidentiality reasons. Effects for country dummies and seasonal dummies are not shown but can be obtained from the authors upon request.

1) Due to the small number of observations and associated collinearity issues we were unable to fit a model that includes competitor price and interactions of the elapsed-time-since-launch variables with total marketing stock. Therefore, results do not reflect interactions but main effects of elapsed time since launch.

2) Spending category was only rarely used by firms.

In a double-log model, parameter estimates for marketing-mix variables correspond to elasticities. These elasticities refer to marketing stock variables and reflect long-term elasticities with respect to current-period expenditures. To obtain short-term elasticities the stock elasticity needs to be multiplied with the decay coefficient. Elasticities for detailing and other marketing activities vary substantially across the different therapeutic areas. In general, they are highest in the Erectile Dysfunction category, which is not surprising as this category is the youngest category and still in its growth phase. Among the detailing elasticities, GP detailing appears to be more effective than detailing at specialists and pharmacists. However, considering that specialists account only for a share of ca. 20% in Antidiabetes and ca. 27% in Hypertension, segment-specific specialist detailing elasticities are 4-5 times higher. Note, for the application of our allocation heuristic, the sales elasticities with respect to total brand sales as reported in Tables 2a and 2b are relevant. Elasticities for professional journal advertising, meeting invitations and OME are usually considerably smaller than elasticities for detailing at physicians. Finally, we note that the estimated effects are within the range of results of recent studies on pharmaceuticals (e.g., Albers, Mantrala and Sridhar 2010; Fischer and Albers 2010).

In terms of control variables, we find significant but inelastic own price effects. For competitive prices, we find negative cross-effects. This finding is consistent with Fischer and Albers (2010) who provide an explanation for negative cross-effects. The impact of competitive marketing expenditures is negative across all therapeutic areas although it is not always statistically significant. We find a negative elasticity for order of entry, as expected. Although not reported in Tables 2a and 2b, seasonal effects are only relevant to Antiinfectives, which experience a high season in autumn and winter.

4.3.2 Model Validation. We checked whether our model specification and estimation is appropriate for the data in several ways. First, we split the data sets into an estimation and a holdout sample. For the holdout, we used the four quarters of the last year of our observation period. Pseudo R^2 in the holdout samples ranged from .922 (Hypertension) to .972 (Erectile dysfunction) and were only slightly lower than those of the estimation samples. The same picture emerges with respect to the Mean Absolute Percentage Error (MAPE) that ranges from 1.14% (Erectile dysfunction) to 4.24% (Hypertension) and strongly supports the predictive validity of our response model. Second, we compared the suggested log-log brand sales model with a linear model, a semi-log model, and an S-shaped model. The Davidson and MacKinnon (1981) test for unnested models suggests that the proposed specification is superior to the alternative specifications. By adding predicted values from an alternative response model to the predictor set of the focal model, the test checks for the additional explanatory power of the alternative specification. Finally, we checked whether the residuals follow an autoregressive process by using the test for common factors (Greene 2006). We did not find evidence for it. Note that our sales model already incorporates dynamics in terms of marketing stock variables and the life-cycle function.

5 Model Implementation and Impact

In this section, we describe how we implemented the allocation heuristic into a Decision Support Tool in a spreadsheet environment. Further, we discuss the various impacts the new tool and the project had on the Bayer organization.

5.1 Excel-based Decision Support Tool

We developed a Decision Support Tool that integrates the proposed allocation heuristic into an Excel-based software program. Excel is particularly suitable for applications in practice as it is widely spread and easy to understand (Albers 2000). The tool is to assist the management with providing budget scenarios and their implications for the development of market shares and profits over the next five years. Specifically, the tool produces a recommendation for the allocation of the total marketing budget that is based on data on the effectiveness of marketing expenditures including carryover and discounting effects, the size of the product's business, product profitability, and growth expectations (see Equations 9 and 10).

The tool applies to Bayer’s Primary Care product portfolio and covers expenditures in six spending categories for 36 products in four therapeutic areas and five countries as described earlier. Hence, at the product-country-activity level, 36 (products) × 6 (spending categories) = 216 allocation decisions are made. It may easily be applied to other product portfolios that may be smaller or larger in size. Consistent with the periodicity of the response model estimation, metrics such as carryover coefficients, growth multipliers, etc. are defined at the quarterly level. The same applies to market-share and profit simulations. Based on the response model (11), the tool demonstrates the impact of budget decisions on sales and profits by extrapolating the evolution of sales and profits over the next five years.

The heuristic rule requires to compute an allocation weight for each marketing spending category and each drug (see Equation 10). Input data have been obtained either from econometric analysis or internal records. The plausibility of input data, especially the estimated sales elasticities, has been extensively discussed with different groups of managers in several workshops (global marketing, market research, product management, sales management, controlling, etc.). Internal records provided data on the discount rate, the profit contribution margin, and last year's product revenues. Estimation of the sales response model (11) produced data on the carryover coefficient, short-term sales elasticities, and the growth potential multiplier. Computation of the growth potential multiplier, ρ, is based on the life-cycle function (7) that is incorporated into (11). Specifically,

$$\text{Growth potential multiplier } \left(\rho_{kit}\right) = \left(\frac{\text{Elapsed Time since Launch}_{kit} + T}{\text{Elapsed Time since Launch}_{kit}}\right)^{\hat{a}_{kit-1}} \exp\left(-\hat{b}_{kit-1} \cdot T\right) \quad (13)$$

where T is the forecast horizon (20 quarters or 5 years, respectively), and $\hat{a}$ and $\hat{b}$ are estimated growth parameters. Since they depend on the marketing stock we obtain estimated values from the last period.

Following the needs of management, we extended the tool in two ways. First, we included a threshold for product budgets. Although our demand analysis did not find evidence for an S-shaped response that justifies a threshold, management required a threshold because of internal setup costs that are fixed at the product and marketing-activity level. Second, we allowed for manual adjustments to budgets recommended by the heuristic. By this feature, management can account for exogenous restrictions to budget setting, e.g., to counter competitive attacks in a predetermined way. In addition, it enables management to investigate the effects of budget scenarios on market share and profit as well as on the recommended budgets for other products and marketing activities. Technically, the budget for an allocation unit is exogenously set and subtracted from the total budget. The remaining budget is allocated according to the heuristic.

The Excel-based decision support system offers a powerful tool to generate budget allocation options and analyze these options with respect to their economic consequences. The tool is easy to use and flexible enough to adapt to varying conditions of decision making.

5.2 Impact on Managerial Decision Making

The effort to develop and implement the budget allocation tool had significant impact on managerial decision making that is reflected in several aspects.

5.2.1. Providing Structure to the Problem. The suggested allocation heuristic provides structure to a complex decision problem. 216 budget decisions arise from allocating a total budget across six spending categories for 36 drugs that are marketed in different countries and therapeutic areas. The market positions of these products are quite diverse and determined by product age and competition. Depending on age and expected changes in the competitive and market environment, products offer different growth potentials. As a first benefit, the allocation rule provides the required information to solve the problem. These information fall into three groups. The first group refers to the effectiveness of marketing expenditures to build goodwill and impact sales in the long run (short-run elasticity and discounted carryover). The second group includes information on a product's contribution to profit. This depends on the contribution margin (price minus marginal cost) as well as the size of the revenue base. The third group emphasizes the growth expectations of the product. It uses information on where the product stands in its life cycle.

5.2.2. Providing Solution to the Problem. While management had a good understanding of the type of information required for budget decisions it benefited much from the new insights offered by the heuristic. Specifically, the allocation rule suggests that information on (1) long-term marketing effectiveness, (2) profit contribution, and (3) growth potential are to be combined in a multiplicative fashion. Implications from this rule are straightforward. (1) Products that generate more incremental sales with the same budget should get a larger slice of the total budget. Of course, relative incremental sales tend to decline as sales and budgets increase due to saturation effects. The budget ratio of two products reflects their ratio in terms of sales elasticity. (2) The same principle of proportionality applies to the size of sales or profit contribution, respectively. Products with a higher level of profit contribution generate more financial resources to cover their own marketing expenditures and contribute more to overall profits. (3) Marketing should support growing and not declining products and shift resources over the life cycle.

The rule also teaches that the drivers of a product's near-optimal budget share interact with each other, i.e. there exist synergies between them. Finally, it makes the tradeoffs in budget allocation transparent. For example, a product with high marketing effectiveness but a low profit contribution level could get a lower budget than a product with a high level of profit contribution but lower marketing effectiveness. Even though that product's spending is less effective it may still contribute more to overall profit because of its larger sales base.

5.2.3. Understanding the Limitations of Separate ROI Analysis. Management was initially very focused on comparing incremental ROIs that result from raising/decreasing marketing expenditures for individual products and marketing activities (hereafter denoted as separate ROI analysis). Profit calculations with the allocation tool quickly revealed the limitations of such an analysis. First, separate ROI analyses for individual marketing activities do not consider synergies between marketing activities that interact with each other. Profit simulations for several brands, for example, showed that the ROI of a 10% budget increase in a specific spending category is negative but turns positive if the budget increase is accompanied by a reallocation across the different spending categories. Hence, the synergy between marketing activities is only exploited by the allocation heuristic but not by separate ROI considerations. Second, separate ROI analyses do not consider the trade-offs that exist with respect to potential profit improvements by other products and activities. For example, even though simulated ROIs for a few products were positive the allocation heuristic suggested reducing the current budget on these products. The reason is that free budget resources were transferred to other products where the incremental return was even higher. Third, separate ROI analyses do not inform about the magnitude of budget changes for products and activities, given a fixed total budget. Marginal returns analysis teaches that it should be increased until ROI gets zero. However, if other products' budgets are also raised it may exceed the total budget constraint. The allocation heuristic produces exact results for the recommended allocation of a fixed budget within one step.

5.3 Organizational Impact

The introduction of the allocation tool had a considerable impact on the organization. The project was part of a larger effort that aimed at revising the organization's tools and processes to evaluate marketing initiatives in terms of their financial implications. This effort had the full attention of the managing board of Bayer. Budget decisions are often associated with several rounds of intensive discussions that follow a bottom-up process, i.e. product and country managers communicate their budget needs for the next year upwards. Budget discussions in companies are probably never fully free of politics and individual agendas. The allocation tool adds an independent, top-down perspective. Since it is strictly based on a range of verifiable input information its recommendations are fully fact-based. Assumptions about marketing effectiveness and other drivers may be discussed. Their implications for budget allocation are immediately transparent through application of the tool. Because of its transparency and top-down perspective, the allocation tool ameliorates the decision process that often appears emotional and inefficient.

Although the allocation tool is not the only source used by Bayer to generate budget options, it has significantly improved the efficiency and quality of the decision process. The project contributed substantially to an organizational transformation that eventually resulted into the creation of a completely new marketing intelligence unit called Global Business Support. This unit supports global marketing management and sales including the global management board with tools, results, and recommendations for a more efficient and effective use of marketing resources.

5.4 Strategic Impact

Application of the tool initiated an important strategic discussion within the firm. The results suggested that some older products which still hold a strong position in sizable markets did not get sufficient marketing resources anymore. The allocation tool showed a substantial profit improvement potential from shifting more resources to these older products.

The results also initiated a discussion about the targets of sales calls and the relevance of accompanying marketing activities. In terms of targets, the results suggested to reconsider the strong focus on specialists. It seemed that due to higher frequency of sales calls at specialists by competitors, effectiveness is lower relative to sales calls at general practitioners. Consequently, the tool proposed to reallocate resources among those two target groups. In addition, the results suggested that the potential of accompanying activities such as meeting invitations and OME were not fully exploited, yet.

5.5 Financial Impact

The tool enables the user to simulate the financial impact of different budget allocation options. By analyzing the simulation results, it provides transparency about the impact of different assumptions on financial results. Based on the year 2007, the simulation suggested an increase in discounted profits of 55% over the next five years due to an optimized allocation. This is worth of EUR 493 m. In contrast, changing the overall budget by 20% promised a profit impact of less than 5%. Even if only a small portion of this increase can be realized, the additional profit for a business unit such as Primary Care with EUR 3 billion worldwide sales is substantial.

Actual profit improvements are hard to evaluate. First, management did not completely follow the suggested reallocation by the tool for several reasons (e.g., varying personal experiences, concerns about errors in IMS data). Second, activities by competitors and exogenous influences on market dynamics impact profit results. Nevertheless, the business area Bayer HealthCare reports an increase in EBIT of 12% (EUR 273 m) compared to a 4% revenue increase for the year 2008 (Bayer 2009). Although we have no validation from a field test, these results are consistent with prior observations that reallocation really focuses on the bottom-line.

5.6 Generalizability

Although the tool was applied to prescription drugs we emphasize that it is suitable for many other industries such as consumer durables, consumer packaged goods, etc. In all these markets, rich information is available at the aggregate product level that allows the calibration of market response models. But even if data on marketing effectiveness, carryover, etc. cannot be estimated with aggregate market response models, other data and methods including choice models and managerial experiments are available to generate the required input data for allocation. In this respect, we are not aware of a limitation to apply the allocation heuristic in other industries.

6 Conclusions, Limitations, and Future Research

In this paper, we suggest an innovative approach to allocate a global marketing budget across countries, products, and marketing activities. Based on the theoretical solution to the dynamic optimization problem, we derive a simple but comprehensive heuristic that accounts for dynamics in marketing effects and product growth. It suggests to allocate a budget proportionally to the size of the business (sales and profit contribution margin), the effectiveness of the marketing activities (short-term elasticity and carryover coefficient), and the growth potential of the product (growth multiplier accounting for time discounting). A simulation study demonstrates that the heuristic quickly converges to the optimal solution under both monopoly and competitive conditions. The implementation of the heuristic at Bayer had various significant impacts on the organization. It revealed substantial profit improvement potentials by reallocating marketing resources for the Primary Care business unit. It also improved the quality and efficiency of the budget allocation process and contributed to organizational change.

Our research has limitations that may stimulate future research. First, we have analyzed budget allocation issues under the assumption of a specific response function which has been found to best represent the data in this study. It would be interesting to extend the application to other response functions including different growth functions. Second, our simulation study covers only a limited range of conditions. Additional conditions such as more competitors and errors in input data may be analyzed and the number of scenarios extended. It would also be good to understand which conditions have a critical influence on the performance of the heuristic. Third, the tool may be extended to compute uncertainty bounds for recommended budget and market share and profit simulations. This would add a risk-analysis perspective to the application. Finally, we note that our research lacks an experimental field test that is hard to implement in a global portfolio worth of EUR 3 billion. Future applications to smaller portfolios might, however, overcome this limitation and test the superiority of the suggested heuristic. Finally, we assume that the overall marketing budget is set exogenously. Unless the budget level is optimal, there is still profit improvement potential. The flat maximum principle, however, suggests that this potential is very small, provided the budget is set within a reasonable wide range around the true optimal level (Tull et al. 1986).

Appendix

1 Derivation of Theoretical Allocation Solution for Arbitrary Growth and Response Functions

We consider the constrained dynamic profit maximization problem as stated in Equations (3)-(3.3). We assume that the sales function in Equation 1 is twice differentiable in t and S. Note that it is sufficient to maximize profit contribution before marketing cost because these cost are fixed by the total budget and thus not relevant to the optimization. Using the state variable equation (3.2) to substitute x_{kin} in the objective function (3), we can write the following Lagrange objective functional

$$L=\int_{t=0}^{T}e^{-rt}\left\{\left[\sum_{k\in K}\sum_{i\in I_k}\left(p_{ki}-c_{ki}\right)q_{ki}\right]+\lambda\left(R-\sum_{k\in K}\sum_{i\in I_k}\sum_{n\in N_i}\frac{dS_{kin}}{dt}+\delta_{kin}S_{kin}\right)\right\}dt. \quad \text{(A.1)}$$

Note that the budget constraint (3.1) has to be fulfilled in each period, which may entail a time-varying Lagrange multiplier. A solution requires solving the $1+\sum_{k\in K}\sum_{i\in I_k}\left|N_i\right|$ Euler-Lagrange equations, which constitute the first-order conditions

$$\frac{\partial F}{\partial S_{kin}}\left[t,S_{kin}^{*},\frac{dS_{kin}^{*}}{dt},\lambda^{*}\right]-\frac{d}{dt}\left[\frac{\partial}{\partial\left(dS_{kin}/dt\right)}F\left(t,S_{kin}^{*},\frac{dS_{kin}^{*}}{dt},\lambda^{*}\right)\right]=0, \quad \text{(A.2a)}$$

$$\forall k\in K,\ i\in I_k,\ n\in N_{i,}\ t\in\left[0,T\right]$$

and

$$\frac{\partial F}{\partial\lambda}=0,\quad \forall t\in\left[0,T\right], \quad \text{(A.2b)}$$

where $F\left(t,S_{kin}^{*},\frac{dS_{kin}^{*}}{dt},\lambda^{*}\right)$ is the Lagrangean integrand and the star indicates that variable values correspond to the optimal solution for the marketing budget. Note that each competitor has to satisfy these conditions under Nash competition. The required derivatives to solve (A.2a) are

$$\frac{\partial F}{\partial S_{kin}}=e^{-rt}\left[\left(p_{ki}-c_{ki}\right)\frac{\partial q_{ki}}{\partial S_{kin}}-\lambda\delta_{kin}\right] \quad \text{(A.3a)}$$

$$\frac{\partial F}{\partial\left(dS_{kin}/dt\right)} = -\lambda e^{-rt} \tag{A.3b}$$

$$\frac{d}{dt}\frac{\partial F}{\partial\left(dS_{kin}/dt\right)} = r\lambda e^{-rt} \tag{A.3c}$$

Setting (A.3c) equal to (A.3a) yields

$$\left(p_{ki} - c_{ki}\right)\frac{\partial q_{ki}}{\partial S_{kin}} = \lambda\left(r + \delta_{kin}\right). \tag{A.4}$$

From Equation (1), we obtain

$$\frac{\partial q_{ki}}{\partial S_{kin}} = \frac{\partial f_{ki}}{\partial S_{kin}} g_{ki} + \frac{\partial g_{ki}}{\partial S_{kin}} f_{ki}$$

that may be expanded into

$$\begin{aligned}\frac{\partial q_{ki}}{\partial S_{kin}} &= \frac{\partial f_{ki}}{\partial S_{kin}}\frac{S_{kin}}{f_{ki}} g_{ki} f_{ki}\frac{1}{S_{kin}} + \frac{\partial g_{ki}}{\partial S_{kin}}\frac{S_{kin}}{g_{ki}} f_{ki} g_{ki}\frac{1}{S_{kin}} \\ &= \left(\varepsilon_{f(S_{kin})} + \varepsilon_{g(S_{kin})}\right)\frac{q_{ki}}{S_{kin}}\end{aligned} \tag{A.5}$$

Inserting (A.5) into (A.4) and solving for S_{kin}^* yields

$$S_{kin}^* = \frac{\left(p_{ki} - c_{ki}\right) q_{ki}^*\left(\varepsilon_{f\left(S_{kin}^*\right)} + \varepsilon_{g\left(S_{kin}^*\right)}\right)}{\lambda\left(r + \delta_{kin}\right)}. \tag{A.6}$$

We multiply both sides of Equation (A.6) with δ_{kin} and use the identities $\delta_{kin} S_{kin}^* = x_{kin}^* - dS_{kin}^*/dt$, $\gamma_{kin} = 1 – \delta_{kin}$, $\varepsilon_{f\left(x_{kin}^*\right)} = \delta\varepsilon_{f\left(S_{kin}^*\right)}$, and $\varepsilon_{g\left(x_{kin}^*\right)} = \delta\varepsilon_{g\left(S_{kin}^*\right)}$ to obtain

$$x_{kin}^* = \frac{\left(p_{ki} - c_{ki}\right) q_{ki}^*\left(\varepsilon_{f\left(x_{kin}^*\right)} + \varepsilon_{g\left(x_{kin}^*\right)}\right)}{\lambda\left(r + 1 - \gamma_{kin}\right)} + \frac{dS_{kin}^*}{dt}, \tag{A.7}$$

whereγmeasures the carryover coefficient and $\varepsilon_{f\left(x_{kin}^*\right)}$ and $\varepsilon_{g\left(x_{kin}^*\right)}$ are (short-term) sales elasticities with respect to marketing expenditures.

Recall that the budget constraint is binding and has to be satisfied in the optimum, i.e. $R=\sum_{k\in K}\sum_{i\in I_k}\sum_{n\in N_i}x^*_{kin},\ \forall t\in[0,T]$. Since this constraint also applies to the end period, S_{kinT} is free but only within the constraint. This turns the problem into a fixed-endpoint problem and we do not need a general transversality condition. From (A.7), we obtain the optimal share of the budget that is allocated to marketing activity *n* of product *i* in country *k* by

$$\frac{x^*_{kin}}{R}=\frac{\dfrac{(p_{ki}-c_{ki})q^*_{ki}\left(\varepsilon_{f(x^*_{kin})}+\varepsilon_{g(x^*_{kin})}\right)}{(r+1-\gamma_{kin})}}{\sum_{l\in K}\sum_{j\in I_l}\sum_{m\in N_j}\dfrac{(p_{lj}-c_{lj})q^*_{lj}\left(\varepsilon_{f(x^*_{ljm})}+\varepsilon_{g(x^*_{ljm})}\right)}{(r+1-\gamma_{ljm})}+\lambda\sum_{l\in K}\sum_{j\in I_l}\sum_{m\in N_j}\dfrac{dS^*_{ljm}}{dt}}+\frac{1}{R}\frac{dS^*_{kin}}{dt},\ \ \forall\, k\in K,\ i\in I_k,\ n\in N_i,\ t\in[0,T], \tag{A.8}$$

which is equivalent to Equation (4).

From the budget constraint, we know that the following linear restriction must hold

$$\sum_{k\in K}\sum_{i\in I_k}\sum_{n\in N_i}\frac{x^*_{kin}}{R}=\sum_k\sum_i\sum_n\left[\frac{\dfrac{(p_{ki}-c_{ki})q^*_{ki}\left(\varepsilon_{f(x^*_{kin})}+\varepsilon_{g(x^*_{kin})}\right)}{(r+1-\gamma_{kin})}}{\sum_{l\in K}\sum_{j\in I_l}\sum_{m\in N_j}\dfrac{(p_{lj}-c_{lj})q^*_{lj}\left(\varepsilon_{f(x^*_{ljm})}+\varepsilon_{g(x^*_{ljm})}\right)}{(r+1-\gamma_{ljm})}+\lambda\sum_{l\in K}\sum_{j\in I_l}\sum_{m\in N_j}\dfrac{dS^*_{ljm}}{dt}}\right]+\frac{1}{R}\sum_{k\in K}\sum_{i\in I_k}\sum_{n\in N_i}\frac{dS^*_{kin}}{dt}=1.$$

In a typical product portfolio that includes several products of different ages and therefore different levels of marketing activity stocks, some stocks will increase and others will decrease from one period to the next because the total budget to be allocated is limited. For a fairly large number of allocations units, which are defined at the country-product-marketing activity level, gains and losses in stocks tend to cancel each other out, so that $\sum_{k\in K}\sum_{i\in I_k}\sum_{n\in N_i}dS^*_{kin}/dt\cong 0$, with *k* = 1, …, *l*, … *K*, *i* = 1, …, *j*, …, I_k, and *n* = 1, …, *m*, …, N_i. As a result, we have

$$\sum_{k\in K}\sum_{i\in I_k}\sum_{n\in N_i}\frac{x^*_{kin}}{R}=\sum_k\sum_i\sum_n\left[\frac{\dfrac{(p_{ki}-c_{ki})\,q^*_{ki}\left(\varepsilon_{f(x^*_{kin})}+\varepsilon_{g(x^*_{kin})}\right)}{(r+1-\gamma_{kin})}}{\sum_{l\in K}\sum_{j\in I_l}\sum_{m\in N_j}\dfrac{(p_{lj}-c_{lj})\,q^*_{lj}\left(\varepsilon_{f(x^*_{ljm})}+\varepsilon_{g(x^*_{ljm})}\right)}{(r+1-\gamma_{ljm})}}\right]\cong 1,$$

and obtain a solution for the optimal budget share that is very close to (A.8)

$$\frac{x^*_{kin}}{R}\cong\frac{(p_{ki}-c_{ki})\,q^*_{ki}\left(\varepsilon_{f(x^*_{kin})}+\varepsilon_{g(x^*_{kin})}\right)\Big/(r+1-\gamma_{kin})}{\sum_{l\in K}\sum_{j\in I_l}\sum_{m\in N_j}(p_{lj}-c_{lj})\,q^*_{lj}\left(\varepsilon_{f(x^*_{ljm})}+\varepsilon_{g(x^*_{ljm})}\right)\Big/(r+1-\gamma_{ljm})}. \tag{A.9}$$

Since we also need to satisfy the condition $x^*_{kin}\geq 0$ that is violated if $\varepsilon_{f(x^*_{kin})}+\varepsilon_{g(x^*_{kin})}<0$ and $\varepsilon_{g(x^*_{kin})}<0$, the optimal marketing budget for marketing activity *n* of product *i* in country *k* is given by

$$x^*_{kin}\cong\frac{Max\left\{w^*_{kin},0\right\}}{\sum_{l\in K}\sum_{j\in I_l}\sum_{m\in N_j}Max\left\{w^*_{ljm},0\right\}}R,\quad \forall k\in K,\ i\in I_k,\ n\in N_i,\ t\in[0,T],$$

$$\text{with }\ w^*_{kin}=\frac{(p_{ki}-c_{ki})\,q^*_{ki}\left(\varepsilon_{f(x^*_{kin})}+\varepsilon_{g(x^*_{kin})}\right)}{r+1-\gamma_{kin}}. \tag{A.10}$$

which is equivalent to Equation (5).

The solution establishes a global maximum because the Integrand $F\left(t,S^*_{kin},\dfrac{dS^*_{kin}}{dt},\lambda^*\right)$ is concave in S^*_{kin} and dS^*_{kin}/dt. For a fixed-endpoint problem, the Euler-Lagrange Equations (A.2a) and (A.2b) are sufficient for an absolute maximum (Kamien and Schwartz 1991).

2 Parametric Growth Model

Consistent with (6), we consider the following parametric growth model

$$g_i(t)=\alpha_i t^{a_i}e^{-b_i t},\ \text{ with } \alpha_i, a_i, b_i>0 \text{ and } t\in[0,\infty). \tag{A.10}$$

Equivalence with the Gamma Distribution. The p.d.f. of a gamma distributed random variable *t* is defined as follows

$$gamma(t) = \frac{\phi^{\theta} t^{\theta-1} e^{-\phi t}}{\Gamma(\theta)}, \tag{A.11}$$

where ϕ and θ are characteristic parameters that define the shape of the distribution. Let the parameters α, a, and b of (A.9) be defined as: $\alpha = \frac{b^{a+1}}{\Gamma(a+1)}$, $a = \theta$-1, $b = \phi$. Then, it can be shown that (A.10) results into (A.11).

Properties of Cumulative Sales. Let (A.10) measure unit sales. We obtain cumulative sales over the total lifetime of product *i* by solving the integral

$$\text{CumSales}_i = \alpha_i \cdot \int_0^{\infty} t^{a_i} \cdot e^{-(b_i)t} dt = \alpha_i \cdot \frac{\Gamma(a_i+1)}{b_i^{a_i+1}}, \text{ with } \alpha_i, a_i, b_i > 0. \tag{A.12}$$

Let $a_i - b_i = \omega_i$ measure the distance in growth parameters for *i*. Substituting b_i for $a_i - \omega_i$ in (A.12) and differentiating this expression with respect to the distance ω_i yields

$$\frac{d\,CumSales_i}{d\omega_i} = (a_i+1)\alpha_i\Gamma(a_i+1)(a_i-\omega_i)^{-a_i-2} \tag{A.13}$$

Expression (A.13) is always greater than zero because all terms are greater than zero. Note that $a_i - \omega_i > 0$ since a_i, $b_i > 0$. From $a_i - b_i = \omega_i$, it follows that $a_i > \omega_i$.

Hence, cumulative sales increase with the difference in the growth parameters *a* and *b*. This result also holds for discounted cumulative sales. Discounting (A.10) at rate *r* and differentiating with respect to ω_i leads to

$$\frac{d\,CumSales_i}{d\omega_i} = (a_i+1)\alpha_i\Gamma(a_i+1)(a_i-\omega_i+r)^{-a_i-2}. \tag{A.14}$$

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Web Appendix

Experimental Simulation Study

We consider two firms with a product portfolio of four products that use two different marketing activities to promote their products. Both firms wish to maximize the discounted profits of the portfolio over a planning horizon of five years. The dynamic optimization problem and its constraints is stated in Equations (3)-(3.3). Sales are generated by a multiplicative response function similar to Equation (11). Specifically, let *u* and *v* denote the two competitors, s_1 and s_2 be the marketing stocks for the two spending categories, and *stot* measure the total marketing stock for a product, i.e. $stot = s_1 + s_2$. We then specify sales *q* for product *i* in period *t* as follows:

$$q_{iu}\left(t, s_{1u}, s_{2u}, stot_u, stot_v\right) = \alpha_{iu} \cdot s_{1iut}^{\varepsilon_{1iu}} \cdot s_{2iut}^{\varepsilon_{2iu}} \cdot stot_{ivt}^{\varepsilon_{3iu}} \cdot t^{a_{1iu}+a_{2iu}\ln stot_{iut}} \cdot e^{-(b_1+b_2\ln stot_{iut})t}, \qquad \text{(W.1)}$$

where α is a scaling constant, ε_1 and ε_2 measure own marketing effects, ε_3 reflects the cross-effect of competitive marketing,and a_1, a_2, b_1, and b_2 are growth parameters. Marketing stocks evolve consistent with Equation (2), whereas the decay coefficient may vary across products.Under monopoly conditions, the competitor stock variable looses its relevance and is excluded from Equation W.1.

We analyze the performance of the heuristic (Equations 9 and 10) for firm *u* by simulating different monopoly and duopoly scenarios. The growth potential multiplier, ρ, of the heuristic is computed according to Equation (13) with a planning horizon of five years (T=5).

We generate different experimental conditions by manipulating the following factors that characterize product portfolios of the two firms:

- Current-period elasticity of the first marketing activity (ε_1)
- Carryover coefficients (δ)
- Size of the revenue bases (*RV*)
- Profit contribution margin (*d*)
- Growth parameter (a_1)
- Launch dates (*ET*)

We define two levels for each factor in the way that we create a situation of (nearly) equal data and a situation of strongly varying data across products. The values of the parameters ε_2, ε_3, a_2, b_1, and $b_2$do not vary since the variation of ε_1 and a_1 already captures the variation in marketing effectiveness and growth pattern. Table W1 displays the chosen values of the parameters for our simulation.

Table W1. Parameter values to generate different scenarios

	ε_1		ε_2	Δ		*RV*		*D*		a_1		*ET*	
Product	Equal	Varied		Equal	Varied	Equal	Varied	Equal	Varied	Equal	Varied	Equal	Varied
A	0.33	0.50	0.20	0.6	0.7	2.5 m	3.0 m	0.5	0.6	1.10	1.20	10	20
B	0.32	0.49	0.40	0.6	0.7	2.5 m	4.0 m	0.5	0.4	1.10	1.10	10	15
C	0.31	0.12	0.30	0.6	0.5	2.5 m	2.0 m	0.5	0.4	1.10	1.00	10	2
D	0.30	0.11	0.50	0.6	0.5	2.5 m	1.0 m	0.5	0.6	1.10	0.95	10	5

We set the cross-effect of competitive marketing stock (ε_3) to -.10 across all products. The remaining growth parameter a_2, b_1, and b_2 are set to .005, .1, and .0001. These parameters generate a life cycle which peaks in about 11 to 12 years. The scaling constant α of the response function is determined endogenously from the initial values of each product in order to be consistent with the initial sales level.

To reduce overall computation time, we construct an efficient Latin-square design containing eight portfolio profiles which we assign randomly across the two firms. Hence, in most scenarios we have an asymmetric competitive market situation. The generated eight profiles are given in Table W2.

Table W2. Scenario design

Scenario	1	2	3	4	5	6	7	8
ε_1	Varied	Equal	Equal	Varied	Equal	Varied	Equal	Varied
δ	Equal	Equal	Varied	Equal	Equal	Varied	Varied	Varied
RV	Varied	Equal	Varied	Equal	Varied	Varied	Equal	Equal
d	Varied	Equal	Varied	Varied	Equal	Equal	Varied	Equal
a_1	Equal	Equal	Varied	Varied	Varied	Equal	Equal	Varied
ET	Equal	Equal	Equal	Varied	Varied	Varied	Varied	Equal

We simulate an annual budget planning process with a five year forecast horizon and investigate 12 planning cycles. Optimal solutions are generated by numerically solving the constrained dynamic optimization problem in (3)-(3.3). Specifically, we use an iterative gradient search algorithm for which we adopt very tight convergence criteria. Since we do not have a closed-form solution, we also numerically compute the Nash equilibrium by iteratively optimizing the marketing mix of one firm while holding the marketing mix of the competitor constant. When we apply this method consecutively for both competitors, we reach a Nash equilibrium if none of the competitors can improve its solution.We compute two indices for measuring the performance of the heuristic. First, we compare the performance of the heuristic in terms of suboptimality (deviations from the discounted profit of the optimal solution):

$$\text{Suboptimality} = \left(\Pi^{\text{optimal}} - \Pi^{\text{heuristic}}\right) \Big/ \Pi^{\text{optimal}}, \text{ for } T = 5. \tag{W.2}$$

Second, we compute a metric that measures the match of the heuristic budget allocation with the optimal budget allocation:

$$\text{Match with optimal budget allocation} = \frac{1}{5}\sum_{t=1}^{5}\left[\sum_{i=1}^{4}\sum_{n=1}^{2} Min\left\{x_{int}^{\text{optimal}}, x_{int}^{\text{heuristic}}\right\} \Big/ R\right], \tag{W.3}$$

Π is defined in Equation (3) and refers to results where budgets are obtained from numerical optimization or the proposed heuristic. x_{int} denotes the budget for marketing activity n of product i in period t and R is the total budget.

We assume a naïve allocation as initial condition, i.e. the total budget is equally allocated across products and marketing activities. We divide these expenditures by the product-specific decay coefficient to obtain initial stocks.

The Tables W3 and W4 display the simulation results for each single-firm scenario and each competitive scenario, respectively.

Table W3. Simulation results for proposed heuristic (single-firm scenarios)

Scenario	1	2	3	4	5	6	7	8
Iteration	Suboptimality							
1	4.98 %	1.34 %	1.42 %	5.07 %	6.66 %	6.59 %	6.83 %	2.75 %
6	1.30 %	0.36 %	1.41 %	1.06 %	2.55 %	3.65 %	1.46 %	2.55 %
12	0.30 %	0.08 %	0.48 %	0.14 %	0.50 %	1.68 %	0.30 %	1.61 %
Iteration	Match with optimal budget allocation							
1	66.62 %	79.32 %	83.00 %	76.23 %	72.53 %	62.29 %	73.77 %	75.43 %
6	86.06 %	92.26 %	90.84 %	97.38 %	93.19 %	81.64 %	96.72 %	77.13 %
12	91.37 %	96.11 %	90.36 %	99.26 %	98.31 %	91.67 %	97.76 %	75.73 %

Table W4. Simulation results for proposed heuristic (competitive scenarios)

Scenario for firm *u*	1	2	3	4	5	6	7	8
Scenario for firm *v*	1	7	4	3	2	6	8	5
Iteration	Suboptimality							
1 6 12	3.39 % 0.55 % 0.10 %	0.81 % 1.38 % 1.79 %	1.73 % 1.64 % 0.44 %	5.11 % 1.80 % 0.18 %	7.19 % 3.65 % 0.66 %	5.23 % 3.14 % 4.06 %	6.35 % 1.68 % 0.48 %	2.90 % 2.97 % 2.46 %
Iteration	Match with optimal budget allocation							
1 6 12	74.83 % 91.09 % 94.36 %	84.27 % 81.63 % 81.50 %	83.64 % 97.62 % 97.42 %	75.86 % 94.75 % 98.78 %	74.09 % 93.88 % 98.60 %	61.13 % 72.45 % 66.92 %	75.60 % 96.83 % 94.39 %	75.31 % 81.81 % 77.83 %

Notes: Scenarios arebased on the design set of Table W2.

The suboptimality criterion for the proposed heuristic already improves dramatically over the naïve allocation in the first iteration and develops very well over the next iterations (planning cycles). In most scenarios, the heuristic converges very close to the optimal solution when it is repeatedly used in the following planning cycles. This convergence can also be seen from the match with the optimal budget, which rapidly gets close to 100%. The Tables W5 and W6 display the development of the two performance criteria if we apply the naïve allocation. It is obvious that this naïve allocation rule produces results that are far away from optimality, and they deteriorate over time.

Table W5. Simulation results for naïve allocation (single-firm scenarios)

Scenario	1	2	3	4	5	6	7	8
Iteration	Suboptimality							
1 6 12	22.53 % 25.59 % 25.69 %	3.45 % 3.53 % 3.54 %	7.25 % 13.28 % 15.41 %	25.77 % 29.11 % 29.56 %	29.66 % 40.53 % 43.81 %	23.44 % 30.50 % 33.47 %	32.89 % 35.14 % 35.35 %	7.91 % 11.21 % 12.36 %
Iteration	Match with optimal budget allocation							
1 6 12	40.91 % 49.89 % 49.77 %	71.30 % 78.46 % 78.38 %	58.27 % 63.78 % 61.52 %	39.33 % 48.19 % 48.90 %	25.00 % 25.03 % 25.25 %	33.57 % 30.83 % 29.75 %	42.06 % 50.00 % 50.00 %	64.30 % 72.03 % 71.76 %

Table W6. Simulation results for naïve allocation (competitive scenarios)

Scenario for firm *u*	1	2	3	4	5	6	7	8
Scenario for firm *v*	1	7	4	3	2	6	8	5
Iteration	Suboptimality							
1	18.93 %	2.42 %	10.10 %	27.33 %	32.26 %	20.05 %	32.58 %	9.94 %
6	20.59 %	4.38 %	20.46 %	38.59 %	45.99 %	26.33 %	36.98 %	28.38 %
12	20.71 %	8.20 %	26.01 %	45.19 %	51.54 %	28.96 %	39.37 %	39.15 %
Iteration	Match with optimal budget allocation							
1	46.96 %	77.16 %	50.50 %	39.05 %	25.00 %	36.97 %	42.94 %	59.62 %
6	57.63 %	70.29 %	52.20 %	46.55 %	25.00 %	34.86 %	50.00 %	64.90 %
12	57.85 %	58.10 %	50.76 %	46.56 %	25.06 %	33.50 %	50.00 %	63.58 %

Notes: Scenarios are based on the design set of Table W2.

As a robustness check with respect to the initial condition, we simulated all scenarios again and assumed that initial budgets are allocated proportionally to the product's profit contribution. This allocation mimics the "percentage of sales" (size of the business) rule, which seems to be frequently applied in practice (see Bigné 1995 again). The size of the business is also recognized as an important allocation-relevant information by our proposed heuristic. The initial condition is therefore more favorable and the performance indices improve across the scenarios when we apply our suggested heuristic.

Investigating the Performance of Budget Allocation Rules: A Monte Carlo Study

Authors: Sönke Albers, Nils Wagner and Marc Fischer

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Abstract

The marketing budget allocation process is one of the most important tasks a manager is being charged with. As firms in general sell a portfolio of products and can choose among various marketing activities with dynamic impact on future sales, their profit maximization problem is characterized by high complexity. For this reason, academics provided practitioners with various optimization approaches to find a solution for the budget allocation problem. But managers still prefer to use simple rules to determine the marketing budget because they find it difficult to fully understand sophisticated optimization algorithms. So in summary a huge variety of budgeting approaches exists. Nevertheless, literature does not provide a systematic analysis and comparison of the performance of these approaches, which would allow deriving implications about which approach should be preferred.

We conduct a comprehensive simulation study by applying several allocation rules in a multitude of different generated scenarios in order to analyze and compare their performance as well as their sensitivity to different changes in the market environment. Specifically, we compare a naïve solution (equal product budgets), a common practitioner rule (percentage-of-sales rule), a recently suggested award-winning allocation heuristic (Fischer et al. 2011), and a numerical optimization method. The evaluation of the performance of allocation rules is based on the profit gained by application of the respective allocation rule compared to the optimal solution. In addition, we analyze the sensitivity of the different rules by imposing an estimation error, which affects the parameters of interest. The authors find that the allocation rule by Fischer et al. (2011) is best performing and may even outperform the numerical optimization in case of estimation error and dynamic information updating.

1 Introduction

Setting the right marketing budget has been a key research problem and a top challenge to management for a long time. For companies that market a portfolio of products and use different marketing tactics, it involves finding the optimal total marketing budget and its optimal allocation across allocation units such as products. Theoretical and empirical research (e.g., Fischer et al. 2011; Mantrala, Sinha, and Zoltners 1992) shows that solving the second problem, the optimal allocation of a marketing budget, is much more important. Better allocation results in profit gains between 40% and 60%, whereas the optimization of the overall budget level improves profit only by 3-5% (Mantrala, Sinha, and Zoltners 1992; Tull et al. 1986). Ideally, both problems are solved simultaneously. Theoretically, this can be achieved but at the cost of higher complexity and imposing restrictions in order to guarantee the uniqueness of an optimal solution. Practically, companies frequently separate these problems. Top management usually determines the overall marketing budget for the next fiscal year first. This budget is then allocated across country units, products, marketing activities, etc. (Fischer et al. 2011).

Consequently, academics have developed methods and algorithms to solve complex allocation problems under a restricted marketing budget (e.g., Doyle and Saunders 1990; Mantrala 2002). These optimization approaches unfortunately rely often on numerical optimization techniques so that they are not used by managers. In fact, surveys among managers consistently reveal that they prefer simple allocation rules such as the percentage-of-sales rule. But these practitioner rules are supposed to lead to allocation results that are rather far from the optimum. Therefore research started to find a way out of this dilemma by suggesting new heuristics that are derived from theory and accepted by managers (e.g., Fischer et al. 2011). In real-world applications, these heuristics seem to lead to large profit gains. However, this performance may be due to the specific conditions and may not generalize to other situations.

To summarize, management can choose among several methods to solve the important marketing budget allocation problem. All these methods probably have their advantages and disadvantages in terms of optimality, practical applicability, etc. Surprisingly, despite the high managerial relevance of budget optimization, we do not know how well the methods perform relative to each other across varying market and firm conditions. Given that practitioner rules and decision heuristics do not guarantee the optimal solution, the question is how close they come to the optimum. What are the conditions that influence deviation from optimality most? Are theoretically derived heuristics really better than simple practitioner rules? Since numerical optimization incorporates demand parameters such as sales elasticities that are measured with error, how do these exact methods perform relative to heuristic decision rules? And how do all these methods perform over time when they are repeatedly applied?

Research on allocation rules. The sparse literature on comparing budgeting approaches cannot answer these questions. Tull et al. (1986) show how deviations from the optimal marketing spending level result in changes of the firm's profit for different types of response functions. Their results indicate that the profit function is rather flat so that investment errors may have only a marginal effect on the firm's profit if the investment decision remains within a range of 25% to the optimal solution. But they focus only on the total marketing budget decision and ignore allocation issues. Mantrala, Sinha and Zoltners (1992) address this gap by analyzing the sensitivity of profit to allocation errors under different scenarios. They solve the allocation problem in several market scenarios which are characterized by different response functions by applying a marginal analysis approach and compare the solution with the outcome of the application of a naïve solution of an equal distribution of the marketing budget. Their analysis shows that the potential for profit improvement is much higher for allocation decisions than for optimal overall budget levels. In particular, one can expect increases of only 2-3% for much larger budgets but up to 40% from better allocation. But their study is subject to several limitations. First, they apply only the naïve solution of an equal distribution across the product portfolio and the marginal analysis approach. But other (and more realistic) budgeting rules are not considered within their study. Second, they vary only the type of the market response function, but ignore for manipulation of other factors which might influence the performance of allocation approaches as well. Third, they do not show how strongly the numerical approach is influenced by estimation error. Thus, literature does not provide a systematic analysis of application and performance of budget allocation decision rules so that we are lacking information about the effectiveness and the value of specific rules compared to other budgeting approaches. A comprehensive understanding about the performance of budget allocation approaches is necessary to derive implications how budgets should be determined under different conditions.

Contribution. We address this research gap by setting up a simulation experiment in which we analyze the performance of several different budgeting rules, manipulate all relevant factors, and further examine the effect of estimation error. The advantage of simulation experiments is that the true parameter values are known, their true relation is given and all characteristics of interest can be fully controlled. As a consequence the optimal solution is known and the suboptimality of applying the various allocation methods can be assessed. This is not possible with real-life data, simply because the real parameters and models are not known (Proppe and Albers 2009). Our experiment is based on a comprehensive variation of data conditions in which we apply four different allocation rules characterized by different complexity. In summary, we consider the naïve budgeting approach of an equal distribution, the most common practitioner rule to allocate the budget proportional to product sales, the award-winning allocation heuristic by Fischer, Albers, Wagner, and Frie (2011), denoted hereafter as FAWF, and a numerical optimization solution. Our experimental design considers dynamic effects and manipulates all factors and functions, which are incorporated into the dynamic profit maximization problem. This allows us to derive generalizable results and to analyze the impact of several factors on the performance of each of the considered budgeting methods. As a further aspect we create more realistic scenarios by imposing estimation errors on unobservable demand parameters. An analysis of the sensitivity to estimation error gives insights into how the performance of allocation rules changes if their estimated parameters are exposed to noisiness. In particular, our simulation study addresses the following four research questions:

- How do the budgeting methods perform relative to the optimal solution? Are they close to being "optimal"?
- How do the budgeting methods perform over time, i.e. by being subsequently applied? Do they converge to the optimal solution?
- If the budgeting methods include unobservable demand parameters that need to be estimated: How strongly are these methods influenced by estimation errors?
- Which are the most important factors that influence the performance (and the convergence properties) of the allocation rules?

We follow prior simulation studies in marketing research to develop a Monte Carlo design (e.g., Andrews, Ainslie and Currim 2002; 2008). Note that these studies have much in common with simulation studies in statistics. They usually analyze the performance of empirical methods to describe and predict demand behavior such as brand choice under different conditions. Typical performance measures are the recoverability of behavioral parameters and predictive accuracy. In contrast, our study shares features of simulation studies in operations research. The objective is to study the optimality of firm behavior, i.e. to set the "right" marketing budget, by using different decision rules. As a consequence, the deviation from profit maximum and the speed of converging to that optimum are the relevant performance measures.

The rest of the paper is organized as follows. We continue in section 2 by presenting shortly the dynamic profit maximization problem on which we base our analysis and the four allocation rules we analyze. Section 3 provides information about the design of the simulation study. The sections 4 and 5 discuss the results of the simulation experiment and identify the drivers of the performance (and the convergence properties) of the allocation rules. We close with limitations and suggestions for future research.

2 Analysis background

2.1 Dynamic profit maximization problem

In the following analyses, we consider the realistic scenario of a multi-product, multi-country firm which wishes to maximize the net present value *Π* of its product portfolio over a planning period *T*, e.g. five years, by effectively allocating the fixed marketing budget *R*. Accordingly, the firm faces the constrained dynamic profit maximization as formulated in equation (1)-(1.3). Under the assumption of known parameters we may be able to solve the profit maximization problem and find the optimal budgets by application of dynamic numerical optimization methods.

$$Max_{S_i}\, \Pi = \underbrace{\int_{t=0}^{T} \underbrace{e^{-rt}}_{\text{Discounting}} \left\{ \left[\sum_{i \in I} \underbrace{(p_i - c_i)}_{\text{Profit contribution margin}} \cdot \underbrace{q_i(ET_i + t, \boldsymbol{S}_i, \boldsymbol{Z}_i)}_{\text{Unit sales}} \right] - \underbrace{\sum_{i \in I} \sum_{n \in N_i} x_{in}}_{\text{Marketing expenditures}} \right\} dt}_{\text{Discounted net value of product portfolio}} \quad (1)$$

subject to $R = \sum_{i \in I} \sum_{n \in N_i} x_{in},\ with\ \frac{dR}{dt} = 0,$ (Budget constraint) (1.1)

$$\frac{dS_{in}}{dt} = -\zeta_{in} S_{in} + x_{in}, with\ x_{in} \geq 0, \quad \text{(State variable equation) (1.2)}$$

$$S_{in} \geq 0, S_{in}(0) = S_{in0}, and\ S_{in}(T) = S_{inT} \quad \text{(Boundary conditions) (1.3)}$$

where *t* is the time period with planning horizon *T*. The product is denoted by *i* with the index set *I*. As the firm may sell its product portfolio with the help of various marketing activities, such as advertising or sales force, *n* denotes the type of marketing activity or spending category, respectively, and N_i is the associated index set that may vary across products. The discount rate is denoted by *r*, $0 < r < \infty$. The absolute profit contribution of product *i* is determined by the profit contribution per unit and the unit sales. The difference of price *p* and marginal cost *c* gives the profit contribution margin. Unit sales *q* are determined by a function which is influenced by the elapsed time since launch of the product *ET*, the marketing stock ***S***, which is a N_i-dimensional row vector summarizing the activity-specific marketing stocks for product *i* and a row vector of other variables ***Z*** (e.g. competitive marketing spending). To reflect the long-term impact of marketing spending, the marketing stock *S* follows a dynamic process that satisfies the differential equation

$$\frac{dS}{dt} = -\zeta S + x, x \geq 0, \text{and } S(0) \text{ known} \tag{2}$$

where x denotes marketing expenditures and ζ is the depreciation rate of the marketing stock. Further, we account for life-cycle effects by including a life cycle function into our sales function, whose growth parameters may be influenced by marketing investments. In our experimental setting we analyze different demand and growth functions. Finally, marketing expenditures are the sum of the activity-specific marketing expenditures x.

2.2 Allocation rules

In our analysis of the performance of allocation approaches we focus on four different allocation rules which are characterized by different degrees of complexity: We apply a naïve solution of an equal distribution of the budget across the product portfolio and the most frequently used budgeting rule by practitioners, the percentage-of-sales rule (Bigné 1995). Further, we analyze the performance of methods that are based on the principle of marginal returns: a heuristic proposed by FAWF (2011) and a numerical optimization algorithm.

2.2.1 Naïve allocation: Equal distribution

The most naïve approach is an equal distribution across all products and activities, which ignores the heterogeneity of the product portfolio. The budget allocation is obtained as follows:

$$\tilde{x}_{int}^{naive} = \frac{R_t}{\sum_{j \in I} N_j}, \forall\, i \in I, n \in N_i, t \in [0, T] \tag{3}$$

where

$\tilde{x}_{int}^{naive}$: Marketing budget for product i and marketing activity n in period t;
R_t : Total budget to be allocated in period t;
n = 1, 2, …, N_i (number of marketing activities); and
i = 1, 2, …, I (number of products);
t = 1, 2, …, T (number of periods);

2.2.2 Percentage-of-sales rule

According to manager surveys (e.g., Bigné 1995) the percentage-of-sales method is the most often applied allocation rule in companies. It proposes to set the marketing budget as a specific percentage of the sales level. Accordingly, the budget is allocated proportional to sales across the portfolio, i.e. products with a greater sales level get a larger proportion of the marketing budget and vice versa. By assuming that product budgets that are derived from the percentage-of-sales rule are allocated equally across the two marketing activities, the allocation solution is given by:

$$\tilde{x}_{int}^{percent} = \frac{1}{N_i} \frac{RV_{i,t-1}}{\sum_{j \in I} RV_{i,t-1}} R_t, \forall\, i \in I, n \in N_i, t \in [0, T], \tag{4}$$

where

$\tilde{x}_{int}^{percent}$: Marketing budget for marketing activity n and product i in period t;
R_t : Total budget to be allocated in period t;
$RV_{i,t\text{-}1}$: Revenue level of product i available from last year;
i = 1, 2, …, I (number of products);
n = 1, 2, …, N_i (number of marketing activities); and
t = 1, 2, …, T (number of periods);

2.2.3 Attractiveness allocation heuristic by FAWF (2011)

FAWF (2011) propose to allocate the budget for spending category n of product i proportional to its allocation weight w:

$$\tilde{x}_{int}^{FAWF} = \frac{\tilde{w}_{int}}{\sum_{j \in I} \sum_{m \in N_j} \tilde{w}_{jmt}} R_t, \forall\, i \in I, n \in N_i, t \in [0, T], \tag{5}$$

$$\text{with } \tilde{w}_{int} = \underbrace{\varepsilon_{in,t-1}/(r + 1 - \delta_{in})}_{\text{Long-term marketing effectiveness}} \cdot \underbrace{cm_i \cdot RV_{i,t-1}}_{\text{Profit contribution}} \cdot \underbrace{\rho_{it}}_{\text{Growth potential}} \tag{6}$$

where

$\tilde{x}_{int}^{FAWF}$: Marketing budget for marketing activity n and product i in period t;
$\tilde{w}_{int}$: Heuristic allocation weight for marketing activity n and product i in period t;
R_t : Total budget to be allocated in period t;
r : Discount rate (capital cost of firm, strategic business unit, etc.);
δ_{in} : Carryover coefficient of marketing activity n for product i;
$\varepsilon_{in,t\text{-}1}$: Short-term sales elasticity with respect to product i's marketing expenditures on activity n available from last year;
cm_i : (Percentage) contribution margin for product i;
$RV_{i,t\text{-}1}$: Revenue level of product i available from last year;
ρ_{it} : Multiplier to measure the growth potential of product i in period t;
i = 1, 2, …, I_k (number of products);
n = 1, 2, …, N_i (number of marketing activities); and
t = 1, 2, …, T (number of periods);

This allocation heuristic is directly derived from the optimality conditions that need to be satisfied for solving the dynamic optimization problem (for details see FAWF 2011). Basically, the rule teaches to allocate the total budget according to the relative attractiveness of an allocation unit, whereas its attractiveness is represented by the allocation weight w. For this reason, we call this rule an "attractiveness allocation heuristic". The allocation weight incorporates information on the profit improvement potential that results from assigning a higher budget to the allocation unit. This information includes the long-term marketing effectiveness of a product's marketing activity, the product's profit contribution level, and its growth potential. FAWF (2011) suggest approximating the growth potential ρ by a multiplier that divides expected product revenues in 5 years (planning horizon) by its current revenue level. In our study, we follow FAWF (2011) by computing the expected product revenues based on the parameters of the growth function. Note that equation (5) reduces to the percentage-of-sales rule (4) if long-term marketing effectiveness, contribution margins, and growth potential multipliers are equal for all allocation units. For application of the attractiveness heuristic, r, cm, and RV are usually readily available from internal records, but δ, ε, and ρ must be estimated by econometric models, as an example (FAWF 2011). In our simulation experiment, we also investigate the performance of the heuristic for parameters that are estimated with error, which is most likely to be the common situation in reality.

2.2.4 Numerical optimization method

We employ a numerical optimization routine to obtain a unique solution to the dynamic optimization problem stated in equations (1)-(1.3). For this procedure, we need to specify the demand function $q(ET+t,S,\boldsymbol{Z})$ and provide parameter values such as r, p, c, etc. The big advantage of numerical optimization is that it generates optimal budgets for the specified problem. The disadvantages in practical application are, however, that we must correctly specify the demand function and know the parameter values. In addition, the black-box character inhibits acceptance by managers (e.g., FAWF 2011, Prendergast, West and Shi 2006). While numerical optimization results are always superior to those of the attractiveness heuristic under full information, it is interesting to compare the performance of both methods under more realistic conditions when demand parameters are subject to estimation error, e.g., marketing elasticities.

We solve our optimization problem by applying the enhanced Generalized Reduced Gradient (GRG) 2 algorithm (for further details see Lasdon et al. 1978) implemented in the Premium Solver Platform of Frontline Systems. The nonlinear optimization algorithm GRG2 iteratively varies the marketing allocation to maximize total discounted profits. It stops when the relative change in the objective is less than the convergence tolerance for the last five iterations. We set the convergence tolerance to the value of 10^{-10}. The constraints of our maximization problem are classified as active when they are within the range of 10^{-12} of one of their bounds.

Since we do not have a closed form solution, we numerically compute the Nash equilibrium in our competition scenarios by iteratively optimizing the marketing mix of one firm while holding the marketing mix of the competitor constant. When we apply this method consecutively for both competitors, we reach a Nash equilibrium if none of the competitors can improve its solution. (Fylstra 1998)

3 Experimental Design

3.1 Setup of the decision problem

FAWF (2011) investigate the performance of their suggested attractiveness heuristic in a small simulation study. They assume a firm using two types of marketing activities to stimulate sales of a product portfolio of four products. The firm sets the total marketing budget at the end of each year. The task is to find an optimal allocation of this budget across the four products and two activities, i.e. in total an allocation decision for eight allocation units has to be made. The discounted profit over the next five years is the objective criterion. Equations (1)-(1.3) formalize the profit maximization problem. The budget planning process recurs every year. As a result, the firm may revise allocation decisions based on new market information that are available for the next budget planning cycle.

We follow the setup of FAWF (2011) to develop our experimental design. This setup fully reflects the conditions of a dynamic multi-product, multi-activity allocation problem. We report on the systematic variation of factors influencing the allocation decision and profit outcome subsequently. Our experimental simulation study, however, differs from the small simulation study of Fischer et al. (2011) in several important ways: First, we analyze and compare more than just one budgeting method. Second, we include all parameters which might have an impact on the performance of the allocation approaches. FAWF (2011) do not analyze the type of the demand model, the type of growth model, and the initial budget allocation. Third, we create a full factorial design in contrast to FAWF (2011) who use only a reduced Latin square design of 16 experimental conditions producing 192 allocation solutions. Our full design with more factors creates 512 experimental conditions and 5,120 allocation solutions. Fourth, we impose an error on unobservable demand parameters which need to be estimated. This allows us to analyze the sensitivity of the allocation approaches to estimation error, which has not been done in FAWF (2011). Because of this error it is no longer guaranteed that numerical optimization produces optimal budgets. Fifth, we conduct a regression analysis to study the relative impact of the various factors on the performance (and the convergence properties) of the four allocation rules.

3.2 Data generation without estimation error

We design a Monte Carlo experiment, in which we experimentally manipulate 9 factors that can be divided into the following groups:

1. Market response model: multiplicative model or modified exponential model;
2. Growth model: symmetric or asymmetric growth function;
3. Product characteristics: equal or unequal values for the five characteristics of marketing elasticities, marketing carryover coefficients, revenue levels, growth parameters, and launch dates across products;
4. Competitive situation: no competition or Nash competition; and
5. Initial budget allocation: equal or proportional-to-sales initial allocation across products.

We create a full factorial design. Group 1, 2, 4, and 5 each includes one factor with two levels. Group 3 includes 5 factors, each with two levels. As a result, we have $2^9 = 512$ experimental conditions under which we use the attractiveness heuristic and numerical optimization to generate allocation decisions. Recall that the objective is to maximize discounted profit over the next five years. Consistent with our setup of the decision problem, we generate allocation decisions and the resulting discounted profit for ten consecutive planning periods. Hence, we observe $512 \times 10 = 5{,}120$ allocation and profit results that can be compared with the optimal solution. The observation of the performance of the decision rule over ten planning periods enables us to investigate the convergence properties of the rule.

Factor 5 is not meaningful for using the naïve and the percentage-of-sales rules to generate data. As a result, the number of experimental conditions and total allocation decisions reduces to $2^8 = 256$ and $256 \times 10 = 2{,}560$, respectively. Since we assume that the true values of all parameters are known, the numerical optimization method by definition yields the true optimum. We next explain the factors and their levels.

Market response model

Hanssens, Parsons, and Schultz (2001) discuss a variety of response functions that have been used in market research. Note that models, which assume linear or increasing returns to scale, are not eligible because the optimal budget is zero or infinity. For the allocation of a fixed budget, this would lead to meaningless corner solutions. We therefore choose functional types that experience diminishing returns for higher levels of spending. Specifically, we use the multiplicative model and a modified exponential model. To keep notation low, we do not use indices for the factor levels. Unit sales q for product i in equation (1) are specified for the multiplicative model as follows:

$$q_{it} = a_i \cdot S_{1it}^{b_{1i}} \cdot S_{2it}^{b_{2i}} \cdot g(ET_i + t, \boldsymbol{S}) f(\boldsymbol{Z}_i) \tag{7a}$$

where a_i is a scaling constant, and b_{1i} and b_{2i} are sales response parameters that determine marketing responsiveness. $g(\cdot)$ represents the growth function and $f(\mathbf{Z}_i)$ represents the influence of other variables summarized in the vector $\boldsymbol{Z}$. We discuss these variables and relations subsequently. Sales elasticities, which we need as input for the attractiveness heuristic, are equal to the power coefficients. Note that they already measure the long-term impact of marketing expenditures. To obtain short-term effects, we need to multiply them with (1-δ_i), the carryover information from the differential equation (2). We use this equation to compute the marketing stock S. The scaling constant a_i is computed in the starting solution of our simulation experiment when the sales level and all other parameters of equation (7a) are known.

We choose the multiplicative response model because it is by far the most frequent aggregate response model type in empirical research. It shows diminishing returns for response parameters between 0 and 1 and accommodates interaction effects among marketing activities. However, this specification has its limitations. It assumes constant elasticities and does not accommodate a saturation level for sales.

The modified exponential model allows for these effects and has seen several empirical applications to marketing spending models (Hanssens, Parsons, and Schultz 2001):

$$q_{it} = M_i\left[1 - \exp\left(b_{1i}\sqrt{S_{1i}} + b_{2i}\sqrt{S_{2i}}\right)\right] g(ET_i + t, \boldsymbol{S}) f(\boldsymbol{Z}_i) \tag{7b}$$

where M_i is the market potential for product i and other terms are defined as earlier. The square root of the marketing stock avoids corner solutions, i.e. an allocation solution where the budget is fully invested in only one of the two marketing activities.

To guarantee comparability with the response parameters of the multiplicative function we estimate the b parameters of the modified exponential function with simulated data for marketing input and sales output generated by the multiplicative function with the respective elasticity values. More specifically, we first generate several auxiliary simulated scenarios of different marketing input and estimate the corresponding sales output based on the multiplicative model. Subsequently, we integrate the marketing input and the corresponding sales output into the modified exponential function for which we assume that the market potential equates to a third of the actual sales level. This allows us to compute the transformed term of equation (7b) $\ln(1-{q_i}/{M_i})$ for each of our generated auxiliary simulated scenarios which we regress on the corresponding square roots of the marketing stocks $\sqrt{S_{1i}}$ and $\sqrt{S_{2i}}$. This provides us with the response parameters *b* as a result of this auxiliary regression.

Growth model

The growth model describes the life cycle of a product. Research (e.g., Fischer, Leeflang, and Verhoef 2010) shows that marketing investments have the power to significantly shape the life cycle, i.e., the growth potential of a new product. Fischer, Leeflang, and Verhoef (2010) discuss several parametric growth functions and differentiate between symmetric and asymmetric life cycles. We adopt a symmetric model (Polli and Cook 1969) and an asymmetric model (Brockhoff 1967). Both specifications are highly flexible and allow capturing a multitude of different shapes and thus represent most forms of growth patterns observed in empirical studies:

(symmetric life cycle) $$g[ET_i+t,S]=\lambda(S)\cdot(ET_i+t)+\eta(S)\cdot(ET_i+t)^2 \quad (8a)$$

(asymmetric life cycle) $$g[ET_i+t,S]=(ET_i+t)^{\lambda(S)}\cdot\exp[\eta(S)\cdot(ET_i+t)^2] \quad (8b)$$

where λ and μ are the growth parameters which determine the shape of the life cycle in terms of their time-to-peak as well as their height-to-peak. Following FAWF the growth parameters λ and η are influenced by the marketing stock according to $\lambda(S)=\lambda_0+0.005\cdot\ln(S)$, and $\eta(S)=\eta_0+0.00005\cdot\ln(S)$, with the basic growth parameters λ_0, and η_0, respectively.[1] Assuming the same growth parameter values across the two specifications (8a) and (8b) yields different results for the time-to-peak and height-of-peak. However, we do not want to vary the length of the growth phase and the level of sales at this point. We include this variation under product characteristics. Instead, we want to vary the shape pattern here. For this reason, we rescale parameters in the symmetric model so that it yields the time- and height-to-peak sales as in the asymmetric model.

[1] The values of 0.005 and 0.00005 which reflects the influence of marketing stocks on growth parameters are chosen in order to generate a significant effect of marketing on the shape of the life cycle, but similarly do not create illegitimate life cycle effects, e.g. negative values generated by *g(.)* in case of the symmetric growth function.

Product characteristics

Table 1 shows the values for the demand parameters and how they vary across products in the experimental conditions. There are five factors for which we create a situation of equal parameter values or unequal parameter values across products. Considering the profit maximization problem of (1)-(1.3), one could think of varying the discount rate, the profit contribution margin, the number of products, and the number of marketing activities. We did not vary these parameters because they do not generate new insights but increase computational burden. Firms usually do not use different discount rates for products in the same portfolio. Because profit margins just scale revenues downwards or upwards, their variation does not add explication beyond varying the revenue level, which we do. Simulation runs with larger product portfolios and more marketing activities did not reveal significant differences compared to the results obtained from our firm setting.

Factor sales elasticity. We assume two marketing activities for each product that could be sales force and advertising, for example. Motivated by meta-analyses we choose an average elasticity of about 0.3 for sales force (Albers, Mantrala and Sridhar 2009) and of about 0.15 for advertising (Sethuraman, Tellis and Briesch 2011; Lodish et al. 1995). To reduce computational burden we vary only the sales force elasticity while keeping the advertising elasticity constant as this satisfies heterogeneity across marketing responsiveness. Based on the chosen elasticity values in Table 1, we derive the response parameters for the response models (see equation (7a) and (7b)). For model (7a) the response parameters b_1 and b_2 correspond to the elasticities. For model (7b), we find response parameters that are consistent with the elasticity estimates and the initial sales level, as described above.

Factor carryover coefficient. Following equation (2) we assume a long-term impact of marketing investments so that we need the carryover coefficient δ to compute the marketing stock S. We set the carryover coefficient to 0.5 in the homogeneity scenario, which is the generalized value found in meta-analyses (Leone 1995; Sethuraman, Tellis and Briesch 2011) and vary these values between 0.4 and 0.6 for the heterogeneity scenarios. Larger carryovers are unrealistic for annual data and resulted into problems that a unique solution often was not found with numerical optimization. Smaller values are less interesting because they take out the dynamics, which we want to analyze.

Table 1. Variation of product cahracteristics

	Elasticity of activity 1		*Elasticity of activity 2*	*Carryover coefficient (δ)*		*Sales level q in t=0*		*Growth parameter λ_0*		*Growth parameter η_0*	*Elapsed time since launch (ET)*	
Product	Equal	Unequal		Equal	Unequal	Equal	Unequal	Equal	Unequal		Equal	Unequal
A	0.33	0.50	0.15	0.5	0.6	2.5 m	3.0 m	1.10	0.95	-0.1/-0.05	3	1
B	0.32	0.49	0.15	0.5	0.4	2.5 m	4.0 m	1.10	1.00	-0.1/-0.05	3	2
C	0.31	0.12	0.15	0.5	0.4	2.5 m	2.0 m	1.10	1.10	-0.1/-0.05	3	3
D	0.30	0.11	0.15	0.5	0.6	2.5 m	1.0 m	1.10	1.20	-0.1/-0.05	3	4

Factor revenue level. The sales level of the product q defines how much sales of the corresponding product are generated in the starting period. While the sales level is constantly 2.5m across the portfolio for the homogeneous case, we vary it from 1m to 4m for the heterogeneous scenario.

Factor growth parameter. For life cycles, we follow Fischer, Leeflang and Verhoef (2010) who find that their products reach the peak after approximately 11 years and ends after approximately 25 years. From this information, we derive the parameters for the asymmetric growth model in the homogenous case: $\lambda_0 =$ 1.1 and $\eta_0 =$ -0.1. The parameter η_0 in the symmetric model assumes a value of -0.05 to yield the same time-to-peak sales. Again, to reduce computational burden, we just vary the growth parameter λ_0 as this is sufficient to model heterogeneous life cycles.

Factor launch time. Finally, we assume that our simulation starts for the homogenous case in year three after product launch and we vary the elapsed time since launch from one to four years across the portfolio in the heterogeneous case. We are limited by year 4 to avoid that the life cycle ends within the simulation time in the case of the symmetric function.

Competitive situation

We test the sensitivity to competitive actions by considering two different scenarios. First, we assume a monopoly situation with just one firm. Second, we assume Nash competition and simulate the dynamic game for two firms with a portfolio of four products and two marketing activities. Both firms face the same profit maximization problem (1)-(1.3). Each product has a direct competitive product in the portfolio of the other firm. One firm is exposed to all possible combinations of experimental factors. We randomly assign experimental conditions to the competitor firm. Trying all possible combinations across the two competitors yields up to 65,536 experimental conditions and 655,360 profit simulations depending on the rule, which increases computation time extensively without generating substantial new insights.
To represent the competitive effects in the sales response functions (7a) and (7b), we specify the respective market response function as follows:

$$q_{it} = a_i \cdot S_{1it}^{b_{1i}} \cdot S_{2it}^{b_{2i}} \cdot S_{Ci}^{b_{Ci}} \cdot g(ET_i + t, S) \cdot f(\boldsymbol{Z}_i) \tag{9a}$$

$$q_{it} = M_i\left[1 - \exp\left(b_{1i}\sqrt{S_{1i}} + b_{2i}\sqrt{S_{2i}} + b_{Ci}\sqrt{S_{Ci}}\right)\right] g(ET_i + t, S) f(\boldsymbol{Z}_i) \tag{9b}$$

with the total marketing stock S_{Ci} of the competitive product of product i and the parameter b_{Ci} that determine responsiveness to competitive marketing of product i. We set the cross-effect of competitive marketing stock elasticity ε_C to -.10 across all products (e.g., Chintagunta and Desiraju 2005).

Initial budget allocation

We need to make an assumption about the allocation of the total marketing budget at the beginning of the first decision cycle. This initializes the marketing stocks across the various products and activities. We assume that firms followed either the naïve rule or the percentage-of-sales rule to set their marketing budgets prior to the start of the simulation experiment. We divide these marketing budgets by the product-specific carryover coefficient to compute the initial marketing stocks.

Since it does not make sense to assume the firm changes the initial allocation rule, we only vary the initial budget allocation for the attractiveness heuristic and the numerical optimization but not for the naïve and the percentage-of-sales allocation rules.

3.3 Data generation with estimation error

The assumption that managers know the true values of unobservable demand parameters is probably a very unrealistic assumption. For that reason, we impose an estimation error on demand parameters and generate data under all 512 experimental conditions again.

Specifically, we impose an error on the response parameters for the two marketing activities b_1 and b_2 and on the growth parameters λ and η. We do not assume an error for the carryover coefficient because that coefficient just scales short-term responsiveness to long-term responsiveness adding no additional insight but increase computational complexity.

The simulation error is randomly generated for each parameter by drawing a number from a symmetric triangular distribution with the lower limit of -25 % of the parameter value and an upper limit of +25 % of the parameter value. A range of 25% is larger than the standard deviation for generalized effects found in meta-analyses (e.g., Albers, Mantrala and Sridhar 2008; Sethuraman, Tellis and Briesch 2011). Specifically, the estimated parameters are obtained by:

$$\mu_{EP} = \mu_{TP} + \xi, \quad \xi \sim T(-0.25\mu_{TP}, 0.25\mu_{TP}) \tag{10}$$

where μ_{EP} is the estimated parameter value, μ_{TP} the true parameter value, and ξ is the error term. We use the triangular distribution to avoid that nonsense values (e.g., negative response parameters) are generated that may happen with extreme value distributions.

To reduce overall computation time we use the technique of common random numbers (Kleijnen and Groenendaal 1992). This technique is widely used in simulation literature. It consists of using the same set of random numbers for all simulation runs within one replication. This guarantees that all variations in the simulation outcome are only due to desired changes in the experimental variables and not due to random changes in the simulation environment. The random numbers only vary across replications. We generate a total of three replications of the random data. This number is consistent with previous simulation studies (Vriens, Wedel and Wilms 1996; Andrews, Ainslie and Currim 2008; Proppe and Albers 2009).

Because the naïve and the percentage-of-sales rules do not use unobservable demand parameters, no new data are generated for these methods. The numerical method, however, does not automatically provide the optimal solution as if true parameter values are known. It is interesting to see how this method performs relative to the attractiveness heuristic rule.

3.4 Measure of Performance

The key single objective is profit maximization. Thus, our performance measure is defined by the extent to which discounted profits under a specific allocation rule differ from the profit generated with the true optimal allocation:

$$Dev\_\Pi_t = (\Pi_t^{optimal} - \Pi_t^{rule})/\Pi_t^{optimal} \tag{11}$$

where $\Pi^{optimal}$ is the discounted profit generated with the optimal budget allocation and Π^{rule} is the discounted profit that results from budget allocation according to a specific rule.

Recall that we apply numerical optimization with true demand parameters to compute profits for the optimum. Our performance measure is indexed by *t* because we simulate an annually recurring budget planning process. For the first planning cycle, discounted profit is obtained from years 1-5, for the second cycle from years 2-6, etc.

We expect the naïve solution to show the worst performance results as it ignores the heterogeneity of the product portfolio. Percentage-of-sales allocates the budget according to the sales output of products and therefore is probably positively correlated with the optimal solution. For this reason, the rule is expected to outperform the naïve solution. FAWF additionally utilizes information about marketing responsiveness and product's growth potential which is supposed to improve the allocation solution further. Finally, numerical optimization provides optimal budgets. The expected performance may change due to inclusion of estimation error. FAWF bases its budget allocation on some unobservable demand parameters which have to be estimated, and numerical optimization even utilizes only unobservable demand parameters so that noisiness in parameters is supposed to reduce their performance.

4 Results

Results of our simulation experiment are summarized in Table 2 and 3. We show means of the deviation from maximum profit for each allocation rule and each of the ten consecutive planning cycles. The results are presented separately for the type of competition, monopoly or Nash competition. All other simulation factors vary within these scenarios. Table 2 includes results under the assumption that true demand parameters are known. Table 3 shows the results for simulations with noisy demand parameters.

4.1. Performance of rules for demand parameters without error

The overall means give an overview of how the allocation rules perform on average in terms of their deviation from maximum profit. By definition, the numerical optimization performs best as it determines the maximum profit. The second best results are provided by the attractiveness heuristic of FAWF which deviates by only .64% from maximum profit, on average (under Nash competition .68%), followed by the percentage-of-sales rule (10.3%, resprectively, 8.7% under Nash competition), and the naïve solution (20.7%, respectively, 22.0% under Nash competition). On average, percentage-of-sales outperforms the naïve solution in the monopoly scenarios by factor 2 (under Nash competition even by factor 2.5). The attractiveness heuristic outperforms in the monopoly scenarios the naïve solution even by a factor of 32.4 (under Nash competition 32.2), and percentage-of-sales still by factor 16.1 (under Nash competition 12.8).

Analyzing the performance over time, the attractiveness heuristic even provides in the first planning cycle of our simulation experiment close-to-optimum results with a deviation of less than 2% on average. When repeatedly using the heuristic the allocation solutions quickly converge to the optimal solution which is in line with the Banach fixed-point theorem as the allocation is subsequently replaced by allocations closer to the fixed point, the true optimum (Granas and Gurundji 2003).[2] These results also hold for the Nash competition scenarios, but the rule performs slightly less optimal in the first planning cycle and the convergence process

[2] To test whether the observed convergence process of FAWF is only the result of a better adaptability in the later stages of the product life cycle, we conduct the simulation experiment again in a static market by ignoring all product life cycle effects. As expected, the allocation rule performs even better in this static market. Results are not shown but are available from the authors.

is slower. Solutions provided by percentage-of-sales are also improving over time because the rule incorporates parts of the solution structure and represents a special case of FAWF. Contrary, the naïve allocation is a static rule that does not process new information over time to adapt the allocation in future planning cycles. The performance even decreases after being subsequently applied.

The informational value from average performance numbers is limited as it is not shown how the rules perform in extreme scenarios. Therefore, Table 2 and 3 also show the maximum deviation from optimal profit overall and in the last planning cycle. The maximum deviation from the profit optimum for the attractiveness heuristic across all 5,120 applications is only 5.72%. Due to its convergence to the optimum over time, it even reduces to only 1.15% in the 10th planning cycle. In contrast, the maximum deviation for the percentage-of-sales rule is 21.91%. It improves only slightly over time to 19.81%. Finally, the naïve solution even shows a maximum deviation of 44.38% overall and in the last planning cycle. All of these extreme scenarios are characterized by heterogeneity across parameters. While FAWF shows the worst performance results for a modified exponential response function, a symmetric growth function, and Nash competition, percentage-of-sales performs worst for a modified exponential response function, a symmetric growth function, and no competition, and the naïve solution provides worst solutions in case of a multiplicative response function, a symmetric growth function, and no competition.

These results demonstrate a remarkable robustness of the attractiveness heuristic under extreme scenarios. The overall standard deviations also show that the profit deviations are much less varying across scenarios if the attractiveness heuristic is applied compared to the other rules. This provides evidence that FAWF is very robust.

4.2. Performance of rules for demand parameters with error

In this section we impose error on the marketing responsiveness parameters and the growth parameters. We only compare the performance of the attractiveness heuristic with the numerical optimization. Simulation results of the naïve solution and percentage-of-sales do not change because the rules do not make use of these parameters.

Interestingly, numerical optimization performs worse than the attractiveness heuristic (see Table 3). This holds both under monopoly and Nash competition. It seems that numerical optimization is more sensitive to error in demand parameters than the heuristic. While the attractiveness heuristic also relies on noisy parameters to obtain the allocation solution, it

Table 2. Deviation from optimal profit means by rule and type of competition assuming no error in demand parameters

	Naïve rule		Percentage-of-sales rule		Attractiveness heuristic		Numerical Optimization method[3]	
	Monopoly	Nash	Monopoly	Nash	Monopoly	Nash	Monopoly	Nash
Planning cycle								
1st	.18501	.19378	.11252	.10620	.01950	.02008	-	-
2nd	.19564	.20927	.11136	.10123	.01417	.01562	-	-
3rd	.20134	.21414	.10762	.09442	.00937	.01048	-	-
4th	.20523	.21723	.10423	.08886	.00610	.00688	-	-
5th	.20837	.22057	.10175	.08486	.00409	.00456	-	-
6th	.21120	.22351	.10009	.08212	.00291	.00318	-	-
7th	.21398	.22653	.09906	.08028	.00227	.00225	-	-
8th	.21670	.22969	.09847	.07906	.00194	.00197	-	-
9h	.21949	.23306	.09817	.07828	.00181	.00174	-	-
10th	.22255	.23674	.09809	.07781	.00180	.00165	-	-
Overall mean	.20706	.22045	.10313	.08731	.00640	.00684	-	-
Overall median	.21171	.21614	.09831	.09635	.00360	.00346	-	-
Overall Std. Dev.	.10179	.09284	.05371	.04264	.00809	.00875	-	-
Overall Min.	.02937	.04552	.02937	.01875	.00000	.00000	-	-
Overall Max.	.44381	.40020	.21910	.18682	.05113	.05727	-	-
Max. for 10th planning cycle	.44381	.40020	.19810	.13304	.01070	.01158	-	-

[3] The deviation from maximum profit is per definition zero for the solution of the numerical optimization as it determines the optimal solution.

Table 3. Deviation from optimal profit means by rule and type of competition assuming error in demand parameters

	Naïve rule		Percentage-of-sales rule		Attractiveness heuristic		Numerical Optimization method	
	Monopoly	Nash	Monopoly	Nash	Monopoly	Nash	Monopoly	Nash
Planning cycle								
1st	.18501	.19378	.11252	.10620	.02116	.02960	.02612	.03118
2nd	.19564	.20927	.11136	.10123	.01561	.01887	.02744	.03085
3rd	.20134	.21414	.10762	.09442	.01094	.01308	.02785	.03086
4th	.20523	.21723	.10423	.08886	.00785	.00931	.02789	.03046
5th	.20837	.22057	.10175	.08486	.00596	.00707	.02870	.03069
6th	.21120	.22351	.10009	.08212	.00485	.00580	.02918	.03101
7th	.21398	.22653	.09906	.08028	.00421	.00513	.03041	.03138
8th	.21670	.22969	.09847	.07906	.00387	.00479	.03070	.03188
9h	.21949	.23306	.09817	.07828	.00371	.00467	.03169	.03263
10th	.22255	.23674	.09809	.07781	.00367	.00467	.03281	.03382
Overall mean	.20706	.22045	.10313	.08731	.00818	.01029	.02932	.03148
Overall median	.21171	.21614	.09831	.09635	.00634	.00627	.01582	.01363
Overall Std. Dev.	.10179	.09284	.05371	.04264	.00935	.00960	.04073	.03517
Overall Min.	.02937	.04552	.02937	.01875	.00026	.00022	.00000	.00000
Overall Max.	.44381	.40020	.21910	.18682	.06397	.07970	. 24645	.26181
Max. for 10th planning cycle	.44381	.40020	.19810	.13304	.01257	.01756	.24645	.26181

incorporates feedback from the market in subsequent periods in terms of actually realized product sales. This information goes directly into the allocation weight and it also contributes to update elasticity and growth multiplier estimates (see again equation 6). The negative influence of noise in demand parameters is compensated to a certain extent by this feedback mechanism. In contrast, the numerical optimization routine has no built-in feedback mechanism but relies on the noisy parameters. The error seems to propagate across subsequent planning periods.

On average, the attractiveness heuristic provides solutions which outperform those of the numerical optimization method by a factor of 3.58 (under Nash competition by a factor of 3.05). This is a significant performance difference between numerical optimization and FAWF. The maximum deviation from the profit optimum for the attractiveness heuristic across all scenarios is 7.97% and decreases to only 1.76% in the 10th planning cycle. For the numerical optimization method the maximum deviation is 26.18% overall and in the last planning cycle. This is even larger than for the percentage-of-sales rule (21.91% overall and 19.81% for the last planning cycle). The performance in the 10th planning cycle by the attractiveness heuristic under the extreme scenario outperforms numerical optimization by a factor of 14.9. The lower standard deviation of .94% versus 4.07% for numerical optimization (.96% versus 3.53% under Nash competition, respectively) strongly underlines the robustness of the heuristic.

5 Influence of experimental conditions on the performance of rules

We now report on the performance of the rules under different experimental conditions.

5.1 Expected effects

The product characteristics vary in terms of the degree of heterogeneity across the product portfolio. We expect for the naïve solution, the percentage-of-sales rule, and the attractiveness heuristic to provide superior solutions for a more homogeneous product portfolio. In case of a homogeneous portfolio the profit maximizing budget allocation is more equally distributed across the products. Therefore the naïve solution which proposes to allocate the budget equally across the portfolio is closer to the optimal solution in case of a homogeneous scenario. Percentage-of-sales utilizes the information of the sales level of products. So differences in the sales base across the portfolio are directly reflected in the proposed budget allocation and therefore are supposed to have no effect on the performance of percentage-of-sales. But information about differences in other factors is not considered and therefore cannot be captured by the percentage-of-sales rule. So we expect that percentage-of-sales is not affected by heterogeneity in the sales level, but is negatively affected by heterogeneity in one of the other product characteristic factors. As shown in equation (6) the attractiveness heuristic takes all of the product characteristics, partly indirectly, into account which may decrease the influence of portfolio heterogeneity on the heuristic performance. For this reason, we do not hypothesize on any effect of product characteristics on the attractiveness heuristic and leave it as an issue to be estimated in this study. Contrary, numerical optimization is supposed to provide better results for a more heterogeneous product portfolio. The reason is that the profit maximizing budget allocation is more likely to be a corner solution if the portfolio is characterized by strong heterogeneity. So in spite of noisy demand parameters numerical optimization is more likely to stay in this corner solution and therefore is less affected by estimation error.

The asymmetric and the symmetric growth functional type are equal in terms of height-to-peak and time-to-peak but vary in their shape. The symmetric function is flatter when approaching the maximum of the function, while the asymmetric function becomes flatter in the extensions of the function. As our simulation experiment generally starts after the product launch phase [4] products are less exposed to differences in life cycle effects during the simulation experiment in case of the symmetric function, i.e. the product portfolio is more likely to stay homogeneous during the experiment. For this reason, the naïve solution which benefits from a more homogeneous portfolio is expected to provide superior solutions in case of the symmetric growth function. Similarly, percentage-of-sales and the attractiveness heuristic are supposed to provide superior solutions in case of the symmetric growth function because they utilize information from the previous period so that they benefit from smaller changes in life cycle effects. We are not able to predict the effect on the performance of numerical optimization.

Due to our model specification, the sales outcome is less affected by estimation error in the demand parameters in case of the modified exponential function within the range of our simulation experiment. For this reason, we expect the numerical optimization to perform better in scenarios characterized by a modified exponential function. Similarly, the attractiveness heuristic may provide superior results in case of the modified exponential function in all scenarios which include an estimation error. But as we are not able to predict the effect of the type of the market response model specifications on the attractiveness heuristic if we assume known parameters we do not hypothesize on the effect of the response

[4] The average of elapsed time since launch is about three years (see section 3).

model specification in general. Thereby, we may also not predict the effect on the naïve solution and percentage-of-sales.

Nash competition is expected to have a negative effect on the performance of the naïve solution, the percentage-of-sales rule, and the attractiveness heuristic because competitive activities complicate the allocation decision by adding further factors which have to be captured by an allocation rule. But we are not able to predict the effect of competition on the performance of numerical optimization.

The initial allocation of the attractiveness heuristic and the numerical optimization approach can be determined by equal distribution or percentage-of-sales. We expect that percentage-of-sales as initial budget allocation provides superior solutions on average because the marketing stocks in the first planning cycles are probably closer to the optimal state so that both rules benefit from superior initial marketing stocks.

The factor of estimation error is only experimentally manipulated for the attractiveness heuristic. The heuristic is a contraction mapping on the theoretical optimum and subsequently approaches to the profit maximum by utilizing information about unobservable demand parameters and the sales outcome. If the utilized demand parameters are exposed to noisiness due to estimation error the rule may not directly point to the true optimum which deteriorates the performance results.

Finally, we expect different effects across the rules due to the factor of time, i.e. how the performance of the rules changes over time if they are subsequently applied. The attractiveness heuristic is an iterative sequence where values are subsequently replaced by values closer to the fixed point. It will converge to the fixed point after being subsequently applied, which is in our case the profit maximum (Granas and Gurundji 2003). So we expect that the attractiveness heuristic converges to the optimal solution over time and therefore time has a positive impact on the performance. Similarly, percentage-of-sales utilizes the information of sales outcome and thereby moves more of the total budget to the more profitable products of the portfolio over time, i.e. time is expected to have a positive effect. Contrary, the performance of the naïve solution is expected to decrease over time because it stays with the initial allocation and is not able to reduce the share of its suboptimal allocated marketing stocks, unlike all other rules, including the optimal solution. Finally, we predict a negative impact of time on the performance of numerical optimization because the true optimal solution is able to build down the suboptimal initial marketing stock over time, while the numerical optimization approach is based on noisy parameters and therefore is expected to replace the suboptimal initial marketing stock by another suboptimal marketing stock.

5.2 Descriptive analysis

Table 4 shows the deviation from optimal profit means by rule and experimental condition. As expected, the naïve solution shows superior performance results for a homogeneous parameter set, only the difference between the two means of carryover coefficients is insignificant. Further, it performs better in case of a modified exponential response function and a symmetric growth function. The existence of Nash competition hampers slightly the performance of the naïve solution.

The percentage-of-sales rule generally performs better if the product portfolio is characterized by homogeneity. Only unequal sales levels and carryover coefficients have no significant effect on the performance. The type of the growth function is not meaningful for the percentage-of-sales rule, but it shows superior results in case of a multiplicative response function. Surprisingly, it performs slightly better under Nash competition.

The attractiveness heuristic provides generally superior results if the product portfolio is characterized by homogeneity. But interestingly, unequality in the sales levels as well as in the growth parameters has a marginal, but significant negative effect. The heuristic performs better in scenarios characterized by a symmetric growth function, but the shape of the response function seems to have no impact on average. As expected, the attractiveness heuristic provides superior results if the initial budget allocated is determined by percentage-of-sales, no competition exists and no estimation error occurs.

Finally, the numerical optimization method performs better if the product portfolio is heterogeneous, only heterogeneity in carryover coefficients and in the elapsed time since launch has a negative effect on the performance. The type of growth function has no influence, but the type of the response function is meaningful as numerical optimization provides clearly superior results in case of a multiplicative response function. If no competition exists and the initial budget allocation is determined by equal distribution the numerical optimization performs better. By definition, numerical optimization provides the optimal solution if no estimation error occurs, but the performance significantly deteriorates due to inclusion of estimation error.

But insights based on the results shown in Table 4 are limited because they are not differentiated between planning cycles. The convergence properties and experimental conditions are analyzed in a regression model, discussed in the next section.

Table 4. Deviation from optimal profit means by rule and experimental condition

Factor	Naïve solution	Percentage-of-sales rule	Attractiveness heuristic	Numerical optimization
Elasticities				
Equal	.15435**	.05164**	.00738**	.03193**
Unequal	.27405**	.13881**	.00979**	.02887**
Sales level				
Equal	.17485**	.09548^{ns}	.00872*	.03388**
Unequal	.25356**	.09496^{ns}	.00845*	.02691**
Growth parameters				
Equal	.20271**	.09336**	.00882**	.03254**
Unequal	.22570**	.09709**	.00835**	.02826**
Carryover coefficient				
Equal	.21356^{ns}	.09503^{ns}	.00634**	.02951**
Unequal	.21485^{ns}	.09541^{ns}	.01083**	.03129**
Elapsed time since launch				
Equal	.16163**	.08848**	.00753**	.04261**
Unequal	.26678**	.10197**	.00964**	.18185**
Growth function				
Asymmetric	.21716**	.09572^{ns}	.00916**	.03067^{ns}
Symmetric	.21125**	.09473^{ns}	.00800**	.03012^{ns}
Market response function				
Multiplicative	.21764**	.08504**	.00869^{ns}	.05039**
Modified exp.	.21076**	.10541**	.00848^{ns}	.01041**
Competition				
Monopoly	.20795**	.10314**	.00774**	.02932**
Nash competition	.22045**	.08731**	.00943**	.03148**
Initial budget allocation				
Equal distribution	-	-	.00913**	.02933**
Percentage-of-sales	-	-	.00804**	.03147**
Estimation error				
Not included	-	-	.00662**	.0000[1)]
Included	-	-	.00924**	.03040
Overall	.21420	.09522	.00859	.03040

Notes: ** p<.01; * p<.05; ^{ns} = not significant (Difference between the two means, based on ANOVA F-test)
1) No deviation from optimal profit by definition.

5.3. Regression analysis

Model specification

To analyze the impact of experimental conditions on performance and convergence property of rules, we specify the following regression model for each rule:

$$\begin{aligned} Dev\_\Pi_{dlz} = \alpha &+ \beta_1 \cdot Fac\_Elast_l + \beta_2 \cdot Fac\_Sale_l + \beta_3 \cdot Fac\_Grow_l + \beta_4 \cdot Fac\_Car_l \\ &+ \beta_5 \cdot Fac\_ET_l + \beta_6 \cdot Fac\_GrM_l + \beta_7 \cdot Fac\_RespM_l + \beta_8 \cdot Fac\_IniB_l \\ &+ \beta_9 \cdot Fac\_Comp_l + \beta_{10} \cdot Fac\_Err_l + \beta_{11} \cdot z + \gamma \cdot [z \cdot \Gamma_l] + e_{dlz} \end{aligned} \quad (12)$$

where

Dev_Π_{dlm} : Deviation from maximum profit for scenario *l* and replication *d* in planning cycle *m*;
Fac_Elast : Heterogeneity of elasticities across products (0: equal, 1: unequal);
Fac_Sale : Heterogeneity of sales level across products (0: equal, 1: unequal);
Fac_Grow : Heterogeneity of growth parameters across products (0: equal, 1: unequal);
Fac_Car : Heterogeneity of carryover coefficient across products (0: equal, 1: unequal);
Fac_ET : Heterogeneity of elapsed time since launch across products (0: equal, 1: unequal);
Fac_GrM : Shape of growth function (0: asymmetric, 1: symmetric);
Fac_RespM : Shape of market response function (0: multiplicative, 1: mod. exponential);
Fac_IniB : Initial budget allocation (0: equal, 1: percentage-of-sales);
Fac_Comp : Competitive situation (0: No competition, 1: Nash competition);
Fac_Err : Estimation error (0: non-included, 1: included);
Γ_l : Vector of all simulation factors for scenario *l*;
α, β, γ : (Unobserved) parameters;
e : Error term;
z = 1, 2, …, 10 (number of planning cycles);
l = 1, 2, …, 1024 (number of scenarios); and
d = 1, …, D_l (number of replications).

All scenarios of our simulation experiment in which we do not incorporate an estimation error are independent, i.e. $e_{dlz} \sim N(0, \sigma^2)$, with the variance σ^2. This allows us to apply OLS for estimating equation (12) for the models of the naïve solution and the percentage-of-sales rule. But in all scenarios in which we incorporate an estimation error we apply the technique of common random numbers. As we use the same error terms for each scenario and each planning cycle we have to account for correlation among regression errors (Kleijnen 1988). The error terms for each replication across scenarios as well as across planning cycles within a scenario are correlated, while the error terms across replications within a scenario are uncorrelated, i.e. $e_{dlz} \sim N(0, \sigma_{lz}^2)$, with the variance σ_{lz}^2, and $Cov(e_{lz}, e_{lz'}) = \sigma_{lz,lz'}$ for $lz \neq lz'$. Therefore, we estimate equation (12) for the models of the numerical optimization and the attractiveness heuristic by using two step GLS which allows us to account for the serial correlation and correlation across scenarios (Greene 2006).
Equation (12) assumes a linear convergence process. We also tested as a log-linear process, i.e. *z* is replaced by *Log(z)*. Estimation results were very similar, so that we do not discuss them here in detail.

5.2. Results

The results of our models are shown in Table 5a and 5b. The constant can be interpreted as the average in our basic scenario, i.e. if all dummies in equation (12) equal zero: a homogeneous parameter set, an asymmetric growth function, a multiplicative market response function, no estimation error, and (if the factor of initial budget is included) an equal initial allocation. The coefficient values of the main effects show how the performance of the allocation rule would change on average in terms of deviation from maximum profit if the corresponding simulation factor changes to the specific experimental condition. A positive value means a worse, a negative value a better performance of the allocation rules. For example, a coefficient value of 0.1 for the simulation factor *unequal elasticities* means that the rule would have a higher deviation from the optimal solution of 10 % on average if we have a scenario characterized by heterogeneous elasticity across the portfolio instead of a homogeneous elasticity set. The interaction effects with the time variable show the impact of the factors over time, i.e. their influence on the convergence properties. A negative coefficient indicates a faster convergence process under the specific experimental condition, while a positive coefficient indicates a slower process.

By comparing the constant across all allocation rules in Table 5a and 5b we see that the attractiveness heuristic has the lowest value which confirms that it outperforms all other allocation approaches in our basic scenario on average.[5]

The effect of heterogeneity across the product portfolio is reflected by the coefficients of the product characteristics. The three simpler rules, i.e. the naïve solution, percentage-of-sales, and the attractiveness heuristic, are all strongly and negatively affected in their performance by heterogeneity in elasticities and elapsed time since launch. But while the interaction effect with time for the naïve solution is positive, i.e. the performance is getting even worse over time, the interaction effects for percentage-of-sales and the attractiveness heuristic are negative, i.e. the negative effect on the performance diminishes if the rule is applied subsequently. This is a reasonable finding as marketing responsiveness as well as life cycle effects are reflected in the sales outcome which is incorporated into both rules. The attractiveness heuristic even directly includes the elasticity and the growth multiplier (see equation (6)). As expected, heterogeneity in the sales level has a negative effect on the performance of the naïve solution, while percentage-of-sales and the attractiveness heuristic are able to capture the heterogeneity. The effect on performance becomes even positive for these two rules. Heterogeneity in the carryover coefficients affects the performance of all three rules negatively, but this effect decreases over time. As expected, numerical optimization generally performs better if the portfolio is characterized by heterogeneity as it has negative coefficients for the elasticity, the sales base, the growth parameters, and the

[5] Note that the constant of the numerical optimization method is not directly comparable as it only includes scenarios with an estimation error.

elapsed time since launch. Only heterogeneity in the carryover coefficient affects the performance of numerical optimization negatively.

The type of the growth model specifications is meaningful for all budgeting methods apart from numerical optimization. As expected, better allocation solutions are provided in the scenarios characterized by a symmetric growth function.

Percentage-of-sales provide superior results in scenarios characterized by a multiplicative response function, while the type of the response function has no impact on the performance of the naïve solution and the attractiveness heuristic. Contrary, numerical optimization works much better in case of the modified exponential function which confirms that the sales outcome based on this model specification is less affected by noisy demand parameters.

Nash competition has a negative effect on the performance of the naïve solution, the attractiveness heuristic, and numerical optimization. Contrary to our expectations, it has a negative effect on the percentage-of-sales rule, which is probably the result of an asymmetric portfolio structure of the two competitors, i.e. the larger products of company A compete with the smaller products of company B and vice versa. Based on this rule the budget is more heavily allocated to the products which generate larger sales so that an asymmetric portfolio structure across competitors avoids negative substitution effects and therefore is closer to the optimal solution.

In line with our expectations, percentage-of-sales as initial budget allocation leads to a superior performance of the attractiveness heuristic. But numerical optimization provides better results if the initial budget allocation is determined by equal distribution. This finding is contrary to our first expectations but may be explained by the replacement of the initial marketing stocks over time. Numerical optimization and the true optimal solution both suffer equally from a suboptimal initial solution but start replacing these stocks subsequently by new stocks based on their calculations. In case of a better initial allocation the suboptimal share of the marketing stocks is faster build down so that they can be replaced by new stocks. But while this is the true optimal stock for the profit maximum solution, the numerical optimization approach builds up another suboptimal stock in case of noisy demand parameters. Therefore, the deviation to the profit maximum is larger in case of superior initial marketing stocks.

Table 5a. Experimental factors influencing the deviation from maximum profit: regression coefficients (standard errors) I

		Naïve solution					Percentage-of-sales				
		Main effects			Interaction with time		Main effects			Interaction with time	
Factor	Level	Exp. sign	Est. coeff.	Est. std. dev.	Est. coeff.	Est. std. dev.	Exp. sign	Est. coeff.	Est. std. dev.	Est. coeff.	Est. std. dev.
Constant			.041	(.005)**				.042	(.002)**		
Elasticities	Equal	0		0		0	0		0		0
	Unequal	+	.118	(.003)**	3×10^{-4}	(.001)	+	.096	(.001)**	-.002	(2×10^{-4})**
Sales level	Equal	0		0		0	0		0		0
	Unequal	+	.084	(.003)**	-.001	(.001)	+/-	-.005	(.001)**	.001	(2×10^{-4})**
Growth parameter	Equal	0		0		0	0		0		0
	Unequal	+	.010	(.003)**	.002	(.001)**	+	.005	(.001)**	-3×10^{-4}	(2×10^{-4})
Carryover coefficient	Equal	0		0		0	0		0		0
	Unequal	+	.008	(.003)**	-.001	(.001)**	+	.003	(.001)**	-.001	(2×10^{-4})**
Elapsed time since launch	Equal	0		0		0	0		0		0
	Unequal	+	.081	(.003)**	.004	(.001)**	+	.032	(.001)**	-.003	(2×10^{-4})**
Type of Growth function	Asymmetric	0		0		0	0		0		0
	Symmetric	-	-.009	(.003)**	.001	(.001)	-	-.003	(.001)**	4×10^{-4}	(2×10^{-4})*
Type of Market response function	Multiplicative	0		0		0	0		0		0
	Modified exp.	+/-	4×10^{-4}	(.003)	-.001	(.001)**	+/-	.012	(.001)**	.001	(2×10^{-4})**
Type of Competition	Monopoly	0		0		0	0		0		0
	Nash competition	+	.011	(.003)**	3×10^{-4}	(.001)	+	-.008	(.001)**	-.001	(2×10^{-4})**
Initial budget allocation	Equal distribution										
	Percentage-of-sales										
Error in demand parameters	Not included										
Time (# planning cycle)		+	.002	(.001)**			-	-2×10^{-4}	(3×10^{-4})		
(Pseudo) R^2			.868					.915			
# of observations			2,560					2,560			

Notes: ** $p< .01$, * $p< .05$

The factor of initial budget allocation and estimation error is not included in our analysis of the naïve solution and the percentage-of-sales-rule (see section 3.2). Numerical optimization is based in simulations with error in demand parameters only.

Table 5b. Experimental factors influencing the deviation from maximum profit: regression coefficients (standard errors) II

		Attractiveness heuristic					Numerical Optimization method				
		Main effects			Interaction with time		Main effects			Interaction with time	
Factor	Level	Exp. sign	Est. coeff.	Est. std. dev.	Est. coeff.	Est. std. dev.	Exp. sign	Est. coeff.	Est. std. dev.	Est. coeff.	Est. std. dev.
Constant			.001	(4×10^{-4})**				.004	(.002)**		
Elasticities	Equal	0		0		0	0		0		0
	Unequal	+/-	.008	(2×10^{-4})**	-.001	($.4\times10^{-4}$)**	-	-.004	(4×10^{-4})**	3×10^{-4}	($.6\times10^{-4}$)**
Sales level	Equal	0		0		0	0		0		0
	Unequal	+/-	-.001	(3×10^{-4})**	1×10^{-4}	($.4\times10^{-4}$)*	-	-.003	(.001)**	-1×10^{-4}	($.8\times10^{-4}$)*
Growth parameter	Equal	0		0		0	0		0		0
	Unequal	+/-	-.001	(2×10^{-4})**	1×10^{-4}	($.4\times10^{-4}$)*	-	-.003	(.001)**	-5×10^{-5}	($.8\times10^{-4}$)
Carryover coefficient	Equal	0		0		0	0		0		0
	Unequal	+/-	.009	(3×10^{-4})**	-.001	($.4\times10^{-4}$)**	-	.003	(.001)**	-.001	($.7\times10^{-4}$)**
Elapsed time since launch	Equal	0		0		0	0		0		0
	Unequal	+/-	.007	(2×10^{-4})**	-.001	($.3\times10^{-4}$)**	-	-.015	(.001)**	-.001	($.5\times10^{-4}$)**
Type of Growth function	Asymmetric	0		0		0	0		0		0
	Symmetric	-	-.002	(2×10^{-4})**	3×10^{-4}	($.3\times10^{-4}$)**	+/-	-.001	(.001)	3×10^{-4}	($.5\times10^{-4}$)**
Type of Market response	Multiplicative	0		0		0	0		0		0
function	Modified exp.	+/-	3×10^{-4}	(2×10^{-4})	-1×10^{-4}	($.3\times10^{-4}$)**	-	-.031	(.001)**	6×10^{-5}	($.5\times10^{-4}$)
Type of Competition	Monopoly	0		0		0	0		0		0
	Nash competition	+	.001	(2×10^{-4})**	-2×10^{-4}	($.3\times10^{-4}$)**	+/-	.005	(.002)**	9×10^{-5}	($.8\times10^{-4}$)
Initial budget allocation	Equal distribution	0		0		0	0		0		0
	Percentage-of-sales	-	-.007	(2×10^{-4})**	.001	($.3\times10^{-4}$)**	-	.005	(.001)**	-.001	($.5\times10^{-4}$)**
Error in demand	Not included	0		0		0					
parameters	Included	+	.003	(2×10^{-4})**	-1×10^{-4}	($.2\times10^{-4}$)**					
Time (# planning cycle)	Planning cycle	-	-.001	(1×10^{-4})**			+	.001	(2×10^{-4})**		
(Pseudo) R^2			.820					.691			
# of observations			20,480					15,360			

Notes: ** p< .01, * p< .05

The factor of estimation error is not included in our analysis of the numerical optimization method (see section 3.2).

The inclusion of estimation error has a negative effect on the performance of the attractiveness heuristic, as expected.

Finally, the estimation results of factor time is only significantly negative for the attractiveness heuristic which confirms that only this rule converges to the optimal solution. The interaction effects across all factors are exactly contrary to the corresponding main effects which indicate that all influences on the performance are overcome over time. So it can be concluded that all simulation factors have no or only a marginal impact on the performance of the attractiveness heuristic and all negative effects diminish when the heuristic is applied subsequently over time.

6 Discussion and Conclusions

We analyzed the performance of four different allocation methods by varying experimentally all factors incorporated in the profit objective function. The performance of the methods is investigated under realistic market conditions, the existence of competitors and the imperfect knowledge of unobservable demand parameters.

We conclude from the scenario results in which no error in demand parameters is assumed that percentage-of-sales outperforms a naïve solution of equal distribution, but that the solutions provided by FAWF are far superior to the other rules and are robust to all changes in the simulation design. The results of the scenarios which assume an estimation error are quite surprising as FAWF even outperforms solutions provided by numerical optimization in most scenarios. Only in the scenarios characterized by strong heterogeneity of the portfolio and a modified exponential response function numerical optimization may outperform the attractiveness heuristic. Thus, our simulation results indicate that numerical optimization is much more sensitive to estimation error than the attractiveness heuristic. In fact, the inclusion of observed past sales overrides the negative effects due to noisiness in the parameters. Similarly, FAWF still outperforms significantly the simpler rules which do not take any unobservable demand parameters into account and therefore are not exposed to noisiness in the parameters.

Our study identified heterogeneity of elasticities and the elapsed time since launch across the portfolio as the most critical variables reducing the performance of the naïve solution, percentage-of-sales, and the attractiveness heuristic. The performance of the naïve solution is further strongly and negatively affected by heterogeneity in the sales base across the portfolio. Contrary, numerical optimization provides better solutions if the portfolio is rather heterogeneous. Our analysis of the factor time reveals that only the attractiveness heuristic converges to the optimum if applied subsequently.

Two main implications for practitioners may be derived from our simulation study. First, we provide strong support for the usefulness of the FAWF heuristic as it shows a high degree of flexibility in the face of a multitude of different market situations and is robust to all kind of changes in our simulation experiment. It provides solutions which are much closer to the profit maximum compared to simpler rules, such as the naïve solution or percentage-of-sales on the one side. And it is not as sensitive to estimation error as numerical optimization on the other side. Only if true demand parameters are known numerical optimization by definition provides optimal values. However, such a situation is unrealistic. Second, our study indicates that practitioners should be not too concerned about noisy parameters due to limited information about future trends or a lack of data and insufficient knowledge of econometric estimation if they apply an approach such as the attractiveness heuristic for budget allocation. Although the estimation error hampers slightly the performance in the beginning, the inclusion of the observable sales outcome outrides the negative effects after a few iterations. As even small estimation errors are unavoidable, this finding contradicts conventional wisdom which holds that by using simpler heuristics the allocation solution are achieved at the expense of poorer profit performance (Blackburn and Millen 1980).

Our study is also subject to a few limitations. The simulation factors are limited to the factors that characterize our profit maximization problem setting. For other settings, other factors might be relevant. However, we believe that this setting is quite realistic as it considers various forms of dynamics, portfolio effects, several marketing activities, competition, and noisy demand parameter information. Our focus is on estimation error in demand parameters, but not on specification error, i.e. assuming a wrong demand model. Since only numerical optimization requires the explicit specification of a demand model but not the other methods, we believe that the performance of that method is negatively affected. This raises even more concern about the practical application value of numerical methods.

For future studies we recommend to analyze and compare the performance of new and old heuristic methods developed in marketing science by a dynamic comprehensive simulation framework, as developed in this study, which also impose an estimation error on demand parameters to simulate realistic scenarios. Hopefully our work will motivate such efforts. Furthermore, we provide a new approach of analyzing the driver of convergence properties for further research.

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DEMOGRAPHICS

Name:	Nils Wagner
Date of birth:	19.12.1982, in Schleswig (Germany)

EDUCATION

05/2008 – current	University of Cologne and University of Passau, Ph.D. Candidate in Marketing
10/ 2003 – 04/ 2008	University of Kiel, Graduate Studies in Business Administration with Majors in Innovation, New Media, Marketing, and Organisation (Diploma in Business Administration)
10/ 2003 – 04/ 2008	University of Kiel, Graduate Studies in Economics with Majors in Statistics, and Econometrics (Diploma in Economics)
10/ 2007 – 12/ 2007	University of Warwick (UK), Graduate Studies in Business Administration
10/ 2002 – 03/ 2003	University of Karlsruhe, Graduate Studies in Business Engineering
07/ 1993 - 06/ 2002	High School Domschule (Gymnasium), Schleswig

ACADEMIC POSITIONS

05/ 2008 – 04/ 2011	Lecturer and Research Assistant, Chair of Marketing and Services, University of Passau
08/ 2006 – 07/ 2007	Student Assistant, Chair of Innovation, New Media and Marketing, University of Kiel
10/ 2005 – 07/ 2007	Student Tutor of Statistics I and II, Chair of Statistics and Empirical Research, University of Kiel
10/ 2004 – 07/ 2006	Student Tutor of Linear Algebra, Institute of Statistics and Econometrics, University of Kiel

PROFESSIONAL EXPERIENCE

07/ 2011 – current	Consultant at Simon, Kucher & Partners, Munich
01/ 2008 – 02/ 2008	Internship at BayerSchering Pharma AG, Berlin
11/ 2006 – 07/ 2007	Junior Consultant at Cornberg Consulting GmbH, Flensburg
12/ 2006 – 05/ 2007	Internship at NeuroScienceAdvice, Kiel
08/ 2006 – 10/ 2006	Internship at Cornberg Consulting GmbH, Flensburg

Nils Wagner October 17, 2011