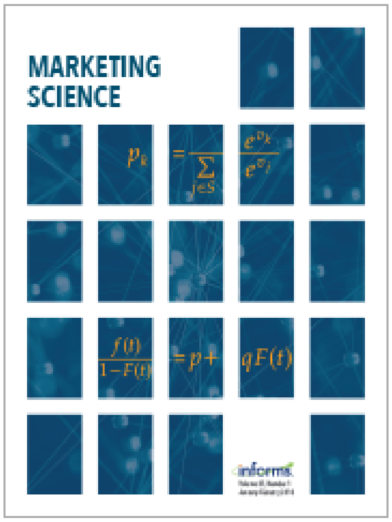

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PRACTICE PRIZE PAPER

Managing Advertising Campaigns for New Product Launches: An Application at Mercedes-Benz

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Abstract. The launch of a new product is one of the most critical activities that product and brand managers are faced with. It requires a substantial communications budget to introduce the new product to the market. As the number of media channels proliferates, however, managers are increasingly held accountable to demonstrate the efficient use of resources. This article introduces a new decision support tool to optimize advertising campaigns for new product launches based on lessons learned from an ex post analysis of prior campaigns. The tool builds on a distinct data collection approach combined with econometric modeling to produce advertising elasticities, which is the key information in the media mix optimization. The approach was implemented at Mercedes-Benz and applied to four major new car launches in Germany in 2012 and 2013. It revealed estimated savings of 15%–30% or EUR 2 million per campaign from a more efficient use of resources.

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Keywords: advertising effectiveness • resource allocation • new product launch campaign • ordered logit models • single-source data

1. Managerial Problem

The launch of a new car model is one of the most critical activities that automotive product and brand managers need to deal with. New car models—be it a model new to the market or the introduction of the next generation—are extremely important for managing portfolios, stimulating sales, and meeting expectations of investors (e.g., Pauwels et al. 2004). Mercedes-Benz, one of the leading global premium car manufacturers, failed to invest in its car portfolio in the 1990s. As a result, the company suffered heavily from stagnating sales and falling market capitalization over a decade. Mercedes-Benz eventually reevaluated its strategic priorities and started a new product offensive with more than 30 new car models between 2012 and 2020 (Daimler 2015). According to the chief executive officer, Dieter Zetsche, this strategic initiative is the key driver behind the lift up in sales from 1.28 million sold cars in 2010 to 2.00 million cars in 2015, which made Mercedes-Benz the world's strongest growing premium car brand (Daimler 2015; see also https://www.daimler.com).

This new model offensive, however, comes with another challenge. Launching a new car needs to be backed up with an advertising campaign to make target customers aware of its availability and features. Such a campaign requires a substantial advertising budget of several million dollars. Like other manufacturers, the Mercedes management is under increasing pressure to justify its campaign budgets. Investors and other stakeholders require doing more with less (i.e., to increase the efficiency of media expenditures). This raised the question of whether and how these efficiency gains can be achieved.

Indeed, management felt there was potential for significant efficiency gains from better launch campaign management. A launch campaign usually lasts for four to eight weeks. During that short time period, sales are not a meaningful outcome variable. The interpurchase time for cars is long, and buyers may start their decision process several months before the actual purchase (e.g., Urban et al. 1990). The key performance indicator (KPI) for Mercedes-Benz and other original equipment manufacturers (OEMs) therefore is recognition of the advertising campaign and other brand knowledge-related KPIs.

For each new model campaign, management set a goal for the recognition rate and assigned a budget allocated across different media channels. Sometimes the goal was not met in the past, but most often goals were met or even overachieved. Management noticed that the productivity of an advertising dollar varied quite substantially across successful campaigns, suggesting room for productivity gains. These gains may be realized from a lower budget and/or a better media mix. To unlock this potential, however, Mercedes-Benz needs to know the advertising production function that describes the relationship between recognition and advertising investment. Knowing the production function is key to identify the required budget level and its optimal allocation for achieving the target recognition level and to avoid overspending.

This paper introduces a model to estimate the advertising production function of launch campaigns for relevant advertising KPIs such as recognition. The model and its implementation as a new strategic monitoring tool in Mercedes-Benz' launch campaign management are the key contributions of this paper. The tool accumulates and exploits knowledge of advertising efficiency from prior campaigns to set future campaign budgets. Because not only Mercedes-Benz may benefit from efficiency gains in launch campaigns, the model should also be relevant to other car manufacturers and other durable goods markets with long interpurchase times.

Estimating advertising efficiency is not a new problem. In principle, econometric market response modeling offers a well-established methodology (Hanssens et al. 2001). However, these models usually refer to advertising–sales relationships and use aggregate data. In our case, advertising response refers to launch campaign KPIs, such as recognition, that cannot be modeled in the same fashion. Hence, we need another approach. In addition, the use of aggregate data are not feasible because a typical launch campaign for a car lasts only four to eight weeks, generating by far too few observations. As a result, we also need an approach to build up an appropriate database at the individual level. Our solution to the sample size issue is to collect data on exposure to various media from target customers through a representative online survey. Matching individual media consumption with the media schedule of the campaign enables us to measure the opportunities-to-see (OTS) by channel, which we then convert into individual-level spend data. As a result, we have a single-source data set with sufficient observations and variance to estimate an econometric marketing spend model that relates to launch KPIs.

The implementation of the model had a major impact on Mercedes-Benz and significantly improved its launch campaign management capabilities. The tool was key to realizing an estimated savings of 15%–30% or up to EUR 2 million per campaign. We have verifiable evidence that the organization significantly improved its advertising productivity. The model eventually became the standard for monitoring Mercedes' integrated advertising campaigns in Germany.

We organize the rest of this article as follows: We start by describing the campaign background and the earlier process of campaign budget setting. We then introduce our model and its use as a decision support tool in the new process. We subsequently discuss sampling and methodology, which is followed by presenting model estimation and its results. We proceed with demonstrating the impact of the model at various levels and conclude with a summary and limitations.

2. New Product Launch Campaign Management at Mercedes-Benz

In this section, we provide information on the new product launch campaigns and the budget setting process at Mercedes-Benz, which form the application background of this study.

2.1. Background on Campaigns

Mercedes-Benz offers cars for most segments of the global automotive market, including compact cars (A/B-class), medium-sized cars (e.g., C-class), upper-medium sized cars (e.g., E-class), luxury and sports cars (e.g., S-class, SLR), and SUVs (e.g., M-class). The extension of the car portfolio is an inherent part of Daimler's growth strategy (Daimler 2015). The company introduced several new car models into the German market and other country markets during the last years. These new product launches include both the next generation of a model such as the A-class and models that are new to the market such as the Mercedes CLA. We applied our methodology to brand advertising campaigns on *four* of these major new car model introductions into the German market in 2012 and 2013. Each campaign lasted between five and eight weeks and used public, private, and pay TV channels; newspapers; magazines and inserts; and online banner advertising. The budget per campaign totaled several million euros. Campaigns were designed as integrated media campaigns; that is, motives, stories, and design elements were consistent across media. Each campaign had a clear target customer definition that was based on age and household net income.

For example, a campaign on the launch of a new car generation in a crossover segment focused on customers aged between 35 and 69 years with a net income of EUR 3,000 or higher. One-sided and double-sided print advertisements for this campaign were delivered in eight weekly magazines and five monthly magazines. The ads showed the new car with a slogan that put forward an innovative feature (e.g., new safety feature). It also announced the availability date at the dealership and suggested to ask for a test drive. The campaign also used 15 public, private, and pay TV channels to show commercials and placed banner ads across 11 websites including car-related websites and websites of national newspapers and magazines. The TV commercials were all 40 seconds long and presented the same story. Banner ads were largely consistent with the print ads but did not show as much information because of size restrictions.

For budget decisions, media expenses per outlet are aggregated at three channels representing TV, print media, and online media. For confidentiality reasons, we cannot report the exact expenditure figures. TV expenditures accounted for the lion's share, followed by print and online expenditures.

2.2. Advertising KPIs to Monitor Launch Campaign Success

Given the long interpurchase time and high-involvement decision process for cars (e.g., Urban et al. 1990, Naik and Peters 2009), sales are a very noisy measure in the short run. Nevertheless, an emerging literature stream shows there is a strong link between mind-set metrics and future transactions (e.g., Stahl et al. 2012, Hanssens et al. 2014). Conceptually, mind-set metrics are informative and predictive for the economic success of an advertising campaign because they are logically a precursor of customer acquisition and retention that drive sales and profits (e.g., Rust et al. 2004b). Because it is unlikely to pick up any sales signal from a launch campaign, Mercedes-Benz and other OEMs focus on intermediate mind-set metrics such as recognition as KPIs to assess the success of their advertising campaigns. The primary objective of these campaigns is to inform potential customers about the new car and to strengthen brand relationship.

Mercedes-Benz collects data related to the various brand communication activities from regular customer surveys throughout the year. Behavioral response of target customers toward an advertising campaign is measured in terms of a mind-set hierarchy. The marketing literature on automobile markets has a long tradition in modeling hierarchy-of-effects systems. For example, Urban et al. (1990) proposed a system that models the whole purchase process from being aware to the final purchase. Naik and Peters (2009) suggested a hierarchical model to measure media synergies with respect to car dealer visits and car configurator visits. Their hierarchy refers to the hierarchical interaction of online and offline media channels. Our focus is on a hierarchical advertising response process that occurs at the start of the purchase process or even earlier. It is similar to a model early introduced by Farley et al. (1976) and proposes a specific hierarchy of advertising mind-set metrics.

In the following, we use the terms "mind-set metric" and "advertising KPI" interchangeably. *Recognition* measures how many target customers do remember the specific advertisement they were exposed to in a specific media outlet. *Involvement* shows how well the advertisement worked and whether the message was relevant to the target group. *Motivation* shows whether the advertisement strengthens the brand relationship and calls for action among target customers. Each KPI is operationalized in terms of relative frequency (percentage of target customers). We measure whether an individual recognizes the advertisement, is involved, and is motivated. The hierarchy implies that a motivated individual must also be involved and an involved individual must have correctly recognized the ad before.

2.3. Prior Budget Setting Process

Before the implementation of the new model, the budget setting process at Mercedes did not incorporate *quantitative* information of an advertising production function, which was not available. The key elements of this process can be described as follows.

It all starts with the communication strategy for the new car model. Senior management sets long-term sales and market-share goals, which are converted into the target recognition level for the launch campaign. From previous campaigns, an average productivity rate in terms of recognition rate per invested euro is available and used to obtain the initial budget. This budget sets the scale. In the following, it is reduced or increased by factoring in characteristics of the new car model, the market segment, the competitive situation, and the campaign itself. For example, a model new to the market requires a higher budget than the introduction of the next generation of an existing model. All this information is integrated in a rather qualitative manner to determine the final budget. The following allocation across media channels is geared to the common allocation observed in the specific car segment. This process is part of the business plan for each new car model and used to estimate the launch budget.

In the next section, we introduce our model and show how it is used as a strategic monitoring tool to improve the budget setting process at Mercedes-Benz.

3. Model and the New Budget Setting Process

3.1. Modeling the Advertising Production Function

The advertising production function provides the framework to derive the necessary budget level for achieving the KPI goal and optimizing the media mix. Our KPIs are mind-set metrics such as recognition that are measured at the individual level. We specify a response model for each advertising KPI. Consider recognition as an advertising KPI. For each respondent and communication channel (e.g., banner advertising), we measure whether he or she correctly recognized the advertisement in the channel. The resulting outcome variable is binary. We aggregate these binary outcomes across the three communication channels to create an ordinal variable y_{it}, where i denotes the person, t is the period (week) of measurement, and $y_{it} = 0, \ldots, 3$; y_{it} equals 0 if a person does not recognize the advertisement in any channel and equals 1 for correct recognition in one channel, 2 for correct recognition in two channels, etc. The outcome variable is ordered because recognition in two channels versus one channel reflects a deeper advertising response; however, we cannot say how much "better" the response is.[1]

For ease of exposition, we suppress the index for KPI. Let y^*_{it} be a latent variable with

$$\ln y^*_{it} = a_i + \mathbf{b}'_i \ln \mathbf{ADV}_{it} + \mathbf{g}'\mathbf{Z}_{it} + u_{it}, \qquad (1.a)$$

where $\mathbf{ADV}_{it}$ is a vector collecting the stocks of expenditures on person i until period t across media channels (TV, print, and online), $\mathbf{Z}_{it}$ is a vector of control variables, a_i, $\mathbf{b}_i$, and $\mathbf{g}$ are parameter vectors to be estimated, and u_{it} denotes an error term following a standard logistic distribution. We do not observe y^*_{it} but y_{it}, the ordinal outcome of recognizing the advertisement:

$$\begin{aligned} y_{it} &= 0 \quad \text{if } \ln y^*_{it} \le q_0 \\ &= 1 \quad \text{if } q_0 \le \ln y^*_{it} \le q_1 \\ &= 2 \quad \text{if } q_1 \le \ln y^*_{it} \le q_2 \\ &= 3 \quad \text{if } \ln y^*_{it} > q_2. \end{aligned} \qquad (1.b)$$

The q's are unknown threshold parameters to be estimated with the parameters of Equation (1.a). Here, a_i is an individual constant, and vector $\mathbf{b}_i$ collects individual advertising sensitivities for the three channels. We assume the individual parameters follow a normal distribution. Vector $\mathbf{Z}_{it}$ includes the log of a competitive brand sympathy index and period dummies to control for weekly shocks such as competitive advertising campaigns.[2] It also incorporates a dummy variable that reflects the additional sampling source TNS Infratest used to recruit participants, which we explain later. Our ordered logit (1) model offers a few noteworthy features that we discuss subsequently.

Heterogeneity. It seems reasonable to assume that participants respond differently to advertising stimuli. In addition, there may be systematic personal differences in recognition rates that are unobserved to us. We effectively control for unobserved customer heterogeneity by specifying the intercept (baseline effect), a_i, and advertising coefficients, $\mathbf{b}_i$, to be distributed multivariate normal.

Nonlinearity and Interaction. By construction, the ordered logit model is nonlinear because the probabilities of the ordered categories must sum to 1. As a result, the marginal effect of a channel's expenditures depends on the category probabilities, which are a function of the other channels' expenditure levels. The latent variable function (1.b) is linear in parameters. However, by taking the antilog, it is straightforward to show that the underlying response function is also nonlinear and corresponds to the multiplicative model (Hanssens et al. 2001). By construction, this model assumes synergy among media channels. The assumption seems reasonable for integrated advertising campaigns and respondents that are exposed to the same advertisement across multiple media outlets. We later test for additional interaction effects that relate to interactions between advertising sensitivities.

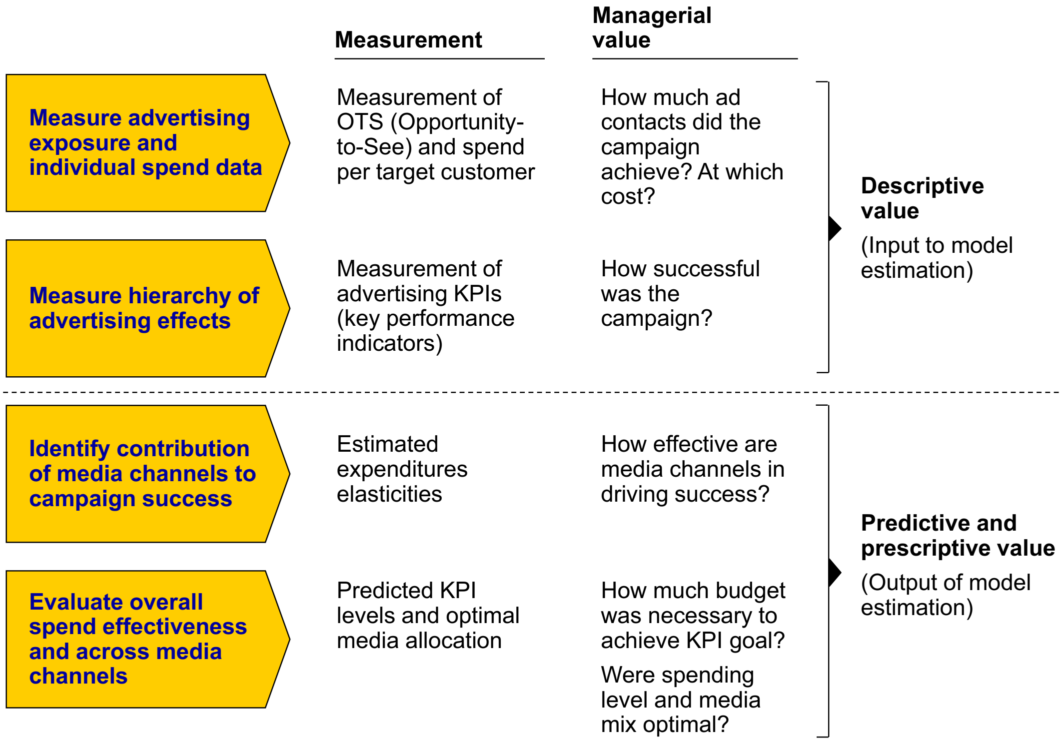
Advertising Dynamics. Advertising response usually shows carryover effects. To capture such effects, a rich literature has evolved offering numerous dynamic modeling approaches such as (autoregressive) distributed lag models, dynamic linear models, and time-series models (e.g., Hanssens et al. 2001), to name a few. The estimation of these models, however, requires repeated measurements over time, which are not available to us. Instead of explicitly modeling carryover, another powerful way of implicit measurement has been suggested through the creation of stock variables (e.g., Nerlove and Arrow 1962, Broadbent 1979). Because we collect data on advertising exposure for each individual from the inception of the campaign, we can construct stock variables. Specifically, we adopt the goodwill stock approach by Nerlove and Arrow (1962) that has been most widely used in the literature (Köhler et al. 2017). We provide details on its measurement when we discuss our method for measuring advertising exposure.

Brand Recall Bias. There may be concerns about a possible bias with respect to the advertising KPIs. It is well known that a better recall of advertisements is characteristic for brands that provide higher equity to individuals (Keller 1993). We control for such biases and for the effect of competition by including a competitive brand sympathy index. This index measures the overall sympathy for Mercedes-Benz relative to its key competitors Audi and BMW.

3.2. Management Information Delivered by the Model

The new model plays a key role in the revised budget setting process. Before we turn to this process, we describe how estimating model parameters and using the model output delivers important information of managerial value at different levels. Figure 1 summarizes which types of information are delivered and what kind of managerial questions they answer.

Figure 1. (Color online) Management Information Delivered by the Model



In the following, we describe how the calibrated ordered logit model is used for determining the optimal campaign budget and media mix.

Setting the Total Campaign Budget. Figure 2 illustrates the advertising production function with respect to advertising KPI. It shows two curves that connect total campaign advertising expenditures with the predicted KPI level, measured in number of target customers. The lower curve refers to the actually chosen media mix. Management can use this curve to predict the increase in target customers by increasing the overall budget but without changing the media mix.

The second curve is based on the optimal media mix. Provided that the actual media mix was not optimal, the predicted KPI level must be higher for each level of total budget. Management can use this curve in combination with the first one to answer various questions. Assume the campaign budget is set at EUR 6 million (m), and the KPI target was set at 2 m motivated target customers. It is now easy to obtain the savings potential of EUR 1.5 m that is realized from reducing the total budget to EUR 4.5 m but allocating the budget in an optimal way (see reading example 1 in Figure 2).

Optimizing the Media Mix. We obtain the optimal media mix by maximizing the advertising KPI at the given campaign budget level. The solution depends on which KPI is to be maximized and is derived in a straightforward manner from the advertising KPI hierarchy. The hierarchy represents a combination of conditional probabilities at the individual level:

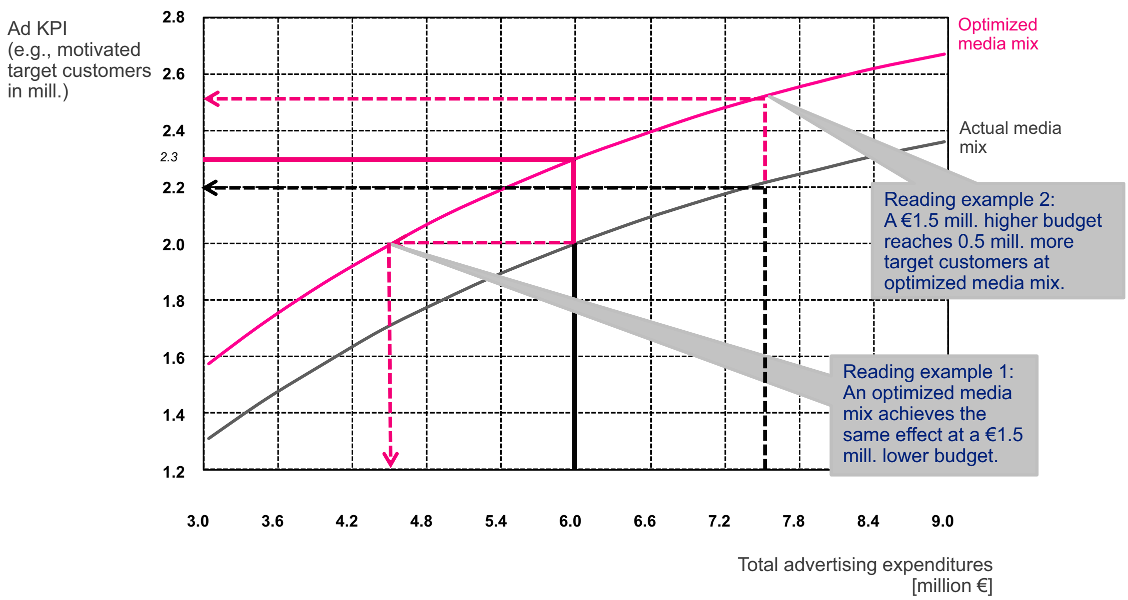
$$P(M|T) = P(M, I, R|T) = P(R|T) \cdot P(I|R, T) \cdot P(M|I, R, T), \tag{2}$$

where $P(M\,|T)$ denotes the probability for being motivated, M, conditional on being a target customer (T); $P(\mathrm{R}\,|\cdot)$ denotes the conditional probability for being aware, R; and $P(I\,|\cdot)$ denotes the conditional probability for being involved, I. Because in our advertising hierarchy individuals at a later response stage are a subset of the preceding stage, we have $P(M|T) = P(M, I, R|T)$.

In a representative target customer sample, we can aggregate these probabilities and express the proportion of motivated customers, P_M, as a function of advertising stocks. Because a carryover of 1 appears to be a reasonable assumption for our short-lived campaigns (for details, see Section 4.2), the problem reduces to a constrained static maximization problem for P_M:

$$\max_{\mathbf{ADV}} P_M = P_R(\mathbf{ADV}) P_{I|R}(\mathbf{ADV}) P_{M|I,R}(\mathbf{ADV})$$
$$\text{subject to} \quad B = \textstyle\sum_{l \in L} ADV_l \quad \text{and} \quad ADV_l \geq 0, \tag{3}$$

Figure 2. (Color online) Use of the Model to Predict Advertising KPI Levels and Optimize Media Investments (Disguised Numbers)



where B measures the total campaign budget. In Online Appendix C, we show how to derive the optimal budget allocated to channel l, ADV_l^*. It equals

$$Adv_l^* = \frac{e^*_{P_R,Adv_l} + e^*_{P_{I|R},Adv_l} + e^*_{P_{M|R,I},Adv_l}}{\sum_{l\in L} e^*_{P_R,Adv_l} + e^*_{P_{I|R},Adv_l} + e^*_{P_{M|R,I},Adv_l}} \times B,$$

$$\text{with} \quad e^*_{P_R,Adv_l} + e^*_{P_{I|R},Adv_l} + e^*_{P_{M|R,I},Adv_l} \ge 0$$

$$\text{and} \quad \sum\nolimits_{l\in L} e^*_{P_R,Adv_l} + e^*_{P_{I|R},Adv_l} + e^*_{P_{M|R,I},Adv_l} > 0, \forall l \in L, \tag{4}$$

where e^*_{P,ADV_l} measures the elasticity of a (conditional) probability with respect to (w.r.t.) the expenditures in channel l in the optimum. Note that our optimization problem is fairly simple. We are not interested in optimal allocation over time. Hence, we do not address a dynamic optimization problem. In addition, we do not consider competitive response, which is a second-order phenomenon in light of the limited campaign length.

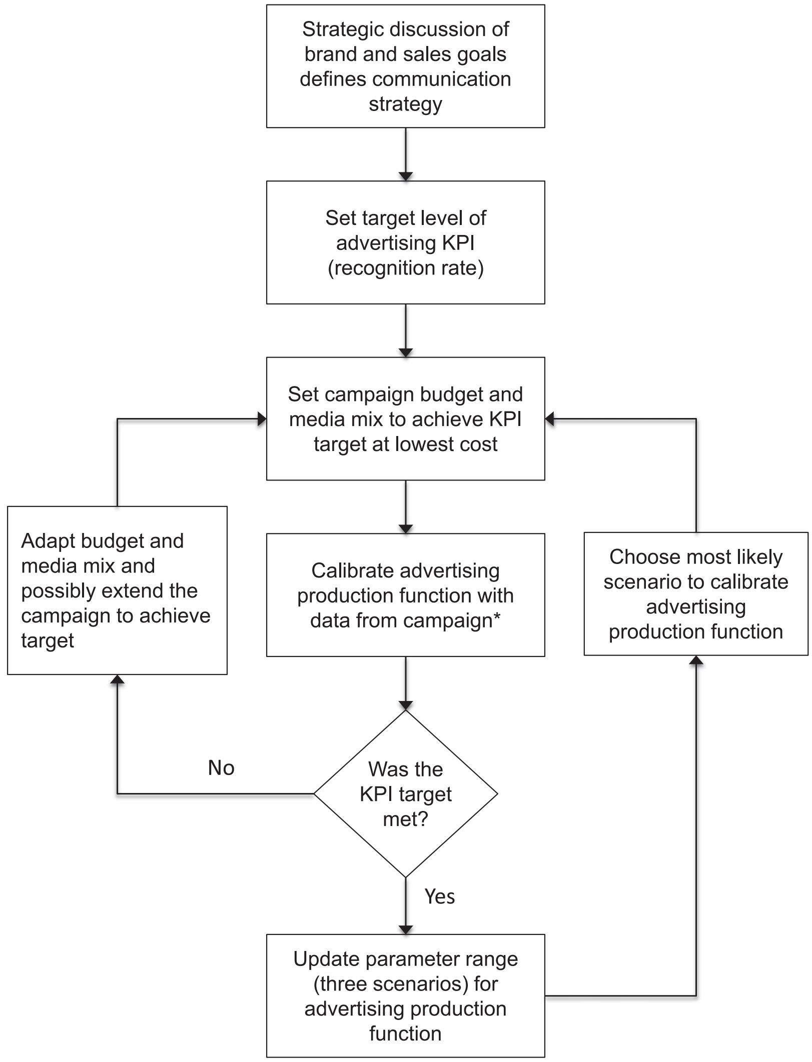
The structure of the allocation formula is intuitive and consistent with more general allocation solutions (e.g., Fischer et al. 2011). A channel receives the more budget the higher its effectiveness is across the advertising KPIs relative to the effectiveness of other channels. As a result, the allocation formula considers both the hierarchical nature of KPIs (expenditures on TV improves recognition rates) and KPI-specific elasticities (TV elasticity might be larger for motivation than for recognition). Expression (4) can also be adapted if management wants to focus on a specific advertising KPI such as recognition. In this case, elasticities for the other two KPIs simply cancel out. We compute elasticities from the ordered logit model (1) by multiplying the estimated advertising parameter for the respective media channel with (1 − conditional probability of the focal advertising KPI).

3.3. New Budget Setting Process

Our model is the core in the revised budget setting process (see Figure 3). The new process starts again with the sales goal and communication strategy from which the target level for the advertising KPI is derived. Recognition remains the objective KPI for budget setting. Involvement and motivation are increasingly considered within the organization according to Mercedes-Benz executives. They are part of compensation packages for creative agencies and used in internal models to predict brand equity and sales. However, it remains a task for the future to base budget decisions on motivation KPI goals. Our model is well prepared for this.

The ordered logit model (1) provides the advertising production function, which precisely prescribes what overall budget and media mix are required to achieve the target recognition rate at minimal cost. Its immediate use in a normative way, however, requires knowledge of effectiveness parameters before the start of the campaign, which are not available. In principle, one could start estimation already after the first week. But it is only meaningful to do so after five to six weeks for practical reasons. First, a typical campaign requires to book advertising time and space in more than 30 TV channels, print outlets, and websites. Although less of an issue for online media, scheduling offline media requires a lead-time of several weeks. Second, we also need

Figure 3. The New Budget Setting Process Across Campaigns



*Reliable parameter estimates are only available toward the end of the campaign (after five to six weeks).

several weeks of observations to allow for the buildup of advertising goodwill.

Given that parameter estimates are only available toward the end of a campaign, our decision tool chooses from a range of parameters available from prior campaigns for planning the budget of the next campaign (see Figure 3). Hence, decision making still involves a substantial qualitative component in the new budget setting process. But, compared with the earlier process, the way in which information is integrated is now consistent, transparent, and model based.

How exactly does the model help set the advertising budget for the next campaign based on previous campaigns? The key element is the advertising production function estimated from the first campaign, which is constantly updated with information from successive campaigns. Using the advertising production function together with the target recognition rate provides the required campaign budget (see Figure 2). Assuming an optimal media mix, we do this for every new campaign by using the updated base production function. Our working hypothesis was that the basic underlying mechanism that translates media expenditures into KPI rates remains the same across campaigns, which proved to be the case. However, advertising and other model parameters are by no means assumed to be the same but shift the production function. The base production function and its potential shifts are implemented in a simple but powerful decision support table that is used to set the budget for the next campaign. This table shows predicted KPI levels that are associated with budget levels in EUR 500,000 steps. Results are available for three scenarios: average, underperforming, and overperforming. The updated base production function delivers the average scenario. The two other scenarios are obtained from the shifted production function where parameters are updated with learnings from every new campaign. For the first application, a simple ±10% adjustment to the average scenario was made.

Setting the new campaign budget now requires the target recognition rate and a decision for the most likely scenario. For this decision, management considers the quality of the ad copy based on ad copy tests, the newness of the car to be launched, the competition in the car segment, and the likelihood that the chosen media mix is optimal. The media mix allocation itself is based on market knowledge and learning from prior campaigns. Market knowledge means that the allocation of recent competitive launches in the respective segment is used as a starting point for the allocation. This allocation is refined by bringing in the insights from model-based optimal allocations of preceding campaigns. For example, campaigns II and IV focused on a largely overlapping target customer group. Consequently, the ex post optimal media mix of campaign II set the allocation for campaign IV.

Finally, we note that the calibrated production function can be used to determine how much additional budget is needed to achieve the goal in situations when the recognition goal is not met (see Figure 3). This situation happened with one of the campaigns. The additional investments recommended by the model indeed delivered the forecasted increase in recognition rate.

4. Data Collection and Method

In this section, we describe the data collection and our method to create a single-source database, which is the most rigorous approach to measure advertising effectiveness (Danaher 2017). We have a single-source database because we measure both advertising exposure across channels and response in terms of advertising KPIs for the same person. This information is collected via an online survey administered to a random sample of target customers.

4.1. Sampling and Questionnaire

Campaign data are collected for a period of up to 10 weeks via a TNS representative online panel, which Mercedes-Benz has been using for its advertising tracking studies for a long time. The survey extends to two weeks after the end of a campaign to better capture carryover effects.

Recall that Mercedes defines the target group on the basis of age and income for each campaign's media planning. The target group definition also specifies the population from which the random sample of at least 800 target customers is drawn. Following Rust et al. (2004a), we apply individual sampling weights to correct for variations in the probability selection of respondents within the defined population. As a result, we have a sample available that is representative along various other sociodemographic characteristics (geographies, household size, etc.) for the defined target population.

Because the target group of a new premium car tends to be rather small, the standard TNS panel may not provide a large enough sample of these target customers. TNS therefore uses an additional source (approximately 15% of the total sample) to recruit participants of the survey to make sure the final sample size includes more than 800 target customers. We control for potential systematic influences on advertising response from this additional sampling source when estimating the response model.[3]

When starting the online questionnaire, respondents need to answer several questions to check for their product category involvement and the actual usage of cars. Then, information on the car brand, the date of purchase, and the market category of the currently owned as well as previous car is gathered. The questionnaire continues with questions about general sympathy for competitive car brands and then presents items to measure (unaided) advertisement recognition, involvement, and motivation (see Online Appendix A) and media consumption habits (see Online Appendix B). Our recognition measure is unaided because respondents are exposed to several debranded advertisements. They must recognize the ad and allocate the correct brand to it. Involvement and motivation are each based on responses to three "yes/no" items. If two of these items are answered with "yes," we code 1 for the respective KPI and 0 otherwise. The decision to use two out of three items as a threshold might miss a deeper conceptual foundation. Here, we follow what Mercedes-Benz has been using for many years and found to be relevant for its business.

Respondents' media consumption habits are key for constructing our media exposure variables. As an example, we show the respondent a list of daily newspapers and ask how often he or she usually reads or browses through the newspaper during the week. We ask similar usage and frequency questions for TV channels and websites.

The survey closes with several demographic questions. Survey items and brands are rotated by chance over respondents to avoid order and priming effects. Depending on the campaign, we eliminated between 1% and 3% of respondents who completed the questionnaire in less than 12 minutes. A pretest revealed that participants needed at least 12 minutes to read all items and mark their answer. The average time needed to complete the questionnaire was about 40 minutes. TNS made sure that the survey was executed in a way that minimizes respondents' fatigue.

4.2. Method

The creation of a single-source database is a key feature of our decision tool. Research on advertising effectiveness using single-source data are very limited; examples include Danaher and Dagger (2013), Deighton et al. (1994), and Tellis (1988). The reason is that it is challenging to measure the exposure of a single person with a specific advertisement in a reliable and cost-effective way. An even greater challenge is that we need these exposures for the same person across different media (TV, print, and online). There are well-known examples from industry (e.g., Katz 2003) to measure media exposure for TV by using a set-top box (Nielsen's people meter) or via a survey to study exposure in newspapers and magazines (conducted by Mediamark Research Inc.). Other examples include Arbitron's panel for radio and comScore's panel for internet usage. Mercedes-Benz also used surveys in the past to collect information about the media behavior of its target customers. However, these activities were not integrated to track the exposure of individuals across several media. "Apollo," a promising industry project that was to jointly measure TV, radio, newspapers, and internet usage, failed as a result of its high cost of implementation and reliance on a "portable people meter" (O'Regan 2008).

Basic Idea. A survey approach appears to be the only feasible solution to bring measurement needs and costs into balance. Our approach is to collect information about which specific media type a person regularly consumes and how often. We then match this pattern with the media schedule of the campaign to estimate media exposure.[4] The basic principle can be illustrated as follows.

Assume a respondent answers to watch TV channel X between 7 and 8 p.m. on two out of four weekends. Assume further an eight-week campaign shows one TV commercial on channel X during this time slot on each Saturday. From this media consumption behavior and media schedule, we infer that the respondent had cumulated OTS the ad of $4 = 2/4 \times 8$. Note that the ad becomes an OTS rather than a definite exposure. Reported media consumption may also suffer from memory bias (Danaher and Dagger 2013).[5] To reduce this error source, we incorporate a recall check that has been successfully used by Mercedes in its previous attempts to survey media consumption.

We further decrease respondent burden by asking only for media exposure to those TV channels, newspapers, magazines, and websites on which the advertisement was actually shown. The advertising agency provided the media schedule before the start of the survey to guide the selection of media outlets. Questionnaire items on the media usage are presented in Online Appendix B. The list of media outlets changed with the target group across campaigns.

Measurement of OTS. We now describe how we calculate individual-level OTS for television. From the questions on TV channel usage in the questionnaire (see Online Appendix B), we know how often a person watches a specific TV channel at a specific timeslot on a weekday and on a weekend. In our earlier example, the person said to watch a certain TV channel between 7 and 8 p.m. on two out of four weekends. Generally speaking, for time slot m and TV channel n, we estimate person i's viewing probability as

$$\hat{p}^{TV}_{i,mn} = \frac{r^{TV}_{i,mn}}{R^{TV}_m}, \quad \text{with } 0 \le r^{TV}_{i,mn} \le R^{TV}_m \quad \text{and } R^{TV}_m \in [4, 5], \tag{5}$$

where $r^{TV}_{i,mn}$ is person i's frequency of watching the TV channel n at time slot m. The term R^{TV}_m measures the total number of time slots available. It is five for weekdays and four for weekends. For the above example, the probability estimate is $(r = 2)/(R = 4) = 0.5$. Because respondents might over- or underestimate their regular TV viewing behavior, we ask a further recall question regarding their TV usage of the previous weekday or weekend, respectively. By relating the estimated sample average from this recall question to the average of expression (5) across all respondents, we obtain a probability adjustment factor w_{mn}. Using the media schedule, it is now straightforward to obtain the OTS for the advertisement shown to individual i in a TV channel and week t. It is given by

$$OTS^{TV}_{it,n} = \sum\nolimits_m w^{TV}_{mn} \hat{p}^{TV}_{i,mn} h^{TV}_{t,mn}, \tag{6}$$

where $h^{TV}_{t,mn}$ measures the number of commercial spots placed in TV channel n at time slot m during week t. Recall that our advertising response model (1) assumes advertising stocks by channel as predictors. We therefore compute the stock of OTS for TV in week t as follows:

$$SOTS^{TV}_{it} = \sum\nolimits_n \sum\nolimits_{s=0}^{t} c^s OTS^{TV}_{it-s,n}, \quad \text{with} \quad 0 \le c \le 1, \tag{7}$$

where c is the carryover rate. We perform a full grid search from 0 to 1—not only for TV but also for print and online. The lowest Bayesian information criterion (BIC) was associated with $c = 1$ in 9 out of 12 models (4 campaigns × 3 KPIs), suggesting that forgetting is negligible (i.e., decay = 0). Consequently, we assume a carryover of 1. Note that this is a data-driven assumption that appears to be particularly reasonable for our short campaign time frame of only a few weeks. We do not claim that this assumption holds for all future periods. We would certainly be in a better position to more accurately estimate the carryover coefficient if we had data from a longer time series available.[6]

Estimating cumulated OTS for newspapers, magazines, and online banner ads follows the same principle. It tends to be less complex for print media. For online banner OTS, we need to consider advertising impressions and the total number of page impressions to compute a web visitor's probability of receiving a banner ad impression. See Online Appendix B for more details.

To check for the validity of our survey-based OTS measurement, we compare the aggregate results by communication channel and campaign with external, aggregate OTS measures from established industry sources. The media agency of Mercedes provided these values. We obtain a high correlation of 0.77 with our proposed measure. We caution that the sample size includes only 14 observations at this aggregate level. However, there is further evidence from other studies that provides external validation of our measurement approach. Beed (1992) reports strong correlations between TV exposure measurements that were collected separately using a diary survey approach and people meters during a transition period from diaries to people meters. Danaher and Dagger (2013) also report a strong correlation between their survey-based exposure measures and ratings from trusted media sources. They range from 0.67 for TV to 0.98 for online media. On the basis of this collective evidence, we conclude that there is significant support for the validity of our measure.

Measurement of Individual-Level Stock of Expenditures. Because we have a representative sample of target customers, we can estimate the effective average cost of a (sample) contact in communication channel l, ac_l. For this purpose, we divide the total net campaign expenditures on the channel by the total cumulated OTS for the channel of the sample. Multiplying ac_l with the estimated cumulated individual-level OTS of a person (Equation (7)) produces the channel-specific stock of expenditures on person i in week t, which we use as predictor in our ordered logit model:

$$ADV_{it,l} = ac_l \cdot SOTS^l_{it}. \tag{8}$$

5. Estimation and Results

We use the maximum likelihood estimator implemented in LatentGold 4.0 (Vermunt and Magidson 2005) to estimate model (1). Because of the heterogeneity imposed on the constant and advertising sensitivity parameters, the likelihood function includes a multidimensional integral that is evaluated by using Gauss–Hermite numerical integration. Employing the expectation-maximization (EM) and the Newton–Raphson algorithms in combination solves the maximization problem of the likelihood function. We start with 500 EM iterations at maximum and switch to the Newton–Raphson algorithm to obtain the final solution. To minimize the danger of finding a local optimum, we use 500 random sets of start parameters.

Note that we estimate model (1) with cross-sectional data. The time index t assigns observations to different weeks of measurement. But we do not have repeated measurements for the respondents available. Model (1) belongs to the class of generalized linear models. It has been shown that the moments of the across-individual distribution of the parameter vector can be consistently estimated for these models, possibly with less precision compared with data with repeated measurements (e.g., Berry et al. 1995, Bodapati and Gupta 2004, McCulloch et al. 2005).

Our model may further be subject to a number of modeling/estimation issues, which we discuss in the following. We start with presenting our identification strategy.

5.1. Identification Strategy

The key question in model estimation is whether our advertising variables really cause the ad KPIs to move. Ideally, we would use data generated by a randomized, controlled field experiment. Because these data are not available, we ask whether the actual data generating process can be considered a quasi-experiment where randomization is the result of some external source (Manski 2007). We do have a source of strong external variation. This is the variation in media consumption across individuals in a randomly drawn sample. The media consumption behavior of an individual is independent of Mercedes-Benz' budget decisions and his or her expected advertising response. Put differently, it is very unlikely that a TV commercial causes an individual to change his or her TV watching behavior. This behavior is truly exogenous and random.[7]

Keeping this in mind, we can think of our design as a quasi-experimental setting with a continuous treatment variable of advertising exposure. The sample for each campaign includes a sufficiently large group of individuals who were not exposed to the ad in TV, print, or online. They represent the control group.[8] It is a key identifying assumption that their behavioral response is a valid counterfactual for the response that would have been obtained for an individual with exposure in the absence of exposure. Note that even though in all campaigns more money was spent on TV relative to print and online, we always observe individuals with larger OTS to print and online than TV. Online Appendix Table D.1 presents empirical evidence of significant variation in the treatment variables and the sizes of quasi-control and quasi-experimental groups across the four campaigns.

5.2. Endogeneity Issues

A common issue in advertising models is endogeneity that violates the independence assumption of the error term and predictors. Although a solid identification strategy helps reduce these issues, we do not claim that they are automatically solved. Four endogeneity issues might specifically affect our model and data. The first three issues arise from firm decisions. (1) Media budgets are the outcome of managers' decision making, which is more or less driven by the expected marginal impact on the advertising KPI. For example, if TV is perceived to be more effective, a larger portion of the budget goes into TV. As a result, the dependent variable drives the independent expenditure variable and thus may raise identification concerns (e.g., Fischer et al. 2016). These concerns clearly apply to aggregate brand-level data where budget decisions at Mercedes-Benz are made. Our identification discussion, however, shows that the media mix at the *individual* level is driven by media consumption habits and not an endogenous firm choice as that at the aggregate brand level. We therefore conclude that such aggregate-level endogeneity concerns are largely mitigated at the individual level.

(2) A similar line of argument pertains to decisions related to the individual customer. Managers may set the level of marketing-mix variables with at least partial knowledge of response parameters. As a result, the usual assumption that the marginal distribution of marketing-mix variables is independent of response parameters is violated (Manchanda et al. 2004). We believe that this type of endogeneity is unlikely to affect our data generating process. As is typical for campaigns in mass media, the advertising tactics were not individualized but aimed at an anonymous member of the defined target group. This does not only hold for TV and print media but also for banner advertising, for which management bought a fixed number of impressions per day and websites (no microtargeting).

(3) Endogeneity may occur in our application because the brand manager chooses media outlets that are more appealing to the target customer group. For example, high-income households are more likely to read business publications than the average household. This may cause a selection bias if not properly controlled for (Danaher and Dagger 2013). It has been shown in the econometric literature (Donkers et al. 2006) that there is no selection bias as long as model estimation is based on a random sample drawn from the same target group as that used for media vehicle selection. All campaigns satisfy this condition. It might still be argued that TV is better targetable along criteria such as age and income than is print and online media and thus attracts a larger share of the media budget. But there is no evidence for such an explanation. Both managers from Mercedes-Benz and its media agency explained that all three media offered a broad range of alternatives to effectively reach the specified target group.

(4) Our last endogeneity concern results from the fact that we can hardly claim our model to be complete. Omitted variables that affect the advertising KPIs may be correlated with variables in the model and lead to biased estimates. We account for unobserved heterogeneity, brand preference, and time fixed effects in the model (see Equation (1)), which should affect ad recognition. Note that including brand preference also controls for the effect that Mercedes fans self-select into seeing and recalling a campaign commercial. But we need to accept that we cannot control for every relevant source.

The discussion shows that we addressed endogeneity issues in various ways. Although we can minimize these issues, we must admit that it is unrealistic to solve every endogeneity issue.

5.3. Common Method Bias

Models based on survey data may suffer from a common method bias—even if data are collected over consecutive periods. A common method bias may arise if predictor variables and outcome variables reflect respondents' evaluations of the same object (Podsakoff et al. 2003). Because our predictor variables are constructed from general media consumption habits that are unrelated to specific Mercedes-Benz advertising campaigns and exogenous aggregate communication expenditures, a common method bias is not very likely to exist. Nevertheless, we used Harman's test to check for the bias but did not find any evidence for it (see Online Appendix D for details).

5.4. Estimation Results

Estimation of the ordered logit model (1) yielded satisfactory model fit across the four campaigns. The pseudo R^2 measure suggested by Vermunt and Magidson (2005) ranges from 0.20 to 0.68, which can be considered very good for individual-level data (Agresti 2002). In addition, we compare our model with other approaches to predict the categories of the ordinal outcome measure. Specifically, we consider predictions according to the maximum chance and the proportional chance rule as a benchmark (Hair et al. 2014). It turns out that the model always beats these benchmarks (see Online Appendix D for detailed results). We also compare predictions with a rival model that represents a hierarchical system of seven specific media-response equations. Our focal model outperforms this rival model in terms of classification (see also Online Appendix Table D.7).

For the sake of brevity, we do not report estimation results for every campaign. Table 1 shows the results for campaign IV. Online Appendix D presents results of the other campaigns. There are three sets of coefficient estimates that relate to the three advertising KPIs. The likelihood that a respondent recognizes the advertisement, is involved, or is motivated is higher if it refers to only one media channel compared with two or all three channels, as the estimated baseline effects show. We also note that this baseline effect varies considerably across individuals, reflecting fundamental customer heterogeneity in the focal mind-set metrics. Customer heterogeneity is also present with respect to advertising sensitivities, albeit not equally strong for each media channel and ad KPI. To avoid overparameterization, we restrict heterogeneity parameters to be 0 when the Wald statistic is below 3.84 and verify that this restriction is supported by a lower BIC compared with the unrestricted model.

Mean estimated advertising sensitivities vary across both the media channel and the dependent variable. The coefficient is highest for TV, followed by classical print media and online media. The stronger impact of TV probably results from the fact that TV is more influential on consumer affect than print and online (Vakratsas and Ambler 1999). For premium cars, affect seems to dominate cognition.

We note that a meaningful comparison of sensitivities should be based on elasticities, which we present subsequently. The basic picture, however, does not change. TV advertising sensitivities seem to increase from unaided advertisement recognition to the stage of being a motivated potential customer. This pattern is different for the two other channels. These differences play a key role for optimizing the media mix where the optimal allocation depends on the focal advertising KPI.

5.5. Robustness Checks

To verify that the model estimation results are robust, we performed several robustness checks.[9] First, note that our ordinal dependent variable aggregates customer responses to the ad across three channels. An alternative formulation would be a hierarchical system of models that estimates seven different media-response functions. This system includes three binary (ordered) logit models to model the response to each channel separately, three ordered logit models that aggregate the responses to each pair of channels, and our suggested ordered logit model (1). Although this system is more informative because it treats responses to just one channel, two channels, and three channels together differently, it also comes at the cost of parsimony. We compared the system with our implemented model (1) in terms of information criteria and hit ratio statistics (see Online

Table 1. Estimation Results for Campaign IV (Equation (1))

		(Unaided) Recognition		*Being involved*		*Being motivated*	
Dependent variable		Coefficient	Wald statistic	Coefficient	Wald statistic	Coefficient	Wald statistic
Baseline for Prob (y_{is} = l)			52.39		77.65		59.78
l = 0		—[a]		—[a]		—[a]	
l = 1		−6.080		−3.960		−5.163	
l = 2		−12.201		−10.084		−11.589	
l = 3		−19.257		−17.254		−18.902	
SD of baseline		16.222	21.99	16.765	11.64	18.276	9.59
Advertising stock by channel							
ln(*TV*)	Mean	0.267	12.36	0.289	9.35	0.308	6.30
	SD	0.038	10.27	0.085	12.36	0.082	11.22
ln(*Print*)	Mean	0.094	11.45	0.055	5.96	0.060	5.98
	SD	0.007	5.45	—	NS	—	NS
ln(*Online*)	Mean	0.030	10.29	0.062	10.69	0.036	4.02
	SD	—	NS	—	NS	—	NS
Controls							
ln(*Competitive brand index*)		0.214	6.81	0.377	5.74	0.507	9.53
Sampling source			11.38		8.06		NS
Source 1		—[a]		—[a]		—[a]	
Source 2		0.367		0.562		—	
Week dummies		—[b]		—[b]		—[b]	
Log likelihood		−1,040.31		−428.61		−392.46	
N (sample size)		930		384		329	

Note. NS, not significant (p > 0.05).
[a]Set to zero for identification purposes.
[b]Not reported (available upon request).

Appendix D). Model (1) always turns out to be the superior model.

Second, we changed model specification and considered different distributional assumptions of the dependent variable. Specifically, we estimated a linear model, a Poisson (count) model and a zero-inflated Poisson model. Results were robust (see Online Appendix D). We also found results to be robust to the exclusion of control variables (i.e., no controls at all and no period dummies).

Third, we checked for various alternative dynamic influences that might impact behavioral response. We specified time in a parametric fashion. The model did not turn out to be superior to our specification with period dummies. In addition, we interacted the advertising expenditure variables with time to test whether sensitivities change over the course of the launch campaign and afterward. Nested model specification tests rejected such a model extension (Greene 2012).

Finally, we constructed direct interactions between advertising channel expenditures (Naik and Peters 2009) and added them to the model. These extensions again were rejected in nested model tests.

6. Managerial Impact

6.1. Strategic Impact of Model Application

Table 2 summarizes the estimated elasticities across the four launch campaigns in 2012 and 2013, the media channels, and the advertising KPIs. Using Equation (4), we also show the resulting optimal media mix across campaigns and advertising KPIs. For confidentiality reasons, we cannot reveal actual expenditure levels and media allocations. The results offer important management insights that drive the discussion about designing new product launch campaigns.

First, results reveal that advertising elasticities are not the same for each KPI of the advertising hierarchy. Generally speaking, it is highest for the first stage of (unaided) recognition. It decreases over the next two stages but not necessarily in a monotonic way. For example, TV elasticities are higher in the motivation stage of campaigns I, II, and IV, but not for III. Elasticities for print and online media show similar patterns. Differences in elasticity across advertising KPIs may reflect different advertising sensitivity parameters (see Table 1 and Online Appendix D). But they also arise from varying saturation levels of KPIs that are a function of the media budget.

Second, the application of the model considerably helped resolve an ongoing discussion about the right media mix in light of the rise of online media. Traditionally, advertising for Mercedes cars has emphasized the TV channel. A working hypothesis was that TV was perhaps overrepresented and should be reduced in favor of online media. To the surprise of management, however, TV did not lose power at all but in fact could even be slightly strengthened. What elasticity estimates rather suggested was that resources be shifted from print to online media.

6.2. Financial Impact

Implementation of the model and the new budget setting process resulted in significant financial impact for Mercedes-Benz. The business plans for the newly introduced car models included an estimate for the campaign budget. This figure can be compared with the revised, actual budget after model implementation. From this, the head of Global Market Intelligence at Mercedes-Benz estimated the savings to be up to EUR 2 m per campaign (15%–30% efficiency gains). In total, these savings estimates add up to EUR 7–8 m across campaigns.

Validation of Estimated Savings. There is no reason to doubt these savings estimates by the company, but business plans and thus budget plans are developed with a substantial time lag (one to two years) before the actual launch of the campaign. Unfortunately, another counterfactual budget planning according to the former budget setting process did not happen. To cross-validate the estimated savings, we therefore try to estimate a baseline budget for each campaign ex post. For this purpose, we collected data from 108 launch campaigns in Germany in the period 2008–2011 and set up a descriptive launch budget model to estimate the impact of various budget drivers for which we know they were part of the previous process. The campaigns cover launches of cars new to the market, new generations, and face-lifts in the 12 largest market segments.[10] We have information available on the size of the segment (number of registrations per year), the expected relative sales two years after launch (number of registered cars relative to segment size),[11] the segment's competitive concentration (Herfindahl index), and the length of the campaign in weeks. We do not observe KPI goals, but we implicitly account for them by the expected relative two-year sales and segment size. KPI goals typically go up with higher market share goals and larger segments. We further include a dummy for campaigns of strategic competitors of Mercedes in the relevant launch categories, a dummy for 2010, and dummies for car makes. The dependent variable is the natural log of campaign budget. Continuous predictor variables are also in logs. The model is linear in these variables and estimated with ordinary least squares (OLS).

Results of model estimation are shown in Table 3. Note that R^2 is high, with 0.814, suggesting that our model describes the drivers of launch budget setting in the industry pretty well. Note that we do not make any causal claims. The vast majority of predictors show a significant influence on launch budgets.

Table 2. Estimated Elasticities and Implied Optimal Media Allocation by Launch Campaign

	(Unaided) Recognition		*Being involved*		*Being motivated*	
Focal advertising KPI	Elasticity	Optimal allocation (%)	Elasticity	Optimal allocation (%)	Elasticity	Optimal allocation (%)
Campaign I						
TV	0.177	77	0.037	77	0.082	77
Print	0.031	14	0.011	15	0.025	18
Online	0.021	9	NS	8	NS	5
Campaign II						
TV	0.130	67	0.073	70	0.094	73
Print	0.040	21	0.012	18	0.012	16
Online	0.024	12	0.009	11	0.014	11
Campaign III						
TV	0.096	52	0.099	65	NS	61
Print	0.021	11	0.017	13	0.017	17
Online	0.068	37	NS	23	NS	21
Campaign IV						
TV	0.130	68	0.036	69	0.078	71
Print	0.046	24	0.007	22	0.015	20
Online	0.015	8	0.008	9	0.009	9

Notes. Optimal media allocation is obtained from maximizing the focal advertising KPI under a budget constraint (see Equation (4)). Figures may not add up to 100% because of rounding errors. Elasticities are calculated based on estimated parameter means and conditional probability for the focal advertising KPI. Note that a channel may still be assigned a budget greater than 0 even if we do not measure an impact of that channel on the focal KPI. This situation occurs when the channel impacts a KPI of an earlier stage of the KPI hierarchy (see Equation (4)). Standard errors (not shown) are approximated by using the delta method. NS, not significant ($p > 0.05$).

Moreover, they provide parameters that enable us to reconstruct an alternative baseline budget for each of the four studied campaigns. For this purpose, we start with the observed mean budget by segment and adjust this budget by accounting for the type of new product introduction, the expected relative sales two years after launch, the length of the campaign, and the strategic competitor dummy variable.[12] All these drivers played a significant role in Mercedes' prior budget setting process. The assumption we make is that the drivers' estimated impact on own and competitive launch campaigns in 2008–2011 is a good proxy for their relative contribution to estimate the baseline budget.[13] Note that the size of market segment is already included in the segment-mean budget. Depending on whether we take the expected sales in the first

Table 3. Estimation Results for Drivers of Launch Campaign Budgets (2008–2011)

	Dependent variable: ln(*Budget for new product launch campaign*)	
	Coefficient	SE
Intercept	−3.636	2.062
Type of new product introduction		
New car model (1 = yes)	1.042	0.337
New car generation (1 = yes)	0.483	0.284
Car face-lift (1 = yes)	—[a]	
Market and competitive characteristics		
ln(*Size of market segment*)	0.498	0.141
ln(*Expected sales in first 24 months relative to segment size*)	0.231	0.104
ln(*Market concentration*)	0.250	0.257[b]
Campaign characteristics		
ln(*Length of campaign*)	1.751	0.137
Strategic competitor in segment (1 = yes)	0.557	0.332
Controls		
Dummy for year 2010	0.678	0.236
Dummies for car makes	—[c]	
Model fit (R^2)	0.814	
Number of launch campaigns (sample size)	108	

[a]Set to zero for identification purposes.
[b]Not significant ($p > 0.10$).
[c]Not reported (available upon request).

24 months after launch into account or not, we now estimate the range of savings for campaign budgets set by our model (see Section 3.2) and for actual budgets. Because the model output is only a recommendation in EUR 500,000 steps, the actual budgets reflect final adjustments as a result of other factors. We present boundaries of the 95% confidence interval obtained from our descriptive launch budget regression. Our estimates of actual budgets savings range from EUR 4.47 m (4.18, 4.77) to 9.45 m (8.84, 10.05) and appear to be slightly lower than estimated model-based savings from EUR 5.21 m (4.87, 5.56) to 10.19 m (9.53, 10.85). These ranges provide support for the savings of EUR 7–8 m estimated by Mercedes' management and demonstrate the financial impact as a result of our model.

Evidence of Improved Advertising Productivity. There is further evidence that model-predicted improvements in media mix indeed lead to a higher advertising KPI productivity. We have information available on KPI productivity and the associated allocation error at the campaign-channel level for the four campaigns. Advertising KPI productivity, *ProdKPI*, is measured by the achieved KPI level divided by the channel-specific budget. The allocation error, *alloc_error*, measures the relative deviation in (absolute) percent of the actual channel-specific budget from the optimal budget, which we derive ex post from expression (4) and estimated model parameters.

We find a strong negative correlation of −0.57 ($n = 54$, $p \leq 0.01$) between observed advertising KPI productivity and the allocation error (both in logarithms).[14] As expected, a smaller error in allocation decisions leads to higher productivity. We emphasize that this result is unlikely to be an artifact of our modeling. Both ad KPIs and actual budgets are observed variables. We compute deviations from the optimal budget ex post by using the decision tool.

We verify this evidence by regressing advertising KPI productivity on allocation error while controlling for the length and the quality of a campaign that may influence productivity as well. Specifically, we estimate the following model:

$$\ln ProdKPI_{kl,s} = d_{0k} + d_1 \ln alloc\_error_{kl,s} + d_2 \ln length_{kl} + v_s + w_{kl,s}, \tag{9}$$

where $length_{kl}$ denotes the number of weeks during which communication channel l was used for campaign k; d_{0k} is a fixed effect that controls for quality differences across campaigns; v_s is a specific error term for advertising KPI s, with $s \in${recognition, involvement, motivation}; and $w_{kl,s}$ is an idiosyncratic independent and identically distributed error term assumed to be uncorrelated with v. With this error term structure, we account for possible error correlation at the advertising KPI level. The parameters d_1 and d_2 measure the effects of allocation error and campaign length on productivity, respectively.

OLS-based R^2 amounts to 0.322, which underlines that the model has significant explanatory power. Most important, we find a highly significant estimate for the coefficient associated with the allocation error $\hat{d}_1 = -0.239$ ($p < 0.01$). Because the model is in log-log form, we can interpret the allocation-error coefficient as elasticity.[15]

The finding that the allocation error predicts advertising productivity also holds in a holdout sample. For this purpose, we randomly split the sample in 41 observations used for estimation and 13 holdout observations. The mean absolute percentage errors of prediction in the estimation and holdout samples are 0.209 and 0.224, respectively. Hence, Equation (9) predicts reasonably well.

7. Conclusion and Limitations

In this article, we introduced a model-based approach to plan short-term advertising campaigns for the launch of a new car model. The approach should extend to other categories where brand building is a major driver of the business, especially if interpurchase times are long. Depending on the specifics of the category, the terminology for the mind-set measures may diverge from the one used in this application to the automotive industry. In addition, our approach to convert aggregate expenditure data into individual-level data and combine them with relevant mind-set metrics offers potential for assessing the effectiveness of other short-term-oriented communication activities that are difficult to measure (e.g., sponsoring, events).

Our study has limitations that might stimulate further research. The implemented decision tool optimizes media expenditures to achieve a KPI goal that is derived from sales goals. Unfortunately, information about this process was not accessible. It remains a task for the future to understand and possibly improve the setting of KPI goals by using a model-based approach.

Although we believe that the model is generalizable to many other industries, it would in fact be interesting to see such additional applications. We are aware of the limitations of survey data such as common-method bias, demand effects, and the subjectivity of respondent answers. Validation tests did not suggest these issues played a significant role in our application. But it would helpful if future research developed ways to collect data in a different manner.

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Endnotes

[1] Alternatively, one could apply count regressions (e.g., hypergeometric or binomial). But we prefer the ordered logit model because of its ease of interpretation and use in the decision-making process. We later test for robustness with respect to other specifications of the dependent variable including count measures.

[2] Note that including weekly competitive advertising is not feasible, as the parameter is not identified. It would only be identified if we dropped the period dummies. The period dummies, however, control for additional unobserved influences, not only competitive expenditures.

[3] We caution that online panels may be subject to representativeness issues as panelists may be more internet savvy.

[4] Independent from us, Danaher and Dagger (2013) developed a similar approach to study a promotion campaign for a national retailer in Australia.

[5] Using electronic devices connected with the TV set (people meter) overcomes this limitation. However, the issue of a definite exposure remains because there is no guarantee that a specific person indeed saw the advertisement.

[6] We check whether there is a positive time trend in KPIs, which does not prove a carryover of 1 but is consistent with it. The mean of the first differences of KPIs measures the (linear) time trend while controlling for fixed level effects for KPI and campaign. It is 0.039 ($p < 0.05$, $N = 98$).

[7] This statement does not imply that the company is not making endogenous advertising decisions. Driven by expected consumer response, management could allocate expenditures across media channels differently, alter ad stimuli, and select specific media vehicles. We discuss the resulting endogeneity challenges subsequently.

[8] Note that we cannot claim that respondents in our quasi-control and quasi-experimental groups match each other in all relevant characteristics. They randomly self-select into their group based on their media consumption habits.

[9] Details are reported in the online appendix and available from the author upon request.

[10] Face-lifts are less innovative and account for 28% of the sample. Their data, however, are still informative and improve the precision of our estimates. Estimates do not change significantly if we exclude face-lifts.

[11] Expected sales is the only driver we do not observe. Because planned production capacity usually limits sales at the beginning of the life cycle, we believe actual registrations are a good proxy for expected sales.

[12] Specifically, we stay in the logarithmic budget space and add estimated marginal effects for deviations of drivers from the segment mean.

[13] This method of projection is not perfect. Although the R^2 for the model is high with 0.81, it implies that approximately 20% of budget variance is not explained by our factors. It might be precisely the factors unobserved to the researcher that management would have considered in setting the budget for the current campaign.

[14] The larger number of observations results from the fact that we have information at a more granular channel level available (e.g., private versus public TV channels).

[15] We estimated various alternative models using relative and absolute measures of KPI productivity and allocation error in linear and log terms. The allocation error parameter turns out to be negative and significant in all these regressions.

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