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**Managing Advertising Campaigns for New Product
Launches in the Automobile Industry: An Application at
Mercedes-Benz**

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ABSTRACT

The launch of a new car model is one of the most critical activities that automotive product and brand managers need to deal with. The challenge is to design an advertising campaign and back it up with appropriate media investment that creates awareness, product involvement and motivates potential target customers to seek further information about the new model. Due to the rise of the Internet, today's car brand managers can choose from a variety of communication channels. A key issue is to understand how effective these channels are relative to each other.

Econometric market response modeling offers a well-established methodology to estimate the relative effectiveness of media channels. However, these models require many observations on brand sales and expenditures, which are hardly available from a single launch campaign lasting no longer than 4 to 8 weeks. In addition, brand advertising rarely shows an immediate effect on sales but rather unfolds its impact in the long run through brand building. Unfortunately, the marketing literature gives only little guidance for market researchers and managers on how to assess the effectiveness of a single short-term launch campaign under real market conditions.

We introduce a new launch campaign management approach that has been implemented at Mercedes-Benz and became the standard for monitoring its integrated advertising campaigns in Germany. 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 dataset with sufficient observations and variance to estimate an econometric marketing spend model. We use this model (1) to monitor the effectiveness of expenditures across media channels and campaigns, (2) to predict advertising key performance indicators (advertising KPIs) at varying budget levels, and (3) to identify potential cost savings from optimizing the total budget and the media mix.

Methodology

Measuring OTS and Ad KPIs. In a *first step* we measure the reach and frequency of all media outlets used in the campaign. We achieve this by obtaining the actual media consumption habits of respondents during the campaign period. By matching the media consumption of a person with the campaign's media schedule, we derive the OTS for the advertisement by channel a person has cumulated over time. From net expenditures on an outlet and the total OTS generated by the campaign, we estimate the average cost of a contact. Multiplying the average cost with the cumulated OTS of a person produces the channel-specific stock of advertising expenditures by person and time that have been cumulated since the start of the campaign. This method of converting brand-level ad expenditures into individual-level expenditures is a unique feature of our approach.

In the *second step*, we measure the behavioral response of target customers towards the ad campaign in terms of the following mind-set hierarchy, which Mercedes-Benz defines as its Ad KPIs:

Target group → (1) Correctly recognize Ad → (2) Being involved → (3) Being motivated

Recognition measures how many target customers correctly remember the specific advertisement. Involvement shows how well the ad worked and whether the message was relevant to the target group. Motivation shows whether the ad strengthens the brand relationship and calls for action among target customers. These Ad KPIs are obtained for each communication channel used. Given the long interpurchase time, sales are a very noisy measure in the short run. However, there is a strong link between mind-set metrics and (future) transactions (Hanssens et al. 2014; Stahl et al. 2012). By regressing sales on recognition and other drivers in a dataset covering 5 years, we can demonstrate the impact of recognition on car sales, albeit with a substantial time lag (for details, see the Impact Statement).

A specific battery of questions measures the three Ad KPIs in a very crisp and valid way. Since the new technique provides us with both cumulated spend and behavioral response data (the Ad KPIs) at the individual level we create a single-source database, which is the most rigorous approach to measure advertising effectiveness.

Estimating advertising effectiveness. For each Ad KPI, we specify a response model at the individual level. The dependent variable is an ordinal variable and created as follows. Consider ad recognition as Ad KPI. For each respondent and communication channel (e.g., banner advertising), we measure whether s/he recognized and assigned the de-branded advertisement to the correct brand. The resulting outcome variable is binary. We aggregate these outcomes across the K communication channels used by the campaign. This creates an ordinal variable y_{is} , where i denotes the person, s is the period, and $y_{is} = 0, \dots, K$. Assuming a standard logistic distribution for the error term, we estimate a conditional ordered logit model for each Ad KPI:

$$\text{Pr ob}(y_{is} = k) = F\left(k, \beta_i' \ln \mathbf{Exp}_{is} + \alpha_i + \gamma' \mathbf{Z}_{is}\right), \quad (1)$$

where \mathbf{Exp}_{is} is a vector collecting cumulated expenditures on person i until period s across media channels, \mathbf{Z}_{is} is a vector of control variables, α_i , β_i , and γ are parameter vectors to be estimated, and $F(\cdot)$ denotes the logistic distribution. α_i is a person-specific constant that accounts for systematic differences in recognition rates among respondents. β_i measures advertising sensitivities by channel and also accounts for heterogeneity. \mathbf{Z}_{is} includes a competitive brand attitude index and period dummies to control for competitive ad campaigns. Note that the nonlinear model (1) already assumes synergy among media channels, but we also test for interactive synergy effects.

Data Collection and Implementation

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 ad tracking studies for a long time. The sample comprises at least 800 target customers including owners of Mercedes cars and competitive car makes.

Model and estimation results are implemented in an easy-to-use Excel program. Senior management sets the target levels for Ad KPIs. The Excel program monitors campaign effectiveness, generates input for budget decisions and provides a factual basis for developing responsive strategies for the current and future campaigns. The program also calculates channel advertising elasticities w.r.t. Ad KPIs that serve as input for optimizing the media mix under a constrained budget.

IMPACT STATEMENT

Background on Company and Campaigns

Company. Mercedes-Benz Cars is the largest division of the Daimler Group. As of 2012, the division had 98,000 employees and sold 1.45 million cars generating revenues of US\$ 83.2 bn. and EBIT of US\$ 5.9 bn. The division 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).

Integrated launch advertising campaigns. We applied our methodology to brand advertising campaigns on four major major new car model introductions into the German market in 2012 and 2013. Each campaign lasted between 5 to 8 weeks and used public and private TV channels, newspapers, magazines, online banner, and social media. The budget per campaign totaled several million US dollars. For budget decisions, media expenses per outlet are aggregated at three channels representing TV, print media, and online media. TV expenditures accounted for the lion's share, followed by print and online expenditures.

Strategic Impact

The application of the tool to several campaigns considerably helped resolving an ongoing discussion about the right media mix in light of the rise of online media. Traditionally, advertising for Mercedes cars has emphasized TV. This focus was perceived to be against the actual development in advertising markets. 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 might even be slightly increased. What elasticity estimates rather suggested was to shift resources from print to online media.

The results from four campaigns also underline how important the quality of a campaign and its execution is for achieving KPI targets. After controlling for budget, media mix, and other factors, differences in Ad KPI levels are attributed to differences in the creative quality of campaigns. For the first time, management has an estimate of quality differences in terms of Ad KPIs available.

Financial Impact

The implemented Excel program is used to simulate the effect of total budget changes on achieving target Ad KPIs and to obtain the optimal media mix. We also have evidence on the impact of recognition on sales conversion. For this and other reasons, management focuses on recognition to estimate cost saving potentials, which may arise from both optimizing the overall budget and the media mix.

Sales impact. We specified a two-equation response model that accounts for the simultaneity and dynamics of recognition and market share. 60 months (2009-2013) of car sales data were available to us. The data covers all major car brands and includes aggregated unaided recognition data as well as marketing-mix variables. The model produced an immediate sales elasticity with respect to recognition of .08 ($p < .01$) for Mercedes-Benz cars. Incorporating the indirect lagged effects via sales, the total elasticity amounts to .27 ($p < .01$).

Savings. The total savings potential across campaigns amounts to remarkable US\$ 15.1 mill. The biggest part of these savings comes from optimizing the overall campaign budget with US\$ 12.8 mill. The savings due to a better media mix, however, are also substantial with US\$ 2.3 mill. Note that these savings only refer to the German market, which accounts for 20% (Daimler 2012, 144) of total sales. On a global scale, these savings could be even larger assuming a comparable improvement potential.

Validation. We have evidence that model-predicted improvements in media mix indeed lead to better results. Using data at the campaign-channel level, we find a strong negative correlation of $-.57$ ($N= 53$, $p = < .01$) between observed Ad KPIs and the allocation error (both in logarithm). We divide Ad KPIs by budget level to control for size effects. A regression model that controls for other factors, e.g., length and quality of campaign, supports the model-free finding with an estimated coefficient for the allocation error of $-.216$ ($p < .01$).

Organizational Learning and Campaign Management

Management used to assess the effectiveness of ad campaigns with the help of laboratory experiments. However, it was unhappy with their inherent lack of external validity. With the new model, it learned that it can use actual behavioral data generated under real market conditions to evaluate the effectiveness of advertising campaigns in near real time.

We have objective information on the influence of the model on management decision-making. Specifically, if management accepts model recommendations and adapts its budget decisions there must be less room for savings as decisions move closer to the optimum over time. Indeed, the savings potential (for total budget) gradually reduced from US\$ 7.9 mill. to US\$ 5.4 mill. from first to last campaign. Probably because it is easier to execute, the decrease rate from optimizing the media mix is even stronger from US\$.99 mill. to US\$.04 mill.

Since model results are already available before the end of a campaign, management may quickly react if KPI targets are not achieved. In one case, it used the model results for determining additional investments into media channels. With the model-suggested additional investment, management successfully achieved the target KPI level.

Using the accumulated knowledge from four campaigns at varying quality levels, management now can also predict the development of Ad KPIs for new campaigns within a trajectory of quality differences.

Finally, the use of the model also improved the cooperation with the media agency that supports planning and executing the campaigns. Input/output relations are more transparent than before and decisions can be better evaluated on such a factual basis.

Generalizability

The focus of the analyzed Mercedes-Benz campaigns was on TV, print media, and online media to carry the ad message. The selection of media was appropriate for these campaigns, but application of the tool may easily be expanded to cover other media channels. In addition, the analyzed Ad KPIs reflect an advertising-effects hierarchy that is not only relevant to cars. It should extend to other categories where brand building is a major driver of the business (Bruce, Peters, and Naik 2012), especially if interpurchase times are longer.

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