A MIXTURE-AMOUNT MODEL FOR MEDIA MIX INVESTMENTS TO MAXIMIZE CAMPAIGN RECOGNITION AND BRAND INTEREST

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Abstract This article proposes a mixture-amount modelling approach as a new methodology to model the impact of advertising effort and allocation across different media. An important innovative aspect of this type of model is that it allows to derive different optimal allocations for campaigns with different weights. The authors demonstrate the usefulness of the model for advertisers by analyzing Belgian data on advertising campaigns for beauty care brands, and show how advertisers can use the model to allocate their effort to different media in function of their total advertising effort, so as to maximize desirable outcomes such as campaign recognition and brand interest. The model also allows to quantify synergy effects between different media. The estimated model provides support for the existence of positive synergy.

Keywords Advertising, media mix, cross-media investments, mixture-amount model, predictive modeling, media synergy

Slant:

- This article proposes a new methodology, mixture-amount modelling, to derive optimal advertising allocations to different media. A key feature of the mixture-amount model is that it allows to derive the optimal allocation for different campaign weight.
- The paper presents an application of the model based on real-live data on Belgian beauty care campaigns involving two types of media, but the model can be applied to other product categories and for any number of media.
- The optimal advertising effort allocation differs not only depending on the total amount of advertising, but also on the desired outcome (campaign recognition versus brand interest).
- Based on the mixture-amount model, advertisers can explore scenarios with different campaign weights and media allocations in a dynamic way, using the prediction profiler in JMP.
- For the data studied in this paper, campaigns employing multiple media result in positive synergy versus single-medium campaigns.

1 Introduction

Advertisers repeatedly have to decide on the total amounts of advertising effort to invest, and on how to allocate this effort across different media. Despite its relevance to advertisers and media planners, research on the optimal allocation of advertising budgets across different media is lacking (Schultz, Block and Raman, 2012). The present study's objective is to partly fill this void by investigating how advertisers can maximize campaign recognition and brand interest by optimizing their advertising effort across different media, and this for different levels of total investments. To this end, the article introduces use a novel approach in advertising research, namely a mixture-amount regression model. The novelty of this model is that it explicitly allows to simulate how the optimal media mix allocation changes for varying amounts of advertising investment.

Existing studies on media mix and synergy effects can be classified into two broad categories: (1) studies involving real-life data and (2) experimental studies. Most published advertising studies on media mix synergy effects are experimental, exposing people to advertising stimuli in different media and measuring their responses in terms of attitudes and behavioral intentions (e.g., Danaher and Rossiter, 2011; Voorveld, Neijens and Smit, 2011). These studies often suffer from a lack of ecological validity, as they include only a single advertising campaign with a limited number of possible allocations to different media, are conducted under forced exposure conditions and measure responses immediately after ad exposure. In the present study, we use real-life data from 34 campaigns with a large spread in advertising effort and allocation to different media. Most prior real-life data studies model an aggregated relation between cross-media ad spends, on the one hand, and product sales or other measures of return on investment (such as shop visits) on the other (e.g., Färe et al., 2004). The outcomes of these studies usually involve a single optimal media-mix allocation for a given budget level. Importantly, neither of the streams of research (experimental or modelling) have investigated how shifting advertising effort allocations between media in a campaign impacts campaign effectiveness, and how this impact can be different for campaigns differing in size, as the present study does.

Based on the results of the mixture-amount model, the authors propose a measure for synergy effects between different media. In his overview article of 50 years of media mix research, Assael (2011) argues that, after 1994, the concept of synergy became increasingly important. Synergy is the interaction of multiple elements in a system (different media), to produce an effect different from the sum of their individual effects. Positive synergy is created when investments in multiple media produce an effect greater than the sum of their individual effects. A large number of studies indicate that marketers can create positive synergy effects by spreading their effort across different media (Chang and Thorson, 2004; Havlena, Cardarelli and De Montigny, 2007; Naik and Raman, 2003; Reynar, Phillips and Heumann, 2010; Vakratsas and Ma, 2005; Voorveld, Neijens and Smit, 2011). At the same time, other studies detect poor or no synergistic effects (Frison et al., 2014; Pfeiffer and Zinnbauer, 2010; Wakolbinger, Denk and Oberecker, 2009), or even negative effects (Dijkstra, Buijtels and van Raaij, 2005; Godfrey, Seiders and Voss, 2011; Tsao and Sibley, 2004). These inconsistencies could be explained by the fact that these studies only consider potential synergistic effects for very specific combinations of media (which are not necessarily optimal) at a specific level of advertising investment. According to Assael (2011), the largest void in the literature on advertising is research on budgetary allocation guidelines that can optimize synergistic cross-media effects. The present paper contributes to the debate by measuring synergy in the optimal, best possible media mix and by investigating how synergistic effects change for a range of advertising investment levels.

In sum, the proposed mixture-amount model provides additional insights into cross-media effects in a dynamic way. It explicitly allows the optimal media mix to depend on the total advertising effort. Compared to more traditional regression models, mixture-amount models do not only allow for optimization, but also for simulations to predict responses for different combinations of advertising effort and cross-media allocation. The estimated mixture-amount models can be interpreted and used for prediction and optimization by means of dynamic prediction profilers available in the software JMP. As such, the article contributes to the literature on synergistic effects of advertising media, and provides a tool to advertisers to help optimize their advertising investments. Mixture-amount models have been widely used in biology, chemistry, food science and agriculture. To the authors' knowledge, this paper represents the first application of the mixture-amount modeling approach in marketing. To illustrate the applicability of the model for advertising planning purposes, the article includes an application involving real-life advertising investment and cross-media allocation data for 34 beauty care campaigns, on the one hand, and data on individual consumer responses (campaign recognition and brand interest) to these campaigns, on the other hand.

2 Literature review

The advertising literature documents a long tradition of sales response modeling to quantify the effect of advertising budgets on sales or market shares (Arndt and Simon, 1983; Dekimpe and Hanssens, 1995; Dukes and Liu, 2010; Gatignon and Hanssens, 1987; Longman, 1971; Porter, 1976; Wright, 2009). However, establishing this relationship is not easy: "there is no more difficult, complex, or controversial problem in marketing than measuring the influence of advertising on sales" (Bass, 1969). The problem becomes even more difficult when modelling not only the effect of the total advertising effort, but also including the effect of the allocation of this effort to different media (e.g., Danaher and Dagger, 2013; Dekimpe and Hanssens, 1995).

A few studies have tried to include allocation considerations in their analyses. For example, Gatignon and Hanssens (1987) and Gopalakrishna and Chatterjee (1992) analyze the optimal resource allocation to advertising and sales force. Aravindakshan, Peters and Naik (2012) empirically validated a model of how national and regional advertising generate sales over time for a cosmetics brand. The authors derive the profit by maximizing total budget, its optimal split between national and regional spends, and its optimal allocation across multiple regions. Naik, Raman and Winer (2005) developed a model to optimize advertising and promotion efforts, which explicitly includes interactions between advertising and promotion, and interactions between actions of competitive brands. These studies do not, however, consider allocations to different media. Danaher and Dagger (2013) developed an advertising response model to determine the optimal budget allocation across 10 different media, based on clients' self-reported media exposure in an online questionnaire. Danaher and Rossiter (2011) examine the relative effectiveness of 11 media in terms of respondents' purchase intention after being exposed to a hypothetical advertising scenario in a survey. Neither of the latter two studies address potential interactions or synergy effects between the different media.

Quite recently, a large number of studies are devoted to studying interactions or synergy between different media. These studies have yielded inconsistent results. The majority of the studies indicate that advertising campaigns involving multiple media produce better results than campaigns using a single medium, i.e. they find a positive synergistic effect (Chang and Thorson, 2004; Havlena, Cardarelli and De Montigny, 2007; Naik and Raman, 2003; Naik, Raman and Winer, 2005; Reynar, Phillips and Heumann, 2010; Vakratsas and Ma, 2005; Voorveld, Neijens and Smit, 2011). For example, an experiment by Chang and Thorson (2004) found that showing an advertisement on both television and the Internet was superior to repeating that advertisement in either of the media in terms of attention, perceived message credibility, and number of total and positive thoughts. In an experimental study by Voorveld, Neijens and Smit (2011), exposure to cross-media advertising (television and the Internet) resulted in a more positive attitude toward the brand, attitude toward the television commercial, and purchase intention than repetitive single-medium exposure (television or the Internet). Reynar, Phillips and Heumann (2010) optimized media spending and allocations of the advertising budget for consumer packaged goods across a variety of media to maximize revenues and profits. Their results support the existence of positive synergy effects through the indirect effect one medium has on another. Naik and Raman (2003) show that sales for Dockers benefit from positive synergy between magazine and television advertising. They derive optimal levels for advertising spending in both magazines and television advertising, and offer a number of propositions concerning the synergy between media. Their proposed model is generalizable to more media.

At the same time, other studies have detected poor or no multimedia synergistic effects (Pfeiffer and Zinnbauer, 2010; Wakolbinger, Denk and Oberecker, 2009), or even negative effects (cannibalization) (Dijkstra, Buijtels and van Raaij, 2005; Godfrey, Seiders and Voss, 2011; Tsao and Sibley, 2004). For example, Havlena, Cardarelli and De Montigny (2007) report positive synergy between television and print advertising measuring on traditional brand metrics and positive perceptions of the brand for a consumer packaged, but find few or no synergy effects when online banner advertising is added to the media mix. An experimental study by Dijkstra, Buijtels and van Raaij (2005) demonstrates the superiority of television-only campaigns over multiple-media campaigns in evoking cognitive responses, and that print-only campaigns are as effective as multiple-media campaigns for most responses.

As mentioned in the introduction, the conflicting evidence between these different studies could be due to the fact that most of these studies only consider potential synergistic effects for very specific combinations of media (which are not necessarily optimal) at a specific level of advertising investment. For example, the experimental studies including two media confront respondents with one ad in each medium, resulting in a 50-50 allocation. In reality, however, brand managers can choose any possible allocation between the media. The optimal media mix and synergistic effects are also likely different for smaller and larger campaigns. While some media-mix modelling papers include a discussion on the total budget (Naik and Raman, 2003), the mixture-amount regression model presented in this paper is the only model that explicitly includes the interaction between the total advertising effort and its allocation across media, thereby allowing to derive multiple optimal allocations in function of the total advertising effort. As a result, the method also allows to investigating how synergistic effects change for a range of advertising investment levels. Table 1 summarizes the major modelling differences between the present study and earlier related modelling studies.

Table 1: Main differences among related studies

Features	Gopalakrishna and Chatterjee (1992)	Naik and Raman (2003)	Bruce, Foutz and Kolsarici (2012)	Danaher and Dagger (2013)	Present study
Interactions	Sales force by advertising	Print by television advertising	WOM by advertising	Sales force by advertising	Print by television advertising
Estimation method	Nonlinear least squares regression	Kalman filter estimation	Bayesian dynamic linear model	Type II Tobit model	Mixture-Amount Model
Investigates effects of interaction on optimal decisions	No	Yes	Yes	Yes	Yes
Cross-validation	No	Yes	Yes	No	Yes
N-media generalization	No	Yes	No	Yes	Yes
Number of brands in dataset	1	1	360	1	13
Synergy changes for a range of advertising efforts	No	No	No	No	Yes

3 Mixture-Amount Models

The type of regression model we use in this study is inspired by research in food science and agriculture, where fertilizers and pesticides are commonly used to enhance the yield of a crop. The fertilizers and pesticides are mixtures of various ingredients. Statistical models for studying the yield of the crop do not only use the amount of fertilizer as an independent variable, but also the proportions of the different ingredients. These models are commonly referred to as mixture-amount models , and allow the optimal proportion of the ingredients to depend on the dose of fertilizer or pesticide (Cornell, 2002). Choosing the right amount of fertilizer and the right proportion of the different ingredients given the amount of fertilizer may lead to an improved plant growth (Niedz and Evens, 2011). Just like farmers and food scientists have to decide on how much fertilizer to use and what its composition should be for an optimal crop yield, advertisers must decide on how much to spend on an advertising campaign and on how to allocate the budget to different media. The effect of a campaign is influenced by the total advertising spends as well as by the allocation of this investment to the different media. So, conceptually, the decision problem of advertisers, on the one hand, and farmers and food scientists, on the other hand, is exactly the same. Therefore, mixture-amount models serve as an excellent tool for studying the impact of the advertising budget and its allocation to different media on advertising effectiveness.

Various types of mixture-amount models have been proposed to model the impact of mixture composition and mixture amount on a dependent variable (Cornell, 2002). Suppose we have q ingredients in a mixture, and denote the proportion of the ith ingredient by x_i and the total amount of the mixture by A. To model linear and nonlinear blending among the q mixture ingredients, a suitable mixture-amount model is

$$\eta = \sum_{i=1}^{q} \beta_i x_i + \sum_{i=1}^{q-1} \sum_{j=i+1}^{q} \beta_{ij} x_i x_j + A\left(\sum_{i=1}^{q} \gamma_i x_i + \sum_{i=1}^{q-1} \sum_{j=i+1}^{q} \gamma_{ij} x_i x_j\right), \tag{1}$$

where η represents an outcome, the regression coefficients β_i and β_{ij} can be viewed as the base effects of the mixture composition, and γ_i and γ_{ij} represent the interaction effects of the amount A with the mixture's composition (i.e., how the amount affects the effects of the mixture composition). The mixture-amount model in Equation (1) is a special type of regression model, involving several terms which capture interaction effects between different ingredients and interaction effects between the total amount and the ingredient proportions. This allows the optimal values of the proportions to depend on the total amount. Regression models for mixture data, such as the model in Equation (1), do not explicitly include an intercept because the sum of all ingredient proportions equals 1. This fact is well documented in literature concerning regression models tailored to data involving mixtures, starting with Scheffé (1958). The (latent) intercept varies from mixture to mixture.

Mixture-amount models are mainly used for prediction and optimization of the optimal proportions of the ingredients for any given total amount (Cornell, 2002). The focus on prediction is to a large extent due to the high degree of multicollinearity in data sets involving mixtures. As a matter of fact, the different proportions cannot be changed independently: when one proportion goes up, at least one other proportion has to go down, since all proportions always sum to 1. This makes the usual significance tests for individual coefficients, which implicitly assume that all the regression coefficients can be interpreted independently, essentially meaningless.

In the context of advertising, q corresponds to the number of media types used, x_i corresponds to the proportion of advertising in the ith medium (e.g, x_1 = proportion of advertising spent on television, x_2 = proportion of advertising spent in magazines, x_3 = proportion of advertising spent on the Internet). The amount A is a measure of the total amount of advertising (i.e., the advertising budget for the campaign). The mixture-amount modeling approach is generic and can be used for any number of media and any range of budgets.

4 Data

Advertising investment data and consumer responses were collected for 34 skin and hair care (shampoo, facial cream, soap) campaigns that ran in magazines and/or on television in Belgium between June and December 2011 (thus, in this dataset, there are two media, television and magazines, so that q = 2). Table 2 provides a snapshot of the data. Eighteen campaigns ran in Flanders (the northern, Dutch-speaking part of Belgium), while the remaining 16 ran in Wallonia (the southern, French-speaking part of Belgium). The campaigns involved 13 brands from 4 mother brands (e.g., the brands Youth Code and Revitalift from the mother brand L'Oréal Paris). Some brands had multiple campaigns in the tested period, and were included several times.

To quantify the advertising effort in each campaign, we use Gross Rating Point (GRP) indicators. A GRP is the number of contacts of a campaign expressed as a percentage of the target audience (De Pelsmacker, Geuens and Van den Bergh, 2010). GRPs are more suitable to measure advertising effort than campaign budgets, because the latter are biased by the discounts offered by media companies which typically vary across campaigns, brands and media. GRPs were calculated for magazine and television campaigns in the six weeks preceding the data collection (this represents the "amount" A). For each campaign, data were available on the number of GRPs invested in television advertising and in magazine advertising. The GRP values for the campaigns under study ranges from 9.2 to 624.4. In correspondence with the model (1), the columns labeled x_{mag} and x_{TV} in Table 2 represent the proportions of magazine and television advertising investments, respectively. Note that these proportions always sum up to 1.

As dependent variables, we use two consumer responses, namely campaign recognition and brand interest. These responses were collected from individual respondents through a survey conducted by GfK, a market research agency. As the selected campaigns involve skin and hair products for women, the respondents in the study were randomly selected women in the age range of 20 to 50 (the target group for these products), which were representative of the Belgian population in terms of education and social class. The data were collected at five different time points, which we refer to as waves. The measurements were spread over time to obtain a larger selection of campaigns. In each wave, about 500 different respondents were recruited for both Flanders and Wallonia to evaluate between 2 and 4 campaigns. In total, the analyzed dataset contains 17793 responses from 4399 respondents, 2135 of which were Flemish.

Table 2: Snapshot of the available data

Campaign	Brand	Mother Brand	Region	Wave	GRPs invested	x_{mag}	x_{TV}	Respondent ID	Campaign Recognition	Brand Interest
1	1	1	Flanders	1	95.6	.21	.79	1	1	4
1	1	1	Flanders	1	95.6	.21	.79	2	0	1.1
…	…	…	…	…	…	…	…	…	…	…
2	2	1	Flanders	1	409.0	.12	.88	1	0	4
3	3	2	Flanders	1	227.4	0	1	1	1	4
4	4	2	Flanders	2	497.8	.40	.60	505	1	5
5	5	3	Flanders	2	385.4	.20	.80	512	0	3.8
8	1	1	Flanders	3	374.5	.21	.79	1023	1	4.9
18	12	3	Flanders	5	48.8	1	0	2356	0	6.5
…	…	…	…	…	…	…	…	…	…	…
19	1	1	Wallonia	1	9.2	1	0	2588	0	4.4
20	2	1	Wallonia	1	255.6	.13	.87	2588	0	4.5
22	11	4	Wallonia	4	190.6	.28	.72	4005	1	3.3
34	13	1	Wallonia	5	624.4	0	1	4690	1	5.6

Note: x_{mag} = Proportion of GRPs spent in magazines, x_{TV} = Proportion of GRPs spent on television

Campaign recognition is a binary variable indicating whether or not a campaign was recognized by the respondent (as self-reported during the survey). The binary response variable takes the value 1 in case a respondent reported she recognized the campaign and 0 otherwise (Table 2). Brand interest was measured using a 10-item 7-point Likert scale (e.g., "This campaign has led me to pay more attention to the brand in the store", "This campaign has encouraged me to try the brand"). To obtain a single score for brand interest, we averaged respondents' scores across the 10 items. This is justified by a factor analysis which showed that 95% of the total variance was captured by a single factor (α = 0.97). As a result, the study includes one binary response variable (campaign recognition) and one metric response variable (brand interest).

5 Method

The specification of the mixture-amount model utilized in this study (1) recognizes that advertising in magazines and on television might have a different impact, (2) allows for a possible interaction effect between magazine and television advertising (i.e., allows for a (positive or negative) synergistic effect), and (3) allows for a possible interaction effect between the amount of advertising and the proportion of magazine or television advertising. Therefore, the model allows to determine an optimal media mix allocation for each advertising amount, including interpolation to advertising amounts not present in this dataset.

The model also includes a fixed effect to allow for different intercepts between the northern and southern parts of Belgium. To capture all the dependencies between responses in the data, the authors include a number of random effects in the mixture-amount model. First, random effects are included to control for the fact that the data include measurements at different points in time (e.g., to capture seasonal effects).Similarly, random effects are included to model the dependency between answers from the same respondent and to capture the dependency between all answers for the same campaign and for the same brand. Hence, we adopt a multilevel generalized linear model (GLM) approach when estimating the mixture-amount model for campaign recognition and brand interest.

Multilevel GLMs have linear predictors that consist of two parts – a systematic part and a random part (Hardin and Hilbe, 2012):

$$\eta = \eta_{sys} + \eta_{random}. \tag{3}$$

For the campaign recognition response model, we use the logit link function and assume a binomial distribution for the response. For the brand interest response, we use the identity link function and assume a normal distribution (Hardin and Hilbe, 2012). The systematic part of the linear predictor in our GLM models for campaign recognition and brand interest is given by

$$\begin{aligned} \eta_{sys} = \beta_{mag} x_{mag} + \beta_{TV} x_{TV} + \gamma_{mag} x_{mag} A + \gamma_{TV} x_{TV} A + \beta_{\text{int}} x_{mag} x_{TV} \\ + \gamma_{\text{int}} x_{mag} x_{TV} A + \theta d_{region}, \end{aligned} \tag{4}$$

where x_{mag} and x_{TV} represent the proportions of magazine and television advertising, respectively, A is the natural logarithm of the GRP value, and d_{region} is a dummy variable that indicates the region. A feature of the linear predictor we use in this paper is that we do not consider interaction effects with the region dummy variable. This is due to the limited number of campaigns in our data set, which did not allow the estimation of different regression coefficients for each region. Therefore, in this study, the optimal media mix allocations we determine are identical for both regions.

6 Results

To assess the goodness-of-fit of the campaign recognition model based on Equation (4), we used a 5-fold cross-validation. Cross-validation has become a standard method in predictive modelling to avoid overfitting and to acquire a nearly unbiased estimate of the future error rate (Efron and Tibshirani, 1997). 5-fold cross validation procedures use 5 training samples and 5 holdout samples. The resulting receiver operating characteristic (ROC) area under the curve (AUC) is 0.74, which indicates a fair model performance (Pepe, 2000; Vitacco et al., 2009). To measure the performance of the brand interest model, we used a concordance correlation coefficient (ρ_c), which is employed in mixed models as a substitute of R^2. The ρ_c value for the brand interest response equals 0.74, which indicates a good fit (Vonesh, Chinchilli and Pu, 1996).

We interpret the estimated regression models for campaign recognition and brand interest in a graphical fashion using the prediction profiler embedded in the software package JMP. The prediction profiler visualizes the change in the predicted responses as a function of the GRP amount and the media-mix allocation, and allows the exploration of the interaction (synergy) effects for various scenarios. It is an interactive tool that can be used to optimize the dependent variable for a given GRP amount, and to investigate to what extent the response value deteriorates if one deviates from the optimal media mix allocation.

In the figures below, the vertical axis represents either the probability of campaign recognition (in %), or the level of brand interest (on a seven-point scale). The horizontal axis shows the levels of the four explanatory variables in the mixture-amount model. The left panel shows the effect of the region dummy variable (where "0" refers to Wallonia and "1" refers to Flanders). The second panel from the left shows the impact of the proportion of magazine advertising, while the third panel shows the effect of the proportion of television advertising (recall that together, these proportions sum up to 100%). The final (right) panel visualizes the effect of the total advertising investment expressed in GRPs. In each of the panels of the figure, dashed vertical lines indicate the selected levels of the explanatory variables (which can be dragged dynamically when using the software package). The solid convex lines in the middle two panels show how the value of the dependent variable changes as a function of the allocation of campaign spends to television and magazines. In the next sections and in Figures 1 to 4 we visualize the two mixture-amount models, for different GRP levels, we obtained from the SAS procedures GLIMMIX and MIXED.

6.1 Campaign recognition

Figure 1 shows that, for a campaign in Wallonia (Region = 0) with a campaign weight of 200 GRPs (right panel), an allocation of 40% (80 GRPs) to magazine advertising and 60% (120 GRPs) to television advertising leads to the highest possible campaign recognition probability, in this case 57%. The curved solid lines in the panels for the proportions of magazine and television advertising show that any other allocation leads to a smaller recognition probability. The fact that the curves are convex indicates a positive synergistic effect. For Flanders, the predicted campaign recognition using the same GRP value and media mix allocation would be 48%.

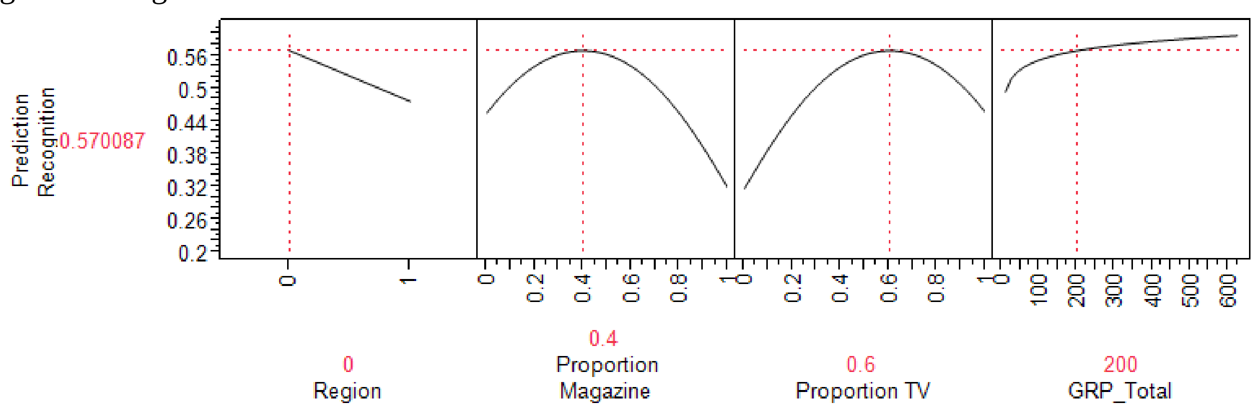

Fig. 1 Optimal media mix allocation for campaign recognition in Wallonia in case the advertising budget is 200 GRPs

In case the advertising budget increases from 200 GRPs to 620 GRPs, the optimal media mix allocation changes. This is shown in Figure 2, where the proportions 20% and 80% turn out to be optimal for magazine and television advertising, respectively. For Wallonia, this results in a predicted campaign recognition probability of 61%. Comparing the results for a GRP value of 200 and for a GRP value of 620, we see that a larger proportion of the campaign budget should be allocated to television advertising in case of a larger GRP value. For Flanders, the predicted probability of campaign recognition is 52% for a GRP value of 620, assuming the same optimal media mix allocation is used.

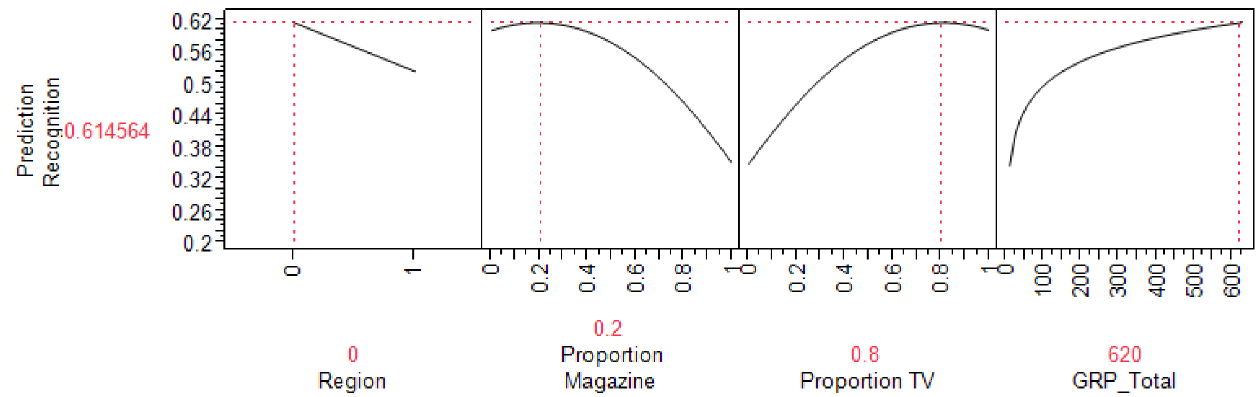

Fig. 2 Optimal media mix allocation for campaign recognition in Wallonia in case the advertising budget is 620 GRPs

6.2 Brand interest

Figure 3 shows that, for a campaign in Wallonia with a weight of 200 GRPs, a proportion of 34% for magazine advertising and 66% for television leads to the highest level of brand interest, with a score of 3.91. For Flanders, the predicted brand interest in this scenario is 3.65 (out of 7).

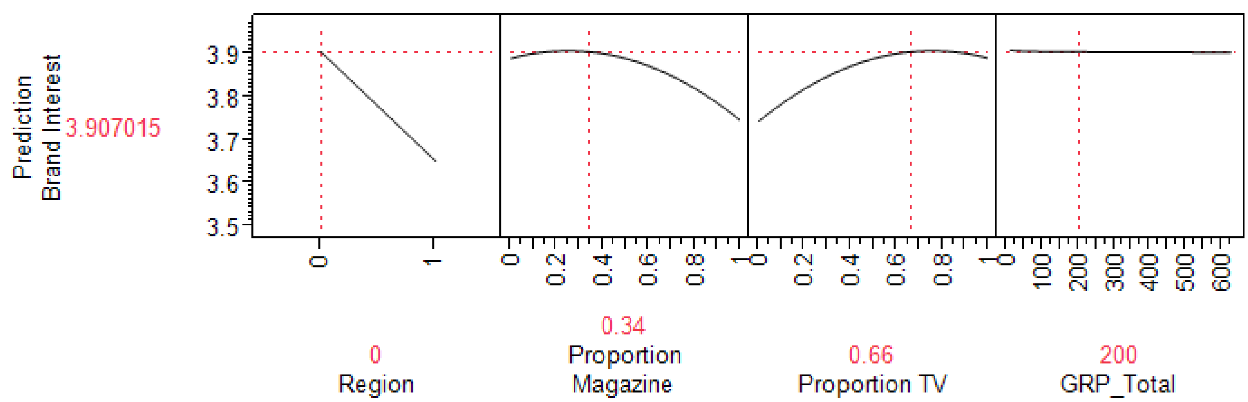

Fig. 3 Optimal media mix allocation for brand interest in Wallonia in case the advertising budget is 200 GRPs

The solid horizontal line for GRPs in the rightmost panel of Figure 3 shows that, given an allocation of 34% for magazines and 66% for television, there is no point in increasing the total budget. All possible GRP levels result in a score of 3.9 for brand interest under the 34/66 allocation. In case the advertising budget increases from 200 GRPs to 620 GRPs, for a campaign in Wallonia, the optimal media mix allocation changes to 50% for magazine and 50% for television advertising. For Wallonia, this results in a predicted brand interest of 3.92 (Figure 4). The increasing curve for GRP in Figure 4 shows that, under the new allocation scheme, it is useful to invest more. For Flanders, the predicted brand interest level is 3.67 when 620 GRPs are used, along with 50/50 allocation to television and magazines.

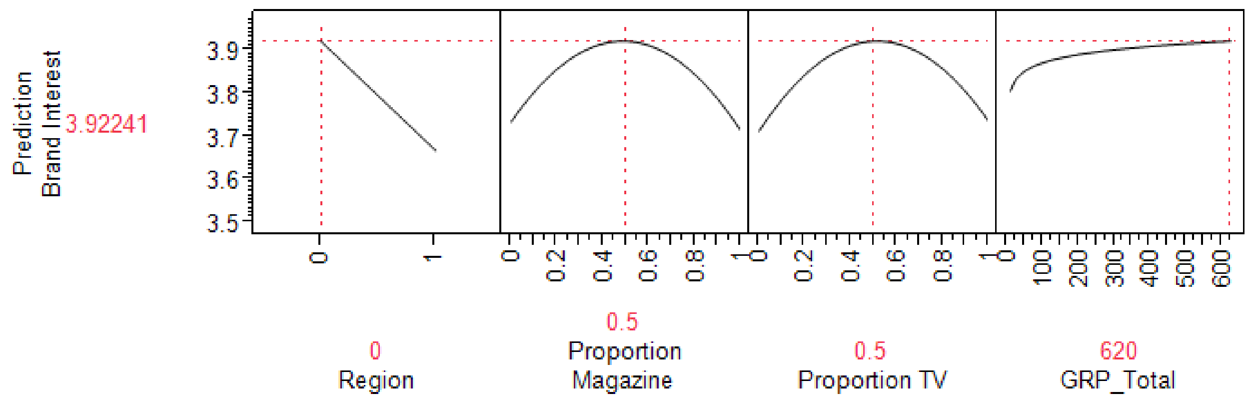

Fig. 4 Optimal media mix allocation for brand interest in Wallonia in case the advertising budget is 620 GRPs

6.3 A measure for the synergistic effect

Our results show that, when the goal is to maximize campaign recognition probability and the level of brand interest, it is generally best to use both magazine advertising and television advertising. To measure the synergistic effect between these two types of advertising, we propose a synergy coefficient (ς_m), that we define as the difference between the value of the dependent variable for the optimal media mix and the average of all scenarios involving single medium investments. The mathematical expression for the synergy coefficient, which can be calculated for any given GRP value, is:

$$\varsigma_m = \tau_{opt} - \frac{\sum_{i=1}^{q} \kappa_i}{q}, \tag{6}$$

where τ_{opt} represents the value of the dependent variable for the optimal media mix allocation, and κ_i represents the value of the dependent variable in case the entire campaign budget is invested in medium i.

As an illustration, we calculate the synergy coefficient for campaign recognition, based on the mixture-amount model estimates. Recall from Figure 1 that the optimal media mix (40% of magazine advertising, 60% of television advertising) resulted in a predicted campaign recognition probability of 57%. From Figure 1, it is clear that, if an advertiser would fully allocate the 200 GRPs to magazine advertising, the predicted recognition probability would be merely 32%. If the

200 GRPs were fully invested in television advertising, the predicted recognition probability would be 46%.

Therefore, the synergy coefficient for campaign recognition under this scenario is equal to

$$\varsigma_m = 0.57 - \frac{0.32 + 0.46}{2} = 0.18.. \tag{7}$$

The synergy coefficient for the same scenario is equal to 0.09 for the brand interest measure. This means that, in the given scenario, by spreading their efforts across magazine and television advertising according to the optimal media mix derived by the mixture-amount model, advertisers can increase the probability of campaign recognition by 18% and brand interest by 0.09 points, compared to when they would invest all of their GRPs either on television or in magazines. In case the advertising budget is 620 GRPs, the media mix synergy coefficient is 14% for campaign recognition probability and 0.20 points for the brand interest score.

To show how the synergistic effect changes as a function of the total advertising investment, we calculate the synergy coefficient for the entire range of GRP values in the dataset, using the results from the prediction profiler outputs. Figure 5 shows how the synergy for campaign recognition drops from about 33% to 14% as the invested GRPs increase. As can be seen by comparing Figures 1 and 2, the curve for 200 GRPs is indeed more convex than the one for 620 GRPs. For 620 GRPs (the maximum in the present dataset), the difference in campaign recognition probability between 100% of television advertising and the optimal media mix allocation is small. For 200 GRPs, this difference is noticeably larger. This difference is numerically captured in the synergy coefficient. For brand interest, we observe a positive relationship between the synergy coefficient and the GRP value (Figure 6). As mentioned above, for 200 GRPs, the synergy coefficient is 0.09, and it increases to 0.20 for campaigns of 620 GRPs.

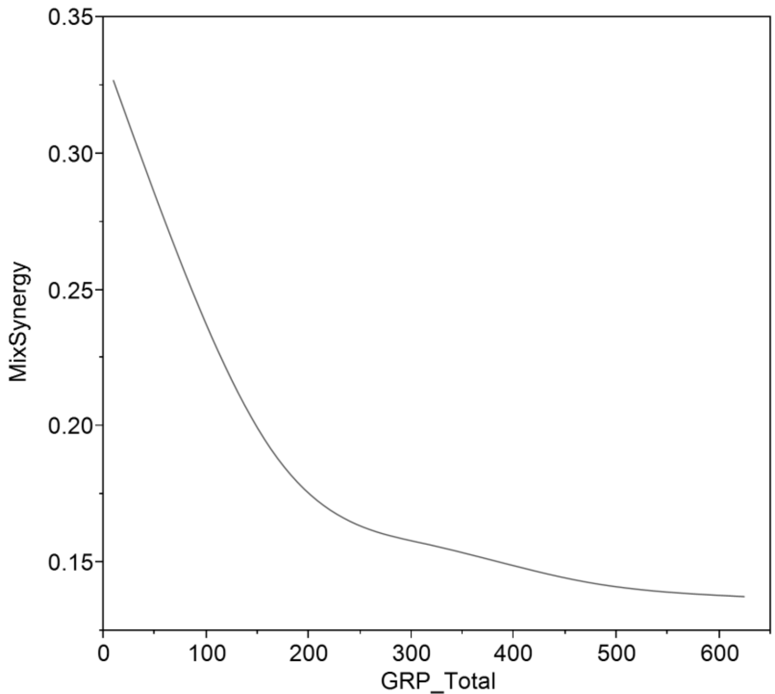

Fig. 5 Synergy coefficient for campaign recognition as a function of the GRP value

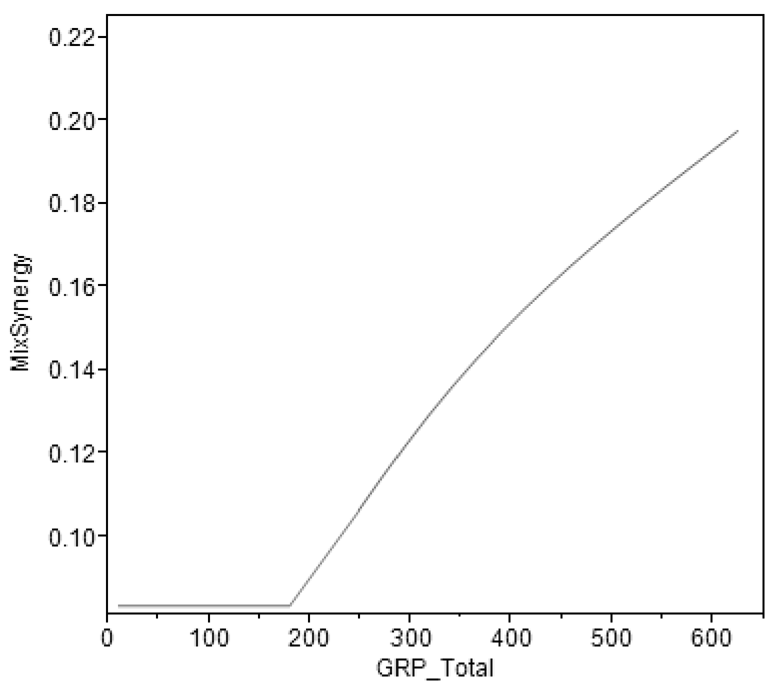

Fig. 6 Synergy coefficient for brand interest as a function of the GRP value

7 Discussion and conclusions

The present article proposes a mixture-amount modeling approach for advertisement investment optimization. It applied the approach to determine optimal cross-media investments to maximize campaign recognition and brand interest based on beauty care data. The results for the given dataset show that both brand interest and the probability of campaign recognition increase with the number of GRPs used. However, the positive effect of adding additional GRPs is greater for campaign recognition than for brand interest. This could be due to the fact that the brands used in the current study are all well-known global brands. Attitudes toward established brands are stable and hard to affect through advertising (Machleit, Allen and Madden, 1993) because consumers are already familiar with the brand and have formed expectations regarding its advertising (Alden, Mukherjee and Hoyer, 2000; Dahlén and Lange, 2005). Therefore, adding additional GRPs to a campaign is unlikely to affect brand interest.

The optimal media mix is also different for brand interest and campaign recognition. With increasing budgets, campaign recognition benefits from a greater focus on television advertising, while brand interest benefits from a relatively larger share of magazine advertising. Several possible explanations exist for this difference. First, television is believed to lead to a more intense visual stimulation, which benefits memory (Leigh, 1991). At the same time, the results of Bronner and Neijens (2006) suggest that television advertising is negatively perceived and has the highest score on irritation. This may reflect negatively on brand interest. Compared to television, magazine advertisements are more self-paced, providing readers with an opportunity to more thoroughly process specific information in advertising (Speck and Elliott, 1997). While magazine advertisements in general may not be so vivid as to be remembered, when noticed, they may do a better job at stimulating brand interest. This may be the reason why the optimal media mix involves a larger proportion of magazine advertising for brand interest than for campaign recognition. The results of the study suggest that increasing the proportion spent on television advertising raises campaign recognition, but at the same time lowers brand interest. Conversely, a relatively larger proportion of advertising effort in magazines has a negative impact on campaign recognition, but enhances positive impact on brand interest. Additionally, the results also show that the optimal media mix changes as a function of the total number of GRPs invested. This result is new to the literature.

Consistent with the majority of previous studies (e.g., Havlena, Cardarelli and De Montigny, 2007; Reynar, Phillips and Heumann, 2010; Vakratsas and Ma, 2005), the results of this study support the existence of a positive synergistic effect between television and magazine advertising. There are several explanations for positive media mix synergy effects. First, different media may catch a different target audience, therefore increasing the reach of a campaign (Havlena, Cardarelli and De Montigny, 2007). In addition, some studies relate synergy to audience duplication between media and to enhanced repetition (Havlena, Cardarelli and De Montigny, 2007; Schumann, Petty and Clemons, 1990). There is ample evidence that people frequently consume several media (simultaneously) (Lin, Venkataraman and Jap, 2013) and advertisers exploit this by using multiple channels to increase the frequency of a campaign. Heavy users of one medium tend to be heavy users of many media (Enoch and Johnson, 2010). Therefore, they are exposed more frequently to the same advertising campaign in different media. This explanation of synergy is also related to the different cognitive processing of different types of stimuli and its reinforcing effect on advertising outcomes. Media contribute differentially to the route to persuasion and in that sense complement each other (Dijkstra, Buijtels and van Raaij, 2005). The dual coding principle (Paivio, Clark and Lambert, 1988) asserts that verbal and nonverbal systems process information using two different cognitive subsystems, one for language (verbal information, such as words) and one for nonverbal objects (e.g., pictures, motion). Because more resources are activated to process both the verbal and the nonverbal information, processing will be more extensive when two representation formats (e.g., television and magazine advertising) are used than when only one is used. Voorveld, Neijens and Smit (2011) suggest three psychological processes that contribute to positive synergy for cross-media campaigns: forward encoding (i.e., the ad in the first medium primes interest in the ad in the second medium); multiple source perception (i.e., believing the brand is good and popular because of the amount of advertising) and image transfer (i.e., mentally replaying the ad previously viewed during exposure to the ad in the second medium). Their results indicate that especially the first two processes contribute to campaign results.

The synergy results uncovered in this dataset are opposing for campaign recognition and brand interest: While the synergy for campaign recognition drops as the invested GRPs increase, the synergy for brand interest increases with the GRP value. The decrease in synergy for campaign recognition for larger campaigns can be explained by ceiling effects. Larger campaigns are more likely to be noticed, but at some point, everyone who will ever notice the campaign will have noticed it in either of the media, and so the added value of optimizing the allocation across the two media decreases. As noted also, campaign recognition requires a fairly large share of television advertising either way, and for large campaigns, the optimum amounts to 80%. As shown in Figure 2 the difference in recognition with campaigns that would invest 100% on television, is small. For smaller campaigns, more can be gained by lowering the proportion of television advertising, and truly finding the optimal media mix becomes more important. In terms of brand interest, advertisements in two media can really be complementary, which may be explained by dual coding theories (Sadoski and Paivio, 2012). In that case, increasing the amount of GRPs can increase the chance that consumers notice the ads in both media, and this produces the strongest effects on brand interest.

8 Implications and further research

Mixture-amount models have the potential to assist advertisers in deciding how much to spend on advertising campaigns and how to allocate these efforts across media to maximize campaign effectiveness. The major advantage of mixture-amount models over existing models is the possibility to identify the optimal media mixes for different levels of advertising effort. A key feature of the models is that they quantify to what extent the optimal allocation of advertising efforts changes with campaign weight. To the authors' knowledge, there are currently no other models that allow to capture such effects. The prediction profiler offers an easy-to-use tool for advertisers to dynamically simulate the effects of different advertising efforts and media mixes. A global survey by McKinsey & Co. (Doctorow, Hoblit and Sekhar, 2009) reports that advertisers tend to allocate spending based on historical allocations and rules of thumb far more than quantitative measures. The optimization of the media mix is especially important because the optimal allocation of advertising effort across media could boost campaign recognition by up to 33%, and can improve brand interest scores by up to .19 scale points in the current dataset. The results of Raman et al. (2012) even suggest that an optimal allocation can enhance a firm's profitability by as much as 400%. When considering the spread in media allocation in the current dataset, it is obvious that in practice, a number of advertisers still bet on single media campaigns, thereby foregoing potential positive synergy effects.

The results presented in this paper illustrate that the optimal media mix indeed differs greatly depending on the total advertising effort, a fact that advertisers should take into account when planning advertising campaigns. In addition, the optimal allocation also largely depends on the objective of the campaign. If the objective is to boost campaign recognition, in case of a small budget, a substantial part of the budget should be allocated to magazine advertising. In case of large budgets, the largest share should be spent on television. If, on the other hand, brand interest is the primary objective, increasing the budget has a relatively small effect, but in case of larger budgets, a more substantial share should be spent on magazine advertising. Importantly, though, while the results derived based on this particular dataset are not necessarily generalizable, the model can be estimated in other contexts and with more or different types of media as well.

In general, the model should be tested further to investigate to what extent the results are context-specific or media mix specific, and to what extent they can be generalized to different products, countries and target groups. Due to a limited availability of data, the illustration of the model applicability presented here includes television and magazine advertising only. While this is justified by the fact that television and magazines are still the two major media employed for beauty care advertising in the country under study, further research should try to expand the model with other media, such as radio, newspaper and/or the Internet. Especially given the increasing importance of online advertising today (Peterson, 2014), the Internet is a medium that should be taken into account. While we have argued that GRPs ought to be preferred over advertising budgets as a measure of campaign weight, studies could also consider starting from advertising budgets.

At the same, the use of GRPs as an input variable also represents a limitation of the application presented here. GRPs are an indication of ‘campaign weight’, and are defined as reach times frequency. Therefore, it is not possible to disentangle the effects of reach and frequency on advertising responses in the current dataset.

In future research, the authors also intend to study other advertising effectiveness measures, such as word-of-mouth effects, brand attitudes and purchase intention and moderating effects of consumers’ media usage and product category experience, for instance. The authors opted for campaign recognition and brand interest because these are important process variables which are often measured in campaign evaluation research. Moreover, research based on traditional hierarchy-of-effects models and on the theory of planned behavior shows that cognitive or memory responses such as campaign recognition, and evaluative responses such as brand interest, are often antecedents of buying behavior, and thus predictive of sales (Ajzen, 1991; Barry, 1987). Most existing ad response models are calibrated on sales data (e.g., Danaher and Dagger, 2013; Luan and Sudhir, 2010). We did not have access to such data, but mixture-amount models could be applied to all sorts of possible binary, categorical or continuous dependent variables.

Obviously, campaign effectiveness also depends on factors other than advertising budgets and media allocation. Future research should try to include these other factors, such as advertising creativity, originality, the quality of advertising executions, or specific information or selling propositions used. For instance, the inclusion of a price level or promotion may impact brand interest or other advertising outcomes, such as buying intention. A content analysis shows that none of the campaigns in the present sample mentioned a price or promotion. Nevertheless, future research should try to control for the potentially confounding effects of different advertising executions.

The model presented in this article allows to capture individual brand campaign differences using random effects, but it is not clear how specific campaign properties affect synergy: how will a more creative campaign execution on television and/or in magazines affect synergy and optimal media mix allocation? Certain outcomes, such as brand interest or purchase intention, could be also indirectly affected by other responses to the advertisements, such as ad likeability. It might therefore be useful to explore the possibilities of using mixture-amount models in mediation frameworks to better understand the mechanism behind the effects found.

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References

AJZEN, I. "The Theory of Planned Behavior," *Organizational Behavior and Human Decision Processes* 50, 2 (1991): 179-211.

ALDEN, D.L., A. MUKHERJEE and W.D. HOYER. "The Effects of Incongruity, Surprise and Positive Moderators on Perceived Humor in Television Advertising," *Journal of Advertising* 29, 2 (2000): 1-15.

ARAVINDAKSHAN, A., K. PETERS and P.A. NAIK. "Spatiotemporal Allocation of Advertising Budgets," *Journal of Marketing Research* 49, 1 (2012): 1-14.

ARNDT, J. and J.L. SIMON. "Advertising and Economies of Scale: Critical Comments on the Evidence," *The Journal of Industrial Economics* 32, 2 (1983): 229-42.

ASSAEL, H. "From Silos to Synergy. A Fifty-Year Review of Cross-Media Research Shows Synergy Has yet to Achieve Its Full Potential," *Journal of Advertising Research* 51, 1, 50th Anniversary Supplement (2011): 42-8.

BARRY, T.E. "The Development of the Hierarchy of Effects: An Historical Perspective," *Current issues and Research in Advertising* 10, 1-2 (1987): 251-95.

BASS, F.M. "A Simultaneous Equation Regression Study of Advertising and Sales of Cigarettes," *Journal of Marketing Research* 6, 3 (1969): 291-300.

BRONNER, F. and P. NEIJENS. "Audience Experiences of Media Context and Embedded Advertising: A Comparison of Eight Media," *International Journal of Market Research* 48, 1 (2006): 81-100.

BRUCE, N.I., N.Z. FOUTZ and C. KOLSARICI. "Dynamic Effectiveness of Advertising and Word of Mouth in Sequential Distribution of New Products," *Journal of Marketing Research* 49, 4 (2012): 469-86.

CHANG, Y. and E. THORSON. "Television and Web Advertising Synergies," *Journal of Advertising* 33, 2 (2004): 75-84.

CORNELL, J.A. *Experiments with Mixtures: Designs, Models, and the Analysis of Mixture Data*, 3d ed. New York, NY: Wiley, 2002.

DAHLÉN, M. and F. LANGE. "Advertising Weak and Strong Brands: Who Gains?," *Psychology & Marketing* 22, 6 (2005): 473-88.

DANAHER, P.J. and T.S. DAGGER. "Comparing the Relative Effectiveness of Advertising Channels: A Case Study of a Multimedia Blitz Campaign," *Journal of Marketing Research* 50, 4 (2013): 517-34.

DANAHER, P.J. and J.R. ROSSITER. "Comparing Perceptions of Marketing Communication Channels," *European Journal of Marketing* 45, 1/2 (2011): 6-42.

DE PELSMACKER, P., M. GEUENS and J. VAN DEN BERGH. *Marketing Communications: A European Perspective*. Harlow: Financial Times/Prentice Hall, 2010.

DEKIMPE, M.G. and D.M. HANSSENS. "The Persistence of Marketing Effects on Sales," *Marketing Science* 14, 1 (1995): 1-21.

DIJKSTRA, M., H. BUIJTELS and W.F. VAN RAAIJ. "Separate and Joint Effects of Medium Type on Consumer Responses: A Comparison of Television, Print, and the Internet," *Journal of Business Research* 58, 3 (2005): 377-86.

DOCTOROW, D., R. HOBLIT and A. SEKHAR. "Measuring Marketing: Mckinsey Global Survey Results," *McKinsey Quarterly*, March (2009): 1-3.

DUKES, A. and Y. LIU. "In-Store Media and Distribution Channel Coordination," *Marketing Science* 29, 1 (2010): 94-107.

EFRON, B. and R. TIBSHIRANI. "Improvements on Cross-Validation: The 632+ Bootstrap Method," *Journal of the American Statistical Association* 92, 438 (1997): 548-60.

ENOCH, G. and K. JOHNSON. "Cracking the Cross-Media Code: How to Use Single-Source Measures to Examine Media Cannibalization and Convergence," *Journal of Advertising Research* 50, 2 (2010): 125-36.

FÄRE, R., S. GROSSKOPF, B.J. SELDON and V.J. TREMBLAY. "Advertising Efficiency and the Choice of Media Mix: A Case of Beer," *International Journal of Industrial Organization* 22, 4 (2004): 503-22.

FRISON, S., M.G. DEKIMPE, C. CROUX and P. DE MAEYER. "Billboard and Cinema Advertising: Missed Opportunity or Spoiled Arms?," *International Journal of Research in Marketing* 31, 4 (2014): 425-33.

GATIGNON, H. and D.M. HANSSENS. "Modeling Marketing Interactions with Application to Salesforce Effectiveness," *Journal of Marketing Research* 24, 3 (1987): 247-57.

GODFREY, A., K. SEIDERS and G.B. VOSS. "Enough Is Enough! The Fine Line in Executing Multichannel Relational Communication," *Journal of Marketing* 75, 4 (2011): 94-109.

GOPALAKRISHNA, S. and R. CHATTERJEE. "A Communications Response Model for a Mature Industrial Product: Application and Implications," *Journal of Marketing Research* 29, 2 (1992): 189-200.

HARDIN, J.W. and J. HILBE. *Generalized Linear Models and Extensions, Third Edition*. Lakeway Drive, College Station, Texas: Stata Press, 2012.

HAVLENA, W., R. CARDARELLI and M. DE MONTIGNY. "Quantifying the Isolated and Synergistic Effects of Exposure Frequency for TV, Print, and Internet Advertising," *Journal of Advertising Research* 47, 3 (2007): 215-21.

KANSO, A.M. and R.A. NELSON. "Internet and Magazine Advertising: Integrated Partnerships or Not?," *Journal of Advertising Research* 44, 04 (2004): 317-26.

LEIGH, J.H. "Information Processing Differences among Broadcast Media: Review and Suggestions for Research," *Journal of Advertising* 20, 2 (1991): 71-5.

LIN, C., S. VENKATARAMAN and S.D. JAP. "Media Multiplexing Behavior: Implications for Targeting and Media Planning," *Marketing Science* 32, 2 (2013): 310-24.

LONGMAN, K.A. "Marketing Science-Market Segmentation vs. Segmented Marketing," *Interfaces* 1, 4 (1971): 38-40.

LUAN, Y.J. and K. SUDHIR. "Forecasting Marketing-Mix Responsiveness for New Products," *Journal of Marketing Research* 47, 3 (2010): 444-57.

MACHLEIT, K.A., C.T. ALLEN and T.J. MADDEN. "The Mature Brand and Brand Interest: An Alternative Consequence of Ad-Evoked Affect," *Journal of Marketing* 57, 4 (1993): 72-82.

NAIK, P.A. and K. RAMAN. "Understanding the Impact of Synergy in Multimedia Communications," *Journal of Marketing Research* 40, 4 (2003): 375-88.

NAIK, P.A., K. RAMAN and R.S. WINER. "Planning Marketing-Mix Strategies in the Presence of Interaction Effects," *Marketing Science* 24, 1 (2005): 25-34.

NIEDZ, R.P. and T.J. EVENS. "Mixture Screening and Mixture-Amount Designs to Determine Plant Growth Regulator Effects on Shoot Regeneration from Grapefruit (Citrus Paradisi Macf. Epicotyls)," *In Vitro Cellular & Developmental Biology-Plant* 47, 6 (2011): 682-94.

PAIVIO, A., J.M. CLARK and W.E. LAMBERT. "Bilingual Dual-Coding Theory and Semantic Repetition Effects on Recall," *Journal of Experimental Psychology: Learning, Memory, and Cognition* 14, 1 (1988): 163.

PEPE, M.S. "An Interpretation for the Roc Curve and Inference Using Glm Procedures," *Biometrics* 56, 2 (2000): 352-9.

PETERSON, T. "Digital to Overtake TV Ad Spending in Two Years, Says Forrester." *Advertising Age* November 4, 2014, [URL: http://adage.com/article/media/digital-overtake-tv-ad-spending-years-forrester/295694/], accessed on May 6, 2015.

PFEIFFER, M. and M. ZINNBAUER. "Can Old Media Enhance New Media? How Traditional Advertising Pays Off for an Online Social Network," *Journal of Advertising Research* 50, 1 (2010): 42-9.

PORTER, M.E. "Interbrand Choice, Media Mix and Market Performance," *The American Economic Review* 66, 2 (1976): 398-406.

RAMAN, K., M.K. MANTRALA, S. SRIDHAR and Y.E. TANG. "Optimal Resource Allocation with Time-Varying Marketing Effectiveness, Margins and Costs," *Journal of Interactive Marketing* 26, 1 (2012): 43-52.

REYNAR, A., J. PHILLIPS and S. HEUMANN. "New Technologies Drive CPG Media Mix Optimization," *Journal of Advertising Research* 50, 4 (2010): 416-27.

SADOSKI, M. and A. PAIVIO. *Imagery and Text: A Dual Coding Theory of Reading and Writing*: Routledge, 2012.

SCHEFFÉ, H. "Experiments with Mixtures," *Journal of the Royal Statistical Society. Series B (Methodological)* (1958): 344-60.

SCHULTZ, D.E., M.P. BLOCK and K. RAMAN. "Understanding Consumer-Created Media Synergy," *Journal of Marketing Communications* 18, 3 (2012): 173-87.

SCHUMANN, D.W., R.E. PETTY and D.S. CLEMONS. "Predicting the Effectiveness of Different Strategies of Advertising Variation: A Test of the Repetition-Variation Hypotheses," *Journal of Consumer Research* (1990): 192-202.

SPECK, P.S. and M.T. ELLIOTT. "Predictors of Advertising Avoidance in Print and Broadcast Media," *Journal of Advertising* 26, 3 (1997): 61-76.

TSAO, J.C. and S.D. SIBLEY. "Displacement and Reinforcement Effects of the Internet and Other Media as Sources of Advertising Information," *Journal of Advertising Research* 44, 1 (2004): 126-42.

VAKRATSAS, D. and Z. MA. "A Look at the Long-Run Effectiveness of Multimedia Advertising and Its Implications for Budget Allocation Decisions," *Journal of Advertising Research* 45, 2 (2005): 241-54.

VITACCO, M.J., G.J. VAN RYBROEK, J.E. ROGSTAD, L.E. YAHR, J.D. TOMONY and E. SAEWERT. "Predicting Short-Term Institutional Aggression in Forensic Patients: A Multi-Trait Method for Understanding Subtypes of Aggression," *Law and human behavior* 33, 4 (2009): 308.

VONESH, E.F., V.M. CHINCHILLI and K. PU. "Goodness-of-Fit in Generalized Nonlinear Mixed-Effects Models," *Biometrics* 52 (1996): 572-87.

VOORVELD, H.A., P.C. NEIJENS and E.G. SMIT. "Opening the Black Box: Understanding Cross-Media Effects," *Journal of Marketing Communications* 17, 2 (2011): 69-85.

WAKOLBINGER, L.M., M. DENK and K. OBERECKER. "The Effectiveness of Combining Online and Print Advertisements: Is the Whole Better Than the Individual Parts?," *Journal of Advertising Research* 49, 3 (2009): 360-72.

WRIGHT, M. "A New Theorem for Optimizing the Advertising Budget," *Journal of Advertising Research* 49, 2 (2009): 164-9.