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A Hierarchical Marketing Communications Model of Online and Offline Media Synergies

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Abstract

We propose a new hierarchical model of online and offline advertising. This model incorporates within-media synergies and cross-media synergies and allows higher-order interactions among various media. We derive the optimal spending on each medium and the optimal total budget. We also develop three hypotheses on the effects of within- and across-media synergies on both the total budget and its allocation. We estimate media effectiveness as well as the within- and cross-media synergies of offline (television, print, and radio) and online (banners and search) ads using market data for a car brand. We show that both types of synergies —within-media (i.e., intra-offline) and cross-media (online-offline)— exist. We show how within- and cross-media synergies boost the total media budget and online spending due to synergies of the online media with various offline media.

Keywords: Optimal allocation; Advertising; Online media; Synergy; Marketing communications budget

Introduction

Online and interactive marketing communication spending continues to grow rapidly (e.g., Shankar and Hollinger 2007). In 2007, U.S. companies spent $10.4 and $7.7 billion on search marketing and display advertising, respectively, and together with other forms of online advertising such as email marketing, the total online media outlay was $24.4 billion (*Advertising Age* 2007). This amount represents approximately 8% of the total media spending, which includes all other offline media (e.g., television, radio, print). Online media spending is expected to more than double in 5 years (i.e., $60 billion by 2012) and to consume 18% of the total media expenditures (*Advertising Age* 2007; Shankar and Hollinger 2007). Indeed, new media comprising online, mobile, and social media are emerging as the growth area for advertising for manufacturers and retailers (Ailawadi et al. 2009).

The surge in online marketing spending and large offline media expenditures raises important questions for managers. How much should managers allocate to online media given their spending in all other media? Do online media interact with offline media to influence marketing outcomes such as brand consideration and brand sales? If so, how?

Previous studies on marketing resource allocation reveal important insights on the effects of within-media synergies on the overall budget and its allocation (e.g., Naik 2007; Naik and Raman 2003; Shankar 1997, 2008; Prasad and Sethi 2009). Of particular interest is synergy, which emerges when the combined effect of two media exceeds their individual effects on the outcome measure (Naik 2007). Naik and Raman (2003) show that, when within-media synergy exists, managers should increase the total media budget and allocate *more* than fair share to the *less* effective medium. That is, managers should spend disproportionately more on the less effective medium because it reinforces the more effective medium. However, they examined only vehicles within-offline media, which could potentially have synergies with online media. That is, there could be *across* online–offline media synergy in addition to within-offline media synergies. For example, online media may enhance not

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just the effectiveness of offline media such as television or print, but also the synergy between those offline media components, television and print.

To understand this phenomenon and test it empirically, we develop a hierarchical marketing communications model of online and offline media synergies. The model captures within-media synergies and across-media synergies and allows for higher-order interactions among various media. We analytically derive the normative spending rules for the model and develop hypotheses on the effects of within- and cross-media synergies on both the total budget and its allocation.

We test the hypotheses from the theoretical model using data from a car company, which advertises on both the online and offline media to keep its brand in consumers' consideration set. The company evaluates the consideration outcomes using offline visits to dealer showrooms and online visits to configure cars on their website. We establish that *both types* of synergies, namely, within-media (i.e., intra-offline) and cross-media (online–offline) synergies exist. In other words, we show that online advertising amplifies the effectiveness and synergies of offline media (television, print, newspapers, and magazines) in increasing the online car configurator visits. To our knowledge, our study is the first one to document this substantive finding, providing evidence to support the hierarchical model of online–offline advertising.

From a managerial standpoint, we address the important issue of the sources of growth in online media spending. The current use of online media is driven by managers' beliefs that it costs less than offline media (Barwise and Farley 2005). Its continued use, however, depends on demonstrating its effectiveness in achieving measurable goals such as awareness, consideration, or sales. Consequently, advocates of online advertising may exaggerate its effectiveness or understate the effectiveness of offline media (e.g., statements such as people zip television ads or direct mailings contain junk). Although online spending can grow by adopting such a competitive orientation to secure resources at the expense of the offline media, we identify alternate sources of growth: within- and cross-media synergies. Our results show how within- and cross-media synergies increase the brand's total media budget. Thus, by eschewing competitive orientation, online spending can grow solely due to the collaborative orientation, which involves building synergies with various offline media.

Our proposed model extends Naik and Raman (2003) by distinguishing between two types (within-media and cross-media) of synergies and advancing new theoretical results. In particular, unlike Naik and Raman (2003), our model includes three-way and higher-order interactions among different media types.

We organize the rest of the paper as follows. We first review the extant literature to develop the theoretical basis for the hierarchical model. We next formulate the hierarchical model of online–offline advertising and derive the new propositions and hypotheses. Subsequently, we describe the data, estimate the proposed model and empirically validate the hypotheses. Finally, we discuss the managerial implications and conclude by summarizing the contributions.

Related literature

We review relevant studies on consumer decision process, offline and online media effectiveness, media synergy effects, and multimedia allocation.

Consumer decision process

Consumers' buying process involves distinct stages such as awareness, consideration, and purchase (e.g., Lavidge and Steiner 1961). In the auto industry, according to J.D. Power and Associates (2004), 64% of the new car buyers become aware of the features and benefits by obtaining information online on cars, even though they purchase their car from an offline dealership. This finding implies that if car manufacturers "do not become part of the consideration sets of customers who are looking for information online, those customers may not show up at dealerships to test drive or purchase" (Rangaswamy and van Bruggen 2005). Consequently, car manufacturers aim to increase both online and offline site traffic. Ilfeld and Winer (2002) show that offline advertising increases website visitation by influencing consumer awareness, while online advertising directly leads to increased website traffic. Therefore, we use both the local dealer visits (offline) and car configurator visits (online) as the dependent variables for car-buying consideration in our model. Based on both measures of consideration, we will estimate the impact of offline advertising, online advertising, and media synergy.

Offline media effectiveness

Offline advertising consists of media spending on television, newspapers, magazines, radio, and direct mail. Several studies in the extant literature document the effectiveness of offline advertising (see Tellis and Ambler 2007). Because offline media, like direct mail, generate website visitors, Bellizzi (2000) urges online businesses to not rely solely on online advertising to create awareness and site visitation. In the context of political campaign ads, Lariscy and Tinkham (1996) find that (i) increasing media allocation to direct mail enhances the share of vote for non-incumbents and (ii) using multimedia campaign via television, newspaper, outdoor, printed literature, and direct mail outperforms a single-media campaign. Hence, we include offline ad spending on mass media (namely, television, radio, newspapers, and magazines) and individually-targeted media (namely, unaddressed and personally addressed direct mail) as the independent variables in our model.

Online media effectiveness

When consumers use online media, they substitute traditional offline search by Internet-based search (Klein and Ford 2003). Besides facilitating the low-cost search, online media also provide display advertising via banners. Banner advertising presents visual and textual information about the brand, occupies approximately 10% of the computer monitor's area, and allows consumers to access the company's website when clicked

(Shankar and Hollinger 2007). Some studies investigate the effectiveness of banner advertising (e.g., Sherman and Deighton 2001; Chatterjee, Hoffman, and Novak 2003; Drèze and Hussherr 2003; Manchanda et al. 2006). Although its click-through rates are small, banner advertising creates a trace of ad exposure at pre-attentive levels of information processing, enhancing advertising and brand recall (Drèze and Hussherr 2003). According to Hollis (2005), who analyzed 1239 campaigns in the AdIndex database, the correlation between online ad awareness and purchase intent is 0.439, suggesting that online advertising builds attitudinal equity of a brand similar to traditional media. Thus, companies can build brands using online media (also see Loechner 2004). In this study, we will explore the effects of online media spending —both the direct effects and joint effects with offline media— on behavioral outcomes (i.e., offline dealer visits, online car configurator visits).

Media synergy effects

Next, we review the literature on synergy via media integration. Table 1 compares their main characteristics and the resulting findings. Jagpal (1981) investigated synergy between radio and newspaper advertising for a commercial bank. Using laboratory experiments, Edell and Keller (1989) studied the joint effects of television and radio ads and found that consumers recall TV ads when they listen to radio ads. Confer and McGlathery (1991) established synergy between magazine and television ads. Sheehan and Doherty (2001) distinguish two kinds of integration: strategic integration, which means thematically integrated messages and communication vehicles (e.g., Deighton 1996; Duncan and Everett 1993; Moriarty 1994) and tactical integration, which means employing similar retrieval cues such as key visuals or distinct slogans (e.g., Keller 1996). To investigate strategic integration (i.e., using print media to build name recognition and web media to provide information), Sheehan and Doherty (2001) examined 180 print and web advertisements and found only 19% of the print and web ads are strategically integrated; in contrast, over 60–80% of the ads were tactically integrated (i.e., creative elements are similar in both the print and web ads). Stafford, Lippold, and Sherron (2003) find that the combined effects of direct-mail and national advertising contribute more to weekly sales. Chang and Thorson (2004) found that television–web synergy leads to higher attention, increased message credibility, and greater number of total and positive thoughts. Dijkstra, Buijtels, and van Raaij (2005) investigated synergies between television, print and the Internet, but found mixed results perhaps due to forced exposures in laboratory setting or the short time interval between exposures and responses. Havlena, Cardarelli, and De Montigny (2007) reported media synergies between TV, print, and online campaigns using individual-level data. Based on individual-level sales data from online sites and offline stores, Abraham (2008) found synergies between online display ads and online search ads.

Recent normative research on dynamic models of within-media synergy has produced interesting results (see Naik and Raman 2003; Raman and Naik 2004; Naik, Raman, and Winer 2005; Prasad and Sethi 2009). Naik and Raman (2003) formulated and estimated the integrated marketing communications (IMC) model by applying Kalman filter estimation. They established a two-way media interaction between television and print advertising for the Dockers brand, and they used retail sales as the single dependent variable. In addition, they derived closed-form optimal allocation rules to discover the counter-intuitive insight: as synergy increases, brand managers should increase the total budget and allocate more than a fair share to the weaker medium. Raman and Naik (2004) incorporated the role of uncertainty and found the catalytic effect, which reveals that a non-zero amount should be allocated to media even if their own effectiveness is zero, provided they exhibit positive synergy with other media in the communications mix. Naik, Raman, and Winer (2005) extended this normative–empirical framework to incorporate the presence of competitor's advertising in dynamic oligopoly markets. Prasad and Sethi (2009) further extended this research stream to incorporate both uncertainty and competitive effects and generalized the above findings, especially using different sales dynamics and thus enhancing our confidence in these findings.

Multimedia allocation

Briggs, Krishnan, and Borin (2005) implemented the IMC model in field for the Ford F-150 brand, which spent 90% of its budget on television ads to generate awareness and consideration goals. Based on the estimated model, this budget was partly re-allocated to magazines and online media, resulting in 20% increase in exposures (relative to the control group). Thus, this field study reaffirms the value of a diversified communications mix. We close this review by noting that all extant studies estimate within-media synergy (i.e., two-way interactions) using a single outcome measure. We subsequently uncover within- and cross-media synergies, establishing the presence of higher-order interactions among different types of media.

Model and analysis

We first describe an interactive model with media synergies, then present a hierarchical interactive model to distinguish within- and cross-media synergies, and finally derive the optimal spending rules for the hierarchical model.

Interaction model

Consider a firm that spends x_{jt} dollars in period t on communications medium (e.g., television, radio) j, where $j=1$, 2. Previous studies (e.g., Edell and Keller 1989; Naik and Raman 2003) show that different media reinforce each other. To incorporate media synergies, we apply the advertising interaction model (e.g., Gatignon and Hanssens 1987) with a stochastic process function:

$$Y_t = \alpha_0 + \alpha_1 X_{1t} + \alpha_2 X_{2t} + \varepsilon_t, \text{ and} \tag{1}$$

$$\alpha_j = \beta_j + \beta_{jj'} X_{j't} + \nu_{jt} \tag{2}$$

Table 1
Selected studies on multimedia synergy.

Author(s) (year)	Dependent variable			Media			Budget allocation	Major findings
	(A)wareness (C)onsideration (S)ales	Offline, online, or common measure	Multiple dependent variables	Offline	Direct mail	Online		
Edell and Keller (1989)	A (Ad and brand recall) C (Purchase intent)	Offline	No	TV Radio	No	No	No	Consumers recall TV ads when listening to radio ads
Confer and McGlathery (1991)	A	Offline	Yes	TV Magazines	No	No	No	No synergy on brand imagery; 10% higher score of print and TV ad on brand selection than single-media campaigns; 12% higher score compared to single-media campaigns on brand recall
Chang and Thorson (2004)	A C (Purchase intent)	Common	Yes	TV	No	Yes	No	Synergy on attention measures, but not with respect to credibility and purchase intention measures
Dijkstra, Buijtels, and van Raaij (2005)	A (Ad and brand recall) C (Purchase intent)	Common	Yes	TV Print	No	Yes	No	TV-only campaigns best on cognitive responses; complementary effect in multimedia campaigns compared to internet-only campaigns
Havlena, Cardarelli, and De Montigny (2007)	A C (Purchase intent)	Common	Yes	TV Print	No	Yes	No	Potential media synergies among heavy media consumer subsamples; positive synergy between print and TV exposures
Abraham (2008)	S	Offline and online	No			Yes	No	People respond more to expensive search than cheaper display ads; using both types of ads in one campaign increases online and offline sales more than two, added together, separate campaigns
Jagpal (1981)	A S	Offline	Yes	Radio Newspaper	No	No	No	Radio advertising relatively ineffective because impact on awareness was low
Naik and Raman (2003)	S	Offline	No	TV Print	No	No	Yes; general closed-form expressions	Synergy present; general rules for allocation derived; comparative statics reveal new insights
Stafford, Lippold, and Sherron (2003)	S	Offline	No	National TV/radio Local TV/radio	Yes	No	No	Primary direct-mail piece used with national advertising most profitable option
Briggs, Krishnan, and Borin (2005)	A C (Purchase intent)	Common	Yes	TV Radio Print Outdoor	Yes	Yes	Yes; numerical amounts for a field study	Best cost per impact coming from magazines and online advertising, although 90% spent on TV; re-allocation to online increased exposure by 20%
This study	C	Offline and online	Yes	TV Radio Magazines Newspapers	Yes	Yes	Yes; analytical expressions	Establishes within-, cross- and higher-order-media synergy, offline–online media synergy, derives and tests new theoretical insights on the budget size and allocation impact of higher-order media synergies; multiple dependents (online-offline)

where Y_t is the outcome of interest (e.g., units sold, the number dealer visits), $X_{jt}=\mathrm{Ln}(x_{jt})$ captures the role of diminishing returns (i.e., the impact of incremental dollars decreases as the spending level increases), β_j represents the effectiveness of medium j, $\beta_{jj'}$ denotes the joint effect of media j and j', and the error terms $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$ and $v_{jt} \sim N(0, \sigma_{vj}^2)$ represent the effects of unobserved variables.

Equation 2 states that the effectiveness of television advertising, α_1, increases when consumers' exposure to a brand increases due to radio advertising (x_{2t}) provided the synergy β_{12} is positive. Similarly, radio effectiveness increases due to exposure to television advertising.

Two counter-intuitive insights emerge from this interactive model. First, as synergy increases, managers should *increase* the total budget and allocate more than fair share to the *less* effective medium (see Naik and Raman 2003). Why? Because television spending enhances the effectiveness of radio ads much more than the radio spending increases the TV ad effectiveness (see Naik 2007 for further discussion).

Second, in the presence of within-media synergy, managers should spend a non-zero budget on a medium even if ads in that medium are completely ineffective. More precisely, it can be shown that (see the Catalytic Effects in Raman and Naik 2004) the optimal spending $x_j^* \neq 0$ even if the ad effectiveness $\beta_j = 0$ provided the within-media synergy $\beta_{jj'} > 0$. In other words, any medium, offline or online, deserves a non-zero budget despite its limited and/or unknown effectiveness.

Hierarchical synergy model

Fig. 1 (see panel A) shows that the above interaction model stems from "within"-media interaction (shown by the boxed arrows), which emerges from the joint spending patterns of offline media such as television, radio, newspaper, or magazines. In contrast, panel B distinguishes the two different types of interactions: within- and cross-media synergies. Specifically, cross-media synergies (shown by the curved arrows) emerge from joint spending patterns across different types of media, e.g., between offline and online media. Consequently, higher-order synergies due to three-way interactions (or four-way interactions) may arise when firms use multiple media to achieve the communication goals.

To quantify the magnitudes of the different types of synergies, we propose a hierarchical interactive model:

$$Y_t = \alpha_0 + \alpha_1 Z_t + \alpha_2 X_{3t} + \alpha_3 Z_t \times X_{3t} + \varepsilon_t \text{ and} \tag{3}$$

$$Z_t = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \beta_3 X_{1t} \times X_{2t}. \tag{4}$$

In Equation 4, Z represents the offline media factor that combines the total effect —direct and interactive— of all individual offline media; β_3 measures the within-media synergy. Equation 3 captures the cross-media interaction between offline and online media via α_3. Together, Equations 3 and 4 form a hierarchical system, wherein the lower-level combines individual media (e.g., television and print) into a broader class (e.g., offline media) and then this resulting factor Z in turn affects the outcome variable (e.g., sales or consideration) either directly and/or interactively along with other media factors.

Two remarks on the proposed model are in order. First, we show two offline media creating Z in Equation 4 for notational simplicity. We clarify that it permits multiple media within each factor and multiple such factors to affect the outcome(s) of interest; for example, see the empirical application. Second, unlike Naik and Raman (2003), the proposed model allows three-way or even four-way interactions. Specifically, we can substitute Equation 4 and 3 to observe the presence of three-way interactions; if we had another factor Z_2 (say) with its own within-media synergies, we would obtain four-way interactions. Thus, the hierarchical synergy model not only incorporates parsimoniously the role of higher-order synergies, but also extends the IMC model of Naik and Raman (2003).

Given that the hierarchical synergy model distinguishes two kinds of synergies (α_3, β_3), how does this distinction affect the budgeting and allocation decisions? To understand their

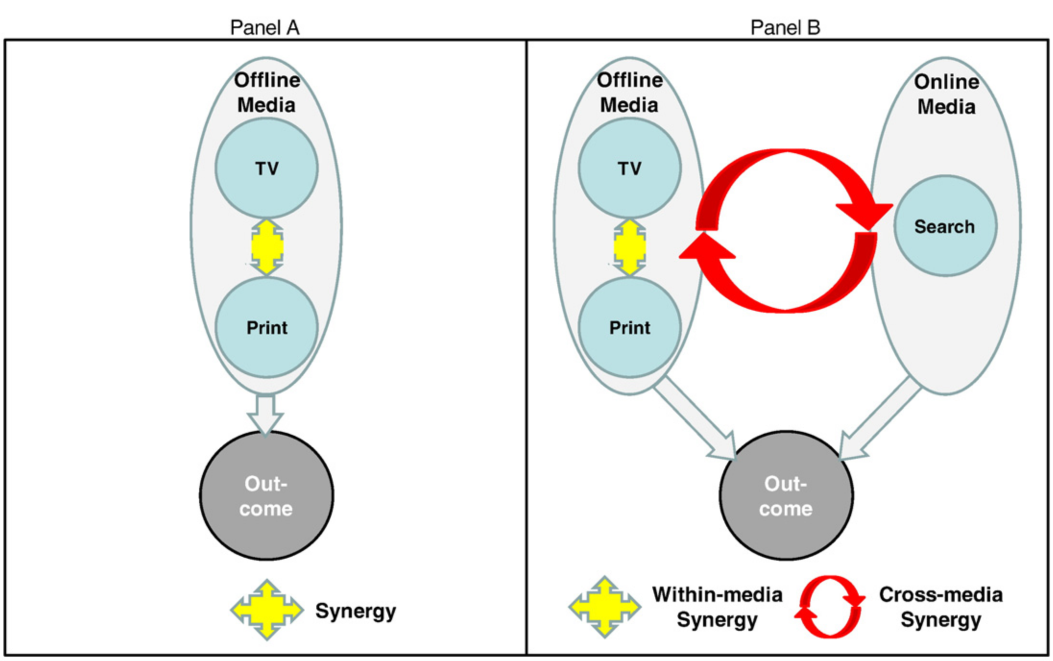

Fig. 1. Within- and cross-media synergies.

differential impacts, we next derive the optimal spending rules and present new theoretical results.

Theoretical results

To decide how much to spend on each media, we maximize profit given by

$$\Pi = mY - x_1 - x_2 - x_3, \tag{5}$$

where m denotes the marginal profit impact of Y, which depends on the model Equations 3 and 4. We solve the maximization problem in Equation 5 subject to Equations 3 and 4 to derive the following result:

Proposition 1. In the hierarchical synergy model, the optimal spending levels are

$$\begin{aligned} x_1^* &= m\left(\alpha_1 + \alpha_3 X_3^*\right)\left(\beta_1 + \beta_3 X_2^*\right) \\ x_2^* &= m\left(\alpha_1 + \alpha_3 X_3^*\right)\left(\beta_2 + \beta_3 X_1^*\right) \\ x_3^* &= m\left(\alpha_2 + \alpha_3 Z^*\right), \end{aligned} \tag{6}$$

where $X_j^* = \mathrm{Ln}\left(x_j^*\right)$, $j=1$, 2 and 3.

By starting from the current spending levels and applying the decision rules in Equation 6 iteratively, managers can arrive at the profit-maximizing spending levels $\left(x_1^*, x_2^*, x_3^*\right)'$ across the three media. As we illustrate in the empirical application, these decision rules generalize to multiple media. In the Appendix, we further generalize them to dynamic settings by incorporating carryover effects (see Proposition 2). Both Propositions 1 and 2 are theoretical contributions to the marketing communications literature.

But, more importantly, Equation 6 reveals that the optimal spending, x_j^*, depends on not only its effectiveness, but also its within- and cross-synergies with other media factors (i.e., α_3, β_3). That is, both types of synergies matter in budgeting and allocation decisions, as we next elucidate.

Consider allocating dollars between medium 1 (say, television) and medium 2 (say, radio) and let $\lambda_{12} = x_1^*/x_2^*$ denote the optimal allocation ratio. It follows from Equation 6 that the allocation ratio λ_{12} equals $\left(\beta_1 + \beta_3 X_2^*\right)/\left(\beta_2 + \beta_3 X_1^*\right)$, which, at first glance, is independent of the cross-media synergy α_3. Yet we claim that the relative allocation to television and radio advertising must change as the online–offline synergy changes *even if* the own effectiveness (β_1, β_2) of television and radio and their within-media synergy β_3 remain unchanged. We state this claim in the following hypothesis:

Hypothesis 1. The allocation ratio within a media factor changes as its cross-media synergy with other media factor changes. Formally, $\frac{\partial \lambda_{12}}{\partial \alpha_3} \neq 0$.

This change occurs because, as α_3 increases, the allocation between Z and X_3 changes, and the resulting change in Z, in turn, drives the re-allocation between X_1 and X_2, thereby influencing λ_{12}. A formal comparative static analysis predicts a non-zero effect (i.e., $\partial \lambda_{12}/\partial \alpha_3 \neq 0$), but it does not yield an unambiguous sign (positive or negative). Hence, we state and test this claim as a hypothesis (rather than a proposition). The next hypothesis states the effects of within-media synergy on the allocation ratio.

Hypothesis 2. The allocation ratio within a media factor changes as within-media synergy changes. Formally, $\frac{\partial \lambda_{12}}{\partial \beta_3} \neq 0$ even if $\alpha_3 \neq 0$.

We state the final hypothesis that predicts the effects of either within- or cross-media synergy on the total budget B.

Hypothesis 3. The total budget B increases as either within- or cross-media synergy increases. Formally, $\frac{\partial B}{\partial \beta_3} > 0$ or $\frac{\partial B}{\partial \alpha_3} > 0$, where $B = x_1^* + x_2^* + x_3^*$.

These hypotheses contribute to the marketing communications literature. They extend the results of Naik and Raman (2003) by incorporating across-media synergy.

We close this section by clarifying an important consequence of online–offline synergies. Specifically, the optimal online spending equals $x^*_{3,\text{ no synergy}} = m\alpha_2$ in the absence of synergy, and $x^*_{3,\text{ with synergies}} = m(\alpha_2 + \alpha_3 Z)$ in the presence of synergy (see Proposition 1). By comparison, the online spending x_3^* *increases* due to the presence of online–offline synergy (i.e., α_3). Hence, managers should adopt a collaborative orientation and build online–offline synergies (i.e., enhance α_3) to grow their online budget rather than pursue a competitive orientation by advocating offline effectiveness has diminished (without solid econometric evidence) to divert the offline budget to online advertising.

Empirical analysis

We show how firms can use readily available market data to estimate not only online effectiveness, but also within- and cross-media synergies.

Data description

We analyze data from a major car company in Germany that sold several million cars worldwide. The company advertises to keep its brand in consumers' consideration set and measures the outcomes every week t based on qualified dealer visits (Y_t^1) to its offline showrooms and car configurator visits (Y_t^2) online. A visit to dealer showrooms is considered qualified when the prospective customer leaves behind a name and contact information, requesting further contacts from dealers' salespersons. Similarly, car configurator visits enable consumers to customize the features and determine the price; cookies track these visits when prospective customers upload their name and addresses requesting a particular offer. Our data set records only the first registration in either online or offline channel (i.e., repeat visits from the same individual are not re-counted). Given the proprietary nature of this data, we scale all the variables and disguise the brand name to maintain confidentiality agreements.

We measure offline advertising spending in Euros spent weekly on television (x_{1t}), radio (x_{2t}), magazines (x_{3t}), and newspapers (x_{4t}). For online advertising, we use the spending on banners and micro-site advertising with major websites (x_{5t}). Direct-mail advertising (x_{6t}) consists of mail contacts, either personally addressed or unaddressed, made on weekends and

Table 2
Descriptive statistics.

Variables	Mean	Std. Dev.	Correlations						
			Y^1	Y^2	X_1	X_2	X_3	X_4	X_5
Qualified dealer visits, Y_1	2134	1092	1						
Car configurator visits, Y_2	3618	2140	.67	1					
TV ad spending, X_1	5.6862	6.7529	.59	.41	1				
Radio ad spending, X_2	0.5947	2.7088	.19	.28	.28	1			
Magazine ad spending, X_3	6.4428	6.0824	.57	.50	.53	.02	1		
Newspaper ad spending, X_4	1.0498	3.3232	.04	−.12	.25	.51	−.08	1	
Online ad spending, X_5	6.8494	5.3362	.52	.63	.18	.17	.40	−.01	1
Direct-mail spending, X_6	1.1920	3.5330	.31	.46	.12	.12	.21	.03	.27

drives online and offline visits about 2 weeks later. We capture diminishing returns by log-transforming the spending in Euros (i.e., $X_{jt}=\text{Ln}(1+x_{jt}), j=1, \ldots, 6$). Table 2 displays the descriptive statistics across the campaign duration of 86 weeks.

Estimation approach

We seek to estimate the hierarchical Equations 3 and 4 for the two dependent variables (Y^1 and Y^2) simultaneously, which may exhibit inter-equation correlations; consequently, the seemingly unrelated regression (SUR) is the appropriate approach (Zellner 1962). In addition, because of the interaction terms due to within- and cross-media synergies, Gatignon (1993) suggests that we correct for potential heteroscedasticity, which results in inefficiency. To address this concern, we apply White (1980) to estimate the heteroscedasticity-consistent standard errors, which are robust to unknown forms of heteroscedasticity (see Davidson and MacKinnon 2004, p. 199). Finally, we may encounter multicollinearity due to within-media synergies and, to mitigate its adverse effects, we follow Hanssens and Weitz (1980) and extract the principal component to obtain the β-weights in Equation 4.

Empirical results

Within-media synergies

Using the correlation matrix across the ten variables —the four offline media (television, radio, magazines, and newspapers) and its six two-way interactions terms— we extract the offline media factor. Table 3 reports the largest eigenvector, which furnishes the ten β-weights to compose the offline media factor:

$$Z=\hat{\beta}_1X_1+\hat{\beta}_2X_2+\hat{\beta}_3X_3+\hat{\beta}_4X_4+\hat{\beta}_5X_1X_2+\hat{\beta}_6X_1X_3+\hat{\beta}_7X_1X_4+\hat{\beta}_8X_2X_3+\hat{\beta}_9X_2X_4+\hat{\beta}_{10}X_3X_4.$$

Substantively, our results show that radio advertising is the most effective component, while magazine advertising is the least effective component. Furthermore, the six within-media synergies are large and vary from 0.16 (for television–magazines synergy) to 0.4 (for television–radio synergy). Next, using this offline media factor, we apply the SUR estimation to both the dependent variables simultaneously to estimate cross-media synergy.

Cross-media and higher-order synergies

Qualified offline dealer visits (Y_t^1=QDV) and online car configurator visits (Y_t^2=CCV) serve as the dependent variables in our two-equation system. Both the equations contain different variables, thus justifying the use of SUR. The inter-equation correlation is 0.46 and the system-wide adjusted R^2=57.31%. Table 4 presents the estimation results.

In panel A of Table 4, we report the parameter estimates for the QDV variable, which indicates that the estimated model is $Y^1=\hat{\alpha}_0^1+\hat{\alpha}_1^1Z+\hat{\alpha}_2^1X_5$. In words, both offline and online advertising expenditures directly increase dealer visits, whereas direct-mail advertising exerts insignificant effect. Also, we do not find cross-media synergies for this measure of consideration.

In panel B of Table 4, we report the parameter estimates for the CCV variable. The estimated model is given by $Y^2=\hat{\alpha}_0^2+\hat{\alpha}_2^2X_5+\hat{\alpha}_3^2X_6+\hat{\alpha}_4^2Z\times X_5$. These results reveal that

Table 3
Principal component of offline media.

Variables	Eigenvector
TV ad spending, β_1	.22
Radio ad spending, β_2	.40
Magazine ad spending, β_3	.08
Newspaper ad spending, β_4	.34
TV–radio synergy, β_5	.40
TV–magazine synergy, β_6	.16
TV–newspaper synergy, β_7	.38
Radio–magazine synergy, β_8	.31
Radio–newspaper synergy, β_9	.38
Magazine–newspaper synergy, β_{10}	.30

Table 4
SUR estimation results.

Parameters	Estimates	Robust Std. Error	*t*-value
Panel A: offline qualified dealer visits (QDV), Y^1			
Intercept, $\hat{\alpha}_0^1$	1340.40	82.30	16.30
Offline principal component, $\hat{\alpha}_1^1$	5.07	2.70	1.87
Online media, $\hat{\alpha}_2^1$	98.03	14.70	6.68
Panel B: online car configurator visits (CCV), Y^2			
Intercept, $\hat{\alpha}_0^2$	1893.50	227.40	8.33
Online media, $\hat{\alpha}_2^2$	199.92	28.90	6.91
Direct mail, $\hat{\alpha}_3^2$	134.02	41.60	3.22
Online–offline synergy, $\hat{\alpha}_4^2$	0.91	0.41	2.24

online advertising and direct mail directly affect car configurator visits. In addition, we find significant cross-media synergy between the offline media factor and online advertising. That is, we find evidence for the presence of cross-media synergy, where the offline media factor Z interacts with online media to drive online visits. Because offline media exhibits significant within-offline media synergies, we establish the three-way interaction effects. We interpret the higher-order synergy effects as follows: online advertising interacts not only with the effectiveness of offline media (i.e., television, radio, newspapers, and magazines), but also with the within-media synergies between television–radio, television–newspapers, television–magazines, radio–newspapers, radio–magazines, and magazines–newspapers.

As for direct mail, it only affects online car configurator visits without any interactions with any other media. An explanation for this finding is that its ad copy was tactically integrated with respect to slogans and key visuals, but not strategically integrated with offline or online campaigns (e.g., with respect to timing or message build-up). See Sheehan and Doherty (2001) for the distinction between tactical and strategic integrations.

Overall, the above findings furnish evidence supporting the presence of within-, cross- and higher-order synergies between offline and online media. Panels A and B in Fig. 2 sketch the mechanisms by which within- and cross-media synergy influence the online and offline car-buying consideration in our empirical setting. Specifically, panel A of Fig. 2 shows how within-media synergies drive offline dealer visits; while panel B shows how cross- and three-way media synergies interact with the direct effects of online advertising.

Model comparisons

We compare the proposed hierarchical synergy model with the model of Naik and Raman (2003) consisting of two-way interactions. Because this full interaction model does not nest the proposed model (or vice versa), we compare the non-nested models using three information criteria: Akaike Information Criterion (AIC), the bias-corrected AIC_C, and Bayesian Information Criterion (BIC). Table 5 presents the scores attained on the three criteria. When the scores between models differ by two, we garner strong support in favor of the model with the lower score (Burnham and Anderson 2002, p. 70). Accordingly, Table 5 indicates that we retain the proposed hierarchical synergy model, which outperforms the full interactions model across all three criteria, enhancing our confidence in this retained model.

Table 5
Model comparisons.

Information criterion	Full interactive model	Hierarchical synergy model
AIC	4427	2630
AIC_C	4220	2456
BIC	4359	2478

Testing the hypotheses

Applying comparative static analysis, we developed the three hypotheses regarding the behavior of the allocation ratio and the total budget with respect to the within- and cross-media synergy. To verify whether the predicted outcomes correspond with the empirical data, we use the estimated parameters to compute the total optimal budget $B = \sum_{j=1}^{6} x_j^*$ and the three allocation ratios: $\lambda_{12} = \frac{(x_1^* + x_2^* + x_3^* + x_4^*)}{x_5^*}$ (offline to online), and $\lambda_{13} = \frac{(x_1^* + x_2^* + x_3^* + x_4^*)}{x_6^*}$ (offline to direct mail), and $\lambda_{23} = \frac{x_5^*}{x_6^*}$ (online to direct mail). Then, to test Hypothesis 1 ceteris paribus, we re-compute these quantities using ±25% of the estimated value of α_3. The two shaded columns in Table 6 report the results, which indicate that our predictions are generally valid. Specifically, as

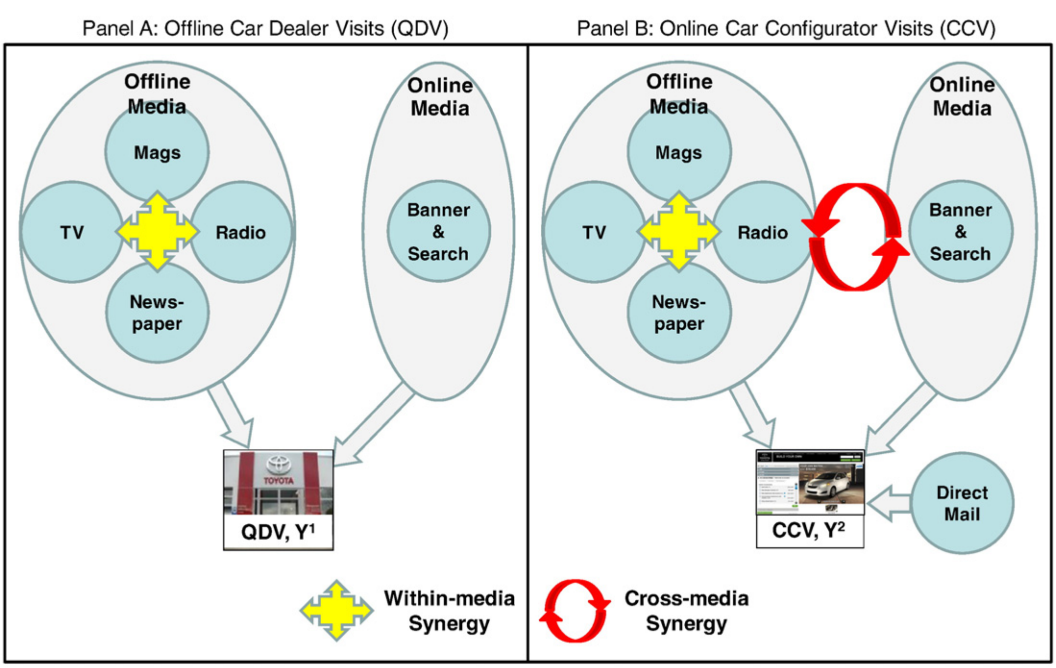

Fig. 2. Higher-order media synergies in offline and online car buying consideration.

Table 6
Hypotheses testing.

Parameters	Hypothesis 1		Hypothesis 2	
	Low α_3 (.75 $\hat{\alpha}_3$)	High α_3 (1.25 $\hat{\alpha}_3$)	Low β_3 (0.75 $\hat{\beta}_{5,\ldots,10}$)	High β_3 (1.25 $\hat{\beta}_{5,\ldots,10}$)
$\lambda_{12} = \sum_j^4 \frac{x_j^*}{x_5^*}$	5.74	5.74	5.65	5.78
$\lambda_{13} = \sum_j^4 \frac{x_j^*}{x_6^*}$	12.90	7.74	7.04	12.40
$\lambda_{23} = \frac{x_5^*}{x_6^*}$	2.25	1.35	1.25	2.15
Hypothesis 3				
$B = \sum_{j=1}^6 x_j^*$	578,394	602,275	443,585	742,287

offline–online synergy increases, all three allocation ratios tend to decrease.

Similarly, to test Hypothesis 2, ceteris paribus, we re-computed these quantities using ±25% of the estimated values of all the six ($\beta_5, \ldots, \beta_{10}$). The last two columns of Table 6 report the results, which indicate that our predictions are valid. Specifically, as within-offline synergies increase, all three allocation ratios increase. Thus, within-media and cross-media synergy exert an opposite impact on the three allocation ratios in this empirical application. Finally, we tested the Hypothesis 3 (viz., the total budget increases as within- or cross-media synergy increases) and found strong support for the assertion (see the last row of Table 6). We next describe how managers should optimally allocate resources across media, incorporating not only the effectiveness, but also within- and cross-media synergies.

Actual versus optimal spending

We apply the methods used to derive Proposition 1, maximize each of the dependent variables, and obtain appropriate expressions for optimal spending, which depend on the estimated parameter vectors $\hat{\alpha}$ and $\hat{\beta}$. We then add the corresponding optimal expenditures on online, offline, and direct-mail advertising from each dependent variable. Fig. 3 presents the comparisons between actual versus optimal spending. We scaled the actual budget to 100% (to maintain confidentiality) and note that the optimal spending is about 5% larger. The current versus optimal comparison reveals three points.

First, the optimal online advertising is 14% of the total optimal budget compared to the current allocation of 7%. Driven by online–offline synergy, this finding further supports our premise that online media companies should aim for increasing their budgets by building synergies collaboratively with offline advertising. Second, direct mailing is as important as the online advertising. The firm should re-consider the role direct mail plays in the overall communications mix and increase its allocation from 3% to 8%. Finally, the firm's current allocation of 90% to offline advertising exceeds the amount we recommend. Recall that the budget allocated for television ads was 90% in the field study for the Ford F-150 brand (see Briggs, Krishnan, and Borin, 2005) and that the exposure increased by 20% when the TV budget was re-allocated to magazines and online media, thus reaffirming the value of diversifying the communications mix. Similarly, based on the estimated model, we recommend that managers reduce offline advertising from 90% to 78% and re-allocate the rest to online and direct-mail advertising. To gain further confidence in the model-based results, managers may wish to set up a field experiment to assess the potential impact of budget re-allocation and accordingly update their future spending.

Other implications

Companies and researchers expect the presence of cross-media effects. Although harder to detect in laboratory and field studies (Chang and Thorson 2004), synergies do exist and can be estimated using readily available market data (as we demonstrated in this study). Furthermore, Stammerjohann et al. (2005) identify three theoretical reasons for the existence of synergies. First, encoding variability theory (e.g., Tassavoli 1998) suggests that when a consumer receives the same message from several media sources, they encode the message in their memory such that the likelihood of recalling information correctly enhances. Second, repetition variation theory (e.g., Sawyer 1981) suggests that pre-cognitive or cosmetic cues aid encoding and improve attitudes toward multiple exposures from different media. Third, selective attention theory (e.g., Kahnemann 1973) states that the use of variety in media and repetition of ads leads to increased attention, resulting in more elaboration and improved attitude toward the advertising message. Based on these foundations, Sheehan and Doherty (2001) distinguish strategic and tactical integration, referring to message and media vehicle coordination on one hand and key visual and slogan coordination on the other.

To generate media synergies, managers should accordingly utilize different messages, media, and designs creatively. These three elements of advertising constitute the main building blocks for creating synergies. Specifically, managers may repeat the same message across media, leveraging the different ways in which the media transport messages based on their different characteristics (e.g., Belch and Belch 2004, pp. 334). Managers may vary ad designs and slogans related to a brand across media to enhance learning by consumers. But as Keller (2003, p. 333) notes, IMC strategies involve certain tradeoffs

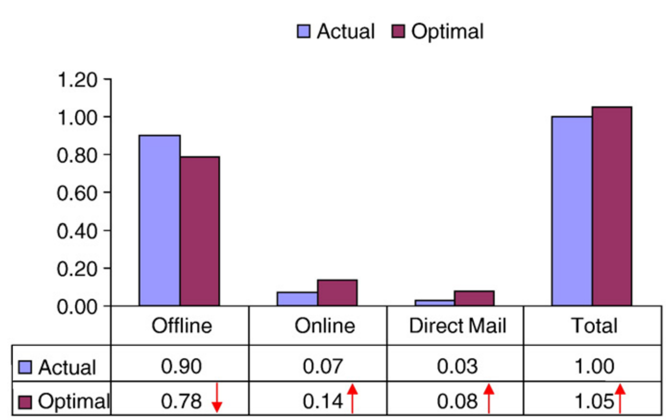

Fig. 3. Actual versus optimal allocation of advertising budget.

that are often inversely related to commonality, complementarity, and versatility of brand messages, all of which highlight the importance and complexity of creating multimedia synergies.

Conclusions and future research

We analyzed the effects of offline media (e.g., television, radio, print), online (e.g., banner and search ads), and direct mail on both online (e.g., car configurator visits) and offline (e.g., dealer visits) consideration metrics for a compact car brand. We focused on detecting within- and cross-media synergies, which together generate higher-order media interactions. Based on our empirical results and normative analyses, we summarize the takeaways from this study. First, the proposed hierarchical synergy model explicitly incorporates within- and cross-media synergies, providing a framework to investigate more complex natures of media synergy effects. Second, offline–online synergies exist and can be quantified. To estimate both the media effectiveness as well as within- and cross-media synergies using market data, managers can apply the proposed model and estimation approach. Third, we provide normative insights on how the overall media budget and its allocation changes in the presence of higher-order synergies. Finally, our findings indicate that collaborative orientation begets growth in online advertising because it reinforces not only the effectiveness, but also within-media synergies amongst various offline media.

Our research limitations provide opportunities for future research. We did not include allocation to other marketing mix variables and media vehicles. We need more research on the role of N-media inputs such as billboards, placement, public relations, and salesforce (e.g., Albers, Mantrala, and Sridhar 2008; Shankar 1997). The proposed framework could be extended to incorporate the hierarchy of buying stages (e.g., awareness, consideration, and sales) and the dynamics of carryover effects. Finally, synergies could be explored within and across new media such as mobile media (Shankar and Balasubramanian 2009) and social media (Winer 2009).

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Appendix: Derivation of optimal spending for the dynamic hierarchical synergy model

We generalize the proposed model by incorporating dynamics. Let λ denote the carryover effect, which transforms the Equation 3 as follows:

$$\frac{dY}{dt} = \alpha_1 Z + \alpha_2 X_3 + \alpha_3 Z \times X_3 - (1 - \lambda)Y. \tag{A1}$$

Next, we maximize the net present value of the profit stream given by

$$\Pi(x_1, x_2, x_3) = \int_0^\infty e^{-\rho t}(mY(t) - x_1(t) - x_2(t) - x_3(t))dt. \tag{A2}$$

To solve this problem, we apply the Maximum Principle (see Sethi and Thompson 2000, Ch. 2) and write the Hamiltonian function

$$H = (mY - x_1 - x_2 - x_3) + \mu(\alpha_1 Z + \alpha_2 X_3 + \alpha_3 Z \times X_3 - (1 - \lambda)Y), \tag{A3}$$

where μ is the co-state variable: it's akin to the Lagrange multiplier in static constrained optimization and can be interpreted as the incremental profit resulting from the future sales growth due to current spending. We differentiate H with respect to the decision vector (x_1, x_2, x_3) to obtain the three first-order conditions (FOCs), which are functions of the co-state variable whose dynamics are given by

$$\frac{d\mu}{dt} = (\rho + \lambda)\mu - m. \tag{A4}$$

Solving the FOCs and co-state dynamics simultaneously, we obtain the optimal solution stated below:

Proposition 2. In the dynamic hierarchical synergy model, the optimal spending levels are

$$\begin{aligned} x_1^* &= \frac{m}{\rho + 1 - \lambda}\left(\alpha_1 + \alpha_3 X_3^*\right)\left(\beta_1 + \beta_3 X_2^*\right) \\ x_2^* &= \frac{m}{\rho + 1 - \lambda}\left(\alpha_1 + \alpha_3 X_3^*\right)\left(\beta_2 + \beta_3 X_1^*\right) \\ x_3^* &= \frac{m}{\rho + 1 - \lambda}\left(\alpha_1 + \alpha_3 Z^*\right), \end{aligned} \tag{A5}$$

where $X_j^* = \text{Ln}(x_j^*)$, $j = 1$, 2 and 3.

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