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Conditions for Owned, Paid, and Earned Media Impact and Synergy

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Report Summary

Paid online media is under fire by recent studies reporting low effects compared to own media for single, well-known brands. However, many question the generalizability of these findings. Neither the relative effectiveness of paid, owned, and earned media nor their synergy with each other and with offline marketing is currently well understood.

In this study, the authors take a contingency perspective to hypothesize and demonstrate how brand strength and the search versus experience nature of the category favors the effectiveness of different types of online media and their synergy with other marketing actions. Their conceptual framework combines source credibility with media coverage and complementarity. Their empirical analysis on four brands uses Bayesian Vector Autoregressive (BVAR) models to estimate long-term sales elasticities.

Overall, their findings confirm the increasing importance of earned media. Earned media brings greater efficiency for all brands across category conditions but especially for familiar brands.

With regard to owned versus paid media, they find that owned media has a higher sales elasticity than paid media for both studied unfamiliar brands and for the familiar brand in the experience category. In other words, owned media becomes a credible source for consumers to decrease the unpredictable nature of experience goods and unfamiliar brands.

However, paid media has higher sales elasticity than owned media for the studied familiar brand in the search category. A familiar brand in a search category is the least risky choice for consumers and paid media can provide enough information to evaluate the quality.

Their findings also provide insights into the potential benefits of synergy in different online advertising mediums. Within-online synergy is significantly higher than cross-channel synergy for familiar brands in their data, which may mean that high and favorable awareness has already been created in traditional media for well-known brands.

Marketing implications

- Paid media is most effective when consumers perceive little risk in their decision.
- Owned media is important for risky purchases. Brand managers for experience goods should ensure their websites provide quality information in order to decrease the consumers' perceived risk for these types of goods.
- Brand managers of unfamiliar brands should use both offline and online marketing to build strong brand associations in consumers' minds. Cross-channel synergy is key.
- Managers of familiar brands can generate more synergy by investing in different online mediums. They leverage the existing brand equity to get high bang for their buck in online media.

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"Earned media is King, Owned Media is Queen and Paid Media is Jester" Society of the Digital Agencies, 2011

"While eBay thinks their results apply to the paid search industry as a whole, most advertisers agree that the study – with its flawed generalizations – further proves the importance of tailoring digital marketing strategies to each unique business", Hull (2013)

Since the introduction of the first banner ad in 1994, online advertising has redefined the global advertising landscape. Spending in the sector has continued to grow, reaching $117.60 billion globally in 2013 and expectations are for this expansion to continue, reaching $132.62 billion in 2014 and up to $173.12 billion by 2017 (EMarketer, 2013). Many of these new advertising forms only materialize when potential customers take action, such as click on a search ad (paid media), go to the company website (owned media) or share comments on social media (earned media). In contrast to traditional firm-initiated communication (FIC), the long-term effectiveness of such customer initiated communication (CIC) is not well understood (Tellis, 2009; Hanssens, 2009). Moreover, the prevalence of synergy of CICs with each other and with FICs remains unanswered questions. While Li and Kannan (2013) found a low value of paid search for a well-known hospitality brand, they acknowledge this result may be driven by the strength of the one brand under study and call for future research. Likewise, the low value of paid search for eBay (Blake, Nosko and Tadelis, 2013), has been questioned as a generalizable finding (Hull, 2013). Beyond the individual effectiveness of online CIC media, their synergy with each other and with FICs has only started to attract academic scrutiny (Naik and Peters, 2009; Li and Kannan, 2013). What are the boundary conditions for these firm-specific tales of success and failure? Which media combinations work best for which kinds of brands and products?

To address these research questions, this paper takes a contingency perspective to demonstrate how brand strength and the search versus experience nature of the category imply different effects for types of CICs and for their synergy with each other and with FICs. In doing so, our conceptual developments incorporate the consumer risk associated with buying different types of products and brands. Moreover, we build on the rich recent research regarding the effectiveness of single or a few CICs, such as banner ads (e.g. Manchanda, Dube, Goh and Chintagunta, 2006), paid search (e.g. Wiesel, Pauwels and Arts, 2011) and social media conversations (e.g. Godes and Mayzlin, 2004; Moe and Trusov, 2011; Sonnier, McAlister and Rutz, 2011). To this literature, we contribute with a conceptual framework and an empirical analysis of the brand and category contexts that favor different types of CICs. Our second contribution is the methodological application of Bayesian Vector Autoregressive (BVAR) models to estimate long-term sales elasticities, while imposing restrictions to avoid over-parametrization and wrongly-signed coefficients. Our analysis on 4 brands shows that, as expected, earned CIC is most effective for both known and unknown brands and for both search and experience goods. As hypothesized, paid CIC is more sales effective than owned CIC for search goods but the opposite result holds for experience goods. The synergy of CICs with firm-initiated (outbound) actions is higher for relatively unknown brands, which are recommended to continue to spend on outbound marketing.

RESEARCH BACKGROUND

Online Customer-Initiated Marketing Actions

Customer-initiated communication actions (CICs) differ from firm-initiated communication (FIC) actions in that they require (potential) customers to actively search for and/or engage in online conversations about the firm's offerings (Bowman and Narayandas, 2001; Gartner, 2008; Hoffman and Fodor, 2010; Wiesel et al., 2011). For instance, emails sent by firms to consumers are regarded as firm-initiated, while customer click-through on paid search is regarded as customer-initiated. We agree with Li and Kannan (2013) that this distinction is a continuum: while organic visits (typing in the website's URL) and emails are respectively customer- initiated and firm-initiated, paid search and display ads require both parties, with paid search being more customer-initiated than display ads (typically targeted by the firm). In terms of spending, customer-initiated search took 47% of the US online advertising market (EMarketer, 2010) while customer-initiated social media is expected to grow from 6% to 18% of the online marketing budget in the next 5 years (Alinean, 2011). Driven by considerations such as the current size and growth projections, marketing academics and practitioners have called for research to justify such large shifts in media channel allocation especially now that online advertising expenditure is exceeding radio and magazines (Dahaner and Dagger, 2013). Beyond the effectiveness of separate CIC actions, their own synergy and their cross synergy with FICs remains an important unresolved puzzle in marketing literature.

Paid customer-initiated media include affiliate marketing and paid search. Affiliate marketing involves merchants (e.g., Amazon) sharing a percentage of the revenue when a customer arrives at the company's website (e.g., Sony) by clicking the content on the merchant's website (Gallaugher, Auger and Barnir, 2001). Hoffman and Novak (2000) found a low effectiveness of online banner ads, and proposed affiliate marketing as a more efficient way of customer acquisition. More recently, paid search has gained popularity, with US companies spending more than 40% of the total online advertising dollars for paid search (Animesh, Ramachandran, and Viswanathan, 2010). In paid search like Google's AdWords, advertisers bid for to be in a place closer to the top in the listing of the paid search results which are displayed on the top or side of organic search results. Two recent studies find little – if any – incremental sales impact from paid search for the studied brand, as verified in a field experiment of shutting off paid search (Blake et al., 2013; Li and Kannan, 2013).

Owned media includes the online assets owned by the company, such as its websites and their search engine optimization qualities. Prospective customers visit a brand's website to obtain more information, regarding the attractiveness of the product or service vis-à-vis competing offers (Li and Kannan, 2013). The strength of owned media shows up in the company's ranking in organic search (Yang and Ghose, 2010), and in the amount of 'direct visits', i.e. visitors that type the company's name directly into the URL (Li and Kannan, 2013). Such 'type-in' traffic may include loyal, repeat customers and late-stage buyers who have already visited the site through other means but needed time to make the purchase decision (Bustos, 2008).

Earned (social) media for a brand is created, initiated, circulated and used by consumers (Blackshaw and Nazzaro, 2006). Social media activities include blogging, microblogging (e.g. Twitter), co-creation, social bookmarking, forums and discussion boards, product reviews, social networks (e.g. Facebook) and video- and photo-sharing (Hoffman and Fodor, 2010). Consumers are motivated to participate in these activities due to their desire to connect, create, control and consume (ibid). Foresee Results (2011) reports that, while search brings more potential customers to company's websites, purchase conversion rates are higher for visitors coming from social media. Recently, social media has drawn criticism given the poor sales results of Burger King and Pepsi, despite social media campaigns that scored in terms of traffic and engagement (Baskin, 2011). However, one needs to control for other sales drivers: for a brand losing share due to higher prices and lower distribution, Pauwels, Srinivasan, Rutz, Bucklin (2013) found that earned media (brand engagement on Facebook) helped stem these losses.

Synergy

Synergy means that the "combined effect of multiple media exceeds the sum of their individual effects" (Naik, 2007). Social psychologists propose that the greater the number of sources perceived to advocate a position, the higher perceived credibility (Cacioppo and Petty, 1979) and hence purchase intention (MacInnis and Jaworski, 1989). At least three theories support synergy among marketing media:

1) Selective attention (Kahneman, 1973) implies that the use of multiple media and repetition of ads lead to increased attention and elaboration.

2) Repetition and variety theory suggest that pictoral cues aid encoding and improve attitudes toward multiple exposures from different media as long as tedium is avoided (Haugtvedt, Schuman, Schneier and Warren, 1994; Batra and Ray, 1986).

3) Encoding variability (Tavassoli, 1998) suggest that when a consumer receives the same message from a variety of media, the message will be encoded into her memory in a more complex way, resulting in stronger and more accessible information (Stammerjohan, Wood, Chang and Thorson, 2005).

When synergy is present, managers should spend relatively more on the less effective marketing activity (Naik and Raman, 2003). Synergy has been demonstrated within offline media (e.g. Edell and Keller, 1989; Raman and Naik, 2004), across offline and online media (e.g. Chang and Thorson, 2004; Naik and Peeters, 2009; Reimer, Rutz and Pauwels, 2011), and within online media (e.g. Schultz, Block and Raman, 2011; Kireyev, Gupta and Pauwels, 2012; Li and Kannan, 2013). However, virtually all these studies analyze a single company, and do not consider under which conditions synergy would be higher within CICs or between CIC and FIC actions. The former (within CIC synergy) implies a stronger allocation towards customer-initiated actions, while the latter (cross-channel synergy) implies a continued role for firm-initiated communication, which typically has lower sales elasticity by itself (Wiesel et al., 2011).

CONCEPTUAL FRAMEWORK: CATEGORY AND BRAND CONDITIONS FOR CIC EFFECTIVENESS AND SYNERGY

The conceptual framework combines the (1) trustworthiness, (2) coverage and (3) complementarity of communication forms with the uncertainty that customers face in different category and brand conditions (Erdem and Swait, 2004).

First, media *trustworthiness* is the most important component of media credibility regarding sales impact (Erdem and Swait, 2004). Source credibility was originally proposed by Hovaland, Janis and Kelly (1953) as an attribute of the communicator, but has been expanded to media credibility with dozens of studies comparing the relative credibility of newspapers, radio, television and the internet (Rieh and Danielson, 2007). According to source credibility theory, the two main components of persuasion credibility are perceived (1) source expertise and (2) source trustworthiness. Among source credibility components, trustworthiness has a higher impact on sales than expertise does (Erdem and Swait, 2004).

How do online paid, owned and earned media and offline marketing compare on trustworthiness? The latest large survey by Nielsen (2013) reports highest trust in earned media (84%), then owned media (69%), followed by offline TV ads (62%) and finally online paid media (between 42% and 48%). The X-axis of Figure 1 (following References) classifies these numbers as 'highest', 'high', 'medium' and 'low' respectively.

Second, *coverage (reach)* is an important consideration and is typically higher for paid media and offline marketing (e.g. Chatterjee, 2012) than for owned media. Prospective customers need to visit the brands' owned media to be exposed to its message, while brands pay to reach a wide audience beyond its core base. Earned media has medium coverage: it requires visiting review sites and blogs, but does not require visiting the brand's own sites. The Y-axis of Figure 1 adds this reach dimension to classify the media under study.

With owned and paid media scoring better on a different dimension, the question becomes when each dimension is most important in increasing sales. Source credibility has a higher sales impact in conditions of uncertainty (Erdem and Swait, 2004), such as uncertainty on the attributes, typical for experience goods. Consumers can evaluate the quality of search goods prior to purchase, but can only determine the quality of experience goods after purchase (Nelson, 1970). Also in the online world, consumers spend more time evaluating experience goods, have a higher willingness to visit owned media (Biswas, 2004) and favor interactive mechanisms (Huang, Luries and Mitra, 2009). Finally, websites typically provide pictures which help consumers to lower uncertainty for experience goods (Weathers, Sharma and Wood, 2007). Such deep information and interactive mechanisms are more readily available on (well executed) owned media than on paid media.

In sum, we expect experience goods will have higher impact of owned media, while for search goods, the higher reach of paid media may prevail.

H1a: For experience goods, owned media has a higher sales elasticity than paid media.

In contrast to experience goods, consumers face less uncertainty when buying search goods. This does not mean that source trustworthiness is unimportant, but rather that the higher reach of paid media may compensate for its perceived lower trustworthiness in the overall sales impact. We propose that this happens when other cues instill trustworthiness – in particular, when the brand is familiar. Erdem and Swait (1998) argue that familiar brands lower perceived risk to consumers and save them information gathering and processing costs. Brands serve as signals for product positions, with credibility as the most important characteristic (Erdem and Swait, 2004; Wernerfelt, 1988). Brand familiarity influences consumer’s information processing (Hoyer and Brown, 1990) and the recall of advertising message (Kent and Allen, 1994). A product’s brand name reduce consumer’s perceived risk in an online buying situation (Huang, Schrank and Dubinsky, 2006) since the brand name is one of the most important signals

(Dawar and Parker, 1994) for consumers. Thus, we expect that, for search goods, the relative sales elasticity of paid versus owned media depends on brand familiarity:

H1b: For familiar brands of search goods, paid media has a higher sales elasticity than owned media

H1c: For unfamiliar brands of search goods, owned media has a higher sales elasticity than paid media.

Which media should be most *complementary* with each other and thus produce synergy? Encoding variability theory (Tavassoli, 1998) proposes stronger synergy among media with different encoding modes do, such as visual and verbal cues. Extending this rationale, Chang and Thorson (2004) propose different encoding of offline and online media. Their laboratory experiment with an unfamiliar brand indeed finds that showing messages on TV and the Internet leads to higher attention, credibility and positive thoughts than did repetition in a single medium. Also, consumers under synergistic conditions formed attitudes under the central processing route.

We propose that the extent of offline-online synergy depends on *brand familiarity*. Kahneman (1973) shows higher attention for stimuli that are both complex and familiar, or both simple and novel, as compared to other combinations. Thus, if the stimulus is complex, the message needs to be repeated in more media to increase familiarity. Therefore, managers of less familiar brands are advised to use multiple tools and invest in integrated marketing communications (Stammerjohan et al., 2005). Unfamiliar brands still have to build brand equity; they do not have the luxury to simply leverage existing brand equity online. As J.G Sandom, co-founder of the world's first interactive agency and one of the former directors of Ogilvy puts it: “you cannot build a brand simply on the Internet. You have to go offline.” (Pfeiffer and Zinnbauer, 2010). Indeed, Ilfeld and Winer (2002) suggest that offline firm-initiated communication will drive website traffic by increasing consumer awareness. Additionally, high ad spending due to use of both CIC and FIC may signal consumers brand’s quality and create credibility. Other studies on unfamiliar brands showed that the combination of traditional and CIC online advertising is more effective than repeated exposures in any either medium (Chang and Thorson, 2004; Dijkstra, Buijtels and Van Raaij, 2005). Likewise, Yoon and Kim (2001) advise the use of both traditional and online media when customers are highly involved – a condition which correlates highly with perceived risk (Rothschild, 1979; Bloch, 1981). In contrast, very familiar brands run the risk of boring consumers (Anand and Sternthal, 1990; Campbell and Keller, 2003) and thus obtain little synergy among firm-initiated actions (Stammerjohan et al., 2005). Instead, familiar brands; achieve higher click-through on their online paid ads and more organic visits to their website (e.g. Yang and Ghose, 2010; Ilfield and Winer, 2002), thanks to their salient, rich and positive associations in consumers’ minds (Keller, 1993). For instance, Vanguard was surprised to learn that most clicks on its banner ads came from existing customers (McGovern and Quelch 2007). Such paid exposure makes the existing link with the familiar brand more salient, and easily drives consumers to the brand’s owned media.

H2: For unfamiliar brands, synergy is higher between online CIC and offline FIC media (cross-synergy) than (a) among online CIC media (intra-online synergy, and (b) among offline FIC media (intra-offline synergy).

H3: For familiar brands, synergy is higher among online CIC media (intra-online synergy) than (a) between online CIC and offline FIC media (cross-synergy), and (b) among offline FIC media (intra-offline synergy).

We summarize our hypotheses for the category and brand conditions in the managerially relevant 2x2 matrix in Table 1 (following References).

METHODOLOGY

Model Requirements

Our objectives and conceptual framework impose specific modeling requirements that we outline here. First and foremost, we require a model that incorporates several offline and online marketing variables in addition to brand performance simultaneously. Second, we need to be able to link these marketing variables to brand performance both directly and indirectly through each other. In addition, the modeling approach needs to control for the effects of other marketing actions (e.g., feature, display) and seasonality to avoid missing variable bias. Third, as the CIC and FIC actions can influence each other over time, we need a model that will accommodate these dynamic dependencies as well. Fourth, we have to control for endogeneity in marketing and capture performance feedback in marketing. Finally, we need to obtain the immediate and the cumulative effect of marketing variables on brand performance.

Unrestricted estimation of models that meet the requirements above requires considerable data and the results are hard to interpret since the parameter space of VARs proliferates with the number of dependent variables and the number of lags. Moreover, the forecasts may appear more precise than they are because standard error bands do not account for parameter uncertainty. The estimates and forecasts can be improved however if one has prior information about the structure of the model or the possible values of the parameters or functions of the parameters. In a classical framework, it is difficult to incorporate non-sample information into the estimation. We therefore outline the Bayesian VAR model (Sims and Zha, 1998; Horvarth and Fok, 2013) specification that meets these requirements.

Bayesian Vector Autoregressive Models

Dynamic system models such as Vector Autoregression (VAR) have been a popular tool to analyze both short-term and long-term marketing effectiveness for offline activities ranging from new product introductions to price promotions, distribution and communication (Bronnenberg, Mahajan, and Vanhonacker ,2000; Dekimpe and Hanssens, 1999; Pauwels, Silva-Rosso, Srinivasan and Hanssens, 2004). Moreover, VAR-models appear especially relevant in an online context, given the multiple touch points brands have with consumers over time (Trusov, Bucklin and Pauwels, 2009; Wiesel et al. 2011). In addition to such 'dynamic synergies', we also allow for same-period synergies by adding the interaction terms among paid, owned and earned media. For one, sales may increase when potential customers are exposed to both paid and organic search listings for the brand (Yang and Ghose, 2010).

Typical issues with VAR-models include overparametrization and wrongly-signed coefficients (Ramos, 2003). We can address both through shrinkage, which imposes restrictions on the parameters of the VAR model. Such Bayesian Vector Autoregressive

(BVAR) models are formulated in Litterman (1986) and Doan, Litterman and Sims (1984), but have seen little application in marketing (Ramos, 2003). Among the possible priors, the Minnesota (Litterman, 1986) prior is the most popular prior for time series data because it imposes only soft restrictions and allows a simple posterior inference involving only the normal distribution (Koop and Korobilis, 2010). Using Doan et al.'s (1984) formula for the uncertainty of the Minnesota prior means, we can specify individual prior variances for a large number of coefficients in the model using only a few parameters (LeSage, 1999). These parameters θ, ϕ and $w(i,j)$ represent the overall tightness, lag decay and the weighting matrix respectively.

We estimate the BVAR model through the "mixed estimation" technique developed by Theil and Goldberger (1961). This method involves supplementing data with prior information on the distributions of the coefficients (LeSage, 1999; Ramos, 2003). A typical unrestricted VAR with n endogenous variables and p lags can be written as:

$$y_{it} = \sum_{k=1}^{p} a_{i1k}\, y_{1,t-k} + \cdots + \sum_{k=1}^{p} a_{ink} y_{n,t-k} + \varepsilon_{it} \qquad (1)$$

Focusing on a single equation of the model:

$$y_1 = XA + \varepsilon_1 \qquad (2)$$

where y_1 is the vector of observations on y_{it}, the matrix X represent the lagged values of $y_{it}, i = 1, \dots, n$ and the deterministic components, the vector A stands for the coefficients of the lagged variables and deterministic components and ε_1 is the residual vector. Prior restrictions for this single equation model can be written as:

$$
\begin{bmatrix} z_{111} \\ z_{112} \\ \vdots \\ z_{nnk} \end{bmatrix} = \begin{bmatrix} \sigma/\sigma_{111} & 0 & \cdots & 0 \\ 0 & \sigma/\sigma_{112} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma/\sigma_{nnk} \end{bmatrix} \begin{bmatrix} a_{111} \\ a_{112} \\ \vdots \\ a_{nnk} \end{bmatrix} + \begin{bmatrix} v_{111} \\ v_{112} \\ \vdots \\ v_{nnk} \end{bmatrix} \qquad (3)
$$

Where prior mean z_{ijk} is the prior mean and σ_{ijk} is the standard deviation of the Minnesota prior imposed on variable *j* in equation *i* at lag k, and $var(v) = \sigma^2 I$.
Standard deviation specification defined by the Minnesota prior is as follows:

$$
\sigma_{ijk} = \begin{cases} \dfrac{\theta}{k^{-\phi}} & if\ i = j \\ \dfrac{\theta.w}{k^{-\phi}} * \left(\dfrac{\hat{\sigma}_j^u}{\hat{\sigma}_i^u}\right) & if\ i \neq j \end{cases} \qquad (4)
$$

where θ represents the tightness of the prior. It shows the standard deviation of the prior on the first lag of the dependent variable. The parameter ϕ stands for the decay parameter taking the value between 0 and 1. Decay parameter reflects the fact that standard deviation of the prior decreases as the lag length of the model increases, i.e. further lagged variables have less importance in the model. The parameter w specifies the relative tightness for variables other than the dependent variables. The prior becomes tighter when its value is reduced. The parameter σ_j^u is the obtained standard error of the residuals from the estimation of unrestricted single-equation autoregression on variable *j*. The ratio of the standard errors in Eq. (4) is called a scaling factor and accounts for the differences in the magnitudes of the variables across equations *i* and *j*.

In order to find the optimum values for the parameters θ, ϕ and *w*, we minimize the log determinant of the sample covariance matrix of the one-step-ahead forecast errors for all the equations of the BVAR (Doan et al. 1984). Using Theil and Goldberger (1961), we rewrite equation (3) as:

$$
r = RA + v \qquad (5)
$$

Then, we can find the estimator for a typical equation by using the following formula:

$$\hat{A} = (X'X + R'R)^{-1}(X'y_1 + R'r) \qquad (6)$$

Modeling Steps

Our BVAR modeling approach consists of the following 5 steps:

Step 1: In the first step, we simply consider the unrestricted VAR(k) model and do not impose restrictions on the coefficients of the VAR model. The optimal lag length is chosen based on the Schwarz Information Criterion (SIC) which is commonly used in the marketing literature (e.g. Pauwels et al. 2004). We opt for taking natural logarithm to smooth the variables and estimating the log-log model to obtain the elasticities.

Step 2: After building the VAR model, the second step is to impose the restrictions on the coefficients of the VAR model by using the set of Minnesota parameters in Eq. (4). In order to find the best parameters, we consider three values for the weight parameter, *w: 0.25, 0.5* and *0.75.* For the tightness parameter θ, we assume four different values: *0.5*, *0.3, 0.1* and *0.05*. The first number (0.5) is a relatively loose value while the last number (0.05) is a tight value. We chose the lag decay parameter ϕ to be 1 as suggested by Doan et al. (1984). As a result, we determine the set of the hyperparameter values, i.e. w, θ, ϕ. Using these preselected parameters, we have 12 alternative specifications. When choosing the best parameters, we also take into account some anomalies such as unexpected sign for the marketing variables, the magnitude of the responses etc.

Step 3: With the selected parameters from Step 2, we estimate BVAR(k) model[1 2].

As explained before, the estimation method is Theil and Goldberger's mixed estimation technique.

Step 4: We calculate the Generalized Impulse Response Functions (GIRF) (simultaneous shocking approach) using the formula by Pesaran and Shin (1998). To find the standard errors of GIRF coefficients we employ the residual-based bootstrap technique. To end, we carry out the following steps:

1) We estimate the BVAR(k) model and obtain the residuals

2) We bootstrap the residuals of the BVAR(k) model

3) Using the estimated parameters from step 1 and the bootstrapped residuals from step 2, we obtain bootstrapped data.

4) Using the bootstrapped data, we obtain new BVAR coefficient estimates and GIRF coefficient estimates.

We repeat the steps 1-to-5, 500 times.

5) Finally, we calculate the standard errors of the GIRF coefficients.

Step 5: After finding the bootstrapped standard errors, we assess whether each impulse-response value is significantly different from zero as suggested by VAR-related literature in marketing (e.g. Pauwels, Hanssens and Siddarth, 2002). Finally, we compute the immediate and cumulative effects based on the significant GIRF estimates.

[1] In a typical VAR model, we include stationary series into the system. In other words, we take the difference of the series until they become stationary. In BVAR modeling, we are not concerned about non-stationarity issue as highlighted by Sims, Stock and Watson (1990) and Ramos (2003).

[2] We do not perform Granger causality tests as they are invalid given the Bayesian prior applied to the model (LeSage, 1999, page 128).

DATA

We estimated our model using data from four companies. The first two brands are not featured in the Interbrand 'Best Global Brands 2013' lists: a brand of standardized test preparation (brand A), and a brand of office furniture (brand B). The next two brands are featured in 'Best Brand Lists;: a brand of online travel (brand C) is a top 5 travel brand in the Annual Harris Poll EquiTrend Study (HarrisInteractive, 2012) and an apparel retailer brand (Brand D) is included in the the Interbrand 'Best Global Brands 2013' . These 4 brands thus fit into our conceptual framework, varying from high perceived risk (unfamiliar service brand A) to low perceived risk (familiar product brand D). We acknowledge that these brands may differ in several other aspects, and strongly encourage managers to perform this analysis for their own brand, and researchers to obtain additional data to investigate the generalizability of our findings.

Brand A was launched less than 5 years ago in the US market for GMAT test preparation. Using an online-only model that incorporates adaptive learning software, the company provides flexibility and individual customization to each student's progress. The absence of fixed overhead costs of a brick-and-mortar location also allows the company to offer one of the lowest prices in the market. However, this is a departure from the traditional face-to-face interaction assumed and expected by the general market. Given this newness, the company aims to communicate its benefits through a variety of online marketing efforts such as display ads and paid search. At the backdrop of the global recession, the company communicated to prospective customers it would vary its price with the stock market indices. These price changes are the main offline communication tool of the firm.

Brand B is a family-run European office furniture supplier without retail stores to sell their products. Instead, they market directly to offices, hospitals and schools that may be in need for furniture. Offline marketing actions constitute the major port of its marketing budget, and include direct mail and faxes sent directly to prospective customers. Online marketing actions include email and paid search. Brand B focuses on its high level of service to their products such as product delivery to the customer, assembling and customized solutions.

Brand C is a global travel search engine, providing service to its customers for finding flights, hotels and cars all around the world. The company started marketing with online communication, but soon switched the budget to mostly offline communication, including global television advertising campaigns. Marketing communication actions include paid search, display, partner site links, television and out-of-home advertising.

Brand D is a US apparel retail brand that scores within the top 30 of Interbrand Best Retail Brands 2013. Positioned as good value, the company aims to provide the latest fashions at great prices for the whole family. The brand's marketing is well-known and prolific, including television, radio, print and paid search advertising. Online and offline store traffic are the main performance indicators for this retailer, who generates substantial revenues from both channels.

All datasets are at the weekly level and for a recent period of over a year. Brand A's data spans 2008 (week 40) to 2010 (week 8), with a total of 73 observations for each variable. Brand B's data spans 2007 (week 1) to 2010 (week 35), with 191 observations.

Brand C’s data spans 2008 (week 1) to 2010 (week 35), with a total of 139 observations. Finally, Brand D’s data spans 2010 (week 25) to 2011 (week 28), with 55 observations.

Data from all companies include the variables on Paid, Search and Owned media, mass offline marketing activities and performance variables. Table 2 (following References) displays the variable operationalization.

Our classification of each marketing action into Paid, Owned, Earned, and Firm-Initiated follows the definitions in our conceptual framework. Note that some CICs are identical among firms (e.g. paid search cost), while others are not (e.g. total website visits versus only organic website visits). Likewise, the FICs differ by firm. This is a key challenge of moving from single-firm to multi-firm evidence. To control for seasonality, we include four-weekly seasonal dummies for brands A-C, using January as our benchmark. For brand D, we use national retail mall index, which offers weekly tracking of overall U.S. retail mall sales. Table 3 (following References) shows summary statistics for the variables included in the model.

As can be seen in Table 3, weekly average sales revenues for brands A and B are below $ 260,000. In contrast, weekly average sales revenues of brands C and D are above $900,000 sales revenues.

EMPIRICAL FINDINGS

For all the brands under our study, both AIC and SBC information criteria suggest to include one lag in the model. The estimated models explain 78% to 91% (adjusted R^2=76% to 90%) of the variation in the performance variables. In addition, the models show no violation of the autocorrelation, heteroscedasticity and normality assumptions for the residuals (Franses, 2005).[3] The Generalized Impulse Response Functions in Figure 2 (following References) show the typical patterns of wear-out and increasing confidence bounds over time.

For each brand's paid and owned media, we show the 'best-in-breed' action; i.e. the marketing activity with the highest long-term elasticity. For brand A, paid search is the most effective paid media, with a same-week performance elasticity of .075 and fast wear-out. In contrast, organic site visits, the most effective owned media, has a same-week performance elasticity of .15 and adds significant effects for several more weeks. The pattern of these response functions are notably different for brand B, whose paid search shows a 1 week wear-in, and whose web visits shows a fast wear-out. However, the cumulative effect over time (long-term elasticity) ranking is similar for both brands: the same % increase in owned media yields a higher performance increase than in paid media. Summarizing for all actions, Table 4 displays the results on immediate and cumulative effects for, respectively, brand A (unfamiliar/service quadrant in conceptual Table 1), brand B (unfamiliar/product quadrant in Table 1), brand C (familiar/service quadrant in Table 1), and brand D (familiar/product quadrant in Table 1).

[3] These results are available from the authors upon request.

For each brand, the elasticity results are consistent with previous research, showing a substantially higher impact of online, customer-initiated communication versus offline, firm-initiated communication (De Haan, Wiesel and Pauwels, 2013; Dinner, van Heerde and Neslin, 2011; Wiesel, Pauwels and Arts, 2011). Specifically, unfamiliar brands A and B show median long-term elasticities of 0.185 and 0.303 for customer-initiated versus 0 and 0.024 for firm-initiated communication. Familiar brands C and D have median long-term elasticities of 0.009 and 0.102 for customer-initiated versus 0.004 and 0.004 for firm-initiated communication (Table 4). Thus, in the absence of synergy, companies would be advised to spend a larger portion of the communication budget on CICs, which have the larger elasticity (Naik and Raman, 2003). This is reflected in company practice to set upper limits to online advertising bids by multiplying short-term conversion probability with margin earned per conversion (Dinner et al., 2011). However, we find evidence of long-term effects and of synergy, which patterns differ by condition. These different patterns allow us to assess our hypotheses.

Results on Owned and Paid Media

To test our hypotheses on results of owned and paid media, we perform these comparisons in two ways. First, we consider for each marketing type the action with the highest estimated elasticity (hereafter 'best in breed') and the action with the median elasticity (across all actions for that marketing type). This allows us to assess the robustness of our results to the different benchmarks. Specifically, based on the GIRF estimates, for each brand we conduct a one tailed t-test to test our hypotheses for (i) the 'typical' (median elasticity) action for each marketing type (Paid, Owned and Synergy), and (ii) the best- in-breed (highest elasticity) action for each marketing type. Table 5 provides these results. The panel on the left corresponds to the tests for the typical marketing action while the panel on the right corresponds to the test for the best in breed action. Within each panel, the marketing type – paid, owned and earned - and the corresponding median or maximum are listed in the first and second columns respectively. The hypothesis tested is in the third column while the inequality being tested in the one-tailed t-test is in the fourth column for both panels. The final column in each panel gives the outcome of the t-test, based on which we make inferences on the hypotheses.

We first report on the median ('typical' action) results. We find that owned media has a higher elasticity than paid media for experience (service) brands A and C (0.394 vs. 0.000 with $p <.01$; 0.557 vs. 0.008 with $p <.01$, respectively). Thus, we find support for H1a in that for both experience brands owned media has a higher elasticity than paid media. In support of H1b, our results for familiar search brand D reveal that paid media has a higher elasticity than owned media (0.242 vs. 0.102 with $p <.01$). For unfamiliar search brand B, we find that owned media elasticity has higher than paid media elasticity (0.407 vs. 0.199 with $p <.01$), lending support to H1c.

Turning to the results on the 'best-in-breed' action, consistent with H1a and H1b, we find that owned media has a higher elasticity than paid media for brand A and C (0.394 vs. 0.096 with $p <.05$; 0.557 vs. 0.009 with $p <.01$, respectively) as well as for brand B (0.407 vs. 0.199 with $p <.01$). For brand D, paid media has a higher elasticity than owned media (0.483 vs. 0.102 with $p <.01$), which is consistent with H1c. Overall, our comparisons on both typical action and the best in breed action for paid, owned and earned media show that H1a, H1b and H1c are supported for both types of effectiveness metrics- typical and best in breed - used to assess relative performance.

Results on Synergy Effects:

We next turn to our results on synergy addressing both cross synergy across offline and online as well intra-online synergy (within online media only) and intra-offline synergy (within offline media only). Once again we report on both the typical and the best-in-breed effectiveness metrics as before.

In order to test H2a, we compare the cross synergy between online CIC and offline FIC media with the intra-online synergy, focusing on the unfamiliar brands A and B. As seen from Table 5, based on the typical action results, we find that cross synergy is higher than intra-online synergy for both unfamiliar brands A and B (0.374 vs. 0.072 with $p < .01$ and 0.044 vs. 0.004, respectively), and that the effect is statistically significant for brand A, but not for brand B. Based on the best-in-breed action results, the same finding holds, i.e. cross synergy is higher than intra-online synergy (0.428 vs. 0.250 for brand A and 0.554 vs. 0.004 with $p < .01$ for brand B). Here the effect is statistically significant for brand B, but not for brand A. Hence, we find partial support for H2a that synergy is higher between online CIC and offline FIC media (cross-synergy) than among online CIC media (intra-online synergy).

Next we compare the cross synergy between online CIC and offline FIC media with the intra-offline synergy to test for hypothesis H2b.[4] As seen in Table 5, for both the

[4] We were not able to test H2b for brand A due to the fact that we had only one FIC variable for that brand.

typical action and best-in-breed results, for brand B we find that cross-synergy is higher than intra-offline synergy (0.044 vs. 0.036 for 'typical'; 0.554 vs. 0.081 with $p < .01$ for 'best-in-breed'). The effect is statistically significant for best in breed metric, but not for the typical action. Thus, we find partial support for H2b suggesting that for unfamiliar brands, synergy is higher between online CIC and offline FIC media (cross-synergy) than among offline FIC media (intra-offline synergy). Turning to our test for H3a, we compare the synergy among intra-online CIC media synergy with cross-synergy between online CIC and offline FIC media for familiar brands. For the typical action results, we find that intra-online synergy is higher than cross-synergy for both brands C and D (0.451 vs. 0.003 with $p < .01$ and 0.213 vs. 0.003 with $p < .01$, respectively). The same finding holds when we consider the 'best-in-breed' action results (0.451 vs 0.006 with $p < .01$ for brand C and 0.336 vs. 0.004 with $p < .01$ for brand D). Overall, H3a finds strong support with either effectiveness metric – typical or best-in-breed.

Finally, to test for hypotheses H3b, we compare the intra-online CIC media synergy with the intra-offline FIC media synergy for both effectiveness metrics as before. .As shown in Table 5, for both brands C and D, based on the typical action result, we find that intra-online synergy is higher than intra-offline synergy (0.451 vs. 0.001 with $p < .01$ and 0.213 vs. 0.006 with p <.01, respectively). When we take into account 'best-in-breed' action results, our conclusion is the same (0.451 vs. 0.001 $p < .01$ for brand C, and 0.336 vs. 0.006 $p < .01$ for brand D). Hence, we find strong support for H3b that for familiar brands, synergy is higher among online CIC media (intra-online synergy) than among offline FIC media (intra-offline synergy).

DISCUSSION

With the objective to discover the role of different types of customer-initiated online media, this study follows a contingency perspective based on the brand strength in search and experience categories. To understand the effects of which online media works best for which kinds of brands and products, we classify the data from four companies into known vs. unknown and search vs. experience goods. For each company, we estimate the long-term sales elasticities based on Bayesian Vector Autoregressive (BVAR) models. Additionally, we analyze the cross media effects of online and offline mediums to see which brand and category conditions lead to more within-online versus cross-channel synergy.

The results of this study shed light on a number of important issues in research in online advertising. First, we proposed and found that owned media has a higher sales elasticity than paid media for unfamiliar brands and the familiar brand in the experience category. Message source is important in persuasion process of consumers and if consumers do not have prior knowledge of a brand's qualities, the communication from high credible sources becomes more effective in persuasion process of experience attributes (Jain and Posavac, 2001). Owned media becomes a credible source for consumers to decrease the unpredictable nature of experience goods and unfamiliar brands. On the other hand, we find that sales elasticity of paid media is higher than owned media for familiar brand in search category. A familiar brand in a search category is the least risky choice for consumers and paid media can provide enough information to evaluate the quality.

Second, our findings provide additional insights to understand the potential benefits of synergy in different online advertising mediums. The results show that ‘within online synergy’ is significantly higher than ‘cross channel synergy’ for familiar brands in our data, which may mean that high and favorable awareness has already been created in traditional media for well-known brands.

Finally, how do our results capture the important recent findings that (certain types of) paid media are not sales effective for a well-known hospitality brand (Li and Kannan, 2013) and for eBay (Blake et al. 2013)? First, the company studied in Li and Kannan (2013) is similar to cell C in our conceptual framework, and they also find a low sales impact for paid media and a large within-online ‘spillover’ (synergy). Our research implies that such findings do not generalize to unfamiliar brands, thus confirming Li and Kannan’s (2013) speculation that unfamiliar brands face a different marketing type effectiveness challenge. In contrast, Blake et al.’s (2013) findings for eBay do not correspond to those for our familiar brand in the product category: we do find a larger elasticity for paid versus owned media. One possible explanation is the poor execution of eBay paid search ads (Hull, 2013). Another explanation is that Blake et al. (2013) model does not incorporate synergy, and thus misses an important benefit of paid online media (Li and Kannan, 2013).

CONCLUSIONS, LIMITATIONS AND FUTURE RESEARCH

In this study, we provide a framework to measure effectiveness of different online advertising mediums by taking into consideration brand familiarity and category conditions. We consider current online advertising actions as forms of paid, owned and earned media based on if they are customer-initiated or firm-initiated. The results obtained from BVAR estimations confirm the increasing importance of earned media. Earned media brings greater efficiency for all brands across category conditions but especially for familiar brands. Our results also present synergy effect of online advertising mediums for familiar brands.

Empirically, our findings on synergy are richer than those reported in previous research: this paper is the first to to show cross-channel synergies of online media with direct mail (brand B) and with radio (brand D). Consistent with previous findings, we also find synergy among TV and the Internet for every brand that invested in TV ads (Chang and Thorson, 2004). As developed in Raman and Naik (2004), synergy effects imply that any medium deserves a non-zero budget despite its limited or unknown effectiveness. The high intra-online synergy for familiar brands also provides a boundary condition for the advice that "Once a brand is familiar; expenses can be curtailed by reducing the number and types of media" (Stammerjohan et al., 2005; p.65). Customer-initiated media show synergy even for familiar brands, which should thus continue to spend on online marketing. Importantly, we note that our findings concern 4 brands, which may differ in other aspects than the brand familiarity/category search nature distinction we make in the conceptual framework. Therefore, we encourage managers to perform this analysis for their own brand, and researchers to obtain additional data to investigate the generalizability of our findings.

Our results have important implications for marketing theory. First of all, our results add value in online advertising research by trying to understand effectiveness for different brand and category conditions. Secondly, although the research on synergy is growing, the conditions for synergy (like product characteristics, brand related effects and use of social media) are still mostly neglected. Our study includes some aspects answering the call for incorporating different product categories and situations into models for integrated marketing communications (Winer, 2009) and the need for new methods and approaches going beyond traditional media forms incorporating new developments on online advertising (Schultz et al., 2011).

Our work has also important implications for marketing practitioners. First of all, for brand managers of unfamiliar brands, in order to get more value they should initially try to find ways to build strong brand associations in consumers' minds. Secondly, our results underscore the importance of owned media especially for risky product choices for consumers. Brand managers for experience goods would benefit from building up-to-date company websites providing quality information in order to decrease the consumers' perceived risk for these types of goods. Lastly, our results show that especially managers of familiar brand can generate more synergy by investing in different online mediums.

Our study has several limitations. The use of data of just one firm for each category and brand conditions may limit the generalizability of our results. However, the aim of this study is to get insights about the effectiveness of especially new advertising formats for different conditions rather than offering empirical generalizations (EGs). Future research should offer EGs on this topic. Additionally, the selection of variables is limited to their availability in the data sets and we used different variables for different online advertising categories. Future research should define metrics that are most appropriate for earned, owned or paid media measurement. Defining and proposing metrics for especially new advertising formats is an important need in the area.

Another research area is to understand the differentiated effect of different online advertising mediums along the different stages of consumer decision-making. The interplay between different online advertising formats and effects of brand familiarity or search-experience dichotomy may vary through these different stages of consumer decision making. Additionally, we show a greater sales elasticity for 'within-online synergy' for familiar brands. However, the results are mixed for unfamiliar brands. This area may need additional investigation.

In sum, our research is the first to conceptually and empirically investigate the conditions for paid and owned media effectiveness and their synergy with other online and offline marketing actions. We believe this work helps put recent single-firm findings into perspective and hope to inspire further research towards empirical generalizations on the effectiveness of new and established media.

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Figure 1: Trustworthiness versus reach of paid, owned, earned and offline media

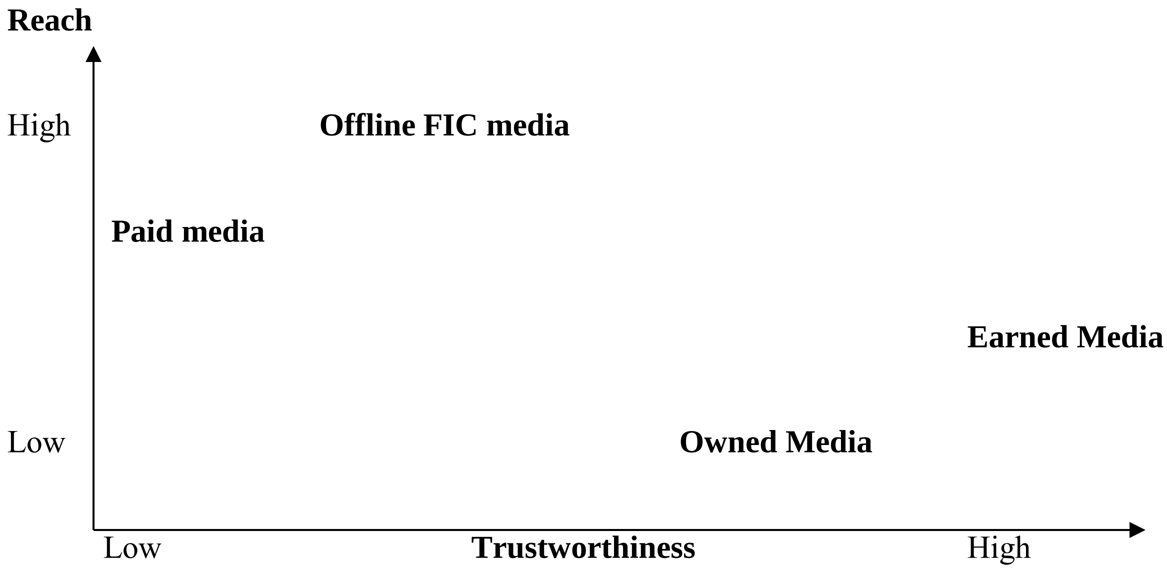
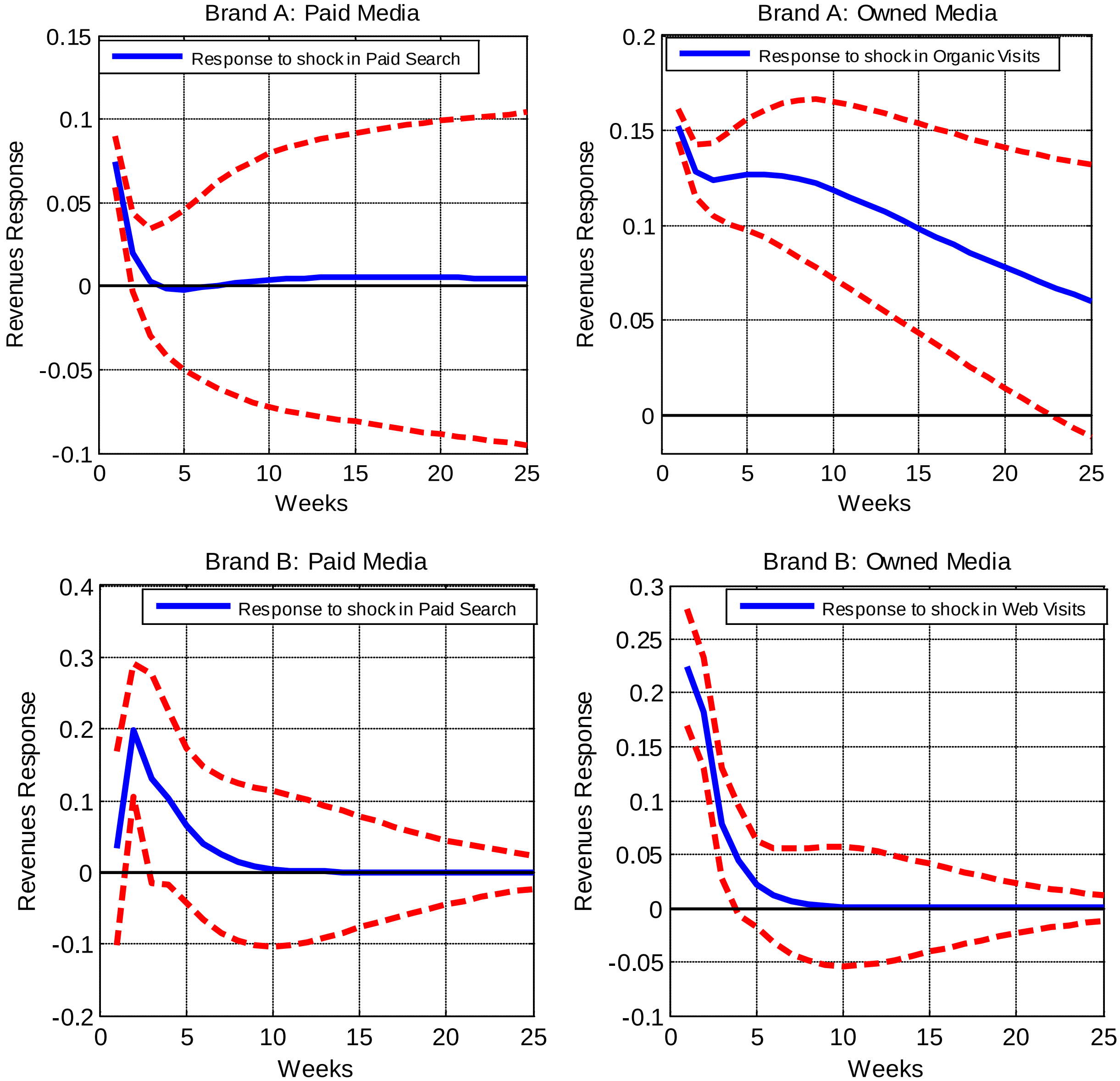


Figure 2: Performance Elasticity of best-in-breed Paid and Owned media action*



* Impulse Response functions in solid lines, 95% confidence bounds in dotted lines

Figure 2 (cont'd): Performance Elasticity of best-in-breed Paid and Owned media action*

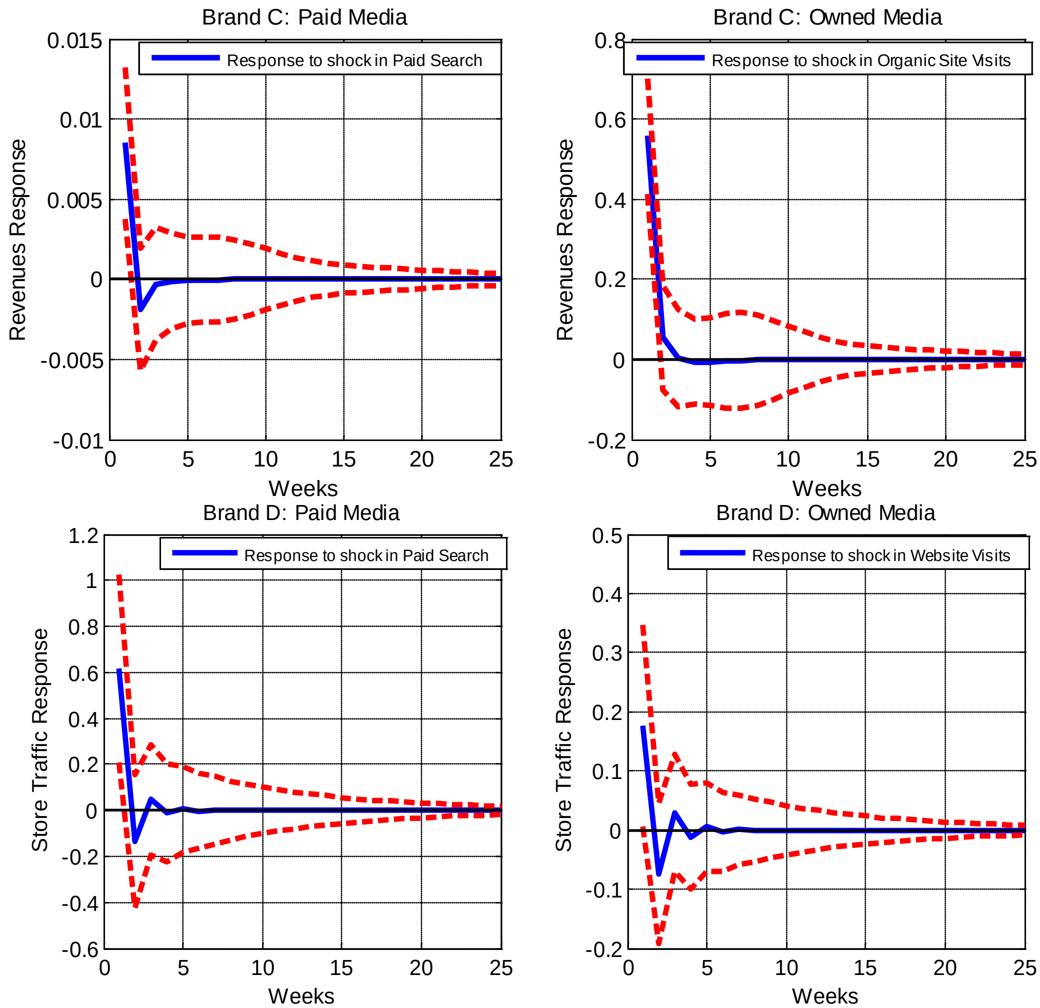


Table 1: Brand-category conditions from highest to lowest perceived risk

	Experience categories (services)	**Search categories (products)**
Unfamiliar brand	**Condition A: High Risk** **Elasticity:** Owned > Paid **Synergy**: FIC/CIC > CIC/CIC	**Condition B:** **Elasticity:** Owned > Paid **Synergy**: FIC/CIC > CIC/CIC
Familiar brand	**Condition C:** **Elasticity:** Owned > Paid **Synergy**: CIC/CIC > FIC/CIC	**Low Risk Condition D** **Elasticity:** Earned > Paid > Owned **Synergy**: CIC/CIC > FIC/CIC

Table 2: Variable operationalization

Firm	Variable	Operationalization	Classification
Brand A	Organic Site Visits	Weekly number of organic visits to the website	Owned
	Paid Search	Weekly cost (per click basis) on Google	Paid
	Amazon Display Ads	Weekly cost (per thousand views) on Amazon display ads	Paid
	US News Display Ads	Weekly cost of a one-page ad in US News	Paid
	Direct Visits	Weekly number of direct visits to the website	Earned
	Price	Weekly average price of an online course	Firm-Initiated
	Revenues	Weekly sales revenues	Performance
Brand B	Web Visits	Weekly total visits to the website	Owned
	Paid Search	Weekly cost of (pay-per-click) referrals	Paid
	Direct Mail	Weekly cost of direct mail	Firm-initiated
	Fax	Weekly cost of faxes	Firm-initiated
	Catalog	Weekly cost of catalogs	Firm-initiated
	Discounts	Percentage of revenue given as a discount	Firm-initiated
	eMail	Weekly number of net emails (sent minus bounced back)	Firm-initiated
	Sales revenues	Weekly sales revenues	Performance
Brand C	Organic Site Visits	Weekly site traffic not coming from paid or earned sources	Owned
	Display Ads	Weekly display advertising (e.g. banners) impressions	Paid
	Paid Search	Weekly cost for all search engines used by brand C	Paid
	Search on partners	Weekly other search engines impressions	Paid
	Organic Google traffic	Weekly traffic on Google related to Brand C	Earned
	TV ads	Weekly cost of TV advertising campaigns	Firm-initiated
	Out of home	Weekly out of home advertising impressions	Firm-initiated
	Revenues	Weekly sales revenues	Performance
Brand D	Owned Site Visits	Weekly total number of visits to the website	Owned
	Paid Search	Weekly paid search advertising in impressions	Paid
	Display Ads	Weekly display (e.g. banner) advertising in impressions	Paid
	Earned General	Weekly number of all social media conversations	Earned
	Organic Google search	Weekly index of searches through Google.com	Earned
	TV GRPs	Weekly gross rating points (GRPs) of TV advertising	Firm-initiated
	Radio GRPs	Weekly gross rating points (GRPs) of Radio advertising	Firm-initiated
	Circulars	Weekly number of circulars distributed	Firm-initiated
	Store Traffic	Weekly traffic to offline store	Performance

Table 3: Summary statistics

Firm	Variable	Mean	SD	Min	Max
Brand A	Organic Site Visits	523.88	380.24	53.00	1386
	Paid Search	4781.67	2694.72	0	12225.74
	Amazon Display Ads	21.90	144.07	0	1153.85
	US News Display Ads	315.47	799.70	0	3373.34
	Direct Visits	3554.34	2532.83	125.00	10477.00
	Price	627.64	48.15	501.25	799
	Revenues	2.58E+05	2.47E+05	799	1.03E+06
Brand B	Web visits	4013.5	1151.7	1507	7425
	Paid Search	1325.5	476.05	619.39	2689.9
	Direct Mail	4790.3	9022.1	0	42774
	Fax	275.13	1027.9	0	7065.9
	Catalog	854.01	5083	0	47728
	Discounts	0.10572	0.030507	0.03488	0.22639
	eMail	4319.9	4895.2	0	19587
	Sales revenues	2.04E+05	72621	52818	4.79E+05
Brand C	Organic Site Visits	2.11E+06	6.39E+05	1.05E+06	3.41E+06
	Display Ads	1.62E+07	2.56E+07	0	9.14E+07
	Paid Search	1.03E+07	3.36E+06	0	1.91E+07
	Search on partners	1.87E+07	8.99E+06	0	3.76E+07
	Organic Google traffic	16.758	4.7903	9.1925	27.636
	TV ads	25157	50022	0	2.17E+05
	Out of home	5.76E+06	1.38E+07	0	4.51E+07
	Revenues	9.23E+05	1.94E+05	5.35E+05	1.37E+06
Brand D	Owned Site Visits	1.62E+06	4.75E+05	8.40E+05	4.29E+06
	Paid search	1.30E+06	4.19E+05	7.28E+05	3.23E+06
	Display Ads	1.89E+07	6.15E+07	0	3.49E+08
	Earned General	2328.5	3177.6	0	15035
	Organic Google search	40.504	13.285	0	96.789
	TV GRPs	134.73	114.67	0	389.4
	Radio GRPs	21.029	48.059	0	177.66
	Circulars	1.03E+05	2.13E+05	0	1.03E+06
	Store Traffic	6.77E+06	1.86E+06	2.02E+06	1.45E+07

Table 4: Short and long-term elasticities

Unfamiliar/Service brand A

Classification	Variables	Immediate Effect	Cumulative Effect
	Main Variables		
Owned	Organic Site Visits	0.148	0.394
Paid	Paid Search	0.075	0.096
Paid	Amazon Display Ads	0.000	0.000
Paid	US News Display Ads	0.000	0.000
Earned	Direct Visits	0.167	0.435
Firm-initiated	Price	0.000	0.000
	All Significant Interactions		
Firm-initiated*Owned	Price*Organic Site Visits	0.145	0.374
Firm-initiated*Earned	Price*Direct Visits	0.168	0.428
Firm-initiated*Paid	Price*Paid Search	0.054	0.069
Owned*Earned	Organic Site Visits*Direct Visits	0.095	0.250
Owned*Paid	Organic Site Visits*Paid Search	0.055	0.072
Earned*Paid	Direct Visits*Paid Search	0.053	0.070

Familiar/Service Brand C

Classification	Variables	Immediate Effect	Cumulative Effect
	Main Variables		
Owned	Organic Site Visits	0.557	0.557
Paid	Display Ads	0.000	0.000
Paid	Paid Search	0.009	0.009
Paid	Search on Partners	0.008	0.008
Earned	Organic Google Traffic	0.898	1.036
Firm-initiated	TV ads	0.008	0.008
Firm-initiated	Out of home	0.000	0.000
	All Significant Interactions		
Paid*Firm-initiated	Display Ads*TV Ads	0.003	0.003
Paid*Firm-initiated	Paid Search*TV Ads	0.003	0.003
Paid*Firm-initiated	Search on Partners*TV Ads	0.003	0.003
Earned*Firm-initiated	Org. Google Traffic*TV ads	0.006	0.006
Earned*Owned	Org. Google Traffic*Org. Site Visits	0.451	0.451
Firm-initiated*Owned	TV Ads*Org. Site Visits	0.003	0.003
Firm-initiated*Firm-initiated	TV Ads*Out of home	0.001	0.001

Table 4 (cont'd):

Unfamiliar/Product Brand B

Classification	Variables	Immediate Effect	Cumulative Effect
	Main Variables		
Owned	Web visits	0.225	0.407
Paid	Paid Search	0.000	0.199
Firm-initiated	Direct Mail	0.021	0.036
Firm-initiated	Fax	0.024	0.024
Firm-initiated	Catalog	0.000	0.000
Firm-initiated	eMail	0.008	0.008
Firm-initiated	Discounts	6.601	6.601
	All Significant Interactions		
Firm-initiated*Firm-initiated	Direct Mail*Fax	0.029	0.029
Firm-initiated*Firm-initiated	Direct Mail *Discounts	0.028	0.049
Firm-initiated*Firm-initiated	Direct Mail*Email	0.011	0.019
Firm-initiated*Owned	Direct Mail*Web Visits	0.011	0.020
Firm-initiated*Paid	Direct Mail*Paid Search	0.069	0.069
Firm-initiated*Firm-initiated	Fax*Discounts	0.035	0.035
Firm-initiated*Firm-initiated	Fax*eMail	0.036	0.036
Firm-initiated*Owned	Fax*Web Visits	0.012	0.012
Firm-initiated*Owned	Discounts*Web Visits	0.461	0.554
Paid*Owned	Paid Search*Web Visits	0.000	0.000

Familiar/Product Brand D

Classification	Variables	Immediate Effect	Cumulative Effect
	Main Variables		
Owned	Owned Site Visits	0.176	0.102
Paid	Paid Search	0.617	0.483
Paid	Display Ads	-0.003	-0.002
Earned	Earned General	0.000	0.000
Earned	Organic Google Search	0.874	0.766
Firm-initiated	TV GRPs	0.006	0.006
Firm-initiated	Radio GRPs	0.004	0.004
Firm-initiated	Circulars	0.004	0.004
	All Significant Interactions		
Firm-initiated*Firm-initiated	TV*Radio	0.006	0.006
Firm-initiated*Firm-initiated	TV*Circulars	0.005	0.005
Firm-initiated*Paid	TV*Paid Search	0.003	0.003
Firm-initiated*Earned	Radio*Org. Google Search	0.004	0.004
Firm-initiated*Owned	Circulars*Owned Site Vis.	0.002	0.002
Firm-initiated*Paid	Circulars*Paid Search	0.002	0.002
Firm-initiated*Earned	Circulars*Org. Google Search	0.003	0.003
Owned*Paid	Owned Site Vis.*Paid Search	0.218	0.177
Owned*Earned	Owned Site Vis.*Org. Google Search	0.286	0.213
Paid*Earned	Paid Search*Org. Google Search	0.419	0.336

Table 5: Hypothesis testing results

Typical Action

Unfamiliar/Experience Brand A

Classification	Median	Hypothesis	Inequality	T-stat
Owned	0.394	H1a (Supported)	Owned>Paid	2.78***
Paid	0			
Cross-synergy	0.374	H2a (Supported)	Cross-synergy>Intra-Online synergy	2.04**
Intra-Online synergy	0.072			
Intra-Offline synergy	N/A	H2b	Cross-synergy>Intra-Offline synergy	N/A

Unfamiliar/Search Brand B

Classification	Median	Hypothesis	Inequality	T-stat
Owned	0.407	H1c (Supported)	Owned>Paid	4.05***
Paid	0.199			
Cross-synergy	0.044	H2a	Cross-synergy>Intra-Online synergy	0.57
Intra-Online synergy	0.004			
Intra-Offline synergy	0.036	H2b	Cross-synergy>Intra-Offline synergy	0.11

Best-in-breed Action

Unfamiliar/Experience Brand A

Classification	Max.	Hypothesis	Inequality	T-stat
Owned	0.394	H1a (Supported)	Owned>Paid	2.00**
Paid	0.096			
Cross-synergy	0.428	H2a	Cross-synergy>Intra-Online synergy	0.99
Intra-Online synergy	0.25			
Intra-Offline synergy	N/A	H2b	Cross-synergy>Intra-Offline synergy	N/A

Unfamiliar/Search Brand B

Classification	Max.	Hypothesis	Inequality	T-stat
Owned	0.407	H1c (Supported)	Owned>Paid	4.05***
Paid	0.199			
Cross-synergy	0.554	H2a (Supported)	Cross-synergy>Intra-Online synergy	5.28***
Intra-Online synergy	0.004			
Intra-Offline synergy	0.081	H2b (Supported)	Cross-synergy>Intra-Offline synergy	4.50***

Table 5 (cont'd):

Typical Action

Familiar/Experience
Brand C

Classification	Median	Hypothesis	Inequality	T-stat
Owned	0.557	H1a (Supported)	Owned>Paid	49.90***
Paid	0.008			
Intra-Online synergy	0.451	H3a (Supported)	Intra-Online synergy>Cross-synergy	11.72***
Cross-synergy	0.003			
Intra-Offline synergy	0.001	H3b (Supported)	Intra-Online synergy>Intra-Offline synergy	29.25***

Best-in-breed Action

Familiar/Experience
Brand C

Classification	Max.	Hypothesis	Inequality	T-stat
Owned	0.557	H1a (Supported)	Owned>Paid	46.24***
Paid	0.009			
Intra-Online synergy	0.451	H3a (Supported)	Intra-Online synergy>Cross-synergy	28.05***
Cross-synergy	0.006			
Intra-Offline synergy	0.001	H3b (Supported)	Intra-Online synergy>Intra-Offline synergy	29.25***

Familiar/Search
Brand D

Classification	Median	Hypothesis	Inequality	T-stat
Paid	0.241	H1b (Supported)	Paid>Owned	5.51***
Owned	0.102			
Intra-Online synergy	0.213	H3a (Supported)	Intra-Online synergy>Cross-synergy	7.36***
Cross-synergy	0.003			
Intra-Offline synergy	0.006	H3b (Supported)	Intra-Online synergy>Intra-Offline synergy	3.60***

Familiar/Search
Brand D

Classification	Max.	Hypothesis	Inequality	T-stat
Paid	0.483	H1b (Supported)	Paid>Owned	15.82***
Owned	0.102			
Intra-Online synergy	0.336	H3a (Supported)	Intra-Online synergy>Cross-synergy	13.20***
Cross-synergy	0.004			
Intra-Offline synergy	0.006	H3b (Supported)	Intra-Online synergy>Intra-Offline synergy	13.13***

Note: ***, **, * signs imply the significance level at 99% level (p <.01), 95% level (p <.05) and 90% level (p <.1), respectively.