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HOW CREATIVE CUES DETERMINE ONLINE RESPONSE TO TV COMMERCIALS: AN EMPIRICAL INVESTIGATION FOR DIGITAL-NATIVE BRANDS

Caroline Julia Meder  
*RWTH Aachen University*, meder@time.rwth-aachen.de

Jan Kemper  
*RWTH Aachen University*, kemper@win.rwth-aachen.de

Malte Brettel  
*RWTH Aachen University*, brettel@time.rwth-aachen.de

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HOW CREATIVE CUES DETERMINE ONLINE RESPONSE TO TV COMMERCIALS: AN EMPIRICAL INVESTIGATION FOR DIGITAL-NATIVE BRANDS

Research in Progress

Meder, Caroline, RWTH Aachen University, Aachen, Germany, meder@time.rwth-aachen.de
Kemper, Jan, RWTH Aachen University, Aachen, Germany, kemper@win.rwth-aachen.de
Brettel, Malte, RWTH Aachen University, Aachen, Germany, brettel@time.rwth-aachen.de

Abstract

This research investigates the effect of TV advertising on website traffic and sales for new and growing e-commerce and online services brands. We created a Python-based extraction and transformation pipeline to join data from four different sources and to establish one of the most comprehensive datasets in this field. It contains approximately 300,000 TV ad airings in 2016/17 of around 800 unique creatives and associated website-tracking and brand awareness data of 23 consumer-facing digital-native brands. We draw on signaling and information processing theory to assess whether companies can boost online consumer activity by aligning creative cues in TV commercials with consumers’ awareness of their brand. Our empirical analyses reveal that informative and imagery-heavy ads are more powerful for lesser-known brands, while better-known brands achieve a higher uplift with emotional commercials. This provides compelling insights for marketing practitioners on how to conceive their TV ads to maximize online response. Our work further shows that e-commerce and media players can generate a competitive advantage by integrating disparate data sources and conducting in-depth analytics on the types of ads that achieve the highest impact for their brands as well as by developing and employing the associated information systems infrastructure to do so efficiently.

Keywords: advertising, e-commerce, consumer behavior, content strategy.

1 Introduction

Traditional TV consumption remains high as it continues to constitute the predominant video viewing source, despite rising popularity of streaming services (The Nielsen Company, 2018b). Many consumer-facing brands thus continue to turn to TV as a central advertising vehicle with 35% of total ad spend allocated to it (Magna Global, 2017). E-commerce and online services companies in particular are increasingly investing in TV advertising (Adweek, 2016), including those in start-up and growth phases (Horizont, 2016). Yet many of them lack a granular understanding of the associated return and of its success drivers (Du, Xu and Wilbur, 2017). Consumers’ media multitasking, in the form of surfing online while watching TV, could offer further insights. 62% of Europeans that are 16 years of age and older engage in such multitasking (Google, 2017), which has proliferated with the pervasiveness of mobile devices (The Nielsen Company, 2018a). This emerging habit enables timely and quantitative evaluation of TV ads’ ability to trigger interest based on real-time online response (Fossen and Schweidel, 2017).

While researchers recently began using online consumer response to evaluate the impact of TV advertising, extant studies largely focus on search engine queries as leading indicators of website visits and sales (e.g., Joo, Wilbur and Zhu, 2016). Due to rare data availability, few examine forms of response later in the buying decision process, although they are more telling measures of advertising effectiveness (Lewis and Reiley, 2013; Du et al., 2017). Liaukonyte, Teixeira and Wilbur (2015) are the first to
explore whether TV ads trigger website traffic and transactions and discover a substantial uplift in the minutes and hours after the respective ads aired. Despite promising findings on certain determinants of TV spot-induced online response such as the placement (e.g., Guitart and Hervet, 2017) and content of ads (e.g., Chandrasekaran, Srinivasan and Sihi, 2017), it remains elusive how TV ad content elements differentially affect viewers’ online reactions based on their familiarity with the advertised brand. Additionally, due to contrary results on the impact of particular creative elements in TV ads on online behavior (Liaukonyte et al., 2015; Chandrasekaran et al., 2017), a more nuanced investigation of these relationships is required.

This study seeks to fill this crucial gap by assessing how the use of different creative cues influences website traffic and sales growth in response to TV ads and how consumers’ awareness of the advertised brand moderates these links. To do so, we use a distinctive combination of datasets obtained in collaboration with a large European media company. We developed a Python-based extraction and transformation pipeline to integrate data from four different sources with the objective of assembling one of the most extensive datasets in this domain. It contains close to 300,000 ad airings in 2016/17 and related website tracking and consumer brand perception data of 23 e-commerce start-up and growth companies. This research is particularly relevant and useful in the context of younger digital-native brands. Given higher online reaction to lesser established brands’ TV ads (Joo et al., 2016), television could be a particularly powerful medium to increase awareness for new and evolving brands.

Our findings contribute to the cross-media effects discourse at the intersection of information systems (e.g., Hill and Benton, 2012; Ghose and Todri-Adamopoulos, 2016; Hinz, Hill and Kim, 2016; Dost and Phieler, 2018) and marketing literature (e.g., Liaukonyte et al., 2015; Fossen and Schweidel, 2017; Guitart and Hervet, 2017; Tirunillai and Tellis, 2017) in three key ways. First, we enhance signaling and information processing theory by demonstrating to what extent different types of TV ad creatives impact online consumer response in terms of website traffic and sales value as well as how brand awareness moderates these relationships. Second, to our knowledge, this marks the first study that conducts a large-scale empirical analysis on TV advertising and online response in the context of new-er rather than mature brands and pure online instead of multi-channel firms (Joo, Wilbur, Cowgill and Zhu, 2014). Finally, our results tie into the research stream on drivers of e-commerce purchase behavior by complementing recent insights on the role and impact of particular marketing tools (e.g., Kemper, 2017; Lohse, Kemper and Brettel, 2017). From a managerial perspective, our study offers guidance to advertising professionals by suggesting a more nuanced approach to developing ad content strategies in consideration of a brand’s lifecycle. This effort also underlines that media and e-commerce players can establish a data-driven competitive advantage by consolidating previously disjoint data and institutionalizing recurring and ad-hoc analyses to enhance advertising effectiveness.

The rest of this paper is structured as follows: First, we review the related literature and derive our research model and associated hypotheses in section 2. We then describe our dataset and the estimation approach in section 3. Subsequently, we demonstrate the results in section 4 and conclude by discussing the implications of these findings, associated limitations and fruitful future research in section 5.

2 Related literature and hypotheses development

2.1 Liability of newness and the signaling effect of advertising

It is well recognized that new ventures are confronted with liability of newness, a higher risk on their quest for growth and survival than established firms (Stinchcombe, 1965; Singh, Tucker and House, 1986; Aldrich and Fiol, 1994). Shepherd et al. (2000) theoretically introduce market novelty risk, meaning customers’ unfamiliarity with their products or services, as a principal mortality risk that new ventures face. This fundamental consumer uncertainty about the quality of sellers’ offerings and associated transaction risk is exacerbated in online environments (Rotman, 2010). Anonymity, due to greater geographical and temporal distance between buyers and sellers, results in higher information asymmetry to the detriment of consumers (Pai and Tsai, 2011). Moreover, low entry barriers to e-
commerce evoke competitive clutter, which further contributes to consumer skepticism (Kotha, Rajgopal and Rindova, 2001).

According to signaling theory (Spence, 1973), individuals thus rely on observable signals as proxies for indiscernible characteristics of sellers, such as legitimacy and trustworthiness (Kirmani and Rao, 2000). Advertising is such an observable signal (Nelson, 1974; Allen, 1984) that consumers consider to infer a firm’s product or service quality (e.g., Milgrom and Roberts, 1986). This implies that advertising plays a critical role for new venture reputation building (Shapiro, 1983) and market novelty risk reduction (Shepherd et al., 2000) to ultimately increase adoption – potentially even more so in the online shopping context. TV advertising, due to its reach and expressiveness (Batra and Keller, 2016), could be an especially suitable instrument for younger digital-native brands. This paper thus focuses on how newer e-commerce and online services companies can use TV advertising as a signal and means to reduce market novelty risk.

2.2 Consumer processing of creative cues and the role of brand awareness

The singular positive effect of TV advertising on online response is established (e.g., Guitart and Hervet, 2017), yet the determinants of it are only partly understood (Fossen and Schweidel, 2017). Recent studies show that the type of ad content used explains some of the substantial variation in online reactions to TV ads (Liaukonyte et al., 2015; Chandrasekaran et al., 2017). However, they provide inconsistent evidence on whether certain creative cues, e.g., informative, encourage or inhibit online response to commercials of established brands. These mixed findings could result from the different and in part restricted empirical contexts of these studies and warrant further, more nuanced analyses. At the same time, it has been shown for a particular service that online response to different types of TV ads is influenced by how long this service has been offered across markets (Tellis, Chandy, MacInnis and Thaivanich, 2005). Thus, it is also crucial to investigate how viewers’ awareness of an advertised brand affects their processing of and eventual online response to different cues. Further, prior related work on TV ad creatives focuses on online brand search (Chandrasekaran et al., 2017), website traffic and number of transactions (Liaukonyte et al., 2015), thereby neglecting the impact on sales volume and value. Accordingly, researchers call for a more holistic view on how creative cues in TV ads impact consumer behavior at later stages in the buying decision process (Joo et al., 2014; Chandrasekaran et al., 2017; Du et al., 2017). This study hence seeks to address these shortcomings by examining how different ad content types impact website traffic and sales growth in response to TV ads of lesser-established brands as well as the moderating role of brand awareness.

We rely on consumer information processing theory, more specifically the elaboration likelihood model (ELM) of persuasion (Petty, Cacioppo and Schumann, 1983), to develop our hypotheses on consumer response to different kinds of advertising appeals. Two distinct modes exist through which individuals process information and, in consequence, potentially change their attitudes and behaviors. These are known as central and peripheral processing (Petty and Cacioppo, 1981; Petty and Cacioppo, 1983). ELM theory postulates that in some situations, positive attitude changes result from diligent deliberation of arguments (central processing), whereas in others, they occur due to simple inferences or associations (peripheral processing) (Petty et al., 1983; Hagtvedt and Wegener, 1994).

When stimuli conform with existing memories, they evoke a feeling of recognition and familiarity, which triggers non-analytical, peripheral processing. On the contrary, unfamiliar messages invoke more analytical, central processing (Radder and Ritter, 1992; Garcia-Marques and Mackie, 2001). Consequently, we assume that the creative used in a TV commercial needs to be selected in such a way that it triggers peripheral processing when consumers recognize the offering, i.e., have prior knowledge of or experience with the product or service advertised, and central processing in the case that the offering is unfamiliar to ultimately generate the most substantial consumer response. In line with this reasoning, signals that invoke peripheral processing should be used for more well-known brands. Cues that conjure feelings are typically emotional ones. Moreover, showing familiar brands should generally lead to peripheral processing, which implies that consumers likely do not indulge in
deep thinking, but that they are more receptive to simple cues that call for immediate action. According to this reasoning, we hypothesise that:

H1. Brand awareness positively moderates the relationship between action-focused TV ad creatives and online consumer response.

H3. Brand awareness positively moderates the relationship between emotion-focused TV ad creatives and online consumer response.

On the contrary, when lesser-known brands air TV ads, we expect that consumers largely cannot draw on existing experiences and associations. In these cases, positive attitude changes should more likely occur due to careful consideration and analytical thinking, thus from central processing taking place. Advertising creatives with more rational appeals, i.e., ones that are informative in explaining the offering and provide the pervasive visuals to allow consumers to better understand the product or service, are envisioned to be more effective in driving online consumer response. We thus formulate the following hypotheses:

H2. Brand awareness negatively moderates the relationship between information-focused TV ad creatives and online consumer response.

H4. Brand awareness negatively moderates the relationship between imagery-focused TV ad creatives and online consumer response.

Figure 1. Conceptual framework with hypotheses (adapted from Liaukonyte et al., 2015).

3 Research methodology

3.1 Research context and data

The data for this empirical study was gathered as part of an exclusive cooperation with a leading European media company. To be able to conduct our analyses, we combined four different data sources using Python, namely information on TV ad airings, the type of creative cues employed in the spots, information about consumers’ awareness of the advertised brands in the focal country, and activity on the advertising brands’ websites. The observations in the joint dataset are at TV ad airing level.

The TV-based part of the data includes information on the context in which each ad is shown, on its viewers and on the creative copy used. In terms of media placement, each ad airing for example entails the start time, spot length, TV channel, the program shown before, which genre that program belongs to and the gross media costs associated with it. The dataset further contains an inference of the TV ad audience’s characteristics with metrics such as overall reach and reach for certain demographic segments as well as overall gross rating points (GRPs) and GRPs for certain segments. GRPs are the number of impressions in a specified population related to the size of the specified population (e.g., Hartmann and Klapper, 2018). This inference is based on the measurement of the TV viewing behavior of a representative panel of the country’s total TV audience population by a third-party provider, which is common practice for the TV broadcasting industry (Kim, 2002). In addition, it encompasses the target audience the creative was designed for.
The second component of the dataset consists of consumer online response information on the focal brand’s website in terms of metrics such as website traffic, transaction count and sales value based on the user sessions that start in the time frame shortly before and shortly after an ad airing. The final dataset comprises aggregate values for each metric for the pre- and post-airing timeframe per airing. Individual user sessions were allocated to these groups using a high-performance computing cluster.

We supplement this information with data on consumers’ aided awareness of the advertising brands from YouGov’s BrandIndex. YouGov is a leading global market research firm (Bowers and Brereton, 2017) and its BrandIndex is the most comprehensive, daily-level brand attitude survey panel (Du, Joo and Wilbur, 2018). Renown academic studies recently employed the BrandIndex (e.g., Luo, Raithel and Wiles, 2013; Colicev, Malshe, Pauwels and O’Connor, 2018). The fourth dimension of our dataset covers the types of creative cues used in the spots based on the constructs developed and validated by Liaukonyte et al. (2015) for action-, information-, emotion- and imagery-focused ads.

Our final sample consist of 281,446 TV ad airings of 778 distinct creatives and related website tracking data of 23 e-commerce and online services brands across seven product categories. All ads aired on one of the media company’s seven free TV channels in the same country in 2016/17 and jointly amount to almost €770 million in gross media volume. We included all brands that aired ads on at least one of the media company’s TV channels and for which brand awareness data is available.

3.2 Key variables and estimation approach

The dependent variables in our multiple linear regression models are website traffic uplift and sales value uplift. We follow the established methodology to assess viewers’ response to a TV ad as the cumulative growth in website traffic and sales value respectively from a particular timeframe before to after ad airing start (Lewis and Reiley, 2013; Liaukonyte et al., 2015). More precisely, in line with the approach of Chandrasekaran et al. (2017), our dependent variable website traffic uplift is defined as the natural logarithm of one plus the growth in cumulative traffic in the eight minutes after the start of the ad airing divided by the cumulative traffic in the eight minutes before the ad airing. The timeframe of eight minutes was derived in accordance with how long it generally takes after the start of an ad airing for the incremental, spot-induced website traffic to become insignificant for the brands in our sample. To better distinguish baseline from TV spot-induced visits and consequently sales, we consider pre- to post-spot changes in visit distribution per source (i.e., direct, search, social, other) and device (i.e., mobile, other). Moreover, in the case that TV ads for the same brand are aired on different channels so that their pre- or post-spot windows overlap, we allocate website visits on a minute-level to the respective spots in proportion with their GRPs. For this, we consider all TV airings in the focal country, not just those on our partner’s channels.

The explanatory variables of interest are ad content type, i.e., extent of action, information, emotion and imagery focus, as well as brand awareness. To operationalize the degree to which each of the four cue types is used per creative, we employ the tested and validated survey-based scales of Liaukonyte et al. (2015). We instructed a research assistant on how to code the full set of ads. She was told to watch each ad more than once including rewatching, pausing and rewinding as needed, to not code for over 1.5 hours at a time to avoid fatigue, and to mark and discuss any uncertainties, which were then resolved in discussion with the authors. One of the authors separately coded a random set of 12% of the creatives, which yielded a high average inter-rater agreement of 95%. To ensure construct reliability, we excluded some items due to poor consistency with the other items in the respective scales (Cronbach, 1951). The final action-, information-, emotion- and imagery-focused constructs consist of four, two, four and two items respectively and are normalized for better comparability. Brand awareness is based on the values provided by YouGov’s BrandIndex. Within the BrandIndex, aided brand awareness is calculated as the weighted share of the respondents that answers the question “Have you ever heard of this brand?” positively and is captured as a percentage of the population (YouGov, 2018).
As controls, we include continuous variables and fixed effects in the form of dummy variables for factors that have been shown to influence consumer behavior in response to TV ads in prior studies. The continuous predictors included are the natural logarithm of one plus the respective airing’s GRPs for adults 14 years of age and older (Guitart and Hervert, 2017) and the spot’s length (Fossen and Schweidel, 2017) to account for both its reach and the duration of consumer engagement. In addition, we include the cumulative GRPs of prior airings of the focal creative for adults 14 years of age and older to consider ad wear-out (Liaukonyte et al., 2015). Table 1 presents descriptive statistics and pairwise Pearson correlation coefficients for all continuous variables. Almost all coefficients are far below the threshold of [0.8], implying that multicollinearity should not be an issue (Kennedy, 2008).

In addition, our models contain a multitude of time fixed effects, i.e., calendar year, week, day type in terms of weekday, weekend or holidays, hour and minute (Joo et al., 2014). Moreover, we factor in unobservable heterogeneity between product categories and brands that could affect website traffic and sales uplift (Liaukonyte et al., 2015) by including six category and 22 brand dummies for the seven categories and 23 brands in our dataset. We further acknowledge other exogenous factors that are specific per category and time by including category-time interaction dummies for all time variables except the year and minute level (Liaukonyte et al., 2015). Finally, we include dummies for the TV channel, for the genre of the show shown before the commercial break as well as for the spot’s position in the commercial break to control for unobserved heterogeneity in consumer behavior based on the context the ad is embedded in (Fossen and Schweidel, 2017).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std.</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Website traffic uplift</td>
<td>0.19</td>
<td>0.85</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 Spot GRPs</td>
<td>0.34</td>
<td>0.42</td>
<td>0.16***</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 Prior GRPs of creative</td>
<td>249.33</td>
<td>365.13</td>
<td>-0.02***</td>
<td>0.05***</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4 Spot length</td>
<td>16.57</td>
<td>11.56</td>
<td>0.01***</td>
<td>0.07***</td>
<td>0.00**</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5 Brand awareness</td>
<td>0.40</td>
<td>0.18</td>
<td>-0.12***</td>
<td>0.09***</td>
<td>0.12***</td>
<td>0.11***</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6 Action-focused</td>
<td>0.36</td>
<td>0.27</td>
<td>0.00</td>
<td>0.05***</td>
<td>0.34***</td>
<td>0.04***</td>
<td>0.05***</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7 Info-focused</td>
<td>0.53</td>
<td>0.42</td>
<td>-0.06***</td>
<td>-0.02***</td>
<td>0.09***</td>
<td>-0.01***</td>
<td>-0.32***</td>
<td>0.23***</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>8 Emotion-focused</td>
<td>0.52</td>
<td>0.40</td>
<td>-0.02***</td>
<td>0.07***</td>
<td>-0.06***</td>
<td>0.31***</td>
<td>0.20***</td>
<td>-0.07***</td>
<td>-0.27***</td>
<td>1.00</td>
</tr>
<tr>
<td>9 Imagery-focused</td>
<td>0.73</td>
<td>0.39</td>
<td>-0.03***</td>
<td>0.06***</td>
<td>-0.02***</td>
<td>0.13***</td>
<td>0.13***</td>
<td>-0.01***</td>
<td>-0.28***</td>
<td>0.53***</td>
</tr>
</tbody>
</table>

*** p<0.001; ** p<0.01; * p<0.05. Notes: Table exhibits pairwise Pearson correlation coefficients between sample variables. Categorical variables like website, product category, minute, day, day type, week, year, channel, genre and spot position not shown. Spot length in seconds. Normalized content measures.

Table 1. Descriptive statistics and correlation matrix.

4 Empirical results

In our sample, the mean website traffic uplift for the post-spot versus the pre-spot time window is 19% (std=85%). The average ad airing has 34 GRPs (std=42) and is 17 seconds long (std=12). The mean brand awareness across the aired spots is 40% (std=18%). In terms of the content cues, action focus is least prominent (mean=0.36, std=0.27), followed by emotion focus (mean=0.52, std=0.40), information focus (mean=0.53, std=0.42) and imagery focus (mean=0.73, std=0.39).
To test our hypotheses, we calculate two OLS regression models with website traffic uplift as the dependent variable, for which the unstandardized beta coefficients are shown in Table 2. The adjusted R² values of 0.365 (controls only) and 0.368 (full model) indicate that the estimated models present a good fit to the data and that the explanatory power increases upon inclusion of ad content characteristics, brand awareness and their interaction terms. The first model only comprises control variables, thereby allowing for the validation of prior research on the effect of these factors (e.g., Liaukonyte et al., 2015; Chandrasekaran et al., 2017; Fossen and Schweidel, 2017). For brevity, we do not address the empirical results for the continuous control variables or fixed effects here in detail.

The full model demonstrates that our empirical analysis confirms most of our hypotheses. We observe a statistically significant moderating effect of brand awareness on the relationship between ad content characteristics and website traffic uplift in response to TV ads for three of the four content types. Emotion-focused ad creatives (b=0.012, p<0.01) are negatively associated with website traffic uplift; however, this effect is positively moderated by brand awareness (b=0.018, p<0.05). This corroborates our hypothesis 3 in that emotion-oriented ads are more effective for more mature brands. In contrast, information-focused (b=0.058, p<0.001) and imagery-focused ad creatives (b=0.095, p<0.001) are positively related to website traffic uplift and this effect is negatively moderated by brand awareness (b=0.083, p<0.001 and b=0.205, p<0.001 respectively). In line with our hypotheses 2 and 4, these results support that imagery- and emotion-heavy spots are associated with higher website traffic uplift for less-established e-commerce and online services brands. Our results do not show a statistically significant effect of action-focus nor of its interaction with brand awareness, thus offering no support for hypothesis 1.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Controls only</th>
<th>Full model</th>
</tr>
</thead>
<tbody>
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<td>Intercept</td>
<td>1.422***</td>
<td>1.468***</td>
</tr>
<tr>
<td>Controls</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Logarithm (Spot GRPs + 1)</td>
<td>0.225***</td>
<td>0.221***</td>
</tr>
<tr>
<td>Prior GRPs of creative</td>
<td>0.000***</td>
<td>0.000***</td>
</tr>
<tr>
<td>Spot length</td>
<td>0.001***</td>
<td>0.001***</td>
</tr>
<tr>
<td>Year (2017)</td>
<td>-0.014***</td>
<td>-0.003**</td>
</tr>
<tr>
<td>Ad content type</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Action-focused</td>
<td>-0.007</td>
<td></td>
</tr>
<tr>
<td>Information-focused</td>
<td>0.058***</td>
<td></td>
</tr>
<tr>
<td>Emotion-focused</td>
<td>-0.012**</td>
<td></td>
</tr>
<tr>
<td>Imagery-focused</td>
<td>0.095***</td>
<td></td>
</tr>
<tr>
<td>Moderation with brand awareness</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brand awareness</td>
<td>-0.401***</td>
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</tr>
<tr>
<td>Action-focused * brand awareness (H1)</td>
<td>0.016</td>
<td></td>
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<tr>
<td>Information-focused * brand awareness (H2)</td>
<td>-0.083***</td>
<td></td>
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<tr>
<td>Emotion-focused * brand awareness (H3)</td>
<td>0.018*</td>
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</tr>
<tr>
<td>Imagery-focused * brand awareness (H4)</td>
<td>-0.205***</td>
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<tr>
<td>Number of observations</td>
<td>281,446</td>
<td>281,446</td>
</tr>
<tr>
<td>R² adjusted</td>
<td>0.365</td>
<td>0.368</td>
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</table>

*** p<0.001; ** p<0.01; * p<0.05. Notes: DV is website traffic uplift, measured as natural logarithm of one plus the incremental cumulative traffic eight minutes after the ad airing over the cumulative traffic eight minutes before the ad airing. Fixed effects for website, product category, minute, day, day type, week, product category-time interactions, channel, genre and spot position not shown. Spot length in seconds. Normalized content measures.

Table 2. Model results from ordinary least squares regression: effect of ad content type and brand awareness on website traffic uplift.
What’s more, brand awareness is negatively associated with website traffic uplift, meaning TV ads are more effective in creating incremental traffic for lesser-known brands. This is in line with the finding of Chandrasekaran et al. (2017) that online search lift for brands advertised on TV is negatively associated with brand age, which is sometimes used as a proxy for brand awareness (Joo et al., 2016). As a next step, we will further leverage this unique dataset to investigate whether these relationships also hold for sales value uplift.

5 Discussion

5.1 Theoretical and managerial implications

This study generates several academic implications. It presents current empirical evidence for the notion that not all start-up and growth company TV ads are created equal. More precisely, it shows that the effectiveness of different types of creative cues in TV advertising depends on the extent to which the brand and its offering are known to consumers. With this, we advance knowledge on and link cross-media effects, consumer information processing and signaling literature – three so far rather independent research fields. It further theoretically contributes to understanding the antecedents of TV advertising effectiveness and thereby its role in reducing start-ups’ and growth ventures’ risk by identifying the type of content that is most compelling at different growth stages. Our work overcomes a key roadblock in TV advertising research to date, which is access to data later in the buying process beyond online search for multiple brands (e.g., Lewis and Reiley, 2013; Srinivasan, Rutz and Pauwels, 2015; Du et al., 2017). To our knowledge, it is also the first large-scale empirical analysis of TV ad creatives and online shopping in the context of younger brands and online pure players.

We also offer practical guidance for marketing managers in e-commerce and online services companies as well as media agencies on how to tailor the design of TV ads to stimulate online performance based on a brand’s maturity. In addition, we provide managers with a means to more accurately assess the impact of TV ads as an input for their media budgeting and controlling process. Moreover, both the Python-based data extraction and transformation pipeline as well as the statistical models are developed in a way that they can be used by our partnering media company to conduct business analytics on a continuous basis to assess the effectiveness of their customers’ TV ads and to consult them regarding necessary adjustments in line with changing circumstances.

5.2 Limitations and areas for further research

Despite its contributions, our study naturally exhibits some limitations that provide opportunities for future research. First, it focuses on how the content of TV commercials affects online consumer response. Based on the already broad scope of our dataset, we did not additionally consider interdependencies with ad exposures in other channels or with the kinds of cues such ad copies employ. A holistic examination of the interaction effects of ad exposures across other channels and the influence of the respective content constitutes a promising extension of this work. Further, the present approach examines antecedents of TV advertising effectiveness based on a short-term view, in part to mitigate noise from other potential influencing factors. An essential area for future studies would be to better understand the determinants of its longer-term impact on viewers’ behavior, which would demand granular longitudinal data on advertising across multiple channels and brands. Third, we do not have visibility on the content individuals encounter upon website visit. Yet it would be beneficial to understand how website quality and product congruency with what is shown in commercials influences further decision making. Fourth, the combination of multiple unique data sources enables our nuanced view on the drivers of online response to TV commercials. In turn, our dataset does not comprise an integrated individual-level view in terms of TV ad exposure, prior knowledge about and interaction with a certain brand, and consequent online response. Pertinent single-source or more precise coupling of TV ad viewing and online consumer shopping data could prove useful for substantiating and expanding our findings.
References


