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# Television Advertising and Online Shopping

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Media multitasking competes with television advertising for consumers' attention, but may also facilitate immediate and measurable response to some advertisements. This paper explores whether and how television advertising influences online shopping. We construct a massive data set spanning $3.4 billion in spending by 20 brands, measures of brands' website traffic and transactions, and ad content measures for 1,224 commercials. We use a quasi-experimental design to estimate whether and how TV advertising influences changes in online shopping within two-minute pre/post windows of time. We use nonadvertising competitors' online shopping in a difference-in-differences approach to measure the same effects in two-hour windows around the time of the ad. The findings indicate that television advertising does influence online shopping and that advertising content plays a key role. Action-focus content increases direct website traffic and sales. Information-focus and emotion-focus ad content actually reduce website traffic while simultaneously increasing purchases, with a positive net effect on sales for most brands. These results imply that brands seeking to attract multitaskers' attention and dollars must select their advertising copy carefully.

*Keywords*: advertising; content analysis; difference-in-differences; Internet; media multitasking; online purchases; quasi-experimental design; television
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## 1. Introduction

As computers have grown smaller and more powerful, simultaneous television and Internet consumption has rapidly increased (Lin et al. 2013). Numerous studies have reported large increases in media multitasking. For example, Nielsen (2010) claimed that 34% of all Internet use time occurred simultaneously with television consumption. Meanwhile, television use has not fallen; Americans still watch about five hours per day. In fact, time spent with television and time spent on the Internet are positively correlated at the household level (Nielsen 2011).

One might therefore suspect that television can effectively engage online shoppers. Yet do multitaskers engage with television ads or does simultaneous media consumption steal consumer attention away from commercials? Numerous surveys suggest that engagement is possible. Among them, Nielsen (2012) found that 27% of U.S. viewers reported searching online for product information after watching a TV advertisement; 22% looked up coupons or deals advertised on TV. Ofcom (2013) reported that 16% of UK consumers surveyed had searched for product information or posted comments to a social network about a television advertisement.

The paper contributes to the literature on cross-media effects by answering the following questions: Does TV advertising trigger online shopping? If so, how does it work? Recent research (Zigmond and Stipp 2010, 2011; Lewis and Reiley 2013) has used online search data to show that search engine queries to Google and Yahoo respond almost instantaneously to television commercials. However, to our knowledge, no past research has examined the effects of television advertising on direct website traffic or online purchase data. This paper establishes that online shopping responds to television advertising. Furthermore, it investigates how those effects depend on the characteristics of the advertisement, such as its content and media placement.

To address these questions, we merged two large television advertising and Internet use databases, and then created a third database of advertising content. The advertising data represent $3.4 billion spent by 20 brands in five categories, spanning 328,212 insertions of 1,224 distinct advertisements in 2010. The contents of these advertisements were coded to assess the extent to which each one incorporated action-focus, information-focus, emotion-focus, and imagery-focus elements. Finally, the advertising data were supplemented with comprehensive, passively tracked brand-level website traffic and sales data from a large Internet research firm.

Advertising response studies are notoriously plagued by endogeneity. To estimate causal effects, we use a quasi-experimental research design in conjunction with narrow two-minute event windows (Chaney et al. 1991). For each ad insertion, online shopping variables are measured in the two minutes before the advertisement. This "pre" period serves as a baseline against which the ad's effect is measured. The same variables are measured again in a two-minute "post" window immediately following the ad's insertion. Systematic differences between the pre- and post-windows are attributed to the ad insertion. The identification strategy is similar to the regression discontinuity approach of Hartmann et al. (2011).

We also measure advertising effects on online shopping in broader two-hour windows of time. Online shopping on nonadvertising competitors' websites is used to parse out unobserved category-time interactions as a potential confound in a difference-in-differences regression framework.

We find that television advertising does influence online shopping and that advertising content plays a key role. Action-focus tactics increase direct traffic to the website and purchases conditional on visitation. Information-focus and emotion-focus elements reduce traffic to the website, but increase the number of visitors that purchase, a process that is consistent with increasing the efficiency of consumer search. Imagery-focus ad content reduces direct traffic to the website, perhaps because it discourages consumers from diverting their attention away from television. To summarize, the results suggest that advertisers must select advertising content carefully according to their objectives.

Section 2 reviews related academic literature. Section 3 describes the data; §4 covers the empirical framework and §5 shows the findings of this paper. Section 6 concludes with a discussion of the implications of this work, and opportunities for future research.

## 2. Relevant Literature and Conceptual Framework

This article is related to several bodies of research. In the literature on multimedia advertising effectiveness, Dagger and Danaher (2013) built a single-source, customer-level database of 10 advertising media spending and sales for a large retailer. They found that single-medium advertising elasticities were highest for catalogs, followed by direct mail, television, email, and search, showing that direct-response channels and television were both effective at increasing short-term sales. Similarly, several recent studies have found synergistic effects on sales between television advertising and advertising in other media (Kolsarici and Vakratsas 2011, Naik and Peters 2009, Naik and Raman 2003, Onishi and Manchanda 2012).

The sum of the evidence suggests that cross-media effects exist. However, researchers are just starting to understand *how* the content of one medium might influence consumers' behavior in another. In an early effort, Godes and Mayzlin (2004) showed that online discussions of new television programs helped to predict those programs' ratings, suggesting that measures of online word-of-mouth reflect broader trends in consumer conversations. More recently, Gong et al. (2014) designed a field experiment to measure the causal impact of tweets and retweets on ratings of a television program. They found that promotional messages increase viewership, with larger effects when they contain informational content and are retweeted by influential users.

Our paper is also inspired by previous work on direct response advertising. A seminal example in this area is Tellis et al. (2000), which estimated how consumer telephone calls responded to television advertisements for a new medical service. Among numerous findings, the results showed that advertising significantly increased the number of calls over a baseline, but that its effect rapidly diminished after the first one or two hours. Chandy et al. (2001) extended this work to consider the influence of specific advertising appeal on consumer response. Informative and emotional appeals were both effective in generating telephone calls, but informational content was most effective shortly after market entry while emotion-based content became more effective with time.

### 2.1. TV Advertising and Online Behavior

Television ads are valuable for generating awareness, knowledge, and interest in new products. A direct consequence is that effective television ads may lead viewers to seek more information about these products and brands (Rubinson 2009). Recently, consumers have started gathering a great deal of product information online. To date, the most studied online behavior among TV viewers has been searching for advertised brands and products using search engines (e.g., Joo et al. 2014). Such online search is obviously important to the brands that sell primarily online, but it also matters to offline retailers as it allows interested consumers to learn more about an advertised product before incurring a costly store visit. Nearly all major retailers provide an extensive assortment of product and price information online, often in formats that can help consumers locate physical products in local (offline) retail environments.

In the literature on advertising and online search, Lewis and Reiley (2013) found that advertisements during the Super Bowl tend to trigger online searches for the advertised brands immediately (i.e., within one minute); smaller effects persist up to an hour after the ad's broadcast time. However, their analysis did not include direct traffic to the brand website or online purchases, thus making it impossible to distinguish interest in the ad's entertainment value from interest in the advertised product. They suggested that "other user data such as site visitation and purchase behavior could provide a more holistic perspective…" (p. 654). The current article examines this suggestion.

Following this observation, we posit that people have two main decisions to make in response to TV ad exposure. First, they choose whether to visit the brand's website. If the website domain is very salient, visitation would most likely occur by a direct route, such as entering the website address into the browser or by clicking a bookmark. If the website domain is unknown or not salient, the consumer might instead visit a search engine and then click a referring link to the brand's website. Second, on arrival at the website, the consumer eventually decides whether to purchase.

When thinking through the possible influence of TV ads on online shopping, one must consider the role of the brand's website. Broadly speaking, the brand's website can serve two roles: It could primarily be a channel for selling (i.e., providing product information and additional persuasive arguments), or it could primarily be a channel for order fulfillment (i.e., minimizing the consumer's transaction cost). An ad that stimulates interest without providing much information might be more effective in conjunction with a brand's website that is primarily a channel for selling. A TV commercial that provides extensive selling arguments might be more effective when used with a website that maximizes order fulfillment.

The interplay between advertising and distribution tactics has been extensively studied. Anderson and Renault (2006) formally modeled this trade-off: In equilibrium, a rational consumer's willingness to incur a search cost (e.g., visit a website) is greater when the firm advertises partial information about product attributes and price than when it provides full information. Empirical evidence also suggests that advertising tactics can influence the quality as well as the quantity of consumers attracted to the brand's distribution channel. For example, Haans et al. (2013) found that text search advertisements with particular content attributes (e.g., statistical evidence, appeals to expert authority) brought a higher number of visitors, whereas other content attributes yielded fewer visitors but higher conversion rates. Similarly, Wu et al. (2005) found that prominently placed magazine advertisements were more effective at generating site traffic than less prominent placements, but that traffic from the latter placements converted to sales at higher rates.

These results about the role of the Internet channel can help to shape expectations about our second research question: How might TV ad content influence online shopping? Similar to magazine and search engine ads, TV commercials may primarily attempt to persuade viewers to visit a brand website, or they might focus on making the sale. Because both approaches might result in a purchase, it may be important to distinguish the ad's ability to generate traffic from the ad's ability to generate sales. In §3 we describe the data set that allows us to estimate these effects.

## 3. Data

The empirical analysis merges two large data sets of television advertising and Internet behavior in 2010 with a newly constructed database of advertising content. We focus on five product categories with extensive online shopping activity: dating, pizza delivery, retailers, telecommunications, and travel.

### 3.1. Web Traffic and Transactions Data

Online traffic and transactions data were collected from comScore Media Metrix. ComScore used proprietary software to passively track all Web use on a large number of Internet-connected desktops and laptops. It reports the Web browsing data at the level of the user/website *session*. Consistent with standard industry practice, a new session is recorded when a user first loads a page from a particular domain (e.g., Amazon.com) after not loading any page from that domain in the past 30 minutes.[1] For each user/website session, comScore reported an anonymous user ID, the domain name (brand website), the domain name of a referral website (if any), and the exact date and start time. Furthermore, comScore identified paid transactions by analyzing the structure of confirmatory URLs for all but a few brands it tracked.[2] We focus on the following three measures of online shopping:

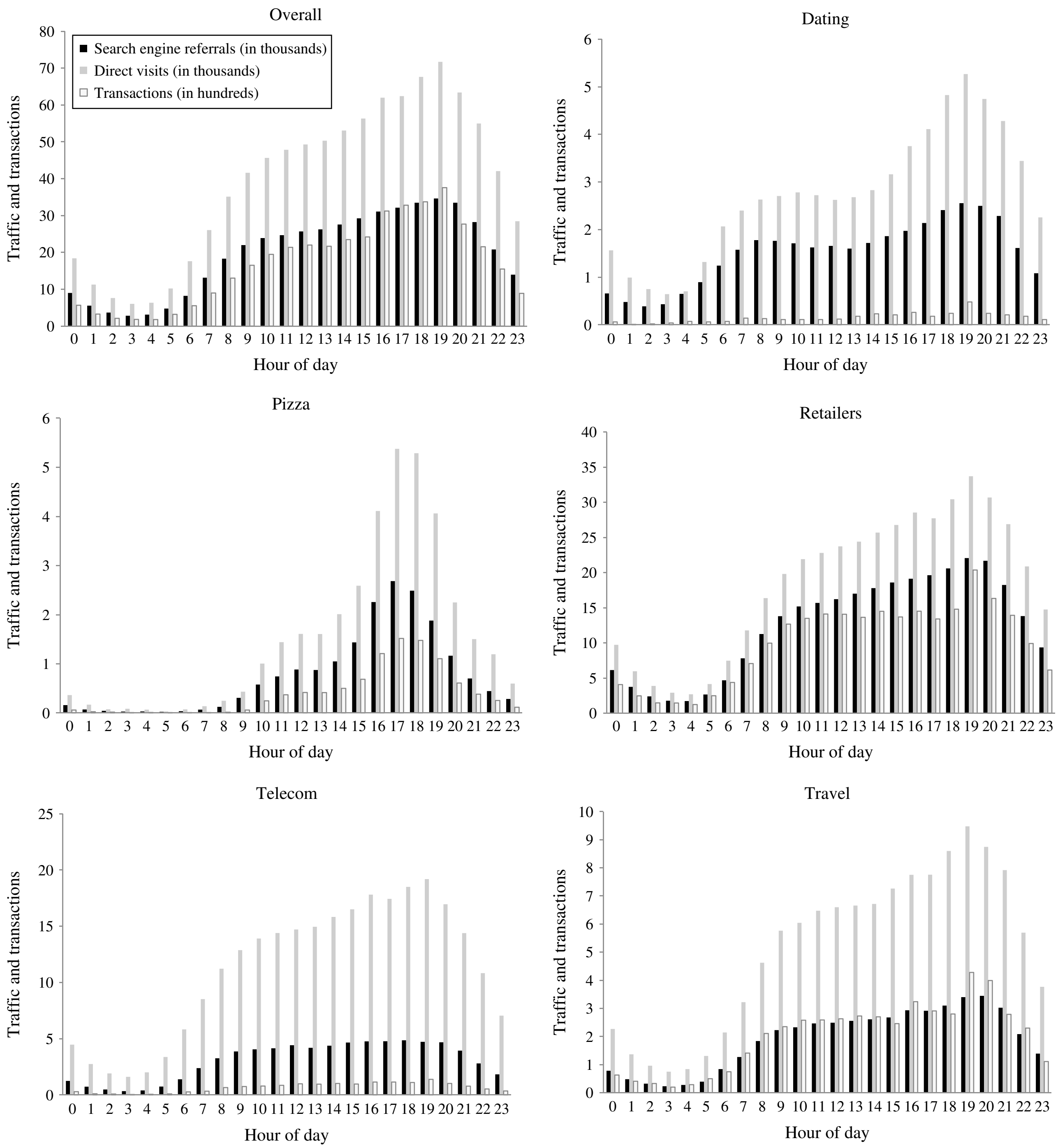
*Direct Traffic* ($d$): the number of new sessions on a brand website that were initiated by direct visits (e.g., URL entry or clicking a bookmarked link) within a particular time window.

*Search Engine Referrals* ($r$): the number of new user sessions on a brand website that were initiated by search engine referrals within a particular time window. Six search engines (*AOL*, *Ask*, *Bing*, *Google*, *MSN*,

[1] Many users stop looking at Web pages without closing a browser tab. Thus, some assumption is required about the maximum time a user might have continued interacting with the site. Thirty minutes is the standard assumption.

[2] Prior marketing research has analyzed comScore data from 2002–2004 (e.g., Moe and Fader 2004, Park and Fader 2004, Montgomery et al. 2004, Danaher 2007, Johnson et al. 2004).

**Figure 1 Search Engine Referrals, Direct Traffic, and Transactions by Product Category and Hour**




*Note.* For Pizza, transactions are in thousands.

and *Yahoo*) are included, accounting for 99% of U.S. searches.[3]

*Transaction Count* (*s*): the number of new sessions on a brand website that are initiated within a particular time window, which are then followed by a transaction within the following 24 hours. Purchase decisions may take much longer than site visits, as they may be delayed by time spent reading reviews, researching competing options or consulting other members of the household. Thus, a one-day window is used, similar to Blake et al. (2014).

Figure 1 summarizes the online shopping data by plotting traffic and transactions within each product

[3] The session-level comScore data do not indicate the precise time when the user initiated the search, but we do observe the exact time that any search engine referral led to a new session on the brand website.

category by the hour of the day. Brand website traffic and transactions rise throughout the day before peaking in the early evening around 7 P.M. Categories differ in the shape of the evening peak, with the sharpest rise observed in the Pizza category.

The Internet use database has two important properties for interpreting the results below. First, the data do not track individuals across computers (an issue faced by many online firms). Second, at the time the data was collected, comScore only measured Internet use on desktops and laptops; it had not yet developed tracking technology for smartphones or tablet computers.[4] Therefore, one might suspect that the effects estimated in this paper are a conservative estimate of the current importance of online response to television ads.

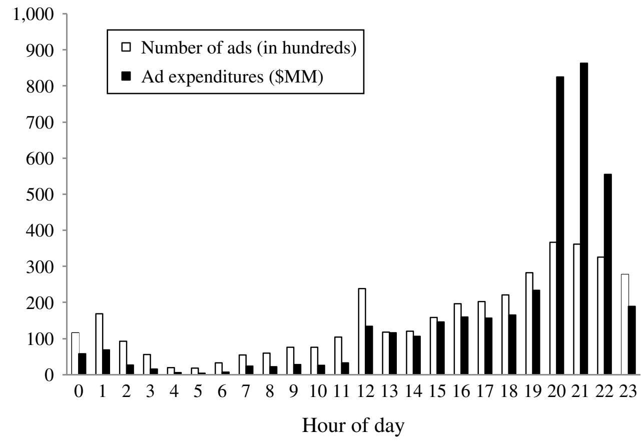
### 3.2. Television Advertising Data

Television advertising data were recorded by Kantar Media. Kantar monitors all national broadcast networks, cable networks, and syndicated programs in the United States. It identifies national commercials using codes embedded in networks' programming streams.

The unit of observation is the "insertion," defined as a single airing of a particular advertisement on a particular television channel at a particular date and time. For each insertion in 2010, the database reports the commercial's duration, the brand and product advertised (some brands advertised many products),the date and start time (in hours, minutes, and seconds (Eastern Standard Time (EST)), and an estimated insertion cost. Cost estimates were reported to Kantar by the networks after ads aired and are commonly used by large advertisers to plan upcoming media buys. The data also include media characteristics, i.e., the "property" (a national television network or program syndication company), program name, program genre, the number of the commercial break in the program, and the number of the slot in the commercial break.

The initial data set included more than 750,000 insertions of 4,153 unique advertising creatives in national networks. We dropped the bottom 5% of creatives by total expenditure, and all insertions whose estimated broadcast cost was less than $1,000, as these corresponded to channels and dayparts with small audiences. These two refinements reduced the number of insertions by about half but eliminated just 6% of total observed ad spending.[5] The final estimation sample consists of 328,212 insertions of 1,224 unique advertisements accounting for $3.4 billion of TV ad spending by 20 brands.

**Figure 2** **Ad Insertions and Spending by Hour**




As shown by the online shopping activity in Figures 1 and 2, most of these brands' advertising insertions occurred after 12 P.M. Insertions and advertising expenditures rose steadily throughout the day before peaking during the evening between 8 and 10 P.M.

### 3.3. Model-Free Evidence and Descriptive Statistics

We measure the brand-specific online shopping variables twice for each window length for each ad insertion. The baseline rates of online shopping variables are measured in a "pre" window of time just before the insertion of the advertisement. These same variables are measured again in a "post" window of time just after the ad starts.

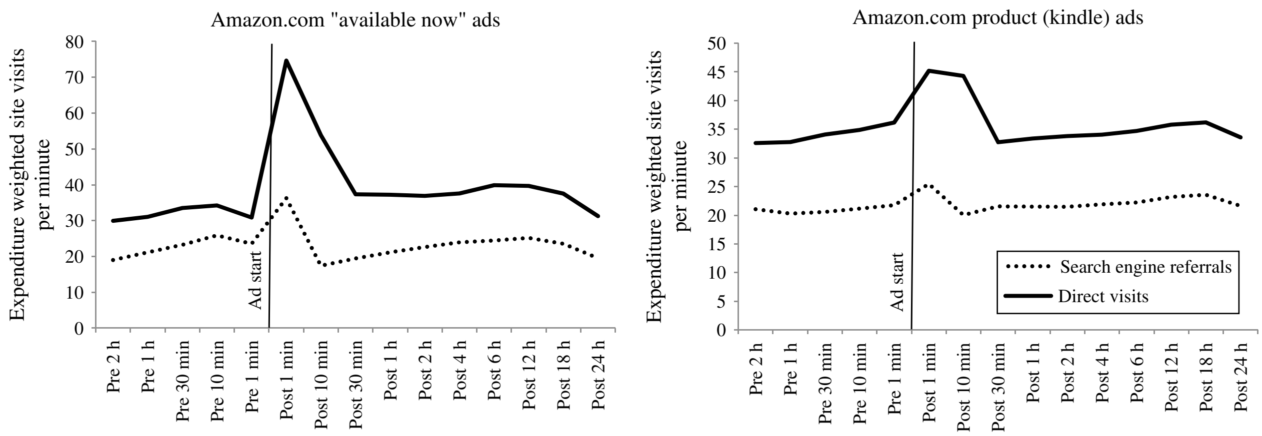
Several exploratory analyses were conducted using subsets of the data. In one, we plotted average brand website visits per dollar spent on various ad creatives. Figure 3 shows Amazon.com traffic per dollar for two distinct ads: (a) "available now" and (b) "Kindle." The data showed a large spike in the minute following the start of the ad, and a small, enduring increase thereafter. The magnitude of these lift patterns seemed to depend on the ad content, highlighting the importance of a more thorough investigation into *how* ad content influences online shopping.

In the second exploratory exercise we plotted browsing activity in shorter time windows for a wider selection of brands. Figure 4 illustrates this for Target and JCPenney. Most of the immediate increase in browsing activity was observed within two minutes after the ad was shown, with some effects persisting

[4] In 2010, smartphone penetration was 22% and the iPad was newly released; both devices were generally less suitable for online shopping than desktops and laptops (Nielsen 2010). By 2014, smartphones and tablets had become more capable and their respective penetration rates had risen to 65% and 29% (Nielsen 2014).

[5] The database did not report program name, genre, break number or slot number for 36,805 (about 10%) of the ad insertions carried by a particular group of program syndication companies. Because the results of primary interest (Tables 6 and 7) are essentially invariant to including or excluding these insertions, we decided to drop them.

**Figure 3 Search Engine Referrals and Direct Traffic by Window Length and Ad Content**




*Note.* Increases prior to the start of the ad are an artifact of the discrete time interpolation in the graph.

up to two hours after the ad. A broadly similar pattern appeared for all of the brands analyzed in this manner. This is how we chose the two particular window lengths of two minutes and two hours.[6]

Table 1 provides advertising and online shopping data for the estimation sample. The average brand used 61 commercials to advertise seven distinct products, and spent $172 million to air those commercials 16,411 times. Consumers initiated 49,402 direct sessions on the average brand website, with an additional 23,061 new sessions coming from search engine referrals; 6.3% of the computers that were observed to initiate a session completed a paid transaction or subscription within 24 hours, with rates that varied from less than 1% in Dating to 43% in Pizza.

### 3.4. Television Advertising Content Data

Wind and Sharp (2009, p. 248) said that "the most dramatic influence on short-term effect is creative copy." Therefore, we coded advertisement contents.

Prior literature helped to identify and define four dimensions of ad content by which each TV commercial in our data set could be assessed. First, we measured the extent to which each ad is *action-focused* and contains direct-response elements. These ads provide (i) a solicitation of specific action(s), (ii) supporting information to encourage a decision, and (iii) a response device or mechanism to facilitate action (Danaher and Green 1997, Bush and Bush 1990). Second, we measured the extent to which each ad is *information-focused*. These ads persuade by informing and rely on evidence about the product, price, and brand information so that viewers can evaluate the offering (Tellis 2004). Third, we measured the extent to which each ad is *emotion-focused* by its use of emotionally rich content such as creative stories, warmth, and humor to attract attention and engage viewers (Teixeira et al. 2012, 2014). Fourth, we measured the extent to which an ad is *imagery-focused*. These ads use multiple perceptual or sensory inputs (often, though not exclusively, visual) intended to evoke visual imagery processing in consumers (MacInnis and Price 1987, Peltier et al. 1992). These four characteristics are not mutually exclusive; one advertisement may use multiple elements, though time constraints discourage extensive use of all four attributes.

*Overview.* We selected 21 survey items reflecting these four attributes that had been collected in previous content analyses.[7] The coding effort addressed all 1,224 unique ad creatives.[8] The process involved three steps. First, trained research assistants collected the data. Second, a separate group of coders assessed a subsample of advertisements to gauge reliability. Third, a survey of 14 academics who conduct behavioral research was conducted to evaluate the classification of survey items to advertisement attributes. Details of each step are provided below.

*Feature Coding.* Ten research assistants were trained to code the advertisements. A budget constraint required that each commercial be assigned to only

[6] Although an ideal approach would be to gauge the sensitivity of the analysis to the length of the window chosen, this was judged to be infeasible due to computational costs. To our knowledge, this data merge had not previously been offered by any commercial research firm. Our merge routine required $3\times10^{13}$ computational queries and about 45 days to run for each shopping variable in each window length.

[7] Original survey items and intercoder reliability scores are provided in the online appendix (available as supplemental material at http://dx.doi.org/10.1287/mksc.2014.0899).

[8] Most prior academic efforts to analyze advertising content have manually coded a few dozen ad creatives. Unusually large exceptions are Buijzen and Valkenburg (2004), who identified the presence of 41 types of humor in 316 advertisements, and Anderson et al. (2013) and Liaukonyte (2014), who coded the product attributes communicated by 1,571 over-the-counter (OTC) pain medication ads.

**Figure 4** Search Engine Referrals and Direct Traffic for Both Window Lengths

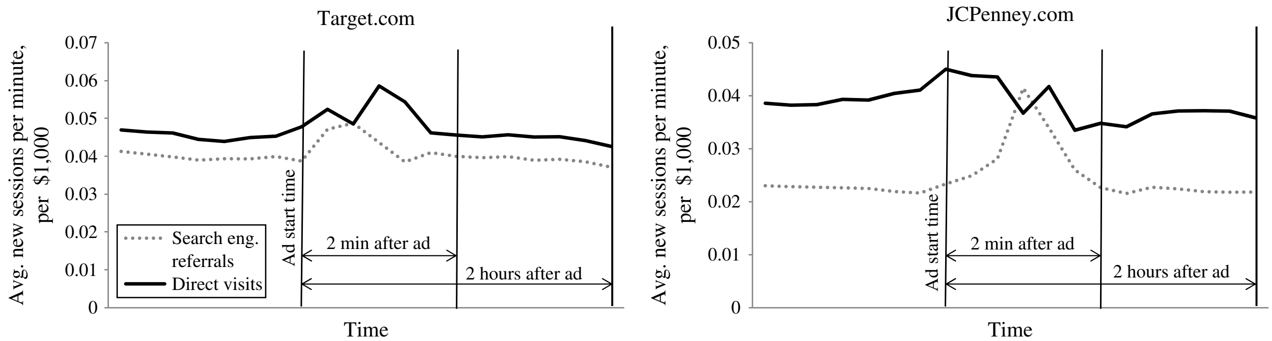



**Table 1** Descriptive Statistics

| Sector | Brand | Kantar: Advertised products | Unique ad creatives | Ad insertions | Total ad spending ($MM) | comScore: Search engine referrals | Direct visit sessions | Transactions | Conversion rate (%) |
|---|---|---|---|---|---|---|---|---|---|
| Dating | Chemistry | 1 | 4 | 2,261 | 5.53 | 2,196 | 2,220 | 15 | 0.34 |
| | eHarmony | 1 | 48 | 15,974 | 35.27 | 7,793 | 19,430 | 58 | 0.21 |
| | Match.com | 1 | 22 | 7,192 | 21.90 | 24,629 | 40,500 | 384 | 0.59 |
| Pizza | Domino's | 5 | 47 | 21,755 | 112.16 | 7,210 | 12,203 | 10,806 | 55.66 |
| | Papa John's | 14 | 25 | 6,693 | 52.63 | 3,019 | 10,817 | 6,740 | 48.71 |
| | Pizza Hut | 13 | 65 | 22,191 | 142.71 | 5,388 | 10,227 | 3,373 | 21.60 |
| Retailers | Amazon | 1 | 3 | 672 | 8.08 | 151,745 | 244,022 | 35,134 | 8.88 |
| | JCPenney | 12 | 93 | 14,401 | 113.13 | 23,208 | 32,596 | 5,137 | 9.21 |
| | Macy's | 14 | 159 | 19,632 | 182.42 | 18,607 | 29,790 | 1,953 | 4.04 |
| | Overstock | 1 | 12 | 3,724 | 11.69 | 17,108 | 20,112 | 1,396 | 3.75 |
| | Sears | 16 | 158 | 24,796 | 159.57 | 16,816 | 22,266 | 919 | 2.35 |
| | Target | 27 | 111 | 18,227 | 215.56 | 52,337 | 65,369 | 1,720 | 1.46 |
| | Victoria's Secret | 1 | 16 | 4,607 | 48.88 | 10,605 | 21,662 | 4,755 | 14.74 |
| Telecom | AT&T | 8 | 177 | 78,089 | 1,043.94 | 41,928 | 166,335 | 3,889 | 1.87 |
| | Sprint | 5 | 44 | 18,721 | 426.62 | 12,110 | 37,053 | 836 | 1.70 |
| | Verizon | 6 | 166 | 51,389 | 693.78 | 24,731 | 138,073 | 8,206 | 5.04 |
| Travel | Expedia | 1 | 18 | 4,865 | 18.15 | 15,972 | 46,832 | 1,611 | 2.57 |
| | Orbitz | 1 | 12 | 4,861 | 13.35 | 6,461 | 22,791 | 786 | 2.69 |
| | Priceline | 1 | 21 | 7,464 | 21.51 | 8,619 | 22,995 | 1,064 | 3.37 |
| | Southwest | 3 | 23 | 698 | 105.71 | 10,732 | 22,747 | 2,026 | 6.05 |
| | Total | 132 | 1,224 | 328,212 | 3,433 | 461,214 | 988,040 | 90,808 | |
| | Average | 7 | 61 | 16,411 | 172 | 23,061 | 49,402 | 4,540 | 6.27 |

one coder. Coders were instructed to watch each ad at least twice and then answer a 21-item questionnaire for that ad. During coding, they could watch, pause, and rewind the ad as many times as needed. If they remained unsure about how to code a particular ad, they were instructed to inform a research associate. Over 99% of ads were coded completely the first time. Coders worked independently, were paid hourly, and were instructed not to work more than two hours at a time to avoid respondent fatigue.

*Reliability.* A separate group of six assistants was hired to code a random sample of 150 ads for eight of the brands (12% of the original 1,224) following the same procedure. We subsequently dropped two survey items ("Is the product demonstrated in the ad?" and "Is the focus of the ad more on the product or on the brand?") due to low intercoder reliability. The match among the remaining 19 survey items was 78%. We judged this figure to be acceptable given the subjective nature of some constructs and coders' inability to resolve discrepancies through discussion.

*Classification validation and descriptive statistics.* To evaluate the four ad content characteristics, we surveyed 14 academic experts in consumer behavior. We asked whether each survey item was "applicable," "somewhat applicable," or "not applicable" to each of the four advertisement characteristics. One of the items ("Would you judge this to be an expensive or cheap ad to make?") had a high rate of disagreement with the original classification, at 50%, and was therefore dropped from the study. Every other item-specific average indicated that at least 12 of the 14 judges agreed that the expected classifications were applicable, with an average agreement of 97%. Following this

**Table 2 Survey Items by Ad Type**

Action-focused
- Is there a call to go online (e.g., shop online, visit the Web)?
- Is there online contact information provided (e.g., URL, website)?
- Is there a visual or verbal call to purchase (e.g., buy now, order now)?
- Does the ad portray a sense of urgency to act (e.g., buy before sales ends, order before ends)?
- Is there an incentive to buy (e.g., a discount, a coupon, a sale or "limited time offer")?
- Is there offline contact information provided (e.g., phone, mail, store location)?
- Is there mention of something free?

Information-focused
- Does the ad mention at least one specific product (e.g., model, type, item)?
- Is there any visual or verbal mention of the price?
- Does the ad show the brand or trademark multiple or few times?

Emotion-focused
- Is the ad intended to be emotional? (You may not agree. But was that the intention of the ad?)
- Does the ad give you a warm feeling about the brand?
- Does the ad tell a story (e.g., with characters, a plot, an ending)?
- Is the ad creative, clever?
- Is the ad intended to be funny? (You may not agree. But was that the intention of the ad?)

Imagery-focused
- Does this ad provide sensory stimulation (e.g., cool visuals, arousing music, mouth-watering)?
- Is the ad visually pleasing?
- Is the ad cute? (e.g., baby, puppy, animated characters)

procedure, 18 survey items were used to create summary indices for each advertisement for each of the four content attributes.

The survey items used in each advertisement content attribute are listed in Table 2. Table 3 reports the correlated uniqueness measures (Campbell and Fiske 1959) evaluating construct validity of the resulting classification. Most of the pairwise correlations between the content attributes (reported on the left side of Table 3) are small, indicating discriminant validity. The one exception is the correlation between action-focus and information-focus, which indicates some co-occurrence of these attributes in the same advertisements. This is to be expected, as direct response advertisements often contain product information (Bush and Bush 1990). The average factor loadings (path coefficients) for each content category are reported on the right side of Table 3 and indicate a reasonable degree of convergent validity.

Table 4 shows how brands differed in their use of advertising content.[9] For example, Papa John's used more action-focus ad content than any other brand, whereas Victoria's Secret ads rated the lowest on this attribute. Although there are differences in means across brands, the standard deviations across insertions within each brand are substantial, and

[9] We standardize the advertising content variables in the regressions to account for differing ranges.

**Table 3 Correlations in Advertising Content Attributes**

| | Correlations across content attributes | | | | Avg. corr. within content attributes |
|---|---|---|---|---|---|
| | Action-focused | Information-focused | Emotion-focused | Imagery-focused | |
| Action-focused | 1 | | | | 0.508 |
| Information-focused | 0.517 | 1 | | | 0.698 |
| Emotion-focused | −0.221 | −0.166 | 1 | | 0.577 |
| Imagery-focused | −0.087 | −0.014 | 0.241 | 1 | 0.652 |

sometimes comparable to the standard deviations across the entire sample. To summarize, every brand used every type of ad content in at least some of its advertisements.

## 4. Model and Estimation

We proceed in three steps. First, we specify a baseline model that describes statistical relationships among the three online shopping variables using brand-fixed effects and a rich set of category-time interactions as control variables. This baseline model is not intended to measure any causal effects; it is only estimated as a flexible representation of the online shopping data. Second, we introduce the treatment effect of an advertising insertion into this baseline specification. Third, we discuss endogeneity and describe two strategies to estimate causal effects of television advertising on online shopping.

### 4.1. Baseline Model Specification

We model the interrelationships among the three online shopping variables, i.e., search engine referrals ($r$), direct traffic ($d$), and transaction count ($s$), using three linear equations. The model relates the post-insertion realizations of online shopping variables to their pre-insertion values and a rich set of brand- and category-time fixed effects.

In describing the model, $i$ indexes advertisement insertions. Each insertion $i$ advertises a particular product (denoted $p_i$) sold by a specific brand (labeled $b_i$) in a product category ($c_i$). The index $t_i$ refers to the specific date and time of insertion $i$. We refer to the windows of time (two minutes or two hours) immediately preceding and following the insertion time $t_i$ as the "pre-window" and "post-window."

The baseline model is specified as

$$r_i^{\text{post}} = r_i^{\text{pre}}\alpha_{b_i}^{rr} + d_i^{\text{pre}}\alpha_{b_i}^{dr} + s_i^{\text{pre}}\alpha_{b_i}^{sr} + \gamma_{b_i}^{r} + X_{c_i t_i}\beta^{r} + \omega_{c_i t_i}^{r} + u_i^{r}, \tag{1}$$

$$d_i^{\text{post}} = r_i^{\text{pre}}\alpha_{b_i}^{rd} + d_i^{\text{pre}}\alpha_{b_i}^{dd} + s_i^{\text{pre}}\alpha_{b_i}^{sd} + \gamma_{b_i}^{d} + X_{c_i t_i}\beta^{d} + \omega_{c_i t_i}^{d} + u_i^{d}, \tag{2}$$

**Table 4 Ad Content Descriptives by Brand**

| Sector | Brand | Advertised products | Num. unique ad creatives | Action-focused min = 0, max = 7 avg. (st. dev.) | Information-focused min = 0, max = 3 avg. (st. dev.) | Emotion-focused min = 0, max = 5 avg. (st. dev.) | Imagery-focused min = 0, max = 3 avg. (st. dev.) |
|---|---|---|---|---|---|---|---|
| Dating | Chemistry | 1 | 4 | 3.8 (2.0) | 1.0 (1.0) | 1.5 (0.9) | 0.3 (0.4) |
| | eHarmony | 1 | 48 | 3.9 (1.2) | 1.2 (0.5) | 2.2 (0.9) | 1.1 (0.9) |
| | Match.com | 1 | 22 | 1.9 (0.8) | 0.5 (0.6) | 2.9 (1.0) | 1.5 (1.1) |
| Pizza | Domino's | 5 | 47 | 3.6 (1.5) | 2.9 (0.4) | 2.0 (1.2) | 1.5 (0.7) |
| | Papa John's | 14 | 25 | 5.6 (1.0) | 3.0 (0.1) | 1.0 (0.9) | 1.4 (0.5) |
| | Pizza Hut | 13 | 65 | 3.1 (1.3) | 3.0 (0.2) | 1.3 (1.4) | 1.5 (0.7) |
| Retailers | Amazon | 1 | 3 | 3.6 (1.1) | 2.7 (0.7) | 3.0 (0.0) | 2.1 (0.4) |
| | JCPenney | 12 | 93 | 3.4 (1.7) | 2.0 (0.8) | 0.8 (1.0) | 1.4 (1.0) |
| | Macy's | 14 | 159 | 3.6 (1.7) | 2.1 (1.1) | 0.9 (1.4) | 1.2 (0.9) |
| | Overstock | 1 | 12 | 2.7 (1.0) | 2.3 (0.7) | 2.3 (0.8) | 1.8 (0.8) |
| | Sears | 16 | 158 | 3.8 (1.2) | 2.0 (0.8) | 1.7 (1.4) | 1.0 (0.8) |
| | Target | 27 | 111 | 1.3 (1.0) | 1.2 (1.0) | 2.1 (1.1) | 1.7 (0.9) |
| | Victoria's Secret | 1 | 16 | 0.9 (0.8) | 1.2 (0.7) | 0.3 (0.6) | 1.6 (0.5) |
| Telecom | AT&T | 8 | 177 | 2.5 (1.6) | 1.5 (1.0) | 2.4 (1.2) | 1.6 (0.9) |
| | Sprint | 5 | 44 | 2.9 (1.2) | 2.0 (0.8) | 1.7 (0.9) | 1.3 (0.7) |
| | Verizon | 6 | 166 | 3.2 (1.9) | 1.9 (1.0) | 1.4 (1.2) | 1.3 (0.6) |
| Travel | Expedia | 1 | 18 | 3.4 (1.5) | 1.5 (0.8) | 1.6 (1.2) | 1.6 (1.0) |
| | Orbitz | 1 | 12 | 1.4 (0.6) | 1.2 (0.4) | 2.1 (1.1) | 0.8 (0.8) |
| | Priceline | 1 | 21 | 2.6 (1.5) | 1.6 (0.6) | 2.4 (1.2) | 1.0 (0.5) |
| | Southwest | 3 | 23 | 2.8 (1.2) | 0.8 (0.9) | 2.4 (0.9) | 0.9 (0.6) |
| | Average (st. dev.) across all treatments | | | 3.0 (1.7) | 1.9 (1.0) | 1.8 (1.3) | 1.4 (0.8) |

$$s_i^{\text{post}} = r_i^{\text{post}}\alpha_{b_i}^{rs} + d_i^{\text{post}}\alpha_{b_i}^{ds} + s_i^{\text{pre}}\alpha_{b_i}^{ss} + \gamma_{b_i}^{s} + X_{c_i t_i}\beta^s + \omega_{c_i t_i}^{s} + u_i^s. \tag{3}$$

Post-window traffic variables $r_i^{\text{post}}$ and $d_i^{\text{post}}$ are specified as functions of all three shopping variables in the pre-window ($r_i^{\text{pre}}$, $d_i^{\text{pre}}$, and $s_i^{\text{pre}}$) to allow for general correlations among the three online shopping variables. The post-window transactions variable $s_i^{\text{post}}$ depends on post-window traffic variables $r_i^{\text{post}}$ and $d_i^{\text{post}}$ for consistency with its definition in the previous section. The nine $\alpha$ parameters governing correlations among online shopping variables are brand-specific to flexibly represent heterogeneous relationships across brands.

Each equation in the baseline model of online shopping data incorporates two sets of fixed effects. The $\gamma$ parameters are brand intercepts, allowing for brand-specific variation in pre/post differences in each of the online shopping variables. The vector $X_{c_i t_i}$ contains a rich set of interactions between product category and time effects. Each product category is interacted with 139 time fixed effects, representing the week of the year (51 fixed effects); day of the week (6); hour of the day (23); and minute of the hour (59). The baseline model in Equations (1)–(3) contains 2,085 brand- and category-time fixed effects (139 time effects × 5 product categories × 3 shopping variables).[10]

[10] A more parsimonious representation would be to replace some of the time controls with a lower order polynomial. We used this more flexible specification because the data set size affords sufficient degrees of freedom.

Equations (1)–(3) also include two sets of residuals. The $\omega_{c_i t_i}^r$, $\omega_{c_i t_i}^d$, and $\omega_{c_i t_i}^s$ represent unobserved drivers of online shopping that vary by product category and time (after accounting for the category-time fixed effects). For example, these might represent unmodeled interactions among the category-time fixed effects, which may be known by the advertiser but not observed by the econometrician.[11]

The second set of residuals, $u_i^d$, $u_i^r$, and $u_i^s$, represent any unobserved drivers of online shopping left unaccounted for by the observed and unobserved category-time demand shifters. It is assumed that brands do not have knowledge of these terms at the time they buy advertisements.

### 4.2. Treatment Effect Specification

The $Y_i$ represents a vector of the observed characteristics of advertising insertion $i$. Its effect enters the baseline model linearly and varies across online shopping variables

$$r_i^{\text{post}} = Y_i\phi^r + r_i^{\text{pre}}\alpha_{b_i}^{rr} + d_i^{\text{pre}}\alpha_{b_i}^{dr} + s_i^{\text{pre}}\alpha_{b_i}^{sr} + \gamma_{b_i}^{r} + X_{c_i t_i}\beta^r + \omega_{c_i t_i}^{r} + u_i^r, \tag{4}$$

$$d_i^{\text{post}} = Y_i\phi^d + r_i^{\text{pre}}\alpha_{b_i}^{rd} + d_i^{\text{pre}}\alpha_{b_i}^{dd} + s_i^{\text{pre}}\alpha_{b_i}^{sd} + \gamma_{b_i}^{d} + X_{c_i t_i}\beta^d + \omega_{c_i t_i}^{d} + u_i^d, \tag{5}$$

$$s_i^{\text{post}} = Y_i\phi^s + r_i^{\text{post}}\alpha_{b_i}^{rs} + d_i^{\text{post}}\alpha_{b_i}^{ds} + s_i^{\text{pre}}\alpha_{b_i}^{ss} + \gamma_{b_i}^{s} + X_{c_i t_i}\beta^s + \omega_{c_i t_i}^{s} + u_i^s. \tag{6}$$

[11] An example of such an interaction might be Monday/6 P.M./Pizza. The fixed effects vector $X$ includes a Monday/Pizza effect and a 6 P.M./Pizza effect, but no third-order interaction.

We refer to the terms $Y_i\phi^r$, $Y_i\phi^d$, and $Y_i\phi^s$ as the treatment effects of TV advertising on search engine referrals ($r$), direct traffic ($d$), and transaction count ($s$).

The vector of advertising insertion characteristics $Y_i$ includes the four standardized advertising content variables described in §3.4, plus an additional 265 fixed effects for advertising insertion characteristics. These include $p_i$, the advertised product (136 fixed effects); the property (national network or syndication company) into whose programming stream the ad was inserted (96); the genre of the program playing in that stream when the ad was inserted (15); the number of the commercial break within the program (9); and the number of the slot within the commercial break (9).

In addition to these main effects, the insertion characteristics vector $Y_i$ contains the following control variables: the estimated expenditure on the advertisement, interacted with a brand fixed effect; the sum of all prior observed expenditures on the advertising creative to control for possible ad wear-out; the total expenditure by the brand on other insertions during insertion $i$'s pre-window, and the total expenditure by the brand during the insertion's post-window; and within-category competitors' total ad expenditures during insertion $i$ in each of the two windows. These final four variables are included to control for clustering, that is, occurrences of neighboring insertions.[12] Investigations showed that the results of primary interest (in Tables 6 and 7) are qualitatively unaffected by the inclusion or exclusion of these controls.

### 4.3. Endogeneity Concerns

To obtain unbiased estimates of the causal effects of advertising insertions, the unobserved category/time interactions ($\omega^r_{c_i t_i}$, $\omega^d_{c_i t_i}$, and $\omega^s_{c_i t_i}$) must be orthogonal to the treatment effects ($Y_i\phi^r$, $Y_i\phi^d$, and $Y_i\phi^s$). The possibility that they may be correlated arises because brands may plan advertising insertions with partial knowledge of the unobserved category/time interactions.[13]

Fortunately, when we use online shopping data measured in two-minute windows of time, typical advertising business practices ensure that *this is not a concern*. The reason is that when a brand buys a television commercial it pays for a network/quarter-hour combination, e.g., ESPN between 8:45:00–8:59:59 P.M. on January 1, 2010. The advertiser does not know the specific time within the quarter-hour that the ad will air, for three reasons. First, the actual timing of the commercial break within that quarter hour is not specified in the contract between the network and the advertiser, and typically has not been determined at the time the spot is sold. Second, unless the advertiser has taken the unusual step of purchasing a specific slot within the break, it does not know which slot its advertisement will occupy.[14] Third, about 80% of the advertising inventory is sold during the May upfront market, 3–15 months before the ads' air dates. Advertisers and networks often do not even know what programs will carry the ads, much less the specific times at which the ads will air.

For all three reasons, it strains credibility to argue that an advertiser could time a specific ad insertion to profit from changes in online shopping behavior between a two-minute pre-window and an immediately subsequent two-minute post-window. Consequently, any systematic differences in online shopping variables between the two-minute pre- and post-windows should be directly attributable to the treatment effect. Therefore, the quasi-differences in Equations (4)–(6) can be directly estimated using the online shopping variables measured in two-minute intervals, allowing for heteroskedasticity-robust standard errors.

However, when analyzing online shopping data measured in two-hour windows of time, one might suspect that advertisers might buy ad slots based on partial knowledge of unobserved category-time interactions $\omega^r_{c_i t_i}$, $\omega^d_{c_i t_i}$, and $\omega^s_{c_i t_i}$. In this case, we use a difference-in-differences approach to control for the unobserved category-time interactions. The idea is to use online shopping data for brands that (i) are in the same product category as brand $b_i$, and (ii) did not advertise during the sample period, to control for unobserved category-time interactions corresponding to each insertion in the sample. Figure 5 illustrates the research design.

We chose the control brands by selecting the largest brands within each product category that did not advertise on television.[15] That resulted in the following sets of control brands for each product category: (1) Dating: OKCupid.com, Plentyoffish.com;

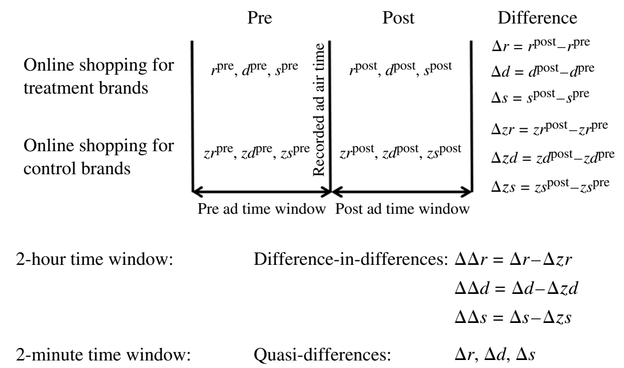
[12] To illustrate the clustering concern, suppose AT&T inserts an advertisement on CBS at 8:41:00 P.M. and another ad on ESPN at 8:42:00 P.M. In this case, the *POST* window of the CBS ad may include some traffic caused by the ESPN ad and both the *PRE* and *POST* windows of the ESPN ad may include some traffic caused by the CBS ad.

[13] For example, suppose that there exists an important Monday/6 P.M./Pizza interaction. If pizza brands were aware of this, they might tend to buy more ads on Mondays at 6 P.M. than at other weekday/hour combinations. It would then be difficult to distinguish the Monday/6 P.M./Pizza interaction from the treatment effects of pizza ads.

[14] Wilbur et al. (2013) discusses and documents the assignment of television advertisements to slots.

[15] Although we believe these brands are the best controls available to account for unobserved category/time interactions in online shopping, the page visits and purchases of the control brands could be influenced by the advertising in the sample (Lewis and Nguyen 2014, Sahni 2012). For example, an advertisement for Match.com

**Figure 5 Research Design**




*Note.* $r$, search engine referrals; $d$, direct traffic; $s$, transactions (sales).

(2) Retailers: Abercrombie, Roaman's, American Eagle, Children's Place; (3) Telecom: LetsTalk, Cricket, Wirefly; (4) Travel: AirTran, Choice Hotels, CheapTickets, JetBlue. We did not find any nonadvertising brands that offered services comparable to pizza delivery, so the difference-in-difference regressions exclude advertising insertions for pizza.

Figure 6 shows patterns in the online shopping data for the control brands in each product category. The peaks are remarkably similar to patterns depicted for the advertising brands in Figure 1. This observation is confirmed by Table 5, which shows hourly correlations between treatment and control brands ranging from 0.76 to 0.99.

To specify the difference-in-differences estimator, we denote the search engine referrals, direct traffic, and transaction count for the set of control brands in category $c_i$ as $zr_i$, $zd_i$, and $zs_i$, respectively. We specify a baseline statistical model for the control brands' online shopping variables that is analogous to the baseline model of advertising brands' data in Equations (1)–(3)

$$\begin{aligned} zr_i^{\text{post}} &= zr_i^{\text{pre}}\kappa_{c_i}^{rr} + zd_i^{\text{pre}}\kappa_{c_i}^{dr} + zs_i^{\text{pre}}\kappa_{c_i}^{sr} + \eta_{c_i}^{r} \\ &\quad + X_{c_i t_i}\kappa^{zr} + \omega_{c_i t_i}^{r} + v_i^{r}, \end{aligned} \tag{7}$$

$$\begin{aligned} zd_i^{\text{post}} &= zr_i^{\text{pre}}\kappa_{c_i}^{rd} + zd_i^{\text{pre}}\kappa_{c_i}^{dd} + zs_i^{\text{pre}}\kappa_{c_i}^{sd} + \eta_{c_i}^{d} \\ &\quad + X_{c_i t_i}\kappa^{zd} + \omega_{c_i t_i}^{d} + v_i^{d}, \end{aligned} \tag{8}$$

$$\begin{aligned} zs_i^{\text{post}} &= zr_i^{\text{post}}\kappa_{c_i}^{rs} + zd_i^{\text{post}}\kappa_{c_i}^{ds} + zs_i^{\text{pre}}\kappa_{c_i}^{ss} + \eta_{c_i}^{s} \\ &\quad + X_{c_i t_i}\kappa^{zs} + \omega_{c_i t_i}^{s} + v_i^{zs}. \end{aligned} \tag{9}$$

Here, the $\kappa$ parameters govern the correlations among online shopping variables in a manner similar to the $\alpha$ parameters in Equations (1)–(3); the same observed

might cause a consumer to think about online dating and then visit OKCupid's website (one of the control brands for Match.com). To the extent that advertising causes category expansion, the use of nonadvertising competitors as control brands may *underestimate* the effects of brands' TV ads on their own online shopping variables by raising the baseline levels of post-window traffic and transactions.

**Table 5 Correlations of Treatment and Control Brands' Online Shopping, by Sector and Hour of the Day**

| Sector | Search engine referrals | Direct traffic | Transactions |
|---|---|---|---|
| Retailers | 0.990 | 0.988 | 0.817 |
| Dating | 0.940 | 0.957 | N/A[a] |
| Telecom | 0.950 | 0.968 | 0.758 |
| Travel | 0.980 | 0.990 | 0.916 |

[a]Control brands are free websites with no purchases.

and unobserved category-time terms ($X_{c_i t_i}$, $\omega_{c_i t_i}^{r}$, $\omega_{c_i t_i}^{d}$, and $\omega_{c_i t_i}^{s}$) enter, and the error terms $v_i^r$, $v_i^d$, and $v_i^s$ are analogous to $u_i^d$, $u_i^r$, and $u_i^s$. The only important difference between the brand-specific baseline model in Equations (1)–(3) and the control-brands model in Equations (7)–(9) is that the $\kappa$ and $\eta$ parameters of the latter are necessarily category-specific, rather than brand-specific. This is because there is one set of control brands for each category in the sample, rather than one control brand for each brand in the sample.

Finally, we use the differences between Equations (4) and (7), (5) and (8), and (6) and (9) to derive our difference-in-differences estimator

$$\begin{aligned} r_i^{\text{post}} - zr_i^{\text{post}} &= Y_i\phi^r + r_i^{\text{pre}}\alpha_{b_i}^{rr} - zr_i^{\text{pre}}\kappa_{c_i}^{rr} + d_i^{\text{pre}}\alpha_{b_i}^{dr} \\ &\quad - zd_i^{\text{pre}}\kappa_{c_i}^{dr} + s_i^{\text{pre}}\alpha_{b_i}^{sr} - zs_i^{\text{pre}}\kappa_{c_i}^{sr} + \delta_{b_i}^{r} \\ &\quad + X_{c_i t_i}\mu^r + w_i^r, \end{aligned} \tag{10}$$

$$\begin{aligned} d_i^{\text{post}} - zd_i^{\text{post}} &= Y_i\phi^d + r_i^{\text{pre}}\alpha_{b_i}^{rd} - zr_i^{\text{pre}}\kappa_{c_i}^{rd} + d_i^{\text{pre}}\alpha_{b_i}^{dd} \\ &\quad - zd_i^{\text{pre}}\kappa_{c_i}^{dd} + s_i^{\text{pre}}\alpha_{b_i}^{sd} - zs_i^{\text{pre}}\kappa_{c_i}^{sd} + \delta_{b_i}^{d} \\ &\quad + X_{c_i t_i}\mu^d + w_i^d, \end{aligned} \tag{11}$$

$$\begin{aligned} s_i^{\text{post}} - zs_i^{\text{post}} &= Y_i\phi^s + r_i^{\text{post}}\alpha_{b_i}^{rs} - zr_i^{\text{post}}\kappa_{c_i}^{rs} + d_i^{\text{post}}\alpha_{b_i}^{ds} \\ &\quad - zd_i^{\text{post}}\kappa_{c_i}^{ds} + s_i^{\text{pre}}\alpha_{b_i}^{ss} - zs_i^{\text{pre}}\kappa_{c_i}^{ss} + \delta_{b_i}^{s} \\ &\quad + X_{c_i t_i}\mu^s + w_i^s, \end{aligned} \tag{12}$$

where

$$\begin{bmatrix} \delta_{b_i}^r \\ \delta_{b_i}^d \\ \delta_{b_i}^s \end{bmatrix} = \begin{bmatrix} \gamma_{b_i}^r - \eta_{c_i}^r \\ \gamma_{b_i}^d - \eta_{c_i}^d \\ \gamma_{b_i}^s - \eta_{c_i}^s \end{bmatrix}, \quad \begin{bmatrix} \mu^r \\ \mu^d \\ \mu^s \end{bmatrix} = \begin{bmatrix} \beta^r - \kappa^{zr} \\ \beta^d - \kappa^{zd} \\ \beta^s - \kappa^{zs} \end{bmatrix} \quad \text{and}$$

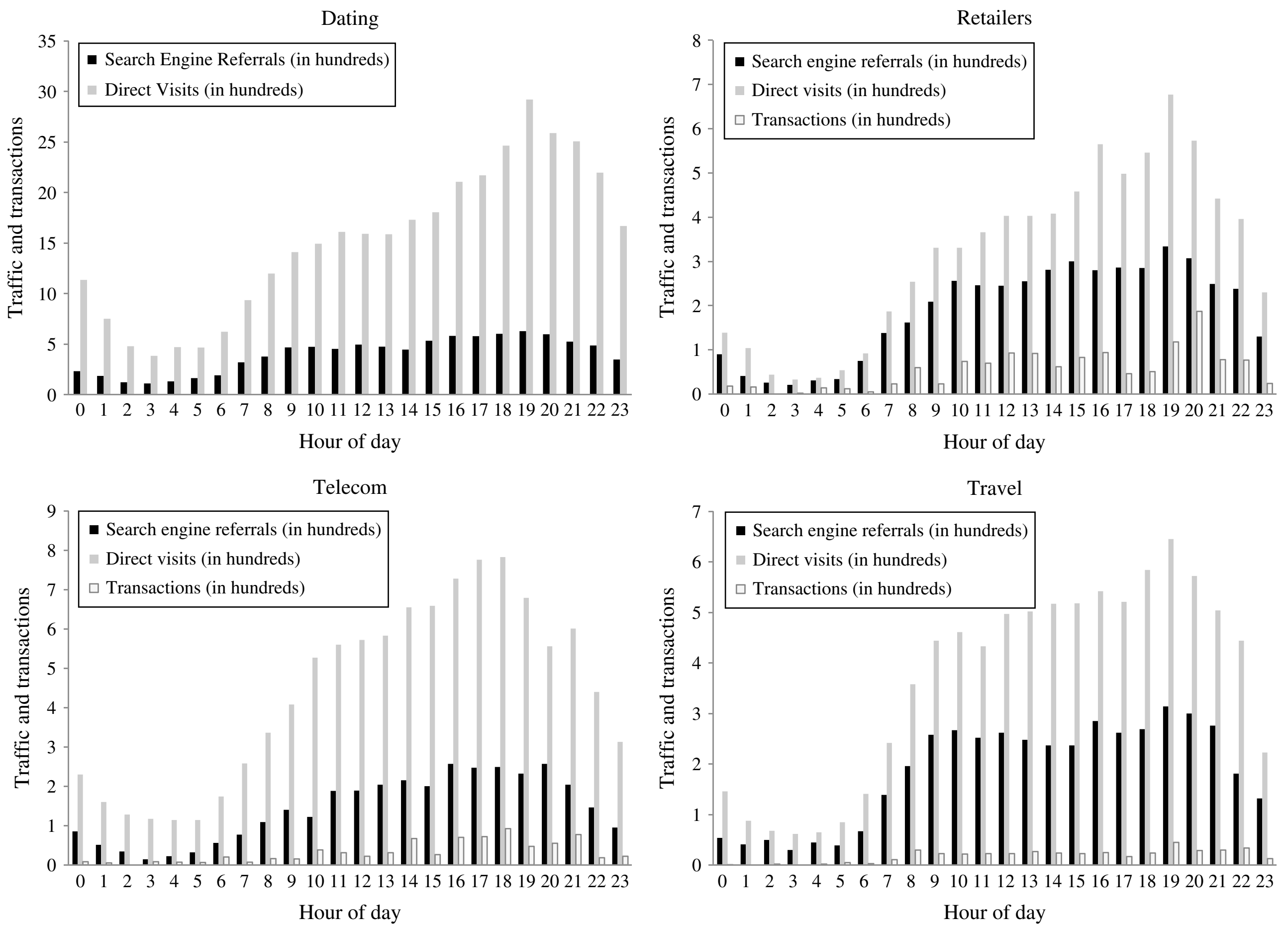
$$\begin{bmatrix} w_i^r \\ w_i^d \\ w_i^s \end{bmatrix} = \begin{bmatrix} u_i^r - v_i^r \\ u_i^d - v_i^d \\ u_i^s - v_i^s \end{bmatrix}.$$

Equations (10)–(12) are estimated directly using the online shopping variables measured in two-hour intervals, allowing for heteroskedasticity-robust standard errors. Section 5 presents the results.

## 5. Findings

The first question to consider is whether television advertising influences online shopping. We answer this by looking at model fit with and without treatment effects, and with and without baseline

**Figure 6 Search Engine Referrals, Direct Traffic, and Transactions for Control Brands by Product Category and Hour**




specifications.[16] Table 6 reports the proportion of the variation explained in the three online shopping variables using several different models.

Several conclusions emerge. First, if we include only data about the advertising insertion treatment effect (excluding all baseline variables), the model can explain 48.7% and 62.2% of the variation in search engine referrals and direct traffic, respectively, in the two-hour window data, and 3.7% and 13.8% of the variation in the two-minute window data.[17] Second, the baseline model (excluding treatment effect variables) explains more of the variation in the dependent variables than the treatment effect alone. When we add the treatment effect to the baseline variables, the model shows a statistically significant increase in its ability to explain all three dependent variables in both the two-minute and two-hour data sets, thereby answering the first question (whether TV advertising influences online shopping) in the affirmative.

Finally, by interacting the continuous advertising content variables in the treatment effect with category-fixed effects, we estimated a model with category-specific treatment effects. However, the $R$-square statistics showed no meaningful increase when we included the category-specific treatment effects. Evaluating all models, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are minimized by the model with the common treatment effect, suggesting that the richer category-specific parameterization does not justify the increase in model complexity. Therefore, we proceed by presenting and interpreting the findings from the common treatment effects model, starting with advertising content.

### 5.1. Effects of Television Advertising Content on Online Shopping

The second research question is: *How*, specifically, does television advertising influence online

[16] The model was also subjected to a random 80% hold-out validation exercise to check for overfitting. The $R$-square and root mean square error (RMSE) statistics were comparable between the full sample, a model estimated with a random 80% subsample, and the predictions from that latter model when compared to the remaining 20% validation subsample.

[17] Note that, in all cases, the model shows a greater ability to explain direct traffic than search engine referrals, perhaps because of the time required to conduct an Internet search and evaluate the results.

**Table 6 Goodness-of-Fit Measures by Online Shopping Variables and Model Specification**

| | 2 hours (diff.-in-diff.) | | | | | 2 minutes (quasi-diff.) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | *R*-square | | | | | *R*-square | | | | |
| | Search engine referrals | Direct visits | Transactions | AIC | BIC | Search engine referrals | Direct visits | Transactions | AIC | BIC |
| Treatment effect only | 0.487 | 0.622 | 0.087 | | | 0.037 | 0.138 | 0.002 | | |
| Baseline only | 0.693 | 0.868 | 0.206 | 862,555 | 887,457 | 0.044 | 0.172 | 0.154 | 2,030,240 | 2,050,468 |
| Baseline + Treatment effect | 0.698 | 0.873 | 0.212 | 858,202 | 891,283 | 0.055 | 0.191 | 0.158 | 2,024,186 | 2,051,297 |
| Baseline + Category-specific treatment effect | 0.698 | 0.873 | 0.212 | 858,215 | 891,809 | 0.055 | 0.191 | 0.158 | 2,024,205 | 2,051,695 |
| Number of observations | | | 277,573 | | | | | 328,212 | | |

shopping? Table 7 presents the effects of TV advertising content on direct traffic, search engine referrals, and transactions. There are 12 such effects, four standardized advertising content variables times three online shopping variables, within each of the two window length models. In the two-hour regression, nine of the 12 parameters are statistically significant at the 95% confidence level, while six of the 12 are significant in the two-minute regression. Four effects correspond in sign and significance level between the two regressions, and there are no cases of contradictory findings between the two-minute and two-hour window regressions. Because the slightly longer time window appears to be the more important measure of consumer shopping activity, we next discuss the two-hour results as summarized in Figure 7.

There are three ways in which each advertising content attribute can affect online sales. First, the attribute could spark interest and increase direct traffic to the website ($d$), thereby indirectly increasing transactions by increasing visitors. Second, the content element could increase search engine referrals ($r$), again increasing transactions indirectly by increasing visitors. Third, TV ad content could increase conversion rates, resulting in more transactions ($s$) conditional on website visitation by either route. Any of these effects may be positive, negative or indistinguishable from zero. Figure 7 summarizes the two-hour results, showing each of these three effects for each advertising content attribute, and reports the findings about brand-specific total effects of advertising content on transactions.[18] We discuss each content attribute in turn.

*Action-focused.* Ads that make heavy use of direct-response tactics are found to have three effects. First, they reduce the number of new sessions at the brand website initiated by search engine referrals. Second, they increase the number of visitors coming through direct means. The positive effect on direct visitation is about six times larger than the decrease in search engine referrals, suggesting that action-focus ad content brings new visitors to the site and simultaneously encourages direct means of visitation rather than requiring a search before visitation. This result is similar to Joo et al. (2014) and is likely a positive consequence for the brand as it suggests that action-focus ad content make the brand website more salient to consumers, helping them to bypass search engines and thereby reducing the toll the brand pays for search engine referral traffic. Third, action-focus content increases the number of sessions with paid transactions conditional on visitation. These effects combine to create a positive, significant total effect of action-focus advertising on purchases for all 17 brands.

*Information-focused and Emotion-focused.* Information- and emotion-focus content in ads are associated with two seemingly contradictory effects: They simultaneously reduce traffic to the website while increasing the number of purchases among those who do visit. The most likely explanation for these phenomena is that this type of advertising content is effective at resolving consumer uncertainty about whether the advertised product fits their needs. In such a case, low-fit consumers would forego visiting the brand website, while high-fit consumers would be more likely to visit and buy, similar to the effects predicted by Anderson and Renault (2006) and found by Wu et al. (2005) and Haans et al. (2013). The positive effect on purchases outweighs the negative effect on traffic for most brands, leading to statistically significant positive total effects of information-focus and emotion-focus content on sales for most brands.

*Imagery-focused.* Imagery content is associated with reduced direct visitation to the website in the two-hour data set. The reason for this may be the

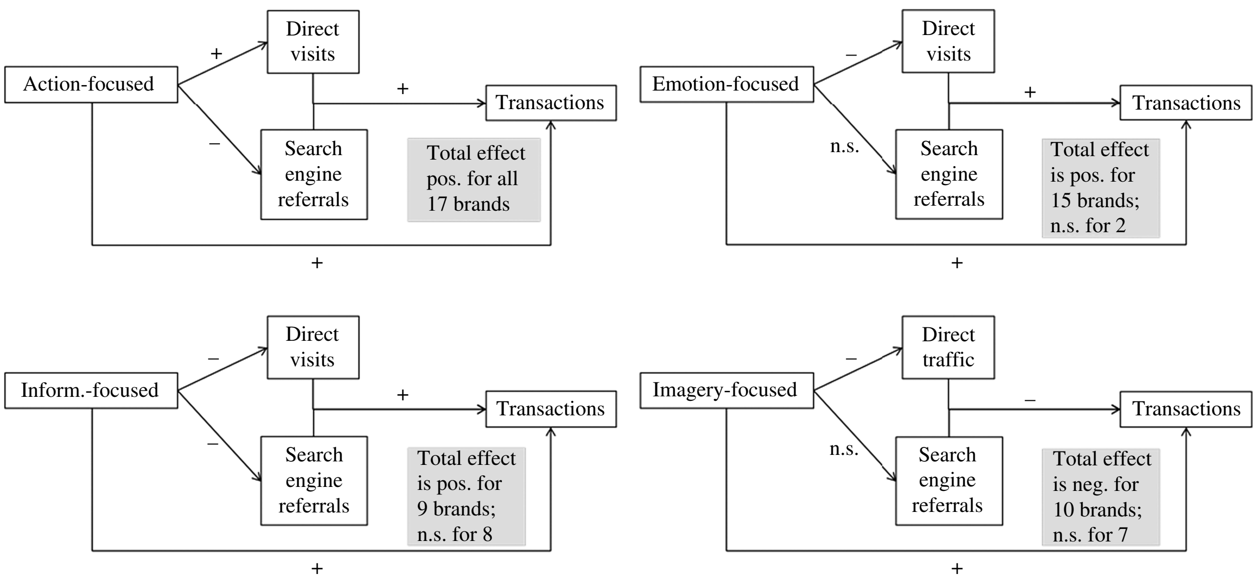
[18] The total effect of content attribute $x$ on brand $b$ transactions is $TotalEffect_b^x = \phi_x^r \alpha_{b_i}^{rs} + \phi_x^d \alpha_{b_i}^{ds} + \phi_x^s$, where $\phi_x^r$, $\phi_x^d$, and $\phi_x^s$ are the effects of content attribute $x$ on $r$, $d$, and $s$, respectively. Standard errors are calculated by bootstrapping from the asymptotic distribution of the parameter estimates.

**Table 7 Effects of Ad Content Attributes on Online Shopping Variables**

| | 2 hours (diff.-in-diff.) | | | 2 minutes (quasi-diff.) | | |
|---|---|---|---|---|---|---|
| | Search engine referrals | Direct visits | Transactions | Search engine referrals | Direct visits | Transactions |
| Action-focused | −0.0304*** | 0.1850*** | 0.0281*** | −0.0029** | 0.0078*** | 0.0010 |
| | (0.0117) | (0.0269) | (0.0094) | (0.0012) | (0.0022) | (0.0009) |
| Information-focused | −0.0264** | −0.2960*** | 0.0357*** | −0.0002 | −0.0117*** | 0.0000 |
| | (0.0120) | (0.0257) | (0.0088) | (0.0013) | (0.0023) | (0.0009) |
| Emotion-focused | 0.0047 | −0.1250*** | 0.0344*** | 0.0005 | −0.0022 | 0.0001 |
| | (0.0100) | (0.0217) | (0.0077) | (0.0010) | (0.0017) | (0.0007) |
| Imagery-focused | −0.0108 | −0.144*** | −0.0037 | −0.0023** | −0.0109*** | 0.0017*** |
| | (0.0092) | (0.0188) | (0.0061) | (0.0009) | (0.0016) | (0.0006) |

*Notes.* Robust standard errors in parentheses. Standardized content measures.
** $p < 0.05$; *** $p < 0.01$.

**Figure 7 Sign of Effects of Ad Content Attributes on Online Shopping Variables (2-Hour Window)**




effect of imagery on multitasking. Intense images are often used in television advertisements to arrest the viewer's attention and to discourage them from disengaging with the commercial. Although imagery-focus ad content had no significant impact on transactions conditional on visitation, its negative impact on direct traffic produced negative, significant total effects on sales for 10 of the 17 brands in the sample.

### 5.2. Additional Treatment Effect Estimates

Table 8 presents additional covariates in the treatment effects of an advertising insertion. Advertising effects vary by program genre. Relative to the excluded genre (Animation), the largest increase in purchases was observed for insertions during live sports. However, our ability to interpret this result is limited. More research is needed to determine whether the effects on purchases come from the program genre itself, which may affect viewer engagement with the advertisement, or whether they are specific to the viewers attracted by those programs.

The break number and slot number results are more clearly interpretable. The results indicate that ad breaks that occur later in the program generate fewer new website sessions than the first break in the program, with little or no apparent impact on purchases. In the two-hour regression, there is no apparent effect of the ad slot within the break on traffic or transactions. However, in the two-minute regression parameter estimates (which are omitted for brevity), there is a strong negative effect of position within the break on direct traffic.

The data show interesting findings for advertisements that have been repeatedly aired. More past spending on an advertisement is associated with a reduced ability to generate new direct traffic, but a higher number of sales among those who do visit.

**Table 8 Additional Treatment Effects**

| | 2 hours (diff.-in-diff.) | | | | 2 hours (diff.-in-diff.) | | | | 2 hours (diff.-in-diff.) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Program type | Search engine referrals | Direct visits | Transactions | Break number (in program) | Search engine referrals | Direct visits | Transactions | Slot number (in program) | Search engine referrals | Direct visits | Transactions |
| Documentary | −0.231** | −0.00274 | 0.177** | 2 | 0.0391 | 0.0253 | −0.0139 | 2 | −0.00957 | −0.0352 | 0.0316 |
| | (0.114) | (0.231) | (0.0751) | | (0.0270) | (0.0558) | (0.0188) | | (0.0289) | (0.0598) | (0.0205) |
| Drama/adventure | −0.206 | 0.0885 | 0.139 | 3 | −0.0210 | −0.127** | −0.0112 | 3 | −0.0314 | −0.0537 | 0.0147 |
| | (0.110) | (0.219) | (0.0716) | | (0.0287) | (0.0587) | (0.0199) | | (0.0288) | (0.0603) | (0.0205) |
| Entertainment | −0.0225 | −0.146 | 0.202*** | 4 | −0.0717** | −0.109 | −0.0135 | 4 | 0.000691 | −0.0832 | 0.000321 |
| | (0.111) | (0.224) | (0.0727) | | (0.0307) | (0.0636) | (0.0215) | | (0.0294) | (0.0616) | (0.0208) |
| Feature film | −0.151 | −0.163 | 0.143** | 5 | −0.0510 | −0.0923 | −0.0503** | 5 | −0.0477 | −0.123 | 0.0282 |
| | (0.108) | (0.216) | (0.0698) | | (0.0347) | (0.0717) | (0.0240) | | (0.0311) | (0.0642) | (0.0220) |
| Instruction/advice | −0.159 | 0.112 | 0.153 | 6 | −0.117*** | −0.120 | −0.0146 | 6 | 0.00915 | −0.0850 | −0.0145 |
| | (0.125) | (0.250) | (0.0792) | | (0.0423) | (0.0894) | (0.0305) | | (0.0335) | (0.0686) | (0.0233) |
| News | −0.128 | 0.0753 | 0.148** | 7 | −0.0389 | 0.0732 | 0.0364 | 7 | −0.0157 | −0.0886 | −0.0284 |
| | (0.113) | (0.228) | (0.0735) | | (0.0499) | (0.106) | (0.0355) | | (0.0367) | (0.0751) | (0.0250) |
| Olympics | 0.192 | 2.356*** | −0.435*** | 8 | −0.138** | −0.217 | 0.0294 | 8 | 0.000799 | −0.0341 | 0.0749** |
| | (0.247) | (0.537) | (0.148) | | (0.0572) | (0.123) | (0.0421) | | (0.0431) | (0.0859) | (0.0291) |
| Other | −0.336*** | −0.190 | 0.188** | 9 | −0.151** | −0.248 | −0.0529 | 9 | 0.0599 | 0.0581 | 0.0418 |
| | (0.127) | (0.258) | (0.0865) | | (0.0645) | (0.141) | (0.0456) | | (0.0521) | (0.102) | (0.0359) |
| Sitcom | −0.137 | 0.0797 | 0.134** | 10 or more | −0.0636 | −0.333*** | −0.00836 | 10 or more | 0.0952** | 0.0181 | 0.058 |
| | (0.102) | (0.208) | (0.0674) | | (0.0445) | (0.0996) | (0.0330) | | (0.0481) | (0.0920) | −0.0323 |
| Slice of life | −0.208 | −0.209 | 0.100 | | | | | | | | |
| | (0.108) | (0.217) | (0.0705) | | | | | | | | |
| Sports | −0.343*** | −0.215 | 0.231*** | Past spend on | −5.68e−10 | −3.63e−08*** | 5.58e−09*** | | | | |
| | (0.120) | (0.249) | (0.0833) | Creative | (1.56e−09) | (3.70e−09) | (1.21e−09) | | | | |
| Suspense/mystery | −0.00685 | 0.357 | 0.132 | | | | | | | | |
| | (0.114) | (0.228) | (0.0743) | | | | | | | | |
| Talk | −0.270** | −0.828*** | 0.162** | Own “Pre” | −9.92e−07*** | −3.19e−06*** | 1.03e−07*** | Comp. “Pre” | 1.13e−07*** | −2.74e−07*** | 1.07e−07*** |
| | (0.115) | (0.229) | (0.0749) | Window spend | (4.16e−08) | (7.89e−08) | (2.59e−08) | Window spend | (1.98e−08) | (4.29e−08) | (1.53e−08) |
| Unknown | −0.287** | −0.0637 | 0.164 | Own “Post” | 3.46e−07*** | −3.70e−07*** | −1.09e−07*** | Comp. “Post” | 9.17e−08*** | 3.71e−07*** | 2.12e−08 |
| | (0.144) | (0.291) | (0.0921) | Window spend | (4.55e−08) | (8.78e−08) | (3.26e−08) | Window spend | (2.21e−08) | (4.77e−08) | (1.92e−08) |
| Variety music | −0.141 | −0.0850 | 0.115 | | | | | | | | |
| | (0.126) | (0.257) | (0.0840) | | | | | | | | |

*Note.* Robust standard errors in parentheses.
$^{**}p < 0.05$; $^{***}p < 0.01$.

This aligns with the dual purpose of TV ads for multitaskers, i.e., generate curiosity among those who have not seen the advertisement before, and remind familiar consumers to purchase when they are in the market for the advertised product.

Table 9 shows how television properties varied in their effects on Internet shopping. For example, ads carried on CNBC are associated with reductions in all three shopping variables, while those appearing on Adult Swim or E! show a large increase in new brand website traffic. Similar to the program genre results, it remains to be determined whether these effects are caused by the networks per se or by the type of viewers each network attracts.

Multiproduct brands often have multiple distinct creatives for each product offered. In those cases, the product advertised sometimes has a substantial effect on traffic and sales. The products found to have statistically significant effects are shown in Table 10. They come primarily from the retail and telecommunications categories, in which brands often market broad lines of related products. It is perhaps not surprising that these products vary in their effects on online shopping, as their value propositions and target demographics differ substantially.

### 5.3. Baseline Model Parameter Estimates

The brand-fixed effects, brand-specific correlations among online shopping variables, and category-time interactions are presented in the online appendix.

## 6. Discussion

The debate in the advertising industry has focused mainly on the negative effects of media multitasking, i.e., distracting consumer attention from advertising. In this research, we hope to emphasize a potentially positive aspect, i.e., that the "second screen" may enable an immediate and measurable response to some television advertisements. The question then becomes, how can brands alter traditional television advertising efforts to influence online shopping?

This paper investigates whether and how television advertising affects traffic and transactions at the advertiser's website. This research contributes to the literature on cross-media advertising effects by showing how brands can benefit from increased media multitasking, particularly the consumer habit of simultaneously watching television and browsing the Internet. The results showed that television advertising influences online shopping and that advertising content plays a key role. Advertisements that use action-focus content increase both website traffic and sales, conditional on visitation, in line with the direct-response advertising literature (Tellis et al. 2000). Information- and emotion-focus elements reduce website visits but increase sales, with positive total effects for most brands. This aligns with prior work showing that advertisements that sell effectively result in fewer website visitors, but that those who do visit are more inclined to make a purchase. Finally, we find that imagery-focus content reduces direct visitation without any meaningful impact on sales.

### 6.1. Implications for Advertising Management

Managers make three major decisions in planning their advertising campaigns: how much to spend, where to spend it (i.e., what media to use), and what to say (i.e., what ad content to use). This research deals with the last two questions. First, it establishes that marketers can use television advertising to influence consumers' actions online. Second, we have shown how four types of advertising content influence online shopping.

Perhaps the most striking finding is that advertising content can have opposite effects on traffic and transactions, increasing one at the expense of the other. Internet sales data are typically sparse and highly variable. An advertising manager who wants to optimize the online effects of her TV advertising budget might naturally consider using website traffic as a success metric. However, our results suggest that such a metric might lead to the wrong conclusions if she is using information- or emotion-focus ad content, as these types of ad content reduce traffic while simultaneously increasing total sales for most brands.

One clear recommendation is that advertisers seeking to stimulate immediate online response might want to avoid heavy use of imagery content in their advertisements. While such content may work for consumers of a single medium (MacInnis and Price 1987), these ads reduce website visitation.

These recommendations should be applied with caution as they may only apply to the two-hour windows within which we monitored online responses. Also, the total effects on sales were found to vary across brands for each type of ad content. Finally, our data only measure online sales, thus our estimates do not distinguish incremental sales from those that may cannibalize traditional channels such as offline retail or telephone.

### 6.2. Caveats and Future Research

As with all research, our analysis is subject to numerous caveats. The most important limitation is that we do not directly observe which ads were viewed or attended to by which households. We designed the research to prevent this unobserved factor from biasing our findings; however, because we did not control what TV or online content consumers were exposed to, we limited our investigations to brief windows of time. Ideally, future research will study multibrand, multimedia, single-source panel data on advertising

**Table 9 Effects of Television Network**

| | 2 hours (diff.-in-diff.) | | | | 2 hours (diff.-in-diff.) | | | | 2 hours (diff.-in-diff.) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| TV network | Search engine referrals | Direct visits | Transactions | TV network | Search engine referrals | Direct visits | Transactions | TV network | Search engine referrals | Direct visits | Transactions |
| ADSM | 0.273$^{***}$ | 0.517$^{***}$ | 0.115 | ESPN | 0.296$^{***}$ | 0.202 | −0.0908 | SPK | −0.0683 | −0.332$^{***}$ | 0.0859$^{**}$ |
| | (0.0832) | (0.194) | (0.0645) | | (0.0818) | (0.184) | (0.0632) | | (0.0588) | (0.129) | (0.0423) |
| AMC | 0.309$^{***}$ | −0.0528 | 0.00471 | FNEW | −0.0836 | −0.413$^{**}$ | 0.0328 | STYL | 0.545 | 3.095$^{***}$ | −0.0312 |
| | (0.0926) | (0.164) | (0.0471) | | (0.0901) | (0.195) | (0.0677) | | (0.761) | (1.146) | (0.222) |
| BBCA | −0.379$^{**}$ | −0.0621 | 0.0546 | FX | 0.0909 | 0.487$^{***}$ | 0.130$^{***}$ | TLC | 0.0435 | 0.343$^{**}$ | 0.0113 |
| | (0.184) | (0.327) | (0.0748) | | (0.0643) | (0.138) | (0.0455) | | (0.0742) | (0.144) | (0.0467) |
| BET | −0.0709 | −0.316$^{**}$ | 0.0692 | GALA | 0.0565 | −0.456$^{**}$ | 0.0892 | TNNK | 1.386$^{***}$ | 0.416 | −0.300$^{***}$ |
| | (0.0685) | (0.144) | (0.0506) | | (0.0846) | (0.193) | (0.0606) | | (0.263) | (0.401) | (0.112) |
| BRAV | 0.0677 | 0.303$^{**}$ | 0.0613 | GSN | 2.040$^{***}$ | −1.050 | −0.346 | TOON | 0.560$^{**}$ | 0.86 | 0.160 |
| | (0.0698) | (0.137) | (0.0452) | | (0.483) | (1.374) | (0.427) | | (0.268) | (0.490) | (0.159) |
| CNBC | −0.457$^{***}$ | −2.522$^{***}$ | −0.237$^{***}$ | HIST | −0.0158 | −0.332$^{**}$ | 0.0744$^{*}$ | TRAV | −0.0465 | −0.339$^{**}$ | −0.0792 |
| | (0.123) | (0.319) | (0.0897) | | (0.0608) | (0.131) | (0.0432) | | (0.0795) | (0.165) | (0.0531) |
| CNN | −0.109 | −0.789$^{***}$ | 0.0726 | MNTV | 0.106 | 1.195$^{**}$ | −0.225 | TRU | 0.290$^{***}$ | 0.107 | 0.107 |
| | (0.0891) | (0.177) | (0.0532) | | (0.237) | (0.573) | (0.207) | | (0.0757) | (0.164) | (0.0574) |
| CW | −0.100 | −0.738$^{***}$ | 0.0316 | MTV | 0.0887 | 0.372$^{***}$ | 0.0657 | TWC | −0.127 | 0.640$^{***}$ | −0.159$^{**}$ |
| | (0.104) | (0.201) | (0.0731) | | (0.0573) | (0.120) | (0.0404) | | (0.0913) | (0.200) | (0.0659) |
| DSCH | 3.649$^{***}$ | 9.450$^{***}$ | −0.981$^{***}$ | NAN | −0.115 | −0.363$^{**}$ | 0.0610 | USA | 0.0254 | −0.0265 | 0.102$^{**}$ |
| | (0.198) | (0.289) | (0.101) | | (0.0756) | (0.148) | (0.0483) | | (0.0660) | (0.130) | (0.0437) |
| DXD | −5.218$^{***}$ | 8.778$^{***}$ | 1.490 | NBC | 0.0911 | 0.323$^{**}$ | 0.0203 | VH1 | 0.0731 | 0.252$^{**}$ | 0.108$^{***}$ |
| | (1.297) | (0.348) | (2.412) | | (0.0747) | (0.152) | (0.0512) | | (0.0540) | (0.112) | (0.0378) |
| E! | 0.197$^{***}$ | 0.375$^{***}$ | −0.0394 | NFLN | 0.517$^{***}$ | 1.759$^{***}$ | −0.583$^{***}$ | WE | −0.0500 | 1.300$^{**}$ | 0.185 |
| | (0.0631) | (0.126) | (0.0397) | | (0.151) | (0.372) | (0.124) | | (0.429) | (0.656) | (0.253) |
| ESP2 | 0.188$^{**}$ | −0.0910 | 0.0307 | NGC | 0.0196 | −0.466$^{***}$ | −0.0771 | | | | |
| | (0.0923) | (0.210) | (0.0761) | | (0.0851) | (0.176) | (0.0614) | | | | |

*Notes.* Robust standard errors in parentheses. Only significant effects of networks are displayed.
$^{**}p < 0.05$; $^{***}p < 0.01$.

exposure and online traffic and sales, and look for longer term effects. We hope our findings help to stimulate attempts to create and share such databases.

Our explanations for the advertising content findings are consistent with some prior research, but they are speculative, as we have treated the effects of advertising content on Internet shopping as an empirical question. This analysis might illustrate the potential of more direct tests (such as laboratory or field experiments) of these effects. One possible design would be to experimentally manipulate the assignment of commercials to slots within a television advertising schedule to measure how content differentially affects multitaskers' online shopping behavior.

Another limitation of our approach is that we do not observe brands' website content or online advertising efforts. While these variables are held constant by our research design, one would naturally expect them to influence the propensity of a consumer to purchase after browsing a brand website. A next logical step would be to quantify the effect of website content on sales, and investigate how it might interact with television advertising content. It would also be interesting to measure how online ads differentially affect households that have been exposed to television advertisements, and vice versa.

Note that some of the empirical findings may be specific to the measures of advertising and shopping. For example, we have not tested the sensitivity of the results to the 24-hour purchase window. Also, although the four summary indices of advertising content used in our paper included many common features in television advertisements, they are not tightly linked to established theories of advertising content. A fruitful area for future research would be to analyze additional commercial characteristics and refine the measures of ad content and online shopping.

In conclusion, brand managers have to address two effects of media multitasking. On one hand, it may divert consumer attention away from advertising. On the other hand, handheld devices may enable a more immediate and measurable response to traditional advertising. This paper takes a first step in showing how marketers can design their traditional television advertising to influence online shopping, by managing the related goals of maximizing website traffic and transactions. In the long run, we expect that marketers will develop a sophisticated understanding of

**Table 10 Advertised Product Effects**

| | 2 hours (diff.-in-diff.) | | | | 2 hours (diff.-in-diff.) | | |
|---|---|---|---|---|---|---|---|
| Product | Search engine referrals | Direct visits | Transactions | Product | Search engine referrals | Direct visits | Transactions |
| AT&T: Consumer wireless service | 1.630$^{***}$ | −0.0535 | −0.183$^{***}$ | Sears: Family apparel | 1.376$^{***}$ | 0.742$^{***}$ | −0.426$^{***}$ |
| | (0.160) | (0.0809) | (0.0515) | | (0.334) | (0.246) | (0.109) |
| AT&T: Pre-paid wireless service | 5.793$^{***}$ | 0.327 | −0.871$^{**}$ | Sears: Gardening tools and supplies | −0.614$^{**}$ | 0.181 | −0.00401 |
| | (1.779) | (0.644) | (0.367) | | (0.275) | (0.173) | (0.0895) |
| AT&T go phone: Pre-paid wireless service | 0.0199 | −1.761$^{***}$ | 0.201 | Sears: General | −0.614 | −0.713$^{**}$ | 0.239$^{*}$ |
| | (1.316) | (0.438) | (0.518) | | (0.441) | (0.296) | (0.141) |
| AT&T Inc: Corporate promotion | 2.084$^{***}$ | −0.900$^{***}$ | −0.0614 | Sears: General NEC | −0.354 | −0.373$^{*}$ | 0.255$^{***}$ |
| | (0.239) | (0.111) | (0.0774) | | (0.298) | (0.193) | (0.0976) |
| AT&T mobile TV: Consumer wireless service | 5.273$^{***}$ | 0.218 | −0.753$^{***}$ | Sears: Jewelry and watches | 2.752$^{***}$ | −0.371 | −0.443 |
| | (0.370) | (0.158) | (0.109) | | (0.543) | (0.510) | (0.246) |
| AT&T unlimited calling plan: Consumer wireless | 4.756$^{***}$ | 0.34 | −0.789$^{***}$ | Sears: Mens apparel | −0.991$^{***}$ | 0.756$^{***}$ | −0.109 |
| | (0.441) | (0.177) | (0.119) | | (0.329) | (0.247) | (0.257) |
| JCPenney: General | −1.651$^{**}$ | −0.260 | 0.171 | Sears: Multi-products | 1.409$^{***}$ | 0.529$^{**}$ | −0.171 |
| | (0.711) | (0.443) | (0.258) | | (0.402) | (0.250) | (0.116) |
| JCPenney: Household | −2.849$^{***}$ | 0.655 | 0.657$^{**}$ | Sears: Optical | 0.655$^{***}$ | 0.0734 | −0.00236 |
| | (0.693) | (0.429) | (0.259) | | (0.248) | (0.155) | (0.0817) |
| JCPenney: Jewelry and watches | −5.369$^{***}$ | 1.255$^{**}$ | 1.113$^{***}$ | Sears: Sales announcement | 0.916$^{***}$ | 0.395$^{**}$ | −0.0581 |
| | (0.727) | (0.493) | (0.303) | | (0.245) | (0.155) | (0.0806) |
| JCPenney: Mens apparel | −2.030$^{***}$ | 0.457 | 0.288 | Sears: Tools and hardware and building materials | 0.974$^{***}$ | −1.145$^{***}$ | −0.437$^{***}$ |
| | (0.676) | (0.405) | (0.242) | | (0.364) | (0.235) | (0.117) |
| JCPenney: Womens apparel | −2.585$^{***}$ | 0.502 | 0.954$^{***}$ | Southwest airlines: Domestic | −1.419$^{***}$ | −0.394 | 0.211 |
| | (0.678) | (0.410) | (0.247) | | (0.518) | (0.299) | (0.114) |
| Macy’s: Childrens apparel | 0.986$^{***}$ | 0.425 | −0.164 | Sprint any mobile anytime plan: Consumer | −1.446$^{***}$ | −0.613$^{***}$ | −0.563$^{***}$ |
| | (0.287) | (0.258) | (0.110) | | (0.283) | (0.100) | (0.0486) |
| Macy’s: Fragrances and cosmetics | 1.082$^{**}$ | 0.381 | −0.240$^{**}$ | Sprint corp: Corporate promotion | −1.095$^{***}$ | 0.00244 | −0.196$^{***}$ |
| | (0.431) | (0.357) | (0.117) | | (0.301) | (0.107) | (0.0572) |
| Macy’s: General | 0.663$^{***}$ | 0.00998 | 0.0706 | Sprint everything data family plan: Consumer | 2.441$^{**}$ | −0.0507 | −0.373$^{**}$ |
| | (0.256) | (0.221) | (0.0981) | | (0.991) | (0.397) | (0.159) |
| Macy’s: General apparel | 1.204$^{***}$ | 0.155 | −0.151 | Sprint everything data plan: Consumer wireless | 0.0156 | −0.0130 | 0.0635$^{**}$ |
| | (0.317) | (0.276) | (0.124) | | (0.151) | (0.0530) | (0.0305) |
| Macy’s: General NEC | 0.787$^{***}$ | 0.149 | −0.0181 | Target: Books and stationery | 0.958 | −1.897$^{**}$ | 0.426 |
| | (0.283) | (0.236) | (0.108) | | (1.036) | (0.857) | (0.419) |
| Macy’s: Mattresses | 1.458$^{***}$ | 0.518$^{**}$ | −0.242$^{**}$ | Target: Sales announcement | 2.654$^{***}$ | 2.053$^{***}$ | 0.00657 |
| | (0.264) | (0.224) | (0.103) | | (0.839) | (0.651) | (0.328) |
| Macy’s: Mens apparel | 0.318 | −0.224 | −0.363$^{**}$ | Target: Tools and hardware and building materials | 3.981$^{**}$ | 0.391 | −0.0188 |
| | (0.849) | (0.590) | (0.184) | | (1.946) | (2.324) | (0.470) |
| Macy’s: Mens apparel and mens shoes | 0.659 | 0.198 | −0.388$^{***}$ | Target: Toy and hobby products | 1.095 | 1.442$^{**}$ | −0.193 |
| | (0.421) | (0.350) | (0.121) | | (0.867) | (0.656) | (0.337) |
| Macy’s: Mens apparel and womens apparel | 3.026$^{***}$ | −0.362 | −0.308 | Target: Video games and systems | −1.538 | 3.490$^{***}$ | 0.291 |
| | (0.486) | (0.337) | (0.168) | | (1.028) | (1.023) | (0.381) |
| Macy’s: Sales announcement | 0.860$^{***}$ | 0.00835 | −0.00696 | Verizon: Business wireless service | 6.386$^{***}$ | 0.771$^{***}$ | −0.965$^{***}$ |
| | (0.233) | (0.205) | (0.0903) | | (0.380) | (0.159) | (0.184) |
| Macy’s: Womens shoes | 1.063$^{**}$ | 0.873$^{***}$ | 0.179 | Verizon: Consumer wireless service | 7.523$^{***}$ | 0.568$^{***}$ | −1.209$^{***}$ |
| | (0.413) | (0.327) | (0.167) | | (0.342) | (0.142) | (0.164) |
| Macy’s department store: Corporate promotion | 1.083$^{***}$ | −0.0939 | 0.0421 | Verizon: ISP/TV/Wireless | 5.384$^{**}$ | 1.007$^{*}$ | −1.624$^{***}$ |
| | (0.265) | (0.226) | (0.0997) | | (2.504) | (0.527) | (0.584) |
| Sears: Electronic equipment and accessories | 0.630$^{**}$ | 0.170 | −0.0578 | Verizon communications: Corporate promotion | 5.955$^{***}$ | 1.435$^{***}$ | −1.207$^{***}$ |
| | (0.262) | (0.163) | (0.0849) | | (0.470) | (0.206) | (0.216) |
| Sears: Electronic equipment and accessories and tools | 0.0126 | 0.558$^{**}$ | 0.185 | Verizon family share plan: Consumer wireless | 4.993$^{***}$ | 0.240 | −0.520$^{***}$ |
| | (0.324) | (0.221) | (0.135) | | (0.424) | (0.163) | (0.196) |

*Notes*. Robust standard errors in parentheses. Only significant effects of networks are displayed.

how communication efforts in various media impact consumers at different stages of the purchase funnel. We hope that this work offers some initial progress in that direction by showing how brands can achieve new goals through old methods.

## Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mksc.2014.0899.

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## References

Anderson SP, Renault R (2006) Advertising content. *Amer. Econom. Rev.* 39(1):305–326.
Anderson SP, Ciliberto F, Liaukonyte J (2013) Information content of advertising: Empirical evidence from the OTC analgesic industry. *Internat. J. Indust. Organ.* 31(5):355–367.
Blake T, Nosko C, Tadelis S (2014) Consumer heterogeneity and paid search effectiveness: A large scale field experiment. *Econometrica.* Forthcoming.
Buijzen M, Valkenburg PM (2004) Developing a typology of humor in audiovisual media. *Media Psych.* 6(2):147–167.
Bush AJ, Bush RP (1990) A content analysis of direct response television advertising. *J. Direct Marketing* 4(1):6–12.
Campbell DT, Fiske DW (1959) Convergent and discriminant validation by the multitrait-multimethod matrix. *Psych. Bull.* 56(2):81–105.
Chandy RK, Tellis GJ, MacInnis DJ, Thaivanich P (2001) What to say when: Advertising appeals in evolving markets. *J. Marketing Res.* 38(4):399–414.
Chaney PK, Devinney TM, Winer RS (1991) The impact of new product introductions on the market value of firms. *J. Bus.* 64(4):573–610.
Dagger T, Danaher PJ (2013) Comparing the relative effectiveness of advertising channels: A case study of a multimedia blitz campaign. *J. Marketing Res.* 50(4):517–534.
Danaher PJ (2007) Modeling page views across multiple websites with an application to Internet reach and frequency prediction. *Marketing Sci.* 26(3):422–437.
Danaher PJ, Green BJ (1997) A comparison of media factors that influence the effectiveness of direct response television advertising. *J. Interactive Marketing* 11(2):46–58.
Godes D, Mayzlin D (2004) Using online conversations to study word-of-mouth communication. *Marketing Sci.* 23(4):545–560.
Gong S, Zhang J, Zhao P, Jiang X (2014) *Tweets and Sales: A Field Experiment* (Massachusetts Institute of Technology, Cambridge, MA).
Haans H, Raassens N, van Hout R (2013) Search engine advertisements: The impact of advertising statements on click-through and conversion rates. *Marketing Lett.* 24(2):151–163.
Hartmann W, Nair H, Narayanan S (2011) Identifying causal marketing mix effects using a regression discontinuity design. *Marketing Sci.* 30(6):1079–1097.
Johnson EJ, Moe W, Fader P, Steven B, Lohse J (2004) On the depth and dynamics of online search behavior. *Management Sci.* 50(3):299–308.
Joo M, Wilbur KC, Cowgill B, Zhu Y (2014) Television advertising and online search. *Management Sci.* 60(1):56–73.
Kolsarici C, Vakratsas D (2011) The complexity of multi-media effects. Marketing Science Institute Working Paper Series 2011, Report 11–100. Marketing Science Institute, Cambridge, MA.
Lewis R, Nguyen D (2014) *Wasn't That an Ad for the iPad? Display Advertising's Impact on Advertiser- and Competitor-Branded Search* (University of Chicago, Chicago).
Lewis RA, Reiley DH (2013) Down-to-the-minute effects of Super Bowl advertising on online search behavior. *14th ACM Conf. Electronic Commerce* 9(4):639–656.
Liaukonyte J (2014) Is comparative advertising an active ingredient in the market for pain relief? Working paper, School of Applied Economics and Management, Cornell University, Ithaca, NY.
Lin C, Venkataraman S, Jap SD (2013) Media multiplexing behavior: Implications for targeting and media planning. *Marketing Sci.* 32(2):310–324.
MacInnis DJ, Price LL (1987) The role of imagery in information processing: Review and extensions. *J. Consumer Res.* 13(4): 473–491.
Moe WW, Fader PS (2004) Capturing evolving visit behavior in clickstream data. *J. Interactive Marketing* 18(1):5–19.
Montgomery AL, Li S, Srinivasan K, Liechty JC (2004) Modeling online browsing and path analysis using clickstream data. *Marketing Sci.* 23(4):579–595.
Naik PA, Peters K (2009) A hierarchical marketing communications model of online and offline media synergies. *J. Interactive Marketing* 23(4):288–299.
Naik PA, Raman K (2003) Understanding the impact of synergy in multimedia communications. *J. Marketing Res.* 13(4):25–34.
Nielsen (2010) Three screen report, 1st Quarter 2010. White paper. Accessed August 8, 2013, http://www.nielsen.com/us/en/newswire/2010/what-consumers-watch-nielsens-q1-2010-three-screen-report.html.
Nielsen (2011) 40% of tablet and smartphone owners use them while watching TV. Accessed August 8, 2013, http://www.nielsen.com/us/en/newswire/2011/40-of-tablet-and-smartphone-owners-use-them-while-watching-tv.html.
Nielsen (2012) State of the media: Advertising and audiences Part 2. Accessed February 4, 2015, http://nielsen.com/content/dam/corporate/us/en/reports-downloads/2012-Reports/nielsen-advertising-audiences-report-spring-2012.pdf.
Nielsen (2014) The U.S. digital consumer report. White paper. Accessed March 14, 2014, http://www.nielsen.com/us/en/reports/2014/the-us-digital-consumer-report.html.
Ofcom (2013) Communications market report 2013. White paper, Ofcom, UK Communications Regulator, London.
Onishi H, Manchanda P (2012) Marketing activity, blogging and sales. *Internat. J. Res. Marketing* 29(3):221–234.
Park YH, Fader PS (2004) Modeling browsing behavior at multiple websites. *Marketing Sci.* 23(3):280–303.
Peltier JW, Mueller B, Rosen RG (1992) Direct response versus image advertising: Enhancing communication effectiveness through an integrated approach. *J. Direct Marketing* 6(1):40–48.
Rubinson J (2009) VIEWPOINT-the new marketing research imperative: It's about learning. *J. Advertising Res.* 49(1):7–9.
Sahni N (2012) *The Effect of Temporal Spacing Between Advertising Exposures: Evidence from Online Field Experiments* (Stanford University, Palo Alto, CA).
Teixeira TS, Picard R, el Kaliouby R (2014) Why, when and how much to entertain consumers in advertisements? A web-based facial tracking field study. *Marketing Sci.* 33(6):809–827.

Teixeira TS, Wedel M, Pieters R (2012) Emotion-induced engagement in Internet video ads. *J. Marketing Res.* 49(2):144–159.

Tellis GJ (2004) *Effective Advertising: Understanding When, How, and Why Advertising Works* (Sage Publications, Thousand Oaks, CA).

Tellis GJ, Chandy RK, Thaivanich P (2000) Which ad works, when, where, and how often? Modeling the effects of direct television advertising. *J. Marketing Res.* 37(1):32–46.

Wilbur KC (2008) A two-sided, empirical model of television advertising and viewing markets. *Marketing Sci.* 27(3):356–378.

Wilbur KC, Xu L, Kempe D (2013) Correcting audience externalities in television advertising. *Marketing Sci.* 32(6):892–912.

Wind YJ, Sharp B (2009) Advertising empirical generalizations: Implications for research and action. *J. Advertising Res.* 49(2):246–252.

Wu J, Cook VJ Jr, Strong EC (2005) A two-stage model of the promotional performance of pure online firms. *Inform. Systems Res.* 16(4):334–351.

Xu L, Wilbur KC, Siddarth S, Silva-Risso J (2014) Price advertising by manufacturers and dealers. *Management Sci.* 60(11):2816–2834.

Zigmond D, Stipp H (2010) Assessing a new advertising effect: Measurement of the impact of television commercials on Internet search queries. *J. Advertising Res.* 50(2):162–168.

Zigmond D, Stipp H (2011) Multitaskers may be advertisers' best audience. *Harvard Bus. Rev.* 12(1/2):32–33.