

Television Advertising and Online Shopping

Jura Liaukonyte,¹ Thales Teixeira,² Kenneth C. Wilbur³

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Media multitasking competes with television advertising for consumers' attention, but it also may facilitate immediate and measurable response to some advertisements. This paper explores whether and how television advertising influences online shopping. We construct a massive dataset 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 non-advertising 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 net effect on sales that is positive 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.

¹ Dake Family Assistant Professor, Cornell University, Dyson School of Applied Economics and Management, <https://faculty.cit.cornell.edu/jl2545>.

² Assistant Professor of Business Administration, Harvard Business School, <http://www.hbs.edu/faculty/Pages/profile.aspx?facId=522373>.

³ Assistant Professor, University of California, San Diego, Rady School of Management, <http://kennethcwilbur.com>.

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1. Introduction

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

One might therefore suspect that television can effectively engage online shoppers. But 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 US viewers reported searching online for product information after watching a TV advertisement, and 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 current paper aims to contribute 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 looked at the effects of television advertising on direct website traffic or online purchase data. The current paper establishes that online shopping responds to television advertising. Further, it investigates how

those effects depend on the characteristics of the advertisement, such as its content and its media placement.

To address these questions, we merged two large databases of television advertising and internet usage, and then created a third database of advertising content. The advertising data represent \$3.4 billion spent by 20 brands in 5 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 employ 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 prior to 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, Nair and Narayan (2011).

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

We find that television advertising does indeed 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 they 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 the television. In sum, the results suggest that advertisers must select advertising content carefully according to their objectives.

The paper proceeds by reviewing related academic literature. It then describes the data, empirical framework, and the findings. The conclusion discusses implications and opportunities for future work.

2. Relevant Literature and Conceptual Framework

The present 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 ten advertising media 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. In a similar vein, 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, Ohnishi 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.

The current 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 diminished rapidly after the first one or two hours. Chandy et al. (2001) extended this work to consider the influence of specific advertising appeals 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 out more information about these products and brands (Rubinson 2009). Recently, consumers have started gathering a great deal of product information online, and 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 prior to incurring a costly store visit. Nearly all major retailers provide extensive assortment, 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, within one minute, with smaller effects persisting 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, 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..." The current article follows up on this suggestion.

Following this observation, we posit that people have two main decisions in response to TV ad exposure. First, they choose whether to visit the brand's website or not. 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, upon arrival at the website, the consumer eventually decides whether to purchase or not.

When thinking through the possible influence of TV ads on online shopping, it is necessary to 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 advertisement 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 studied extensively. 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. There is also empirical evidence suggesting 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, while 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 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, that is, how TV ad content might influence online shopping. Similar to magazine and search engine ads, TV commercials may attempt to persuade viewers primarily to visit a brand website or they might primarily focus on making the sale. While 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 the next section we describe the dataset that allows us to estimate these effects.

3. Data

The empirical analysis merges two large datasets 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 usage 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. Further, 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* 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.

¹ Many users stop looking at webpages without closing a browser tab; therefore, some assumption is required about the maximum time a user might have continued interacting with the site. 30 minutes is the standard assumption.

² Prior research in marketing has analyzed comScore data from 2002-2004 (e.g., Moe and Fader 2004, Park and Fader 2004, Montgomery, Li, Srinivasan, and Liechty 2004, Danaher 2007, Johnson et al. 2004).

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 a search engine referral led to a new session on the brand website.

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 employed, similar to Blake et al. (2014).

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

[Figure 1 about here]

The internet usage database has two properties that are important 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 were collected, comScore only measured internet usage 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 U.S. 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

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).

E.S.T.), and an estimated cost of the insertion. 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: the “property” (a national television network or program syndication company), program name, program genre, the number of the commercial break within the program, and the number of the slot within the commercial break.

The initial dataset 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 cost to broadcast was less than \$1,000, as these corresponded to channels and dayparts with very 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.

Like the online shopping activity in Figure 1, Figure 2 shows that 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 hours of 8-10 P.M.

[Figure 2 about here]

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 prior to the insertion of the advertisement. These same variables are measured again in a “post” window of time just after the ad starts.

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. The results of primary interest (tables 6 and 7) are essentially invariant to including or excluding these insertions, so we decided to drop them.

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.

The second exploratory exercise involved plotting browsing activity within shorter time windows for a wider selection of brands. Figure 4 illustrates this for Target and JC Penney’s. Most of the immediate increase in browsing activity was observed within two minutes after the ad, with some effects persisting 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

[Figures 3 and 4 about here]

Table 1 provides advertising and online shopping data for the estimation sample. The average brand used 61 commercials to advertise 7 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*

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 3×10^{13} computational queries and about 45 days to run for each shopping variable in each window length.

Wind and Sharp (2009) 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 dataset 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, the 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 in order to attract attention and engage viewers (Teixeira et al. 2012). 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 can make use of 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

⁷ Original survey items and intercoder reliability scores are provided in the Online Appendix.

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 (2013), who coded the product attributes communicated by 1,571 OTC pain medication ads.

survey of 14 academics who conduct behavioral research was conducted to evaluate the classification of survey items to advertisement attributes. The details of each step follow.

Feature coding. Ten research assistants were trained to code the advertisements. A budget constraint required that each commercial be assigned to only one coder. Coders were instructed to watch each ad at least twice and then answer the 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 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 inter-coder reliability. The percentage 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 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 lone exception is the correlation between action-focus and information-focus, which indicates some co-occurrence of these attributes within 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.

[Tables 2, 3 and 4 about here]

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, while 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 sometimes comparable to the standard deviations across the entire sample. In summary, 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

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

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—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). 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:

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

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

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

Post-window traffic variables r_i^{post} and d_i^{post} are specified as functions of all three shopping variables in the pre-window (r_i^{pre} , d_i^{pre} , and s_i^{pre}) to allow for general correlations among the three online shopping variables. The post-window transactions variable s_i^{post} depends on post-window traffic variables r_i^{post} and d_i^{post} for consistency with its definition in the previous

section. The nine α parameters governing correlations among online shopping variables are brand-specific, in order to flexibly represent heterogeneous relationships across brands.

Each equation in the baseline model of online shopping data incorporates two sets of fixed effects. The γ 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

Equations (1)-(3) also include two sets of residuals. $\omega_{c_i t_i}^r$, $\omega_{c_i t_i}^d$, 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 , are intended to 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*

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 dataset size affords sufficient degrees of freedom.

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

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:

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

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

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

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 counts (s).

The vector of advertising insertion characteristics Y_i includes the four standardized advertising content variables described in section 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 also 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 wearout; 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 's during 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*

In order to obtain unbiased estimates of the causal effects of advertising insertions, it must be the case that the unobserved category/time interactions ($\omega_{c;t}^r$, $\omega_{c;t}^d$ and $\omega_{c;t}^s$) are 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, for example, 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 advertising inventory is sold during the May “upfront” market, 3-15 months prior to the ads’ air

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, then they might tend to buy more ads on Mondays at 6 P.M. than at other weekday/hour combinations. It then would 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.

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 estimated directly 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 ω_{c,t_i}^r , ω_{c,t_i}^d and ω_{c,t_i}^s . 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; (2) Retailers: Abercrombie, Roamans, American Eagle, Children’s Place; (3) Telecom: Letstalk, Cricket, Wirefly; (4) Travel:

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

Airtran, ChoiceHotels, Cheaptickets, JetBlue. We did not find any non-advertising 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.

[Figures 5 and 6 and Table 5 about here]

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):

$$zr_i^{post} = zr_i^{pre} \kappa_{c_i}^{rr} + zd_i^{pre} \kappa_{c_i}^{dr} + zs_i^{pre} \kappa_{c_i}^{sr} + \eta_{c_i}^r + X_{c_i t_i} \kappa^{zr} + \omega_{c_i t_i}^r + v_i^r \quad (7)$$

$$zd_i^{post} = zr_i^{pre} \kappa_{c_i}^{rd} + zd_i^{pre} \kappa_{c_i}^{dd} + zs_i^{pre} \kappa_{c_i}^{sd} + \eta_{c_i}^d + X_{c_i t_i} \kappa^{zd} + \omega_{c_i t_i}^d + v_i^d \quad (8)$$

$$zs_i^{post} = zr_i^{post} \kappa_{c_i}^{rs} + zd_i^{post} \kappa_{c_i}^{ds} + zs_i^{pre} \kappa_{c_i}^{ss} + \eta_{c_i}^s + X_{c_i t_i} \kappa^{zs} + \omega_{c_i t_i}^s + v_i^{zs} \quad (9)$$

Here, the κ parameters govern the correlations among online shopping variables in a manner similar to the α parameters in Equations (1)-(3); the same observed 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 κ and η parameters of the latter model 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 take differences between equations (4) and (7), (5) and (8), and (6) and (9) to derive our difference-in-differences estimator:

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

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

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

where $\begin{bmatrix} \delta_{b_i}^r \\ \delta_{b_i}^d \\ \delta_{b_i}^s \end{bmatrix} = \begin{bmatrix} \gamma_{b_i}^r - \eta_{c_i}^r \\ \gamma_{b_i}^d - \eta_{c_i}^d \\ \gamma_{b_i}^s - \eta_{c_i}^s \end{bmatrix}$, $\begin{bmatrix} \mu^r \\ \mu^d \\ \mu^s \end{bmatrix} = \begin{bmatrix} \beta^r - \kappa^{zr} \\ \beta^d - \kappa^{zd} \\ \beta^s - \kappa^{zs} \end{bmatrix}$ 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. The next section 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 specifications.¹⁶ Table 6 reports the proportion of the variation explained in the three online shopping variables by several different models.

[Table 6 about here]

¹⁶ The model was also subjected to a random 80% hold-out validation exercise to check for overfitting. The R-square and 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.

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 datasets, thereby answering the first question (whether TV advertising influences online shopping) in the affirmative.

Finally, we estimated a model with category-specific treatment effects. This was done by interacting the continuous advertising content variables in the treatment effect with category fixed 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 both 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 television advertising influences online shopping. Table 7 presents the effects of TV advertising content on direct traffic, search engine referrals, and transactions. There are twelve such effects—four standardized advertising content variables times three online shopping variables—within each of the two window length models.

¹⁷ It is noteworthy 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.

In the two-hour regression, 9 of the 12 parameters are statistically significant at the 95% confidence level, while 6 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. We proceed by discussing the two-hour results, as summarized in Figure 7, as the slightly longer time window seems like the more important measure of consumer shopping activity.

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.

[Table 7 and Figure 7 about here]

Action-focus. 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

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 ϕ_x^r , ϕ_x^d and ϕ_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.

encourages direct means of visitation rather than requiring a search prior to 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 makes the brand website more salient to consumers, helping them to bypass search engines and thereby reducing the “toll” the brand has to pay 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-focus and Emotion-focus. 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 positive total effects of information-focus and emotion-focus content on sales that are statistically significant for most brands.

Imagery-focus. Imagery content is associated with reduced direct visitation to the website in the two-hour dataset. We suspect the reason for this is the 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 Parameter 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 will be needed to determine whether the effects on purchases comes 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 aired repeatedly. 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. This aligns with the dual purpose of TV ads for multitaskers: 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.

[Tables 8-10 about here]

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.

Multi-product 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, wherein brands often market broad lines of related products. It is perhaps unsurprising 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: distracting consumer attention from advertising. In this research, we hope to emphasize a potentially positive aspect: the “second screen” may enable an immediate and measurable response to some television advertisements. The question then becomes, how can brands alter their traditional television advertising efforts to influence online shopping?

The purpose of this paper is to investigate 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 are found to 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 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, so 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 precisely 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 they

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, so 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. Future research will ideally be able to study multi-brand, multi-media, single-source panel data of advertising exposure, online traffic and sales, and look for longer-term effects. We hope our findings might 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 in order 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.

It must be noted 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 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 deal with 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 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 with old methods.

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Table 1. Descriptive Statistics

Sector	Brand	<i>Kantar</i>				<i>Comscore</i>			
		Advertised Products	Unique Ad Creatives	Ad Insertions	Total Ad Spending (\$MM)	Search Engine Referrals	Direct Visit Sessions	Trans-actions	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%
	JC Penney's	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%
	<i>Total</i>	<i>132</i>	<i>1,224</i>	<i>328,212</i>	<i>3,433</i>	<i>461,214</i>	<i>988,040</i>	<i>90,808</i>	
<i>Average</i>	<i>7</i>	<i>61</i>	<i>16,411</i>	<i>172</i>	<i>23,061</i>	<i>49,402</i>	<i>4,540</i>	<i>6.27%</i>	

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)

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

Table 4. Ad Content Descriptives by Brand

Sector	Brand	Advertised Products	Num. Unique Ad Creatives	Action-focused	Information-focused	Emotion-focused	Imagery-focused
				min=0,max=7 avg. (st.dev.)	min=0,max=3 avg. (st.dev.)	min=0,max=5 avg. (st.dev.)	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)
	JC Penney's	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)
<i>Average (st. dev.) across all treatments</i>				3.0 (1.7)	1.9 (1.0)	1.8 (1.3)	1.4 (0.8)

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*
Telecom	0.950	0.968	0.758
Travel	0.980	0.990	0.916

* Control brands are free websites with no purchases

Table 6. R-Square Statistics by Online Shopping Variable and Model Specification

	2 Hours (Diff.-in-Diff.)					2 Minutes (Quasi-Diff.)				
	R-square			<i>AIC</i>	<i>BIC</i>	R-square			<i>AIC</i>	<i>BIC</i>
	Search Engine Referrals	Direct Visits	Trans-actions			Search Engine Referrals	Direct Visits	Trans-actions		
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				

Table 7. Effects of Ad Content on Search Engine Referrals, Direct Traffic and Transactions

	2 Hours (Diff.-in-Diff.)			2 Minutes (Quasi-Diff.)		
	Search Engine Referrals	Direct Visits	Trans-actions	Search Engine Referrals	Direct Visits	Trans-actions
Action-focused	-0.0304*** (0.0117)	0.1850*** (0.0269)	0.0281*** (0.0094)	-0.0029** (0.0012)	0.0078*** (0.0022)	0.0010 (0.0009)
Information-focused	-0.0264** (0.0120)	-0.2960*** (0.0257)	0.0357*** (0.0088)	-0.0002 (0.0013)	-0.0117*** (0.0023)	0.0000 (0.0009)
Emotion-focused	0.0047 (0.0100)	-0.1250*** (0.0217)	0.0344*** (0.0077)	0.0005 (0.0010)	-0.0022 (0.0017)	0.0001 (0.0007)
Imagery-focused	-0.0108 (0.0092)	-0.144*** (0.0188)	-0.0037 (0.0061)	-0.0023** (0.0009)	-0.0109*** (0.0016)	0.0017*** (0.0006)

Notes: *** p<0.01, ** p<0.05. Robust standard errors in parentheses. Standardized content measures

Table 8. Additional Treatment Effects

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

Notes: *** p<0.01, ** p<0.05. Robust standard errors in parentheses.

Table 9. Effects of Television Network (Significant Effects Only)

TV Network	2 Hours (Diff.-in-Diff.)			TV Network	2 Hours (Diff.-in-Diff.)			TV Network	2 Hours (Diff.-in-Diff.)		
	Searh Engine Referrals	Direct Visits	Trans-actions		Searh Engine Referrals	Direct Visits	Trans-actions		Searh Engine Referrals	Direct Visits	Trans-actions
ADSM	0.273*** (0.0832)	0.517*** (0.194)	0.115 (0.0645)	ESPN	0.296*** (0.0818)	0.202 (0.184)	-0.0908 (0.0632)	SPK	-0.0683 (0.0588)	-0.332*** (0.129)	0.0859** (0.0423)
AMC	0.309*** (0.0926)	-0.0528 (0.164)	0.00471 (0.0471)	FNEW	-0.0836 (0.0901)	-0.413** (0.195)	0.0328 (0.0677)	STYL	0.545 (0.761)	3.095*** (1.146)	-0.0312 (0.222)
BBCA	-0.379** (0.184)	-0.0621 (0.327)	0.0546 (0.0748)	FX	0.0909 (0.0643)	0.487*** (0.138)	0.130*** (0.0455)	TLC	0.0435 (0.0742)	0.343** (0.144)	0.0113 (0.0467)
BET	-0.0709 (0.0685)	-0.316** (0.144)	0.0692 (0.0506)	GALA	0.0565 (0.0846)	-0.456** (0.193)	0.0892 (0.0606)	TNNK	1.386*** (0.263)	0.416 (0.401)	-0.300*** (0.112)
BRAV	0.0677 (0.0698)	0.303** (0.137)	0.0613 (0.0452)	GSN	2.040*** (0.483)	-1.050 (1.374)	-0.346 (0.427)	TOON	0.560** (0.268)	0.86 (0.490)	0.160 (0.159)
CNBC	-0.457*** (0.123)	-2.522*** (0.319)	-0.237*** (0.0897)	HIST	-0.0158 (0.0608)	-0.332** (0.131)	0.0744* (0.0432)	TRAV	-0.0465 (0.0795)	-0.339** (0.165)	-0.0792 (0.0531)
CNN	-0.109 (0.0891)	-0.789*** (0.177)	0.0726 (0.0532)	MNTV	0.106 (0.237)	1.195** (0.573)	-0.225 (0.207)	TRU	0.290*** (0.0757)	0.107 (0.164)	0.107 (0.0574)
CW	-0.100 (0.104)	-0.738*** (0.201)	0.0316 (0.0731)	MTV	0.0887 (0.0573)	0.372*** (0.120)	0.0657 (0.0404)	TWC	-0.127 (0.0913)	0.640*** (0.200)	-0.159** (0.0659)
DSCH	3.649*** (0.198)	9.450*** (0.289)	-0.981*** (0.101)	NAN	-0.115 (0.0756)	-0.363** (0.148)	0.0610 (0.0483)	USA	0.0254 (0.0660)	-0.0265 (0.130)	0.102** (0.0437)
DXD	-5.218*** (1.297)	8.778*** (0.348)	1.490 (2.412)	NBC	0.0911 (0.0747)	0.323** (0.152)	0.0203 (0.0512)	VH-1	0.0731 (0.0540)	0.252** (0.112)	0.108*** (0.0378)
E!	0.197*** (0.0631)	0.375*** (0.126)	-0.0394 (0.0397)	NFLN	0.517*** (0.151)	1.759*** (0.372)	-0.583*** (0.124)	WE	-0.0500 (0.429)	1.300** (0.656)	0.185 (0.253)
ESP2	0.188** (0.0923)	-0.0910 (0.210)	0.0307 (0.0761)	NGC	0.0196 (0.0851)	-0.466*** (0.176)	-0.0771 (0.0614)				

Notes: *** p<0.01, ** p<0.05. Robust standard errors in parentheses.

Table 10. Advertised Product Effects (Significant Effects Only)

Product	2 Hours (Diff.-in-Diff.)			Product	2 Hours (Diff.-in-Diff.)		
	Searh Engine Referrals	Direct Visits	Trans- actions		Searh Engine Referrals	Direct Visits	Trans- actions
AT&T : Consumer Wireless Service	1.630*** (0.160)	-0.0535 (0.0809)	-0.183*** (0.0515)	Sears : Family Apparel	1.376*** (0.334)	0.742*** (0.246)	-0.426*** (0.109)
AT&T : Pre-Paid Wireless Service	5.793*** (1.779)	0.327 (0.644)	-0.871** (0.367)	Sears : Gardening Tools & Supplies	-0.614** (0.275)	0.181 (0.173)	-0.00401 (0.0895)
AT&T Go Phone : Pre-Paid Wireless Service	0.0199 (1.316)	-1.761*** (0.438)	0.201 (0.518)	Sears : General	-0.614 (0.441)	-0.713** (0.296)	0.239* (0.141)
AT&T Inc : Corporate Promotion	2.084*** (0.239)	-0.900*** (0.111)	-0.0614 (0.0774)	Sears : General NEC	-0.354 (0.298)	-0.373* (0.193)	0.255*** (0.0976)
AT&T Mobile TV : Consumer Wireless Service	5.273*** (0.370)	0.218 (0.158)	-0.753*** (0.109)	Sears : Jewelry & Watches	2.752*** (0.543)	-0.371 (0.510)	-0.443 (0.246)
AT&T Unlimited Calling Plan : Consumer Wireless	4.756*** (0.441)	0.34 (0.177)	-0.789*** (0.119)	Sears : Mens Apparel	-0.991*** (0.329)	0.756*** (0.247)	-0.109 (0.257)
JC Penney : General	-1.651** (0.711)	-0.260 (0.443)	0.171 (0.258)	Sears : Multi-Products	1.409*** (0.402)	0.529** (0.250)	-0.171 (0.116)
JC Penney : Household	-2.849*** (0.693)	0.655 (0.429)	0.657** (0.259)	Sears : Optical	0.655*** (0.248)	0.0734 (0.155)	-0.00236 (0.0817)
JC Penney : Jewelry & Watches	-5.369*** (0.727)	1.255** (0.493)	1.113*** (0.303)	Sears : Sales Announcement	0.916*** (0.245)	0.395** (0.155)	-0.0581 (0.0806)
JC Penney : Mens Apparel	-2.030*** (0.676)	0.457 (0.405)	0.288 (0.242)	Sears : Tools & Hardware & Building Materials	0.974*** (0.364)	-1.145*** (0.235)	-0.437*** (0.117)
JC Penney : Womens Apparel	-2.585*** (0.678)	0.502 (0.410)	0.954*** (0.247)	Southwest Airlines : Domestic	-1.419*** (0.518)	-0.394 (0.299)	0.211 (0.114)
Macys : Childrens Apparel	0.986*** (0.287)	0.425 (0.258)	-0.164 (0.110)	Sprint Any Mobile Anytime Plan : Consumer	-1.446*** (0.283)	-0.613*** (0.100)	-0.563*** (0.0486)
Macys : Fragrances & Cosmetics	1.082** (0.431)	0.381 (0.357)	-0.240** (0.117)	Sprint Corp : Corporate Promotion	-1.095*** (0.301)	0.00244 (0.107)	-0.196*** (0.0572)
Macys : General	0.663*** (0.256)	0.00998 (0.221)	0.0706 (0.0981)	Sprint Everything Data Family Plan : Consumer	2.441** (0.991)	-0.0507 (0.397)	-0.373** (0.159)
Macys : General Apparel	1.204*** (0.317)	0.155 (0.276)	-0.151 (0.124)	Sprint Everything Data Plan : Consumer Wireless	0.0156 (0.151)	-0.0130 (0.0530)	0.0635** (0.0305)
Macys : General NEC	0.787*** (0.283)	0.149 (0.236)	-0.0181 (0.108)	Target : Books & Stationery	0.958 (1.036)	-1.897** (0.857)	0.426 (0.419)
Macys : Mattresses	1.458*** (0.264)	0.518** (0.224)	-0.242** (0.103)	Target : Sales Announcement	2.654*** (0.839)	2.053*** (0.651)	0.00657 (0.328)
Macys : Mens Apparel	0.318 (0.849)	-0.224 (0.590)	-0.363** (0.184)	Target : Tools & Hardware & Building Materials	3.981** (1.946)	0.391 (2.324)	-0.0188 (0.470)
Macys : Mens Apparel & Mens Shoes	0.659 (0.421)	0.198 (0.350)	-0.388*** (0.121)	Target : Toy & Hobby Products	1.095 (0.867)	1.442** (0.656)	-0.193 (0.337)
Macys : Mens Apparel & Womens Apparel	3.026*** (0.486)	-0.362 (0.337)	-0.308 (0.168)	Target : Video Games & Systems	-1.538 (1.028)	3.490*** (1.023)	0.291 (0.381)
Macys : Sales Announcement	0.860*** (0.233)	0.00835 (0.205)	-0.00696 (0.0903)	Verizon : Business Wireless Service	6.386*** (0.380)	0.771*** (0.159)	-0.965*** (0.184)
Macys : Womens Shoes	1.063** (0.413)	0.873*** (0.327)	0.179 (0.167)	Verizon : Consumer Wireless Service	7.523*** (0.342)	0.568*** (0.142)	-1.209*** (0.164)
Macys Department Store : Corporate Promotion	1.083*** (0.265)	-0.0939 (0.226)	0.0421 (0.0997)	Verizon : ISP/TV/Wireless	5.384** (2.504)	1.007* (0.527)	-1.624*** (0.584)
Sears : Electronic Equipment & Accessories	0.630** (0.262)	0.170 (0.163)	-0.0578 (0.0849)	Verizon Communications : Corporate Promotion	5.955*** (0.470)	1.435*** (0.206)	-1.207*** (0.216)
Sears : Electronic Equipment & Accessories & Tools	0.0126 (0.324)	0.558** (0.221)	0.185 (0.135)	Verizon Family Share Plan : Consumer Wireless	4.993*** (0.424)	0.240 (0.163)	-0.520*** (0.196)

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

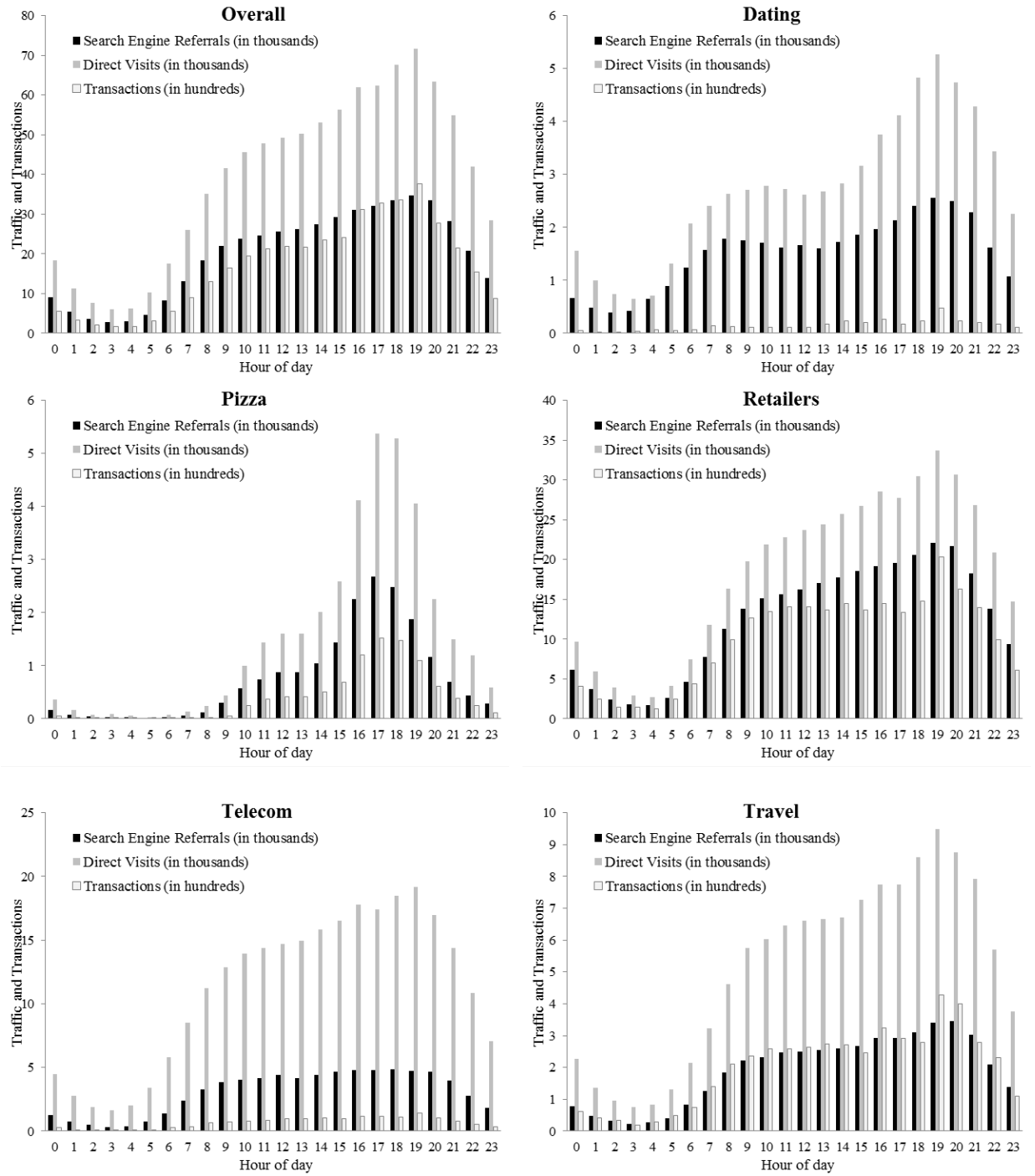


Figure 2. Ad Timing and Frequency

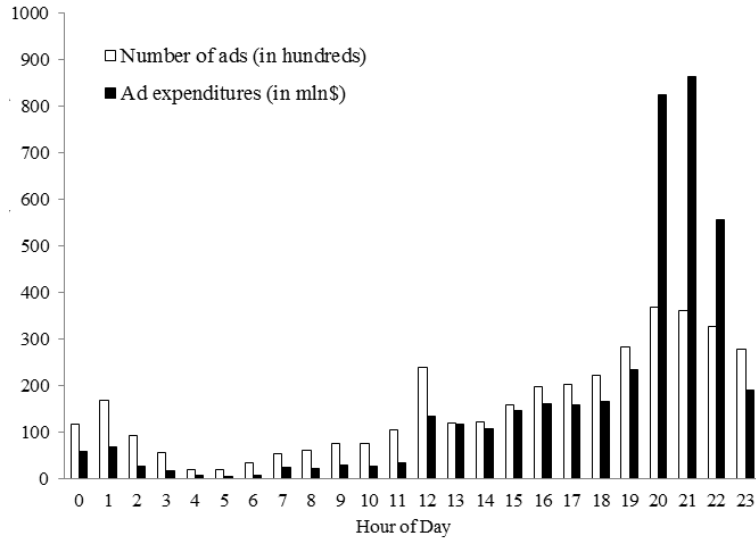
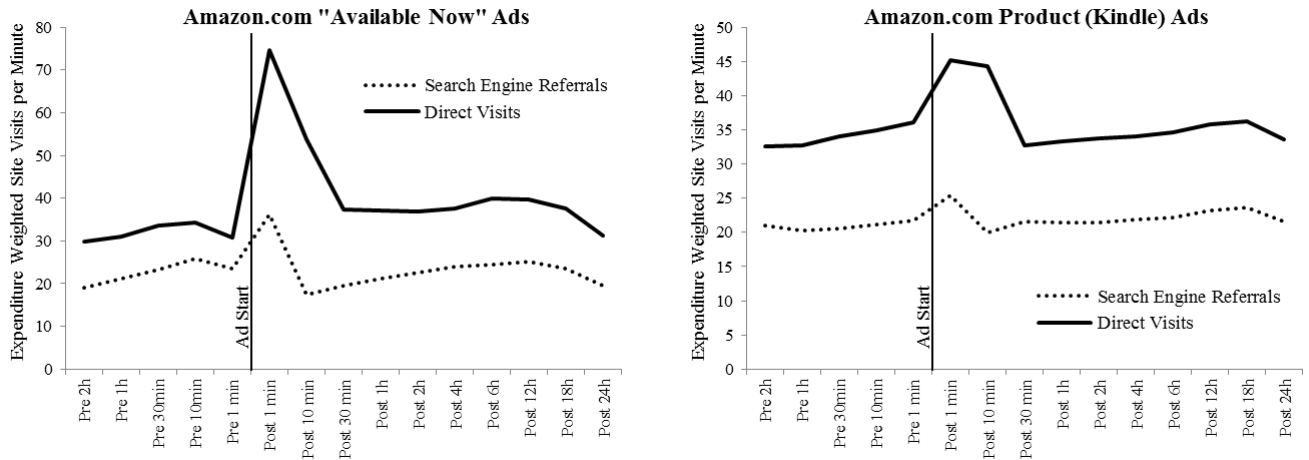


Figure 3. Search Engine Referrals and Direct Traffic by Window Length and Ad Content



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

Figure 4. Search Engine Referrals and Direct Traffic within Shorter Window Lengths

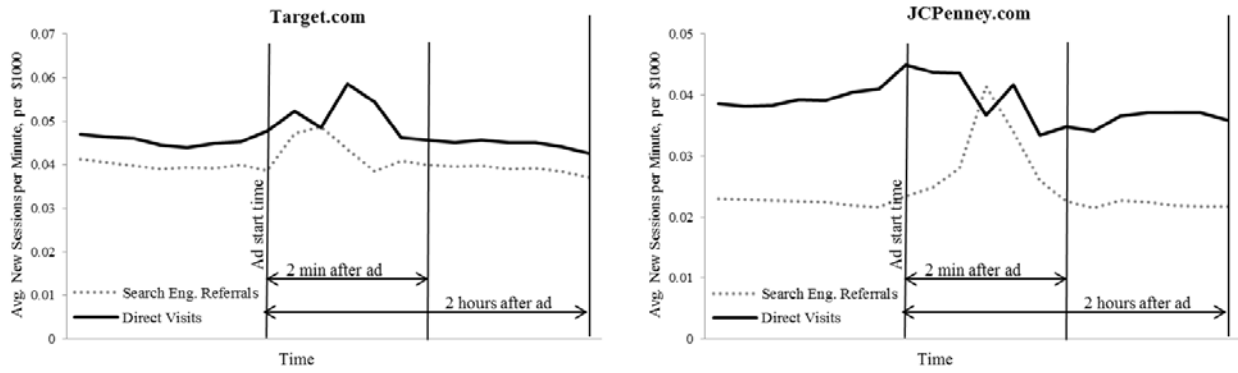
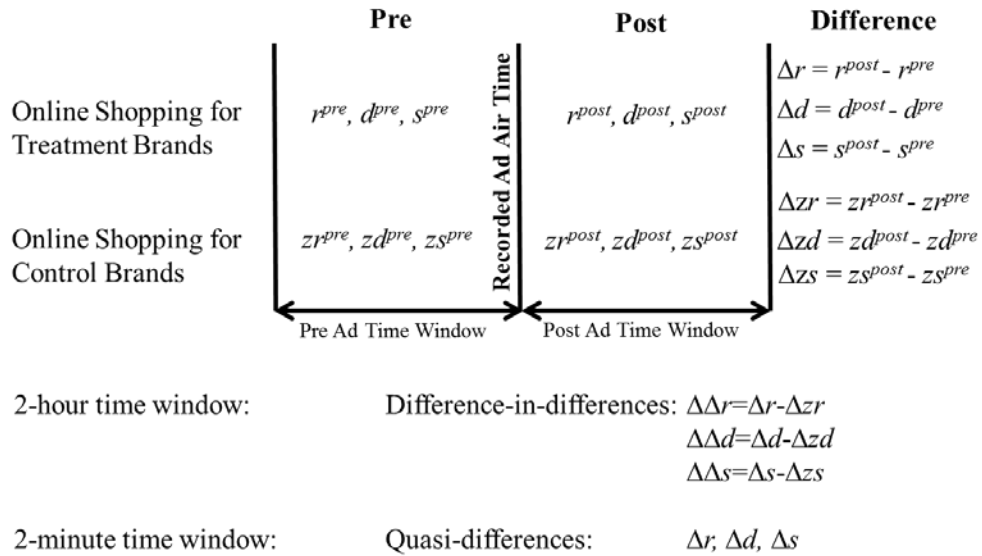


Figure 5. Research Design



Notes: r – search engine referrals; d – direct traffic; s – transactions (sales).

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

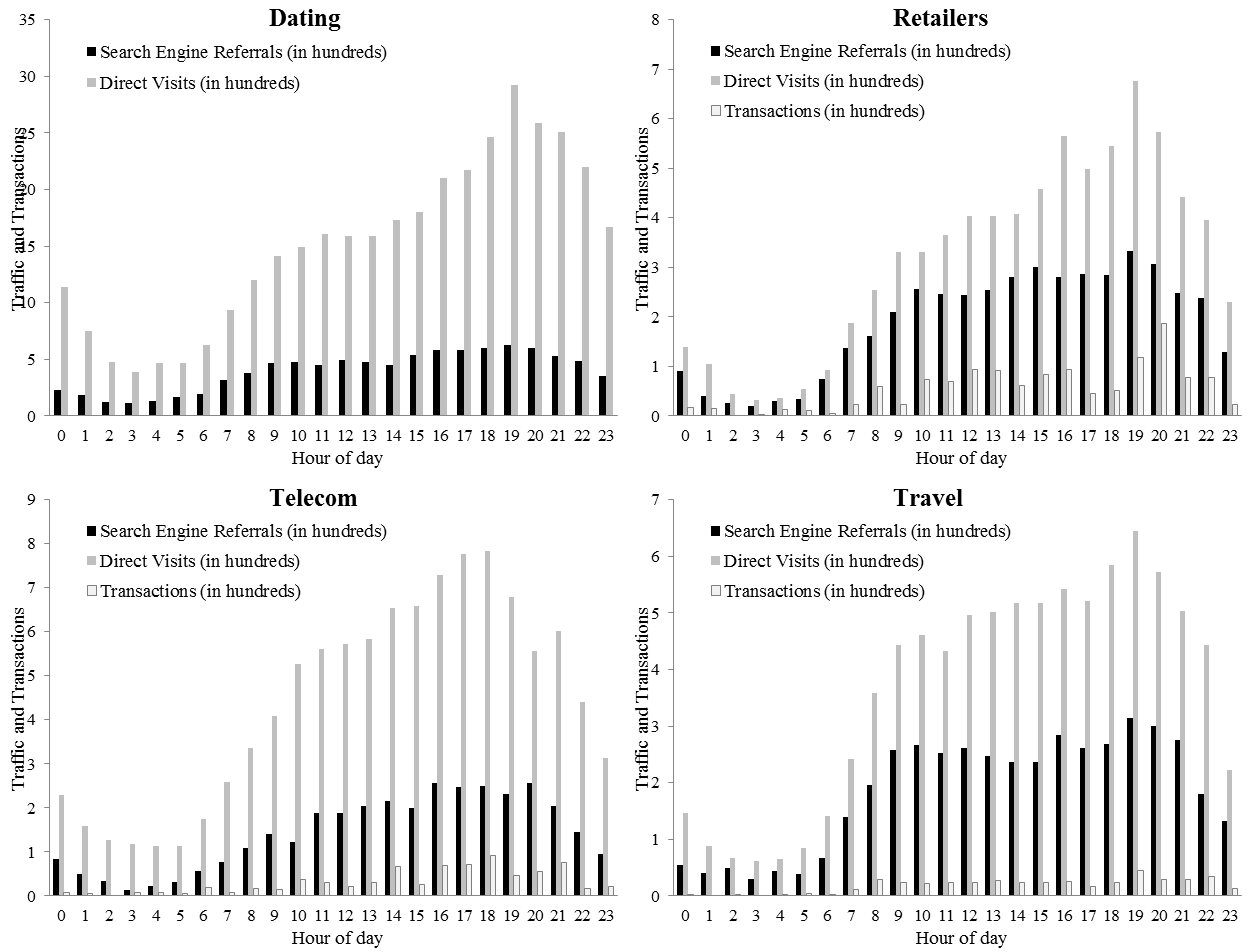
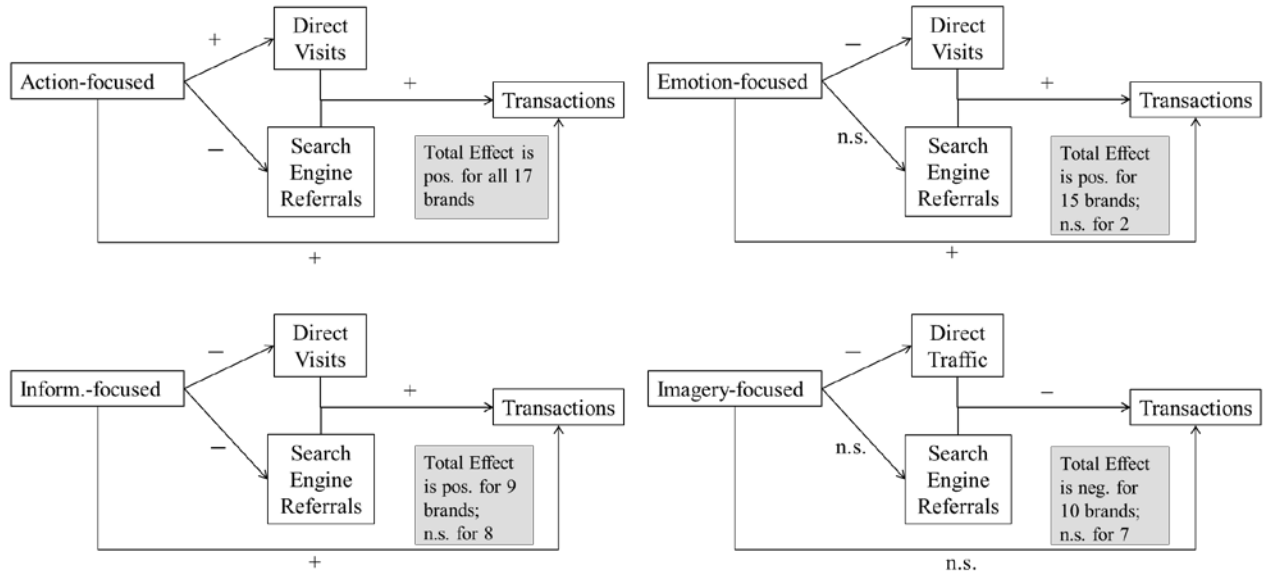


Figure 7. Effects of Ad Content on Search Engine Referrals, Direct Traffic and Transactions (2-hour data)



Online Appendix

This Appendix presents survey items and empirical results that were omitted from the main body of the article for brevity. Table A1 provides the original survey items that were coded by the research assistants in the exercise described in section 3.4. Tables A2 and A3 present the brand fixed effects and correlation parameters in the baseline model of online shopping that were estimated using the two-hour window regression data (the δ and μ parameters in Equations 10-12). These effects should not be interpreted as causal, but they do describe some interesting patterns. The effects of advertising expenditure are also reported here, but are difficult to interpret because the model includes a large number of insertion covariates (category/time interactions, TV property and genre fixed effects, etc.) and cost estimates are highly correlated with these variables. Figures A1-A4 graph the category-time interactions for each of the three online shopping variables; point estimates are shown in the solid line, with 95% confidence interval indicated by colored dots above and below the lines.

Table A1. Full List of Content Survey Questions

	% Match	Alpha
Action-focused		
Is there a call to go online (e.g., shop online, visit the web)?	79%	.71
Is there online contact information provided (e.g., URL, website)?	89%	.83
Is there a visual or verbal call to purchase (e.g., buy now, order now)?	70%	.51
Does the ad portray a sense of urgency to act (e.g., buy before sales ends, order before ends)?	79%	.65
Is there an incentive to buy (e.g., a discount, a coupon, a sale or “limited time offer”)?	80%	.75
Is there offline contact information provided (e.g., phone, mail, store location)?	91%	.68
Is there mention of something free?	94%	.86
Information-focused		
Does the ad mention at least one specific product (e.g., model, type, item)?	79%	.69
Is there any visual or verbal mention of the price?	93%	.92
Does the ad show the brand or trademark multiple or few times?	61%	.24
Emotion-focused		
Is the ad intended to be emotional? (You may not agree. But was that the intention of the ad?)	89%	.67
Does the ad give you a warm feeling about the brand?	61%	.30
Does the ad tell a story (e.g., with characters, a plot, an ending)?	73%	.39
Is the ad creative, clever?	54%	.31
Is the ad intended to be funny? (You may not agree. But was that the intention of the ad?)	83%	.78
Imagery-focused		
Does this ad provide sensory stimulation (e.g., cool visuals, arousing music, mouth-watering)?	61%	.31
Is the ad visually pleasing?	66%	.37
Is the ad cute? (e.g., baby, puppy, animated characters)	87%	.05

Table A2. Brand Effects

Brand	2 Hours (Diff.-in-Diff.)			Brand	2 Hours (Diff.-in-Diff.)		
	Search Engine Referrals	Direct Visits	Trans-actions		Search Engine Referrals	Direct Visits	Trans-actions
ATT	-2.814 (1.488)	-10.00*** (2.412)	2.453*** (0.434)	Overstock	-0.208 (1.432)	-1.878 (2.323)	3.271*** (0.377)
Chemistry	-4.355*** (1.498)	-7.555*** (2.427)	2.226*** (0.414)	Priceline	-3.519** (1.551)	-3.556 (2.432)	2.189*** (0.426)
eHarmony	-3.761** (1.496)	-4.441 (2.421)	2.207*** (0.414)	Sears	-0.517 (1.436)	-3.278 (2.331)	3.219*** (0.383)
Expedia	-2.925 (1.549)	-1.661 (2.431)	2.154*** (0.426)	Southwest	-3.073** (1.559)	-3.057 (2.447)	2.273*** (0.431)
JC Penney's	-0.615 (1.467)	-0.442 (2.387)	2.391*** (0.440)	Sprint	-4.434*** (1.487)	-10.52*** (2.412)	2.286*** (0.433)
Macy's	-0.228 (1.444)	-2.245 (2.332)	2.812*** (0.386)	Target	-0.876 (1.544)	-2.346 (2.444)	2.678*** (0.493)
Match	-2.449 (1.499)	-2.165 (2.423)	2.242*** (0.414)	Verizon	-3.687** (1.493)	-15.91*** (2.435)	2.905*** (0.463)
Orbitz	-3.583** (1.552)	-3.684 (2.433)	2.292*** (0.426)	Victoria's	-1.836 (1.438)	-2.015 (2.327)	2.654*** (0.384)

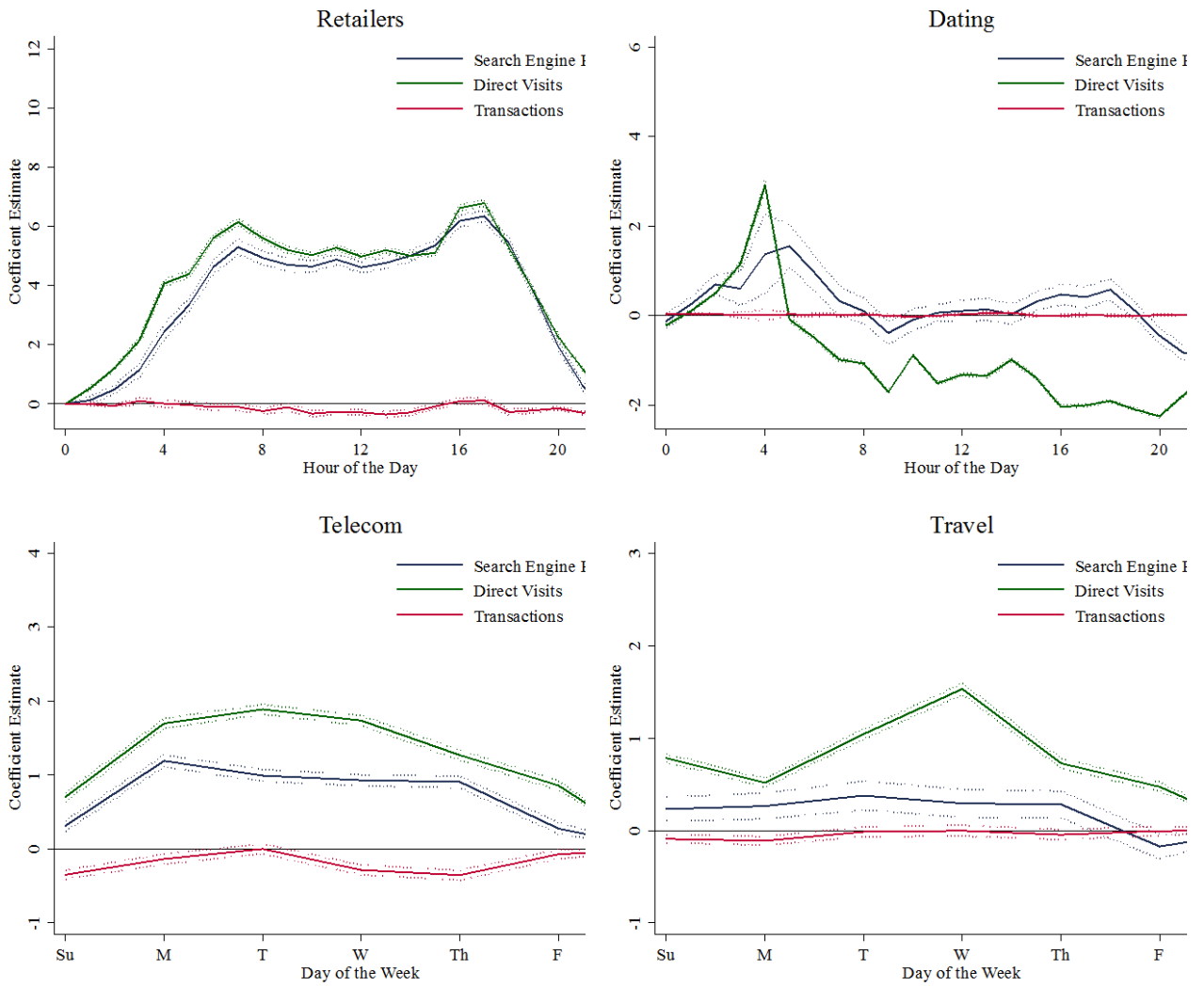
Notes: *** p<0.01, ** p<0.05. Robust standard errors in parentheses.

Table A3. Brand-Specific Parameter Estimates

2 Hrs. (D-in-D)DV:		<i>SE</i> ^{POST}				<i>Dir</i> ^{POST}				<i>TC</i> ^{POST}			
Predictor:	<i>SE</i> ^{PRE}	<i>Dir</i> ^{PRE}	<i>TC</i> ^{PRE}	<i>Est. Cost</i>	<i>SE</i> ^{PRE}	<i>Dir</i> ^{PRE}	<i>TC</i> ^{PRE}	<i>Est. Cost</i>	<i>SE</i> ^{POST}	<i>Dir</i> ^{POST}	<i>TC</i> ^{PRE}	<i>Est. Cost</i>	
Dating	Chemistry	0.0289 (0.0419)	0.138*** (0.0304)	-2.235*** (0.666)	4.63e-05 (2.93e-05)	-0.184*** (0.0691)	0.235*** (0.0703)	-2.416*** (0.678)	-0.000232*** (5.71e-05)	-0.00278 (0.00240)	-0.0114*** (0.00317)	0.0550** (0.0258)	1.05e-05** (4.14e-06)
	eHarmony	0.150*** (0.0116)	0.104*** (0.00614)	-0.406*** (0.0912)	-7.78e-06 (7.61e-06)	0.265*** (0.0223)	0.203*** (0.0130)	-0.515*** (0.181)	-2.49e-05 (2.09e-05)	0.00166 (0.00111)	0.00605*** (0.000809)	0.108*** (0.0200)	-1.64e-06 (1.74e-06)
	Match.com	0.388*** (0.0176)	0.0391*** (0.00883)	0.210** (0.104)	-2.39e-05 (1.86e-05)	0.178*** (0.0165)	0.283*** (0.0130)	0.535*** (0.157)	-8.73e-05*** (2.32e-05)	0.00271 (0.00175)	0.0139*** (0.00151)	0.0214 (0.0128)	-6.84e-06** (2.71e-06)
Retailers	Amazon	0.561*** (0.0571)	0.152*** (0.0381)	-0.0283 (0.110)	-9.26e-05*** (2.27e-05)	0.550*** (0.0833)	0.488*** (0.0578)	-0.0419 (0.156)	-0.000161*** (3.55e-05)	0.107*** (0.0266)	0.0786*** (0.0155)	0.128*** (0.0341)	-6.87e-06 (9.36e-06)
	JC Penney's	0.187*** (0.0104)	0.0851*** (0.00783)	-0.0503*** (0.0177)	1.62e-06 (1.24e-06)	0.300*** (0.0171)	0.260*** (0.00964)	-0.147*** (0.0315)	6.58e-06*** (1.68e-06)	0.0797*** (0.00719)	0.172*** (0.00571)	0.0185 (0.00950)	5.16e-07 (7.91e-07)
	Macy's	0.0508*** (0.00801)	0.0673*** (0.00597)	0.104*** (0.0238)	5.35e-06*** (9.79e-07)	0.186*** (0.0106)	0.235*** (0.00862)	0.0940*** (0.0275)	4.27e-06*** (1.52e-06)	0.0920*** (0.00618)	0.104*** (0.00411)	0.0392*** (0.0102)	-1.32e-06*** (4.89e-07)
	Overstock	0.0681*** (0.0180)	0.0599*** (0.0174)	0.0238 (0.0747)	5.11e-06*** (1.64e-06)	0.0538*** (0.0184)	0.106*** (0.0200)	0.0704 (0.0942)	1.27e-05*** (1.19e-06)	0.0508*** (0.00914)	0.0802*** (0.00744)	0.0110 (0.0394)	-1.54e-06** (6.50e-07)
	Sears	0.0174** (0.00744)	0.0725*** (0.00626)	0.0204 (0.0288)	1.67e-06** (6.80e-07)	0.0347*** (0.0105)	0.312*** (0.00881)	0.0761** (0.0338)	2.27e-06* (1.34e-06)	0.0519*** (0.00428)	0.0792*** (0.00543)	0.0253*** (0.00970)	7.75e-07** (3.26e-07)
	Target	0.289*** (0.00852)	0.253*** (0.00833)	-0.0922** (0.0364)	-9.81e-06*** (1.78e-06)	0.255*** (0.00913)	0.445*** (0.0110)	-0.231*** (0.0433)	-1.12e-05*** (2.77e-06)	-0.00471 (0.00388)	0.0822*** (0.00441)	0.0763*** (0.0122)	6.57e-07 (4.01e-07)
	Victoria's S.	0.104*** (0.0275)	0.0359** (0.0147)	0.0329 (0.0232)	1.03e-05*** (1.84e-06)	0.0604*** (0.0228)	0.276*** (0.0175)	-0.0968*** (0.0302)	1.01e-05*** (2.67e-06)	0.153*** (0.0353)	0.257*** (0.0176)	0.00159 (0.0118)	-1.57e-06 (1.15e-06)
Telecom.	AT&T	0.0739*** (0.00359)	0.0860*** (0.00117)	-0.0995*** (0.00553)	-7.63E-07 (4.34e-07)	0.207*** (0.00838)	0.568*** (0.00289)	-0.306*** (0.0133)	-3.63e-06*** (8.15e-07)	0.0973*** (0.00432)	0.0216*** (0.00118)	-0.00977*** (0.00362)	-4.28E-07 (2.42e-07)
	Sprint	-0.0677*** (0.00890)	-0.0474*** (0.00437)	0.000613 (0.0176)	1.39e-06*** (3.92e-07)	-0.0175 (0.0265)	0.0491*** (0.0127)	-0.0233 (0.0534)	8.26e-06*** (1.30e-06)	0.105*** (0.00718)	0.0791*** (0.00350)	0.0843*** (0.0111)	-1.75e-07 (2.32e-07)
	Verizon	0.0695*** (0.00481)	0.00984*** (0.00122)	-0.0133*** (0.00367)	4.79e-07 (3.83e-07)	0.222*** (0.0127)	0.545*** (0.00360)	-0.452*** (0.00992)	-1.04e-06 (1.05e-06)	0.184*** (0.00876)	0.0642*** (0.00199)	-0.00414 (0.00452)	1.02E-06 (5.35e-07)
Travel	Expedia	0.0797*** (0.0160)	0.110*** (0.00916)	-0.109*** (0.0380)	-1.05e-06 (6.76e-06)	0.155*** (0.0245)	0.264*** (0.0140)	-0.203*** (0.0616)	-4.77e-06 (9.79e-06)	0.0381*** (0.00863)	0.0338*** (0.00402)	0.0746*** (0.0143)	-1.87e-06 (2.42e-06)
	Orbitz	-0.0210 (0.0166)	-0.0143** (0.00690)	0.0921 (0.0571)	-2.51e-05*** (7.17e-06)	0.0571 (0.0305)	0.0254** (0.0128)	0.122 (0.0841)	-1.45e-05 (1.84e-05)	0.0358*** (0.00700)	0.0269*** (0.00360)	0.114*** (0.0204)	-1.01e-06 (4.02e-06)
	Priceline	0.0570*** (0.0153)	0.0212*** (0.00747)	-0.00277 (0.0401)	-2.63e-07 (1.90e-06)	0.0940*** (0.0187)	0.000921 (0.0116)	0.208*** (0.0550)	3.71e-07 (4.09e-06)	0.0243*** (0.00710)	0.0425*** (0.00374)	0.0751*** (0.0142)	2.31e-07 (4.33e-07)
	Southwest	0.0584 (0.0394)	0.0679*** (0.0249)	0.0248 (0.123)	1.39e-06** (6.56e-07)	-0.0779 (0.0711)	-0.00653 (0.0407)	0.590*** (0.202)	5.96e-06*** (1.24e-06)	0.0557*** (0.0179)	0.0645*** (0.0127)	-0.0599 (0.0441)	-6.90e-07*** (2.55e-07)

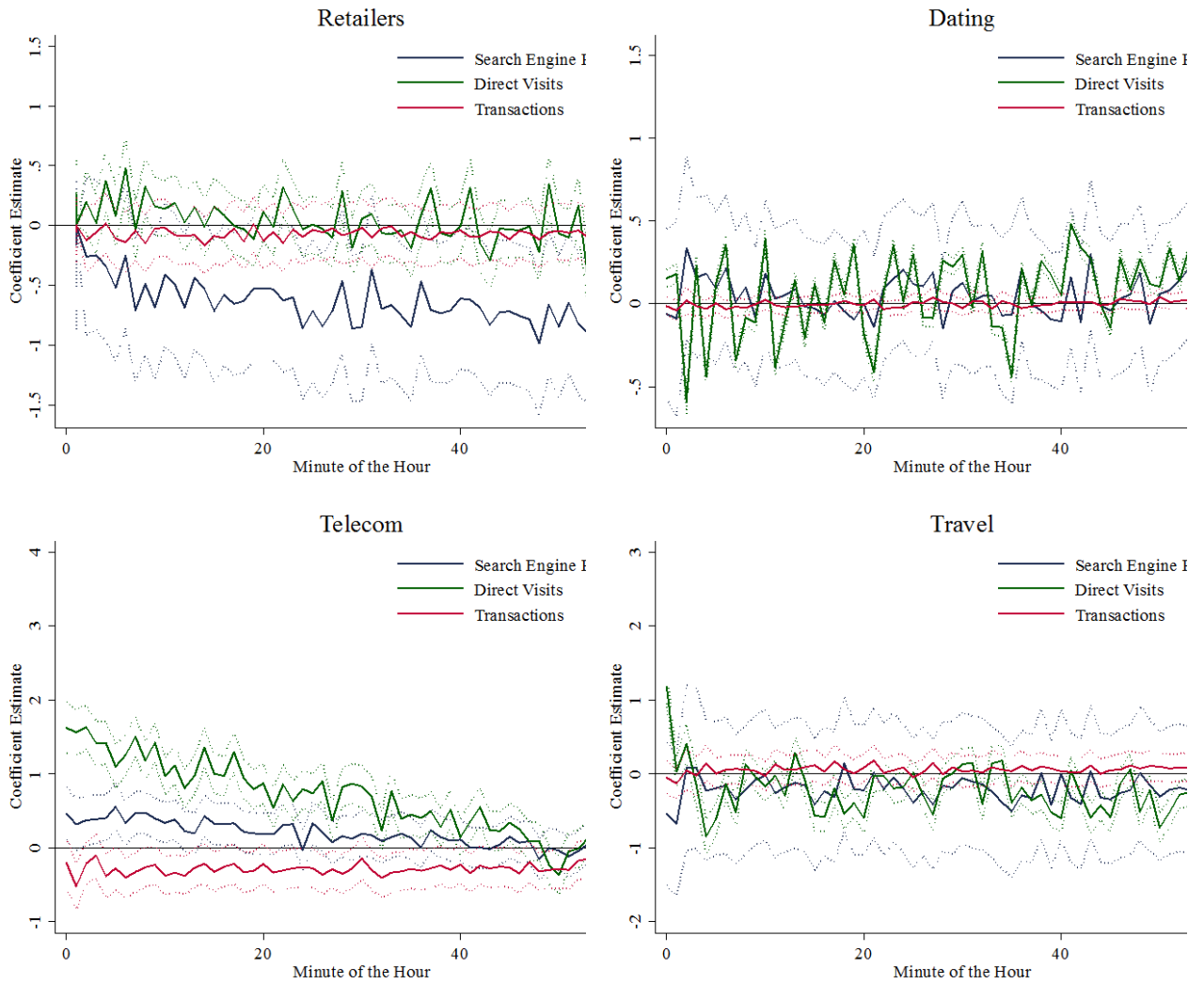
Notes: SE - search engine referrals; DIR - direct traffic; TC - transactions. Robust standard errors in parentheses. *** p<0.01, ** p<0.05.

Figure A1. Fixed Effect Estimates by Product Category and Hour of the Day



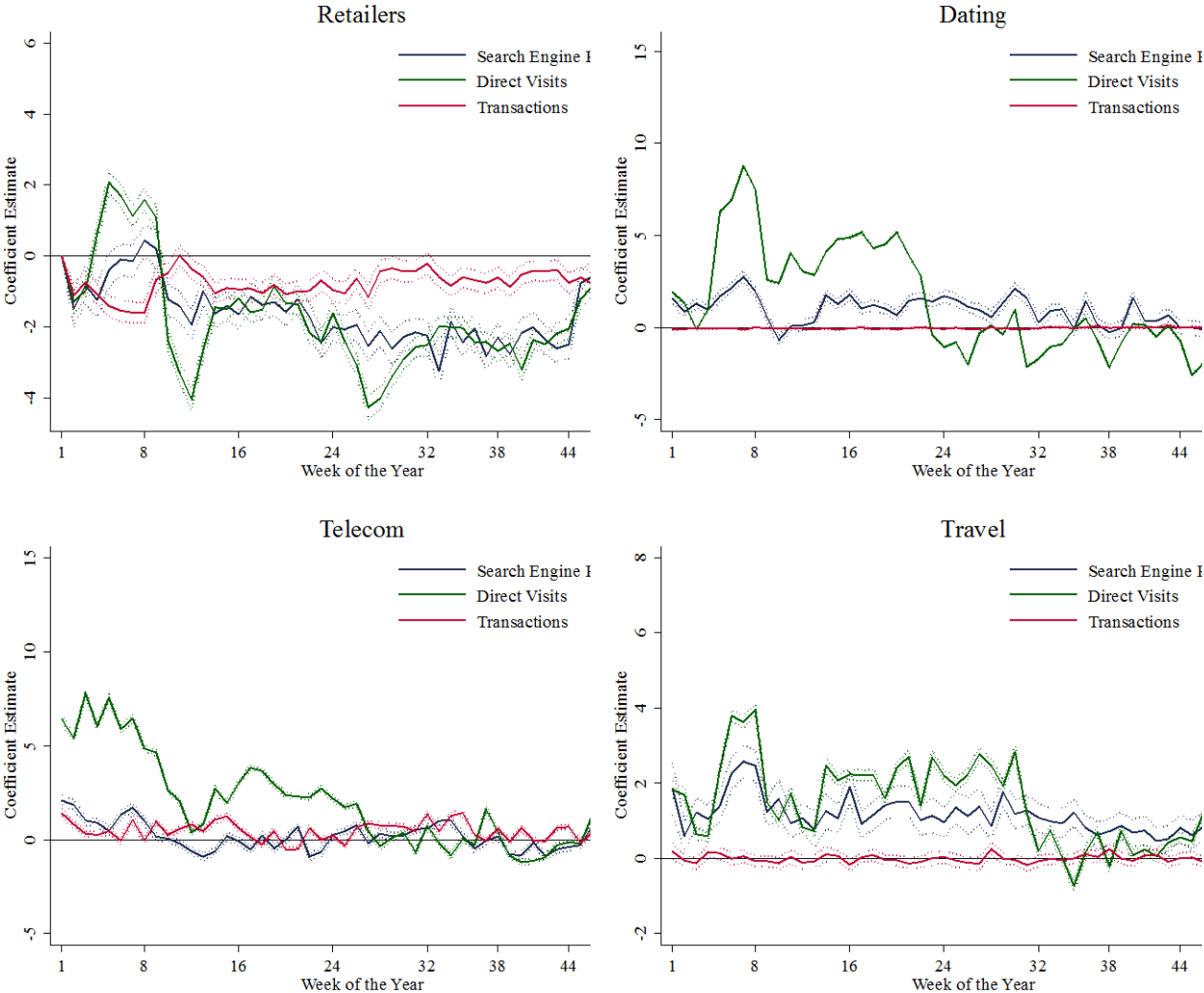
Notes: 24th hour omitted; Dotted lines indicate 95% confidence interval.

Figure A2. Fixed Effect Estimates by Product Category and Minute of the Hour



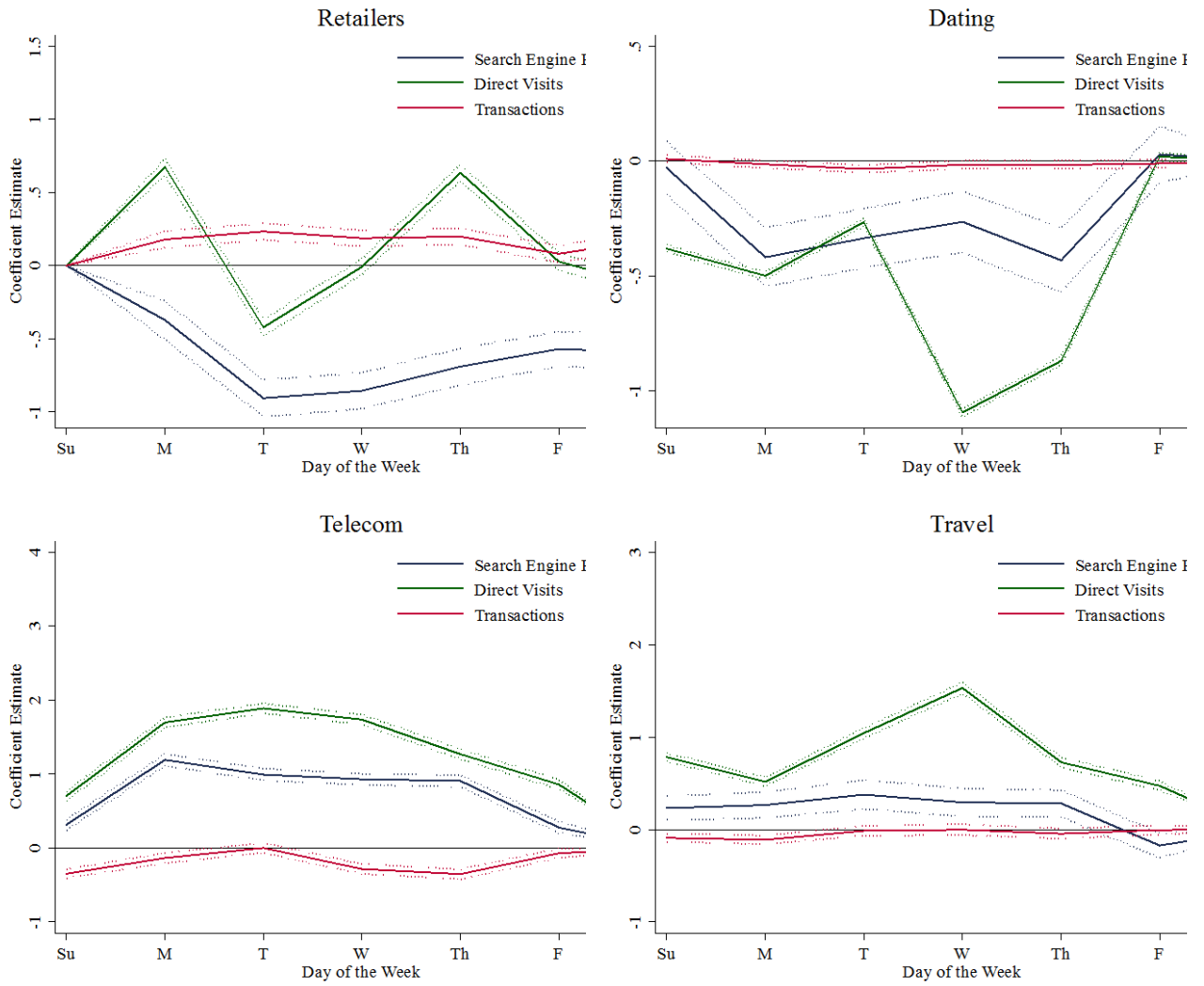
Notes: 60th minute omitted; Dotted lines indicate 95% confidence interval.

Figure A3. Fixed Effect Estimates by Product Category and Week of the Year



Notes: Week 1 means the week starting January 3, 2010; 52nd week is omitted; Dotted lines indicate 95% confidence interval

Figure A4. Fixed Effect Estimates by Product Category and Day of the Week



Notes: Saturday omitted; Dotted lines indicate 95% confidence interval