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Television Advertising and Online Search

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Despite a 20-year trend toward integrated marketing communications, advertisers seldom coordinate television and search advertising campaigns. We find that television advertising for financial services brands increases both the number of related Google searches and searchers' tendency to use branded keywords in place of generic keywords. The elasticity of a brand's total searches with respect to its TV advertising is 0.17, an effect that peaks in the morning. These results suggest that practitioners should account for cross-media effects when planning, executing, and evaluating both television and search advertising campaigns.

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1. Introduction

It is difficult to overstate the importance of television. The average American household contains 2.6 people and 2.5 televisions (Nielsen 2011, U.S. Census Bureau 2011). Television remains the most trusted source of news and information by a wide margin (Danaher and Rossiter 2011, eMarketer 2012). The average American watches 5.1 hours of television per day, more than the 4.6 self-reported daily hours spent on all work-related, educational, and housework activities (Nielsen 2011, Bureau of Labor Statistics 2011). The typical consumer is exposed to about 29 minutes of paid television advertising per day.[1]

Also remarkable is the growth of online search. Americans used core search engines like Google and Bing 17.7 billion times in July 2012, or about 1.8 times per person per day (comScore 2012). In other words, the average consumer now practices, about twice per day, an activity that barely existed 15 years ago. Perhaps the best evidence that search converts prospects to customers is provided by changes in advertising budgets. Marketers spent $14.8 billion on search advertising in 2011, a substantial amount relative to the $69.6 billion spent on television advertising in the United States (Internet Advertising Bureau 2012, Television Bureau of Advertising 2012).

Two decades of research and practice on integrated marketing communications have shown that delivering a consistent message through multiple consumer touch points is more effective than managing disparate, medium-specific campaigns. One might expect that advertisers would coordinate their television advertising and search advertising campaigns. After all, synchronizing "push" and "pull" tactics is an old topic in marketing.

Despite these apparent incentives, a review of Advertising Age's top traditional and online advertising agencies (AdAge 2011) showed that coordination of advertising campaigns across television and search media remains unusual. Client-facing agency websites were examined to determine each agency's services and areas of expertise. Table 1 presents some surprising results from this survey.

Twenty-four of the top 25 online advertising agencies do not offer television advertising services in-house. Twenty-four of the top 25 traditional advertising agencies do not offer search advertising services in-house. Only three of these 50 agencies coordinate online/offline advertising campaigns, and they define coordination as media budget planning or showing Web addresses in TV ads. The scarcity of coordinated television/search campaigns is further con-

[1] This inference assumes 11.3 minutes of advertising per hour, as is typical in prime time, and an advertising avoidance rate of 50%.

Table 1 Top Advertising Agencies' Service Offerings

	No. of top 25 search advertising agencies	No. of top 25 traditional advertising agencies
In-house services for both TV/search advertising		
No	24	24
Yes	1 (PlattForm)	1 (Ogilvy & Mather)
Online/offline coordination		
No coordination	23	24
Provide Web address in offline creative	1 (iProspect)	0
Provide media budget planning across media	1 (Covario)	0
Coordination offered but no details provided	0	1 (Leo Burnett)
Online/offline integrated performance metrics		
None offered	21	21
Media budget allocation only	2 (Acronym, Rosetta)	2 (Doner, Martin)
ROI across all media	1 (Covario)	2 (Campbell Ewald, Leo Burnett)
Metrics for effects of TV to online	1 (iProspect)	0

firmed by the topic's absence in leading advertising textbooks and academic literature and by personal conversations with dozens of researchers and managers at Amazon, Google, Yahoo! and other firms. As Enge (2012) explained, "there is a big gap between traditional marketing thinking and the way search marketers typically think. For [the search marketing] industry to reach full maturity, that gap needs to close, and there needs to be movement on both sides."

The purpose of this paper is to investigate whether and how television advertising expenditures influence online search behavior. The empirical analysis combines two comprehensive databases of television advertising and consumer search in the financial services product category. The Internet search data are provided by Google and include well over one billion searches for financial services keywords. The advertising data record the exact times and estimated expenditure on 58,226 television advertisements aired by 15 financial services brands at a total cost of about $200 million. The effects of television advertising on online search are identified by changes in the hourly time series of search behavior corresponding to brands' placements of television advertisements. The effects of primary interest are highly robust and can be reproduced through several different estimation techniques.

Although the academic literature has not explored the effects of television advertising on online search, a few practitioner studies have considered it. iProspect (2007) surveyed consumers and found that 37% of Internet users reported that a television ad had prompted them to conduct an Internet search. However, work of this kind is typically based on searchers' self-reports, includes limited controls for competing explanations and often focuses on a single brand. The one extant study based on passively measured search data is that by Zigmond and Stipp (2010). They presented several case studies that showed peaks in Google searches corresponding to several TV ads that aired during the Vancouver Winter Olympics. We extend this research by examining a mature product category over a three-month period, estimating both short- and longer-run effects of advertising, and by separately considering how TV advertising may affect both the volume of category search and the probability of choosing a branded keyword.

The analysis indicates that TV advertising increases the number of product category-relevant searches and increases consumers' tendency to use branded keywords. The elasticity of a financial services brand's online searches with respect to its advertising is 0.17, an effect that is largest in the morning and smallest in the late afternoon. These findings suggest that brands might profit from coordinating their television and search advertising campaigns.

1.1. Relationship to Prior Literature

A burgeoning literature is finding that advertising in one medium may influence the results of advertising in another medium (Assael 2011). Naik and Raman (2003) and Vakratsas and Ma (2005) gave evidence of advertising synergies among multiple offline media, and Naik and Peters (2009) found synergies between spending in online and offline media. Lewis and Reiley (2011) found via a large-scale controlled experiment that 93% of the effects of *online* display advertising were found in *offline* retailer sales. Goldfarb and Tucker (2011) found a substitution pattern between online advertising and offline advertising: advertisers pay more for online search keywords when offline advertising is prohibited. Lewis and Nguyen (2012) and Papadimitriou et al. (2011) ran field experiments and found that display advertising increased searches for both the advertised brand and its competitors. Rutz and Bucklin (2012) found a similar effect: users exposed to a display advertisement on a product search engine were subsequently more likely to browse pages related to the advertised brand. The current paper buttresses the existing media synergies literature by showing specifically how advertising in one medium can change consumer behavior in another.

A small number of recent papers have predicted ways in which cross-media advertising effects might influence market competition. Kim and Balachander (2010) showed how an advertiser's cost per consumer in traditional media influences its optimal bid on search results. They found that advertisers have incentive to coordinate search advertising with traditional advertising, even when doing so is costly. Bergemann and Bonatti (2011) investigated the role of targeting in the competition between offline and online media. They predicted that the entry of highly targeted media (online) will increase the price of less targeted media (offline) and reduce their revenues. The possibility that advertisers may free ride on competitors' offline advertising was explored by Sayedi et al. (2011). They showed that symmetric firms may develop asymmetric strategies, with one firm investing in offline advertising to build category demand while the other firm uses targeted search advertising to free ride on competitors' investments. Our findings help to explain how online and offline media interact with each other to generate such effects in a market.

These effects are particularly relevant to the literature on search engine marketing (Jerath and Sayedi 2011, Jerath et al. 2011, Katona and Sarvary 2010, Rutz and Bucklin 2011, Rutz and Trusov 2011, Wilbur and Zhu 2009, Yang and Ghose 2010, Yao and Mela 2011, Zhu and Wilbur 2010). As competition in the search engine setting becomes better understood, a natural way to extend this literature is to consider how search marketers may use traditional "push" media such as television to compete before consumers even arrive at the search engine.

2. Data and Measures

This section explains why we chose to study the financial services category, introduces the measures and data, and describes how their characteristics influence the modeling choices presented below.

2.1. Research Context: Product Category Choice

A product category suitable for determining how offline advertising influences online search should exhibit four characteristics. The first criterion relates to whether effects of advertising on search exist, whereas the other three relate to an analyst's ability to detect those effects in market data.

1. *Consumers must search category brand names online.* High-involvement categories may be most appropriate since consumers are likely to actively gather information related to brands and products within those categories. Categories with infrequent choices or high prices might be most appropriate, since consumers cannot gather information easily through product trial.

2. *Category brands' offline advertising must be measured with high frequency.* Television advertising expenditures may be observed by day and precise time, as are online search data. Advertising expenditure data for other offline media such as radio, magazines, and billboards are typically only observed to vary monthly. Variation in advertising expenditure over time is critical to identify the effect of advertising on search behavior.

3. *Category brand names should not overlap too much with commonly searched keywords.* Otherwise, category searches cannot be separated from unrelated searches. For example, it would not be clear whether a search for "Apple" is for a fruit or a computer. Many well-known brands—like Miller, Target, and Visa—present this problem.

4. *The category should not be subject to obvious simultaneity concerns.* For example, advertising and consumer search for a movie both peak around the date the movie is released in theaters. It would be difficult to tease apart the effect of advertising from the effect of the movie release date or other contemporaneous promotions without good instrumental variables. Ideally, the researcher should be able to get data on exogenous time-varying factors that may shift searchers' tendency to search for brands in the category to separately identify the effect of television advertising from other factors that vary over time.

The financial services product category scores well on all four criteria. It is a high-involvement category with infrequent choice, as consumers tend to stay with investment brokerages for long periods of time. It is the seventhmost advertised product category on television. Most major financial services brand names, such as Schwab and Ameritrade, generally do not overlap with commonly searched keywords, as shown in Table 2. The data do not suggest simultaneity, as §4 below explores in depth.[2]

2.2. Dependent Variables: Consumer Search Behavior

Marketing academics have studied consumer search extensively since the 1970s. The literature implies three primary reasons that television advertising is likely to influence online search: objective knowledge, perceived knowledge, and incidental exposure.

First, television advertising may increase consumers' objective knowledge of product or category features and benefits, and this may influence consumer search. For example, Brucks (1985) found that some objective knowledge increases consumers' ability to acquire additional knowledge and makes search more efficient. Several studies have related these effects directly to objective knowledge provided by

[2] Several other product categories were considered. The automotive category scores well on all criteria except the third. The pharmaceutical category scores well on all criteria except the first, since most consumers (but certainly not all) get information about most drugs from their doctors rather than from search engines. For example, the keyword "fidelity" is searched about 60 times as frequently as the keyword "Vioxx." Movies and video games score well on all criteria except the fourth.

Table 2 Most Common Financial Services-Related Keywords

Most common generic keywords		Most common branded keywords	
SEP	INVESTORS	AGEDWARDS	ML
401 K	IRA	AMERITRADE	MORGANSTANLEY
ANNUITY	LIABILITY	AMERIVEST	NETBENEFITS
BALANCE	LIQUIDITY	CITI	NUVEEN
BENEFITS	LOAN	CITIBANK	OPPENHEIMER
BONDS	LOANS	CITIFINANCIAL	OPPENHEIMERFUNDS
BROKER	MUTUAL	CITIGROUP	OPTIONSXPRESS
BROKERS	OPTIONS	CITIMORTGAGE	RAYMONDJAMES
CHECKING	PAY	CLEARSTATION	SCHWAB
CONTRIBUTION	PAYMENT	CYBERTRADER	SCOTTRADE
CREDIT	PREPAID	EBTACCOUNT	SHAREBUILDER
DEBIT	PROFIT	EDWARDJONES	SOUTHTRUST
DIVIDEND	RETIREMENT	ETRADE	TD
DIVIDENDS	SECURED	EWORKPLACE	TDWATERHOUSE
EBT	SECURITIES	FIDELITY	TROWE
EQUITY	SHARES	FIDELITYINVESTMENTS	VANGUARD
ETF	SHARING	FOREX	VANKAMPEN
FIXED	STATEMENT	FXCM	WACHOVIA
FUND	STOCK	LEGGMASON	WATERHOUSE
FUNDS	STOCKS		
INCOME	TRADE		
INVEST	TRADING		
INVESTING	TRUSTS		
INVESTMENT	UGMA		
INVESTMENTS	YIELD		

advertising. Newman and Staelin (1973) showed that advertising may enlarge the set of brands a consumer can recall easily. Bettman and Park (1980) found that consumers with moderate amounts of prior product information are more likely to search for a brand than those with little prior information. Therefore, television advertising might stimulate online search if it increases consumers' stock of objective knowledge.

Second, advertising may alter how much a consumer thinks she knows ("perceived knowledge"), which may influence how the consumer searches. Numerous studies have shown perceived knowledge to differ from objective knowledge with correlations ranging from 0.05 (Radecki and Jaccard 1995) to 0.65 (Park et al. 1994). Moorman et al. (2004) experimentally manipulated perceived knowledge by first testing subjects' knowledge in a particular domain, then randomly giving artificially low test results to some knowledgeable subjects and artificially high test results to some unknowledgeable subjects. Inflated test scores (high perceived knowledge) led to search strategies that were less likely to uncover disconfirming information. Therefore, if branded television advertising increases consumers' perceived knowledge, it may increase the chance the consumer enters branded keywords into a search engine.

Third, incidental exposure to advertising has been found to influence consumers outside their conscious awareness. Incidental exposure refers to advertising that is perceived but not processed. It commonly occurs when consumers redirect their attention during television commercial breaks. Janiszewski (1993) found that incidental exposure enhances brand liking. Shapiro et al. (1997) found that incidental exposure to advertising influenced the products that enter consumers' consideration sets, even when the consumers are not consciously aware that they saw the ads. Shapiro (1999) took this a step further, showing that incidental ad exposure led to consideration set inclusion, even when subjects were explicitly instructed to avoid choosing products depicted in ads. Therefore it is possible that incidental exposure to television advertising changes the keywords a consumer would use to search.

This literature indicates that information can affect both the likelihood of search and the means of search. We therefore distinguish between *category search* and *keyword choice*. Category search is defined as the number of searches in a period that contained generic or branded financial services-related keywords. Keyword choice is defined as the fraction of all keywords entered that are related to a particular brand in the category. In earlier research, a data mining technique was developed to identify a set of generic and branded keywords and determine which searches were relevant to the financial services product category; for full details, see Joo et al. (2013). This procedure identified several previously unknown branded keywords and a large set of generic keywords that were frequently used in searches that led to clicks on financial services brands' websites. Table 2 provides the common branded and generic keywords in the data set.

This distinction between category search and keyword choice has important implications for consumers as well as marketers. People who search a branded keyword receive less information about competitors than those who search generic keywords. Paid advertising clicks also tend to cost less when consumers search branded keywords, because these keywords' auctions typically enroll fewer bidders than generic keyword auctions. It also may be the case that a consumer who searches a branded keyword has revealed a greater willingness to purchase than one who has used a generic keyword.

2.3. Data Sources

The analysis combines a large online search data set with a comprehensive television advertising database. The online data count all searches containing product category-relevant keywords received by Google from U.S. users in the eastern time zone between October 1 and December 31, 2011.[3] The search counts were aggregated hourly at the state level; information about individual users, their characteristics, or search history was not included. Company disclosure policies prevent us from revealing the specific number of searches for this set of keywords, but we are able to report that it was substantially more than one billion.

Television advertising expenditure data were gathered from Kantar Media's "Stradegy" database. Kantar computers monitor all paid advertisements in national broadcast and cable networks and all local broadcast stations in the United States. Each unique new advertising creative is flagged and watched by a Kantar employee, who then records the advertised brand, product, and product category. Kantar supplements the ad occurrence data with program-specific average advertising prices reported by the networks.[4] For each ad in the sample period, the data report the brand advertised (e.g., Fidelity), the network, start time, duration, and the estimated cost.

These two time series are linked at the hour level. The choice of the hour as the unit of analysis balances the competing concerns of data sparseness and possible aggregation biases. It also requires fewer lags to be estimated than if the data were combined at a more disaggregate level (e.g., minute or second). The sample period includes 2,208 hours in 92 days. There are 22 brands in the data, so the sample size in the keyword choice analysis is 48,576.

2.4. Control Variables: Time Effects and Stock Market Indices

The empirical model relies on brand dummies, time fixed effects, and movements in a stock market index to estimate baseline consumer tendencies to search. Advertising effects on search behavior are then identified by deviations from this baseline corresponding to brands' TV advertising expenditures.

The time controls consist of fixed effects for each week in the sample, to allow baseline category search tendency to vary across weeks, and two sets of hourly fixed effects: one for weekdays and another for weekends.[5] This allows baseline tendencies to vary according to times when white-collar workers are in the office or not.

A stock performance index, the Dow Jones Industrial Average (DJIA), is used as an exogenous variable to control for unobserved time-varying determinants of searchers' online actions. DJIA levels are widely reported in the media; recent movements in the stock index may lead consumers to check their account balances by searching their financial service providers' brand names. Two variables based on DJIA are included: (1) the absolute *positive* percentage change since the most recent trading day's opening value and (2) the absolute *negative* percentage change since the most recent trading day's opening value. These variables allow the effect to be asymmetric around zero and proved to fit the data better than several alternate specifications.

2.5. Descriptive Statistics

Table 3 describes the advertising and search data. To comply with company disclosure policies, the search data are normalized so that the weekday average totals 100. Keyword search and advertising expenditures varied considerably across brands. Four brands (Charles Schwab, CitiGroup, *E*-Trade, and TD Ameritrade) spent more than $100,000 per day on TV advertising, whereas nine other brands spent less than $1,000 per day. Generic financial services keywords are searched three times as frequently as branded keywords. Category search fell by 29% from weekdays to weekend days, whereas brand advertising expenditures were 85% higher on weekend days than on weekdays.

Figure 1 shows the variation in the advertising expenditures of the three highest-spending brands across days in the sample. Whereas CitiGroup spent about equally on weekdays and weekends, *E*-Trade

[3] Only searches in the eastern time zone were considered to match the data on TV ads' times of airing.

[4] Advertising ratings and demographics would be preferable to expenditures, but these additional data were cost prohibitive. In their absence, it is necessary to presume that ad prices correlate with program audiences. This presumption is common in the literature and has substantial empirical support (e.g., Wilbur 2008).

[5] Specification tests preferred these two sets of day/hour dummies to a simpler alternative (24 hourly dummies that did not vary across weekdays) and a more complex alternative (a different set of 24 hourly dummies for each of the seven weekdays). The advertising response parameter estimates were robust to the alternate day/hour specifications.

Table 3 **Descriptive Statistics**

	Monday–Friday daily averages		Saturday–Sunday averages	
Brands	Normalized query volume[a]	Adv. exp. ($000)	Normalized query volume[a]	Adv. exp. ($000)
AG Edwards	0.00	0	0.00	0
Charles Schwab	0.27	130	0.11	298
CitiGroup	5.18	1,075	3.41	1,153
E-Trade	0.19	151	0.09	635
Edward Jones	0.01	38	0.00	89
Fidelity	0.66	96	0.31	365
Forex	0.38	4	0.34	8
FXCM	0.01	2	0.01	3
Legg Mason	0.00	0	0.00	0
Merrill Lynch	9.65	3	7.52	2
Morgan Stanley	0.03	0	0.02	0
Nuveen	0.01	0	0.00	0
Oppenheimer	0.05	0	0.02	0
OptionsXpress	0.01	5	0.00	0
Raymond James	0.00	14	0.00	31
Scottrade	0.19	22	0.05	64
ShareBuilder	0.03	0	0.01	0
T. Rowe Price	0.09	32	0.06	255
TD Ameritrade	6.67	166	5.15	311
Vanguard	0.34	0	0.21	0
Van Kampen	0.00	0	0.00	0
Wachovia	0.26	0	0.16	0
All brand keywords	24.00	1,738	17.48	3,214
All generic keywords	76.00	—	54.17	—
Total (brand+generic)	100.00		71.65	

[a]Normalized query volume standardizes query totals so that the daily average of total searches (branded plus generic) on weekdays is 100.

and TD Ameritrade spent two to four times more on weekend days. Figure 2 shows the distribution of these brands' expenditures across hours on weekdays and weekend days. The correlations are much higher here, as television viewing peaks at prime time. However, Citi's media strategy relies on prime time to a proportionally greater extent, whereas *E*-Trade and TD Ameritrade tend to spend more money on weekend afternoons.

3. Empirical Model

This section derives estimating equations to relate category search and keyword choice to television advertising.

3.1. Models

Equation (1) relates category search in each day/hour period t to advertising and control variables:

$$y_t = \sum_{\tau=0}^{T} a_{t-\tau}\beta_\tau + X_t\alpha + \varepsilon_t, \tag{1}$$

where $y_t = \ln(Y_t)$ is the log of the total number of category searches Y_t (including both generic and branded keywords) in period t, $a_t = \ln(1 + A_t)$ is the log of one plus category television advertising expenditure A_t in period t,[6] β_τ is the effect of TV advertising done in period $t - \tau$ on the number of category searches performed in period t, and $T = 96$ is the number of hourly lags of advertising included in the model. The vector X_t contains control variables—an intercept, day/hour fixed effects, week fixed effects, and the two DJIA index variables—described in §2.4; α is a vector of parameters that represent the effects of the exogenous variables on category search, and ε_t is an error term that accounts for any unobserved determinants of the number of category searches in period t.

Given a volume of category searches, Equation (2) relates the keyword choice share for each brand $k = 1, \ldots, K$ in each period t to advertising and covariates:

$$s_{kt} = \frac{\exp(\sum_{\tau=0}^{T} a_{k,\,t-\tau}\gamma_\tau + X_{kt}\delta + \xi_{kt})}{1 + \sum_{k'=1}^{K}\exp(\sum_{\tau=0}^{T} a_{k',\,t-\tau}\gamma_\tau + X_{k't}\delta + \xi_{k't})}, \tag{2}$$

where s_{kt} is the share of keywords entered in period t that are directly related to brand k (as defined in §2.2); $a_{kt} = \ln(1 + A_{kt})$ is the log of one plus the television advertising expenditure A_{kt} of brand k in period t; γ_τ is the effect of TV advertising done by brand k in period $t - \tau$ on its keyword choice share in period t; X_{kt} is a vector of exogenous control variables that includes an intercept, fixed effects for brand, day-hour, and week, and the two DJIA index variables; and ξ_{kt} is an error term that represents all unobserved determinants of brand k's keyword choice share in period t.

Equation (2) can be transformed into a linear model by taking logs and subtracting the log of generic keywords' share from both sides (Berry 1994):

$$z_{kt} = \sum_{\tau=0}^{T} a_{k,\,t-\tau}\gamma_\tau + X_{kt}\delta + \xi_{kt}, \tag{3}$$

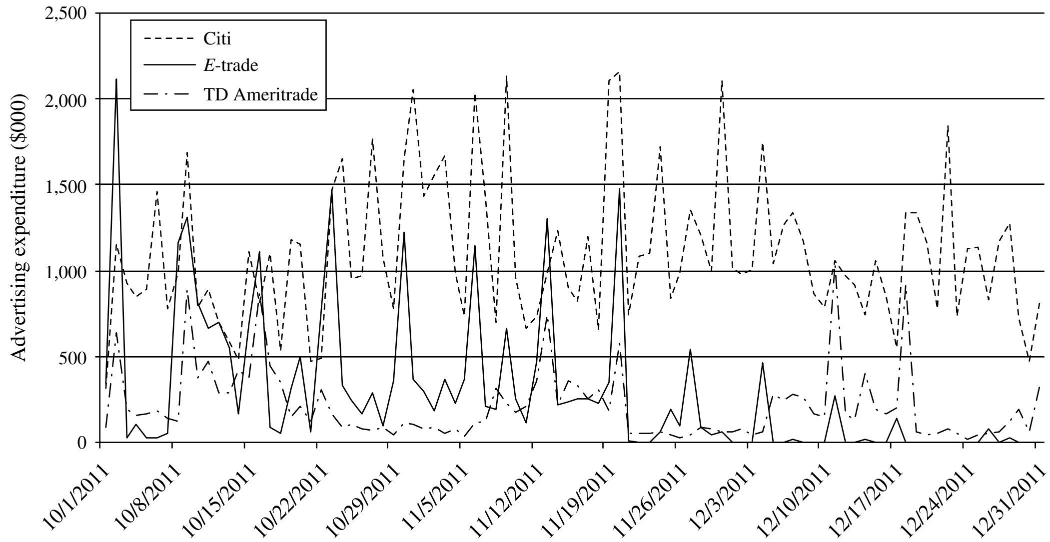
where $z_{kt} = \ln(s_{kt}) - \ln(s_{0t})$ and s_{0t} is the fraction of total category searches in period t for purely generic keywords (i.e., the share of searches that do not contain any branded keywords).

3.2. Almon Parameterization of Advertising Effects

The primary drawback of direct estimation of distributed-lag models such as (1) and (3) is that, for

[6] The empirical findings are qualitatively robust to replacing this measure of advertising with raw expenditure or share of voice. We use logs of search volume and advertising expenditures because visual inspection of the data showed the relationship between these two variables to be approximately log-linear.

Figure 1 **Major Brands' Ad Spending by Date**



large T, the number of β_τ and γ_τ parameters to be estimated is large. Almon (1965) proposed a simpler parameterization of distributed-lag models to address this issue. The fully specified distributed-lag function is replaced with an assumption that the effects of lagged television advertising on search behavior can be approximated by a p–degree polynomial function of the time lag; that is, we assume

$$\beta_\tau = \sum_{\rho=0}^{p_1} \theta_\rho \tau^\rho \quad \text{and} \tag{4}$$

$$\gamma_\tau = \sum_{\rho=0}^{p_2} \eta_\rho \tau^\rho, \tag{5}$$

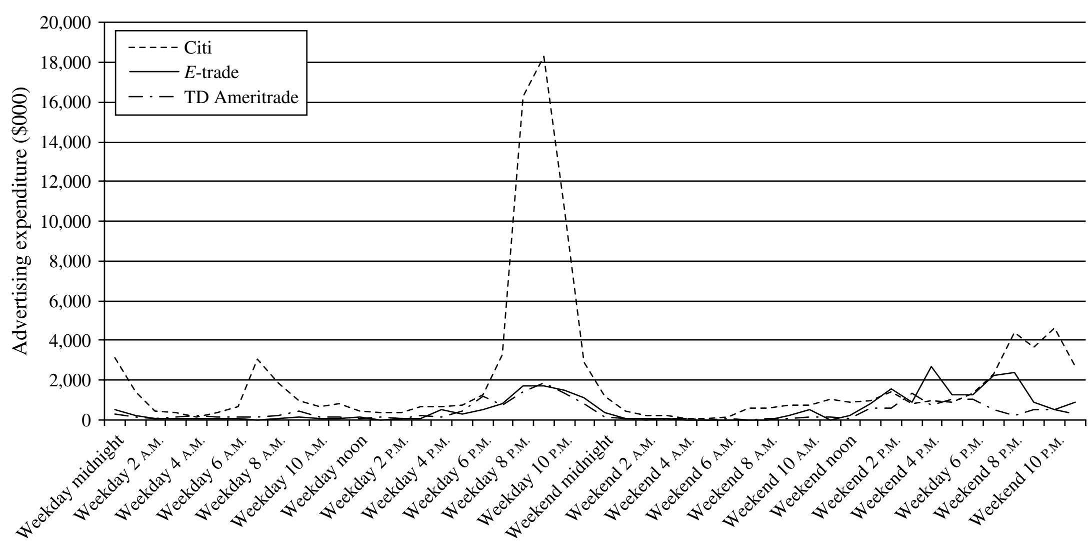
where the θ_ρ and η_ρ terms are parameters to be estimated. In other words, the Almon (1965) model assumes that the effect of the τth lag on current search behavior is given by a p-order polynomial in τ. For large p, this can provide a very flexible representation of the effects of lagged advertising on search behavior. This transforms Equations (1) and (3) into

$$y_t = \sum_{\rho=0}^{p_1} \theta_\rho v_{\rho t} + X_t\alpha + \varepsilon_t \quad \text{and} \tag{6}$$

$$z_{kt} = \sum_{\rho=0}^{p_2} \eta_\rho w_{k\rho t} + X_{kt}\delta + \xi_{kt}, \tag{7}$$

where $v_{\rho t} = \sum_{\tau=0}^{T} \tau^\rho a_{t-\tau}$ and $w_{k\rho t} = \sum_{\tau=0}^{T} \tau^\rho a_{k,\,t-\tau}$ are functions of past advertising that may be constructed

Figure 2 **Major Brands' Ad Spending by Day/Hour**



directly from the data (Gujarati 2003 provides a detailed explanation). The number of advertising effectiveness parameters to be estimated has fallen from $2T$ to $p_1 + p_2$, and the original effects of the lags can be recovered by plugging the estimates of θ_ρ and η_ρ into Equations (4) and (5).[7]

Davidson and MacKinnon (1993) and Gujarati (2003) give prescriptive advice on how to choose the number of lags (T) and degree of polynomials (p_1 and p_2).[8] The number of lags is settled first by including a relatively large number of lags and then dropping some to check whether including fewer lags appreciably reduces the fit of the model. Second, the degree of the polynomial is specified for each model by starting from the lowest-order polynomial and incrementing p until either the last parameter added contains zero within its 95% confidence interval or until the covariance matrix of the parameter estimates becomes noninvertible because of multicollinearity.

3.3. Serial Correlation in Search Behavior

The measures of online search behavior are serially correlated. A common remedy for this is to estimate the model by taking the first differences of Equations (6) and (7),

$$y_t - y_{t-1} = \sum_{p=0}^{\rho} \theta_p (v_{pt} - v_{p,\,t-1}) + (X_t - X_{t-1})\alpha + \varepsilon_t - \varepsilon_{t-1}, \quad (8)$$

$$z_{kt} - z_{k,\,t-1} = \sum_{p=0}^{\rho} \eta_p (w_{kpt} - w_{kp,\,t-1}) + (X_{kt} - X_{k,\,t-1})\delta + \xi_{kt} - \xi_{k,\,t-1}. \quad (9)$$

Analytically, Equations (8) and (9) estimate the same parameters as direct estimation of Equations (6) and (7), but the first differences estimator is more efficient than fixed effects estimator when the errors are serially correlated (Wooldridge 2010). The appendix provides further information about estimation, including modeling choices, serial correlation tests, and standard errors.

[7] A popular alternative to the Almon (1965) parameterization is the Koyck model, which would assume that an infinite number of lags enters Equations (1) and (2) and that the effects of those lags decrease monotonically and exponentially. Clarke (1976) discusses the application of the Koyck model to advertising response, and Gujarati (2003) compares the Koyck and Almon models. The Almon model is more flexible and can replicate a Koyck decay pattern when the number of lags is large and the degree of the polynomial is two or larger.

[8] For further discussion, see Thomas (1977).

3.4. Measure of Advertising Elasticities

A standard approach to presenting the size of an advertising effect is to calculate it as an elasticity (e.g., Ataman et al. 2010, Lodish et al. 1995). We measure the percentage change in total future searches for brand k (defined as $q_{kt} = \sum_{\tau=0}^{T} Y_{t+\tau} s_{k,\,t+\tau}$, the number of branded searches between points t and $t+T$, inclusive) given a change in brand k's television advertising expenditure (A_{kt}) at time t. From Equations (1) and (2), this elasticity is

$$\frac{\partial q_{kt}}{\partial A_{kt}} \frac{A_{kt}}{q_{kt}} = \frac{A_{kt}}{q_{kt}(1+\sum_k A_{kt})} \sum_{\tau=0}^{T} Y_{t+\tau} \beta_\tau s_{k,\,t+\tau} + \frac{A_{kt}}{q_{kt}(1+A_{kt})} \sum_{\tau=0}^{T} Y_{t+\tau} \gamma_\tau s_{k,\,t+\tau} (1 - s_{k,\,t+\tau}). \quad (10)$$

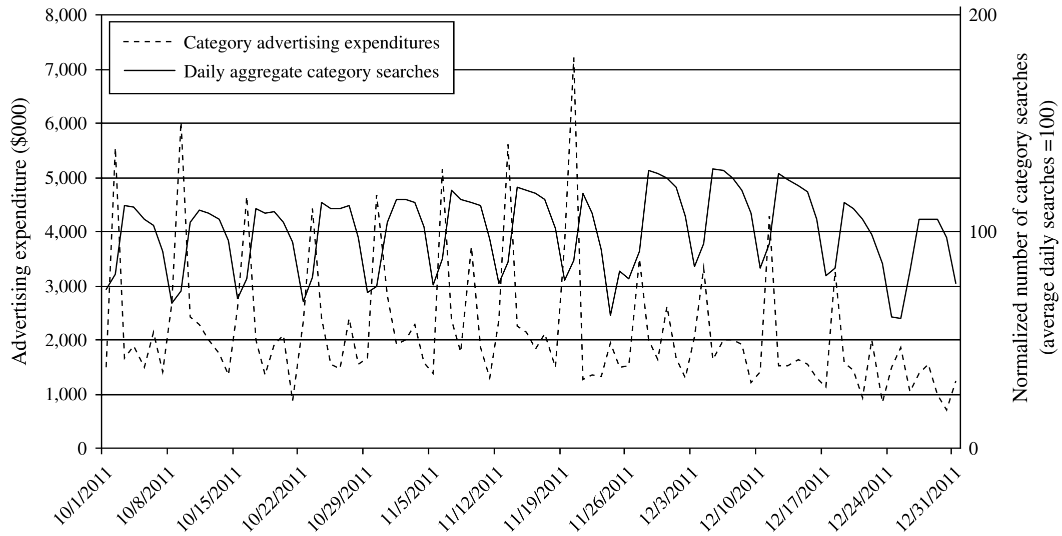
The first term on the right-hand side of Equation (10) represents the increase in searches for brand k's keywords due to the expansion in the number of category searches, holding brand k's share of category searches constant. The second term is the increase in searches for brand k's keywords accruing to its increase in keyword choice share, holding total category searches constant. The first term is analogous to a "category expansion" effect, measuring the increase in brand searches accruing to an increase in category search total, holding the brand's keyword choice share constant. The second term is similar to a "business stealing" effect, showing the increase in the brand's searches due to its change in keyword choice share, holding total category search constant. The relative size of each effect will influence the managerial implications of the results.

4. Identifying Assumptions

In the present application, the temporal ordering that advertisements must be purchased prior to airing rules out the possibility that consumer search data (y) directly cause TV advertising placements (x). However, there are two ways in which television advertising (x) may depend indirectly on online search behavior (y).

One possible source of endogeneity is that brands anticipate when consumers will search and purchase television advertising at times that will maximally influence that search. To investigate this, we held a series of several dozen informal conversations with managers and researchers working in marketing and advertising at three leading Internet companies (Google, Yahoo!, and Amazon) and two leading financial services brands in the sample. We began each conversation by asking whether brands typically

Figure 3 **Category Search and Ad Spending by Date**

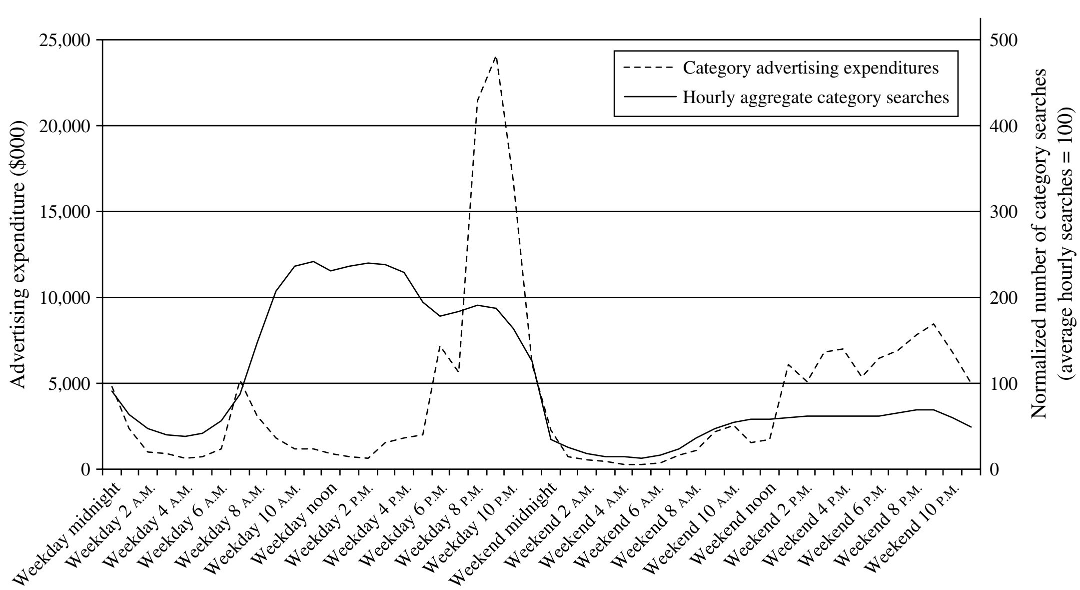


coordinate their television advertising and search engine marketing campaigns. Our conversation partners were unanimous that they did not know of any firms who were using *any* online search data to plan their television advertising campaigns.

We also investigated the available data to check for evidence that brands were anticipating spikes in online search activity. If television advertising expenditures were planned on the basis of expected search volume, one would expect advertising expenditures to increase immediately before or during periods of intense category search. Figures 3 and 4 present data showing that such covariation is not obvious. Although category search and television advertising show extensive variation across days within the week, search varies reasonably little over weeks in the sample. In addition, the two variables do not seem to correspond in their extremes. Advertising peaked on November 20, but there was no apparent movement in search volume, at least in the daily aggregates. Search activity peaked on December 5, but advertising expenditures lay below their sample average on this date. Search volume stayed high in the several weeks following December 5, whereas advertising expenditures remained fairly low. The correlation between daily advertising and daily search volume was −0.28.

Figure 4 corroborates this pattern among hours within weekdays and weekend days. The majority of advertising expenditures occur during prime time and weekend afternoons when category search is

Figure 4 **Category Search and Ad Spending by Day/Hour**



significantly lower than its peak during standard business hours. The available data do not allow us to falsify the hypothesis that brands planned advertising expenditures based on expectations of search data; there is no clear evidence to support that hypothesis.

The other possible source of endogeneity is that television advertising expenditures may be correlated with unobserved variables that also influence online search behavior. For example, if a financial services brand pulses its television advertising with advertising expenditures in other media (such as Internet display advertising), and those other media influence online search behavior, then one would expect the estimates reported in §5 to be inflated.

Under the identifying assumptions that (1) intertemporal variation in category television advertising is exogenous with respect to category searches and (2) intertemporal variation in brand television advertising is exogenous with respect to brands' keyword choice shares, the estimates may be interpreted as causal. We believe these assumptions to be credible based on our understanding of the industry and our inspection of the data. However, the possibility remains that unobserved variables may lead to inflated estimates of the effects. This alternate hypothesis is not falsifiable using the available data.

5. Findings

This section presents results of first-difference regressions of Equations (8) and (9).

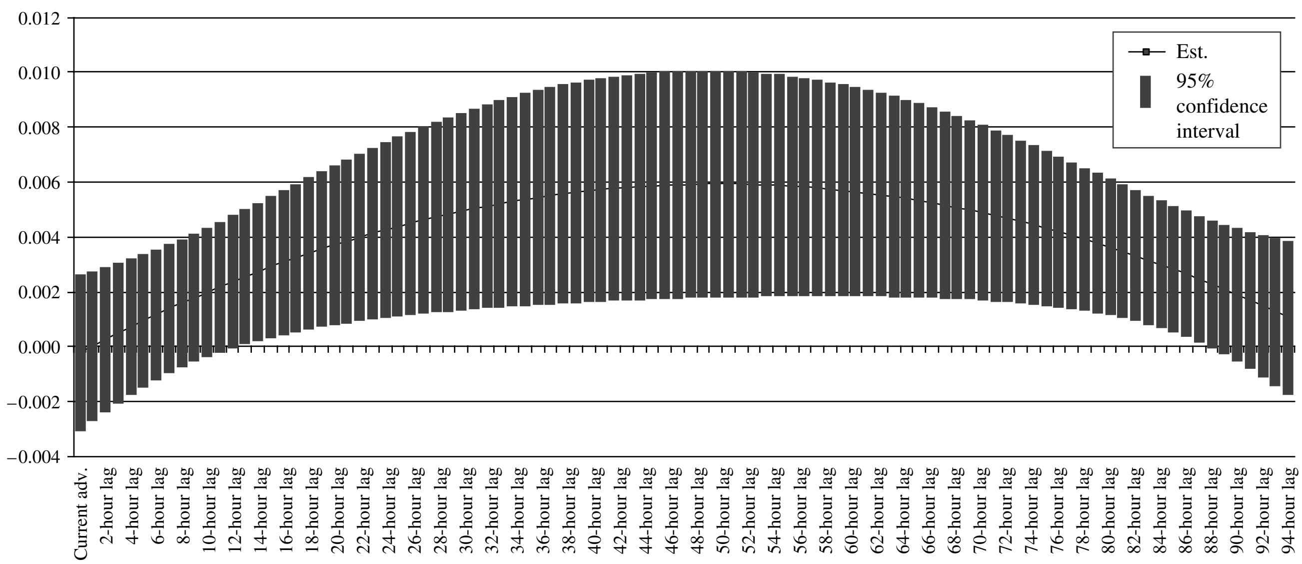
5.1. Effects of Television Advertising on Category Search and Keyword Choice

Figure 5 displays the 95% confidence intervals for the effects of lagged category advertising expenditures on category search. TV advertising has a small but positive effect on category search. Of the 96 lag effects, 76 are positive and statistically significantly different from zero. None may be proven to be less than zero at a regular confidence level. However the effects are quite small. A unit increase in log category advertising expenditures will lift the number of queries for category-related keywords by about 0.5% per hour over a period of about three days. This nonimmediate, sustained, subtle effect may indicate that category advertising acts as a "reminder" that increases the likelihood that a consumer will think about and search category-relevant keywords. Overall, the results indicate that category search rises after financial services advertising, showing that TV advertising has category expansion effects.

Figure 6 shows the 95% confidence intervals for the effects of lagged brand advertising expenditures on searchers' tendency to choose branded keywords instead of generic keywords. TV advertising increases branded keyword choice. Sixteen of the first 18 lagged effects are positive and statistically significantly different from zero, indicating elevated levels of branded keyword choice corresponding to the placement of that brand's commercials on television. The estimates indicate an inverted-"U" pattern peaking in the 6–11 hour range after TV advertising goes on the air. All of the confidence intervals after the 17th lag include zero. Along with the category expansion effects of advertising, brand advertising also increases the tendency to use branded keywords, but this effect is much shorter lived.

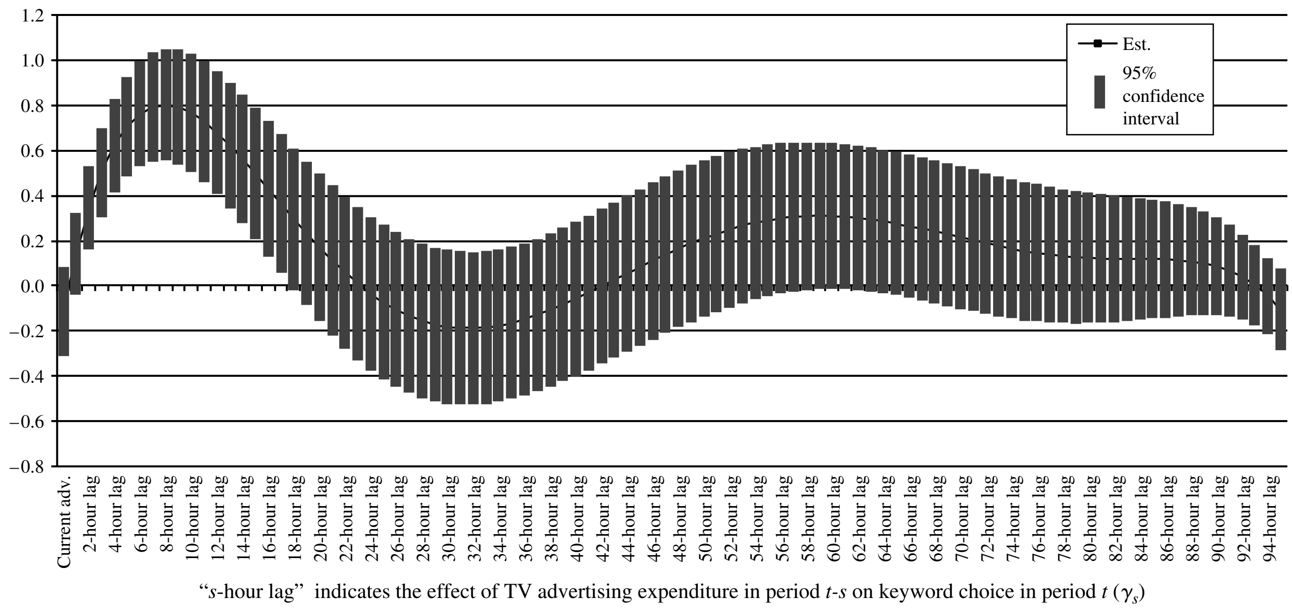
How big are these effects? The elasticity of a brand's total searches with respect to television advertising may be calculated according to Equation (10).

Figure 5 Effects of Television Advertising on Category Search



"*s*-hour lag" indicates the effect of TV advertising expenditure in period *t*-*s* on category searches in period *t* (β_s)

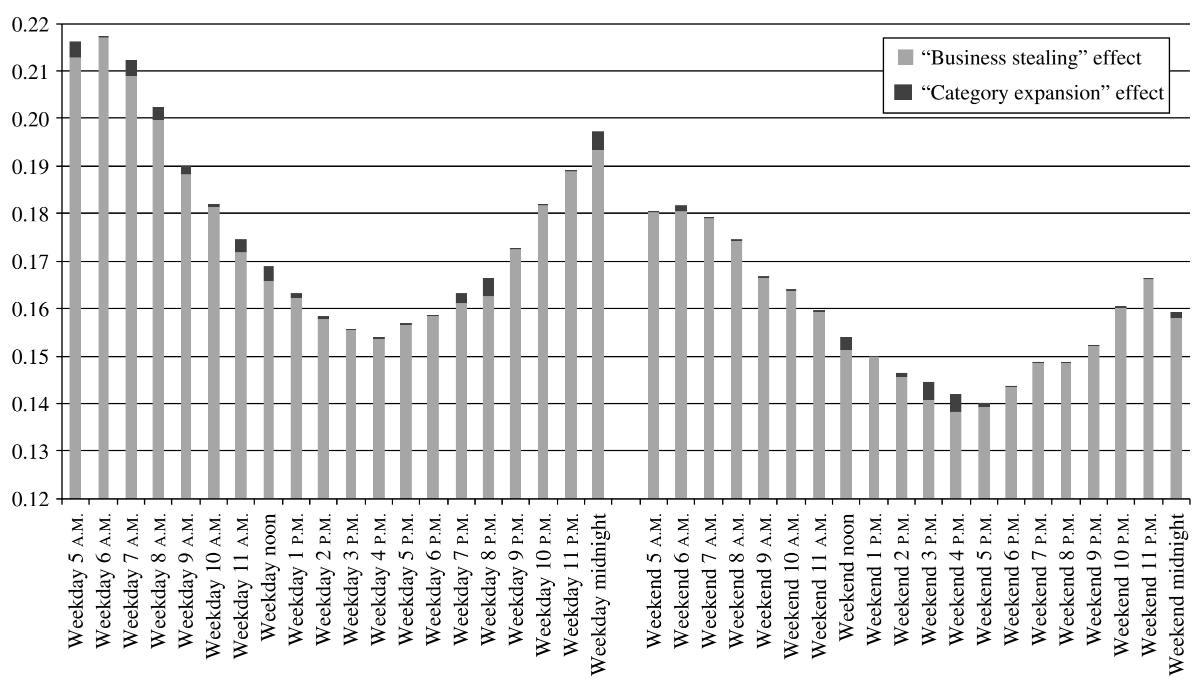
Figure 6 Effects of Television Advertising on Keyword Choice



Given a 10% increase in a brand's television advertising expenditures, the model predicts a 1.7% increase in its number of branded searches over the following 96 hours. This elasticity is statistically significantly different from zero at the 99% confidence level, with a standard error of 0.2%. This effect magnitude is larger than both the short-term market share elasticity of advertising (0.05) and the long-term market share elasticity of advertising (0.10) reported by Lodish et al. (1995). Similarly, it exceeds both the short-run (0.01) and long-run (0.12) advertising elasticities found by Ataman et al. (2010). Perhaps its magnitude can be explained by the fact that consumer search is an action that takes place at the top of the funnel, where advertising is thought to be relatively more effective; previous studies more frequently measured advertising's effect on sales, which requires consumers to go deeper into the purchase funnel and convert.

Figure 7 shows how the elasticity estimate breaks down across sources of brand searches (the "category

Figure 7 Elasticities by Day/Hour



expansion" and "business stealing" effects discussed in §3.4) and by hours on weekdays and weekend days. The effects of TV advertising on online search are greatest in the morning and decrease throughout the day, before rising again after 5 P.M. and throughout the evening. This pattern seems to be consistent with exposure to advertising during prime time and a gradual wearout prior to the next day's evening television. The effects are slightly higher on weekdays than on weekends.

The dark area of the figure represents contribution of category search expansion to the percentage increase in searches for the brand's keywords. On average, business stealing effects are about two orders of magnitude larger than category expansion effects. The graph shows that television advertising does not generate large positive spillovers, suggesting that brands will not benefit much by free riding on competitors' advertising expenditures.

Analyses of secondary data are typically unable to discern precise behavioral mechanisms, but we can speculate on the causes. There are two overlapping explanations for the pattern in Figure 7 in which elasticities peak in the morning and fall throughout business hours. First, it is possible that the part of the audience whose search for financial services brands is influenced by television advertising is more likely to search in the morning. For example, it might be that working professionals are both more likely to be exposed to television advertising for financial services brands, and more likely to enter Google searches in the morning, than the average person. Another possible explanation is that these effects could be due solely to consumers' memories and the duration of the effect of advertising on search. It may be that most advertising exposure occurs during prime time and that its effects have mostly dissipated within the following 16 hours or so (as shown by Figure 6). Both explanations probably help to explain the pattern of elasticity effects in Figure 7.

5.2. Effects of Control Variables

Here we present some of the effects of control variables on category search and keyword choice. Figures 8 and 9 display the 95% confidence intervals of the effects of day/hour dummies on category search and keyword choice, respectively. Category search rose rapidly between 6 A.M. and 10 A.M. on weekdays and then laid approximately flat until about 10 P.M. Its pattern on weekend days was similar. Keyword choice increased quickly from 5 A.M. until 10 A.M., but started to fall after 5 P.M. On weekend days it laid mostly flat between 10 A.M. and 10 P.M.

Stock market index parameter estimates (in Table 4) cannot be distinguished from zero.

5.3. Polynomial Parameters and Alternative Specifications

The procedure described in §3.2 led us to set $T = 96$, $p_1 = 2$, and $p_2 = 6$. We found that estimating higher-order polynomials did not change the statistical significance of the lower-order polynomial parameters. Table 5 reports the parameter estimates (θ_p and η_p) underlying the effects of lagged TV advertising in Figures 5 and 6. Individual polynomial parameters do not correspond to marginal effects, but they are included for completeness.

We previously estimated distributed-lag models without the Almon parameterization. The unrestricted distributed-lag models found qualitatively similar effects (positive effects of TV advertising on

Figure 8 Day/Hour Fixed Effect Estimates in Category Search Model

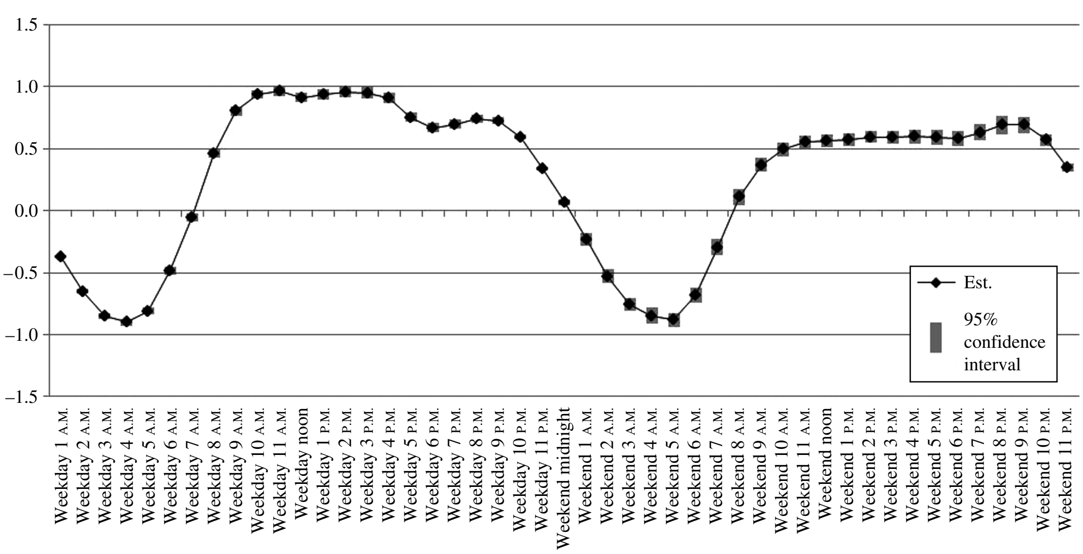
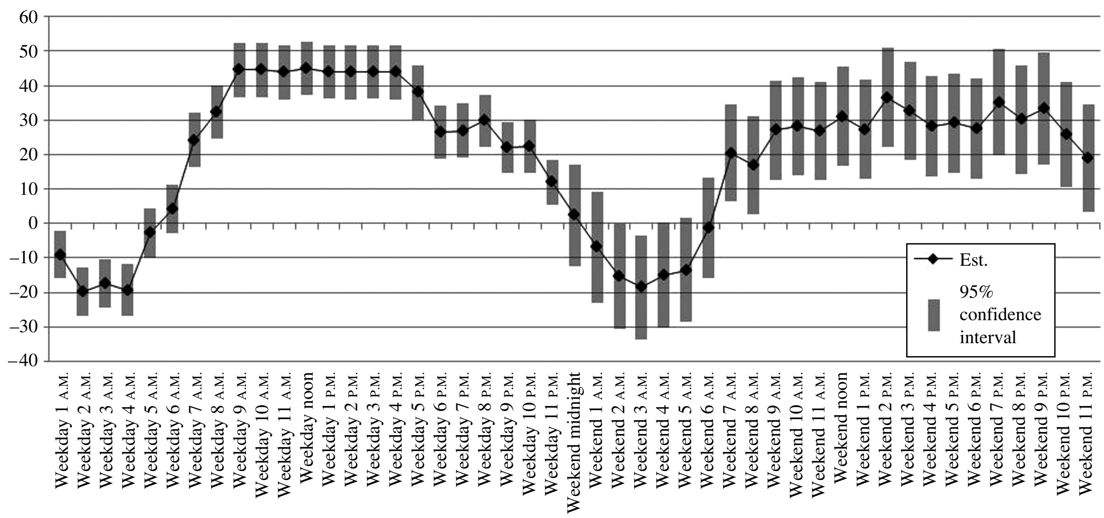


Figure 9 Day/Hour Fixed Effect Estimates in Keyword Choice Model



both category search and use of branded keywords), but the lagged advertising parameters showed a cyclical pattern with a 24-hour frequency and little apparent decay over time. The fluctuations seemed to match the pattern of autocorrelation in the advertising expenditure data, so the Almon parameterization was thought to be a reasonable way to simplify the model specification.

Table 4 Stock Index Effects

	Parameter estimate	Newey–West std. err.
Category search		
Absolute positive % DJIA change	−0.012	0.008
Absolute negative % DJIA change	0.006	0.007
Adjusted R^2	0.944	
Keyword choice		
Absolute positive % DJIA change	1.57	6.32
Absolute negative % DJIA change	−5.08	6.40
Adjusted R^2	0.005	

Table 5 Advertising Polynomial Parameter Estimates

	Parameter estimate	Newey–West std. err.
Category search		
θ_0	−2.0E−04	1.5E−03
θ_1	2.4E−04	1.1E−04**
θ_2	−2.4E−06	1.1E−06**
Keyword choice		
η_0	−1.1E−01	1.0E−01
η_1	2.8E−01	3.7E−02**
η_2	−2.8E−02	4.2E−03**
η_3	1.0E−03	1.8E−04**
η_4	−1.8E−05	3.6E−06**
η_5	1.4E−07	3.3E−08**
η_6	−4.5E−10	1.1E−10**

**Significant at the 99% confidence level.

6. Discussion

This paper has investigated two large data sets to investigate how television advertising expenditures are related to online search. It found that television advertising increases the number of product category-relevant searches and increases the advertised brand's share of keywords searched. For financial services, this latter effect dominates; the primary effect of a brand's advertising expenditure is to "steal" query share from rivals more so than to increase the number of searches in the product category. The elasticity of a brand's searches with respect to its advertising is 0.17.

The most important implication of these results is the need for advertisers to consider how television advertising may impact their search advertising campaigns. Search engine marketing is typically run as a standalone activity that seeks to maximize its incremental profits. The importance of cross-channel strategy in marketing has been documented previously, but managers are still relying on experience and gut intuition to decide how to divide advertising budgets across media (Pfeiffer and Zinnbauer 2010).

The effects of television advertising on online search may differ across product categories, consumers, or time. The easiest way for a brand to investigate these effects is to use A/B tests to measure changes in online behavior corresponding to the occurrence of television advertisement. It would also be possible to use the number of people exposed to a TV advertisement within a local market to explain market-specific measures of online activity. Lewis and Reiley (2013) explore these issues in greater depth.

Knowledge of these effects may lead a marketer to alter its pulsing, creatives, budgets, and return-on-investment metrics for both television and search advertising. It is likely advisable to facilitate or require coordination between the two agencies executing the advertising campaigns in each medium. For example, Web search metrics could be used as an input into the TV advertising campaign dashboard to help guide realtime creative decisions.[9] When television advertising increases branded keyword choice, it will reduce the number of expensive clicks on generic keyword searches and increase the number of clicks paid for on cheaper branded keywords. (Costs per click are typically higher for generic category keywords because of greater competition in the keyword auction.) It also might increase the conversion rate of both branded and generic search keywords. The marketer who remains ignorant of these effects may risk underspending on television advertising and overspending on search advertising.[10]

This study has a number of limitations. It considered only one product category. Television advertising for new brands or for evolving categories would likely show stronger category expansion and lower business stealing effects than the ones found here. The available data excluded direct website traffic, additional search engines, social networks, paid search advertisements, and click-through and conversion information. The effects were based on time series identification and did not come from a single-source panel in which advertising exposures and search behavior are observed within a single household.

We hope that some of the issues raised in this paper will stimulate field experiments. Though it is well known that exposure to online advertising affects online purchase behavior (e.g., Manchanda et al. 2006), more information is needed about how advertising creative elements interact with consumers' stages in the purchase funnel to determine product choices. Although Internet commerce enables marketers to observe many aspects of the consumer choice process, further research is needed to determine how to optimize all types of advertising to maximize advertising effectiveness.

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[9] With DVRs found in nearly 45% of U.S. households (Television Bureau of Advertising 2012) and live audiences falling by as much as 30% during commercial breaks (Schweidel and Kent 2010), search data may offer an important means to test television advertising effectiveness. As Swasy and Rethans (1986, p. 33) suggested, "advertisers should begin to incorporate a measure of curiosity generation and question solicitation in their new-product ad concept and ad-testing procedures."

[10] As Wiesel et al. (2011, p. 609) noted, "it is unwise to credit a marketing activity only for orders in 'its' channel, a practice typical in companies with different managers for different channels."

Appendix. Further Empirical Details

This appendix gives further details about the estimation and results.

Functional Forms

Several functional forms were considered for use in Equation (1). Figure A.1 plots the log of category search against

Figure A.1 Log Category Search vs. Category Advertising Expenditure

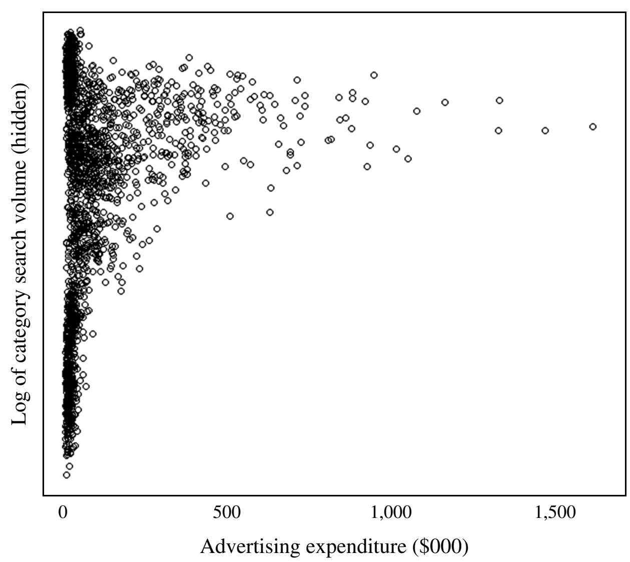

Figure A.2 Log Category Search vs. Log Category Advertising Expenditure

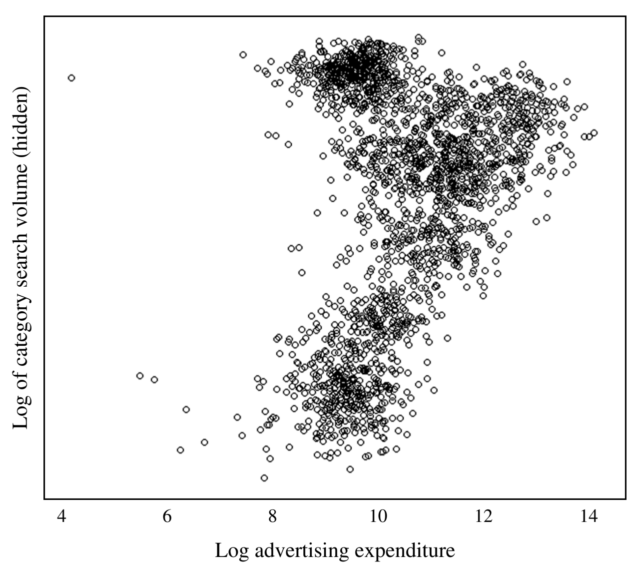

Table A.1 Week Fixed Effects to Control for Seasonality

	Category search		Keyword choice	
	Parameter estimate	Newey–West std. err.	Parameter estimate	Newey–West std. err.
Week 3 (Oct.)	−0.005	0.019	−4.4	22.4
Week 4 (Oct.)	0.003	0.039	−49.9	43.2
Week 5 (Oct.)	0.015	0.058	−74.7	55.7
Week 6 (Oct./Nov.)	0.049	0.077	−58.5	61.7
Week 7 (Nov.)	0.040	0.097	−83.3	73.8
Week 8 (Nov.)	0.080	0.116	−128.4	91.4
Week 9 (Nov.)	0.134	0.134	−112.1	102.0
Week 10 (Nov./Dec.)	0.132	0.154	−75.5	114.1
Week 11 (Dec.)	0.187	0.173	−100.3	124.1
Week 12 (Dec.)	0.220	0.193	−83.9	134.3
Week 13 (Dec.)	0.309	0.212	−47.7	143.0
Week 14 (Dec.)	0.387	0.232	−72.3	153.0

the level of category advertising expenditures. It is difficult to discern the shape of the relationship because there are many time periods with zero category advertising dollars. Figure A.2 shows a log–log plot. Based on this, a log-linear specification represents the data better.

Serial Correlation Tests
The standard Arellano and Bond (1991) test for serial correlation was applied to Equation (1) and rejected the null hypothesis of no serial correlation with a z-statistic of 41.84 ($p < 0.05$). When first differences are taken and Equation (8) is estimated instead, the z-statistic is -1.45 ($p > 0.05$), which fails to reject the null of no serial correlation. Therefore, estimation results based on first differences are preferred (Wooldridge 2010).

Standard Errors
The first-difference estimator controls completely for time-invariant unobserved heterogeneity, but it remains possible that the standard errors are biased by serial correlation (Bertrand et al. 2004). Therefore all estimates are reported using the standard errors suggested by Newey and West (1987), which are robust to heteroskedasticity and serial correlation of unknown form. Clustered standard errors and nonparametric “bootstrap” standard errors were similar in magnitude to the Newey–West standard errors and did not change the qualitative conclusions. Wooldridge (2010) provides a complete discussion.

Week Fixed Effects
Week fixed effects are presented in Table A.1 as controls for seasonality in category search tendency and keyword choice. Category search was lowest in the third week of the sample, 0.5% lower than in the baseline second week. It peaked in the fourteenth week of the sample, 38.7% higher than the baseline week. The baseline tendency to choose branded keywords also varied over time.

Table A.2 Lagged Advertising Parameter Estimates

	Category search		Keyword choice			Category search		Keyword choice	
	Est.	Newey–West std. err.	Est.	Newey–West std. err.		Est.	Newey–West std. err.	Est.	Newey–West std. err.
Current advertising	−0.0002	0.0015	−0.113	0.101	Lagged advertising (48 hrs)	0.0059	0.0021**	0.163	0.178
Lagged advertising (1 hr)	0.0000	0.0014	0.140	0.093	Lagged advertising (49 hrs)	0.0059	0.0021**	0.187	0.178
Lagged advertising (2 hrs)	0.0003	0.0014	0.343	0.094**	Lagged advertising (50 hrs)	0.0059	0.0021**	0.210	0.177
Lagged advertising (3 hrs)	0.0005	0.0013	0.502	0.100**	Lagged advertising (51 hrs)	0.0059	0.0021**	0.231	0.177
Lagged advertising (4 hrs)	0.0007	0.0013	0.622	0.107**	Lagged advertising (52 hrs)	0.0059	0.0021**	0.249	0.176
Lagged advertising (5 hrs)	0.0010	0.0012	0.708	0.113**	Lagged advertising (53 hrs)	0.0059	0.0021**	0.265	0.175
Lagged advertising (6 hrs)	0.0012	0.0012	0.764	0.119**	Lagged advertising (54 hrs)	0.0059	0.0021**	0.279	0.173
Lagged advertising (7 hrs)	0.0014	0.0012	0.794	0.123**	Lagged advertising (55 hrs)	0.0059	0.0021**	0.290	0.172
Lagged advertising (8 hrs)	0.0016	0.0012	0.803	0.127**	Lagged advertising (56 hrs)	0.0059	0.0021**	0.299	0.171
Lagged advertising (9 hrs)	0.0018	0.0012	0.792	0.130**	Lagged advertising (57 hrs)	0.0058	0.0020**	0.305	0.169
Lagged advertising (10 hrs)	0.0020	0.0012	0.767	0.133**	Lagged advertising (58 hrs)	0.0058	0.0020**	0.309	0.168
Lagged advertising (11 hrs)	0.0022	0.0012	0.728	0.136**	Lagged advertising (59 hrs)	0.0058	0.0020**	0.311	0.166
Lagged advertising (12 hrs)	0.0024	0.0012	0.680	0.139**	Lagged advertising (60 hrs)	0.0057	0.0020**	0.310	0.165
Lagged advertising (13 hrs)	0.0026	0.0013**	0.624	0.143**	Lagged advertising (61 hrs)	0.0057	0.0020**	0.307	0.164
Lagged advertising (14 hrs)	0.0027	0.0013**	0.563	0.146**	Lagged advertising (62 hrs)	0.0056	0.0019**	0.301	0.163
Lagged advertising (15 hrs)	0.0029	0.0013**	0.498	0.150**	Lagged advertising (63 hrs)	0.0055	0.0019**	0.294	0.163
Lagged advertising (16 hrs)	0.0031	0.0013**	0.431	0.153**	Lagged advertising (64 hrs)	0.0055	0.0019**	0.286	0.162
Lagged advertising (17 hrs)	0.0032	0.0014**	0.364	0.157**	Lagged advertising (65 hrs)	0.0054	0.0018**	0.276	0.162
Lagged advertising (18 hrs)	0.0034	0.0014**	0.297	0.160	Lagged advertising (66 hrs)	0.0053	0.0018**	0.265	0.162
Lagged advertising (19 hrs)	0.0036	0.0015**	0.233	0.164	Lagged advertising (67 hrs)	0.0053	0.0018**	0.253	0.161
Lagged advertising (20 hrs)	0.0037	0.0015**	0.171	0.167	Lagged advertising (68 hrs)	0.0052	0.0017**	0.240	0.161
Lagged advertising (21 hrs)	0.0039	0.0015**	0.112	0.169	Lagged advertising (69 hrs)	0.0051	0.0017**	0.227	0.161
Lagged advertising (22 hrs)	0.0040	0.0016**	0.058	0.171	Lagged advertising (70 hrs)	0.0050	0.0017**	0.213	0.161
Lagged advertising (23 hrs)	0.0041	0.0016**	0.009	0.173	Lagged advertising (71 hrs)	0.0049	0.0016**	0.200	0.161
Lagged advertising (24 hrs)	0.0043	0.0016**	−0.035	0.174	Lagged advertising (72 hrs)	0.0048	0.0016**	0.188	0.160
Lagged advertising (25 hrs)	0.0044	0.0017**	−0.074	0.175	Lagged advertising (73 hrs)	0.0047	0.0016**	0.176	0.159
Lagged advertising (26 hrs)	0.0045	0.0017**	−0.107	0.175	Lagged advertising (74 hrs)	0.0046	0.0015**	0.164	0.158
Lagged advertising (27 hrs)	0.0046	0.0017**	−0.134	0.175	Lagged advertising (75 hrs)	0.0044	0.0015**	0.154	0.157
Lagged advertising (28 hrs)	0.0047	0.0018**	−0.156	0.175	Lagged advertising (76 hrs)	0.0043	0.0014**	0.145	0.156

Table A.2 (Continued)

	Category search		Keyword choice			Category search		Keyword choice	
	Est.	Newey–West std. err.	Est.	Newey–West std. err.		Est.	Newey–West std. err.	Est.	Newey–West std. err.
Lagged advertising (29 hrs)	0.0048	0.0018**	−0.172	0.175	Lagged advertising (77 hrs)	0.0042	0.0014**	0.138	0.154
Lagged advertising (30 hrs)	0.0049	0.0018**	−0.183	0.174	Lagged advertising (78 hrs)	0.0041	0.0014**	0.131	0.152
Lagged advertising (31 hrs)	0.0050	0.0019**	−0.188	0.174	Lagged advertising (79 hrs)	0.0039	0.0013**	0.126	0.150
Lagged advertising (32 hrs)	0.0051	0.0019**	−0.189	0.173	Lagged advertising (80 hrs)	0.0038	0.0013**	0.123	0.147
Lagged advertising (33 hrs)	0.0052	0.0019**	−0.185	0.173	Lagged advertising (81 hrs)	0.0036	0.0013**	0.121	0.145
Lagged advertising (34 hrs)	0.0053	0.0020**	−0.177	0.173	Lagged advertising (82 hrs)	0.0035	0.0012**	0.119	0.143
Lagged advertising (35 hrs)	0.0054	0.0020**	−0.164	0.173	Lagged advertising (83 hrs)	0.0033	0.0012**	0.119	0.140
Lagged advertising (36 hrs)	0.0054	0.0020**	−0.149	0.173	Lagged advertising (84 hrs)	0.0032	0.0012**	0.118	0.137
Lagged advertising (37 hrs)	0.0055	0.0020**	−0.130	0.173	Lagged advertising (85 hrs)	0.0030	0.0012**	0.118	0.135
Lagged advertising (38 hrs)	0.0056	0.0020**	−0.108	0.173	Lagged advertising (86 hrs)	0.0028	0.0012**	0.116	0.131
Lagged advertising (39 hrs)	0.0056	0.0021**	−0.084	0.174	Lagged advertising (87 hrs)	0.0027	0.0012**	0.113	0.128
Lagged advertising (40 hrs)	0.0057	0.0021**	−0.059	0.174	Lagged advertising (88 hrs)	0.0025	0.0012**	0.108	0.1233
Lagged advertising (41 hrs)	0.0057	0.0021**	−0.031	0.175	Lagged advertising (89 hrs)	0.0023	0.0012	0.099	0.118
Lagged advertising (42 hrs)	0.0058	0.0021**	−0.003	0.176	Lagged advertising (90 hrs)	0.0021	0.0012	0.086	0.112
Lagged advertising (43 hrs)	0.0058	0.0021**	0.025	0.176	Lagged advertising (91 hrs)	0.0019	0.0012	0.066	0.105
Lagged advertising (44 hrs)	0.0058	0.0021**	0.054	0.177	Lagged advertising (92 hrs)	0.0017	0.0013	0.039	0.097
Lagged advertising (45 hrs)	0.0059	0.0021**	0.082	0.178	Lagged advertising (93 hrs)	0.0015	0.0013	0.002	0.090
Lagged advertising (46 hrs)	0.0059	0.0021**	0.110	0.178	Lagged advertising (94 hrs)	0.0013	0.0014	−0.046	0.087
Lagged advertising (47 hrs)	0.0059	0.0021**	0.137	0.178	Lagged advertising (95 hrs)	0.0011	0.0014	−0.107	0.093

**Significant at the 99% confidence level.

Table A.3 Day/Hour Fixed Effect Parameter Estimates

	Category search		Keyword choice	
	Est.	Newey–West std. err.	Est.	Newey–West std. err.
Weekday 1 A.M.	−0.371	0.005**	−9.094	3.514**
Weekday 2 A.M.	−0.650	0.009**	−19.643	3.582**
Weekday 3 A.M.	−0.851	0.011**	−17.311	3.634**
Weekday 4 A.M.	−0.901	0.013**	−19.306	3.799**
Weekday 5 A.M.	−0.812	0.014**	−2.742	3.690
Weekday 6 A.M.	−0.485	0.016**	4.160	3.629
Weekday 7 A.M.	−0.055	0.017**	24.220	4.010**
Weekday 8 A.M.	0.461	0.018**	32.410	3.950**
Weekday 9 A.M.	0.804	0.019**	44.488	4.011**
Weekday 10 A.M.	0.937	0.018**	44.481	3.966**
Weekday 11 A.M.	0.962	0.018**	43.821	3.967**
Weekday noon	0.913	0.019**	44.880	3.954**
Weekday 1 P.M.	0.939	0.020**	43.972	3.924**
Weekday 2 P.M.	0.955	0.022**	43.811	3.971**
Weekday 3 P.M.	0.950	0.022**	44.021	3.962**
Weekday 4 P.M.	0.912	0.022**	43.842	3.974**
Weekday 5 P.M.	0.752	0.020**	38.060	4.040**
Weekday 6 P.M.	0.669	0.018**	26.419	3.945**
Weekday 7 P.M.	0.698	0.017**	26.860	4.021**
Weekday 8 P.M.	0.740	0.016**	29.770	3.886**
Weekday 9 P.M.	0.724	0.014**	21.931	3.751**
Weekday 10 P.M.	0.595	0.010**	22.363	3.874**
Weekday 11 P.M.	0.338	0.007**	12.034	3.338**
Weekend midnight	0.067	0.012**	2.379	7.567
Weekend 1 A.M.	−0.233	0.026**	−6.906	8.147
Weekend 2 A.M.	−0.531	0.028**	−15.228	7.772
Weekend 3 A.M.	−0.757	0.027**	−18.421	7.679**
Weekend 4 A.M.	−0.847	0.032**	−14.926	7.733
Weekend 5 A.M.	−0.880	0.028**	−13.538	7.693
Weekend 6 A.M.	−0.681	0.030**	−1.379	7.450
Weekend 7 A.M.	−0.298	0.033**	20.490	7.245**
Weekend 8 A.M.	0.109	0.032**	16.891	7.203**
Weekend 9 A.M.	0.369	0.029**	27.072	7.354**
Weekend 10 A.M.	0.493	0.028**	28.180	7.300**
Weekend 11 A.M.	0.553	0.026**	26.779	7.244**

Table A.3 (Continued)

	Category search		Keyword choice	
	Est.	Newey–West std. err.	Est.	Newey–West std. err.
Weekend noon	0.560	0.025**	31.015	7.330**
Weekend 1 P.M.	0.572	0.025**	27.231	7.337**
Weekend 2 P.M.	0.595	0.026**	36.510	7.385**
Weekend 3 P.M.	0.592	0.027**	32.692	7.288**
Weekend 4 P.M.	0.596	0.030**	28.062	7.417**
Weekend 5 P.M.	0.591	0.031**	29.132	7.360**
Weekend 6 P.M.	0.582	0.032**	27.634	7.413**
Weekend 7 P.M.	0.632	0.035**	35.117	7.854**
Weekend 8 P.M.	0.689	0.039**	30.201	8.052**
Weekend 9 P.M.	0.691	0.032**	33.279	8.306**
Weekend 10 P.M.	0.567	0.025**	25.718	7.813**
Weekend 11 P.M.	0.348	0.017**	18.908	7.940**

**Significant at the 99% confidence level.

For completeness, Tables A.2 and A.3 present the parameter estimates and standard errors used to construct Figures 5, 6, 8, and 9.

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