An Exploration of Multimedia Multitasking:
How Television Advertising Impacts Google Search

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Abstract

A 2010 study conducted by Nielson on behalf of Yahoo reveals that three out of every four Americans use television and internet simultaneously, up nearly 20 percent year-to-year. Yahoo concludes that this disproves the myth that "traditional media is dead," instead affirming "convergence is a reality." Joo, Wilbur, and Zhu (2010) explore the growing trend of simultaneous online and offline media consumption by measuring the impact of television advertisement on online search, finding that TV advertising is positively associated with consumers' choice of branded keywords in the financial services category. This paper builds upon their results by extending the analysis to the bundled Internet/TV/phone product category, applying regression analysis to evaluate whether local television advertising expenditure impacts the Google search queries from IP addresses in the same area. The impact of television advertising is found to be both positive and significant in the short-term (same day), with a cumulative effect of more than twice the magnitude of the same day effect. These results suggest numerous practical implications for marketers and companies, as well as a variety of avenues for future research.

JEL classification: M; M31; M37

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I. Introduction

"One should hardly have to tell academicians that information is a valuable resource: knowledge *is* power."[1] This conclusion drawn by Nobel Laureate George Stigler in his 1961 article "The Economics of Information" continues to ring true for customer information search even fifty years later. However, the process of searching for product information today looks quite different from that of Stigler's time, largely revolutionized by the advent of the Internet. Online search engines dramatically cut the time and cost of information acquisition for consumers, employing algorithms to comb the Internet for relevant results to user queries.

Interestingly, the first step in this process is not the search itself; rather, the user must first conceive of the idea to search for a given product or brand. In designing advertisements, marketers attempt to spark an interest with their target audience, encouraging them to seek more information and, ultimately, to purchase the item.

Despite the fact that companies tend to focus separately on offline and online media, recent research suggests that the two may be significantly intertwined. A 2010 study conducted by Nielson on behalf of Yahoo reveals that three out of every four Americans use television and internet simultaneously, up nearly 20 percent year-to-year. Nine in ten respondents claim simultaneous use once a week, while half do so on a daily basis (see visual diagram in Figure 1 of the Appendix). Yahoo concludes that this disproves the myth that "traditional media is dead," instead affirming "convergence is a reality."[2]

A substantial academic literature investigates the connection between advertising and sales, as well as consumer search as a predictor of sales. However, minimal attention has been focused on the possible influence of advertising on consumer search in a multimedia context. Joo, Wilbur, and Zhu (2010) explore the growing trend of simultaneous media consumption by studying the effects of television advertising on online search, empirically determining that television advertising for financial services providers is positively associated with the choice of branded keywords, but not with generic category search or the choice to click a link. This paper builds upon their results by measuring the impact of television advertising on online search

[1] Stigler, George J, (1961). The Economics of Information. *The Journal of Political Economy*, 69:3, 213.
[2] Molina, Dianne. "New study reveals 75 percent of Americans use the Internet and TV simultaneously." Yahoo!

within the bundled Internet/TV/phone product category, focusing on the effect within localized metropolitan area markets through the use of Google Insights for Search data.

The empirical results reveal that the same-day effect of television advertising is both positive and significant at the 1% confidence level. Furthermore, the magnitude of the cumulative effect (including a geometrically decaying effect over the subsequent days) is twice the size of the short-term impact. This positive effect suggests considerable strategic implications for marketers; its incorporation would likely impact TV advertisement design and purchase decisions, as well as search engine optimization techniques and paid keyword choices and budgets, ultimately leading to more cohesive multimedia advertising efforts. Because Nielson's "American Media Multitasker Study" reveals that simultaneous media consumption is heaviest amongst females and those in the 18-30 age bracket, marketers can identify techniques to specifically target these users. Furthermore, the study shows simultaneous use to be lowest during scripted dramas and comedies, providing valuable insight into cohesive purchasing strategies for marketers hoping to leverage the trend in simultaneous television and internet usage. Lastly, the incorporation of an established link between offline advertising and online information gathering would improve return on investment (ROI) calculations for both media, allowing for better optimization of marketing budgets.

Section II reviews the existing streams of academic work to which this paper will contribute, followed by a brief theoretical framework in Section III. Section IV introduces the data sources and discusses the selection of an appropriate product category and time window for the analysis. Section V describes the empirical methodology and Section VI establishes the results and introduces the Koyck model of cumulative advertising impact. Finally, Section VII concludes the paper and presents limitations and implications for subsequent academic research efforts and industry practices.

II. Relevant Literature

This paper addresses a somewhat new area of research on the potential impact of an offline advertising medium on consumer internet search behavior, building upon a recent study by Joo, Wilbur, and Zhu (2010). Additionally, the analysis adds to multiple disparate but related streams of academic work. These topics include the effectiveness of television advertising in generating demand, the theory of consumer information search, the synergies possible between multimedia communications, and advertiser strategy in search engine marketing.

A. Joo, Wilbur, and Zhu (2010)

Joo, Wilbur, and Zhu (2010) construct an empirical model to investigate the impact of television advertising for financial services on each of three online search choices. Firstly, television advertisement might prompt a consumer to choose to search for the overall product category when he or she might otherwise not have done so. Secondly, advertisement might increase brand salience, prompting the user to choose a branded keyword rather than a generic one. Thirdly, advertisement might improve the likelihood that the consumer feels satisfied with the results of their search and proceeds to click a link. For their analysis, the authors develop a new query mining technique to identify a set of branded and generic queries relevant to the financial services product category. Their results indicate that television advertisement for financial services providers is positively associated with consumers' keyword choice behavior, prompting viewers to select branded keywords rather than generic ones. The effect is most pronounced for young brands (less than 50 years old) advertising during business hours with an elasticity of 0.07, which is comparable to academic measurements of advertising's impact on sales. This figure can be interpreted as the percentage change in brand keyword choice probability, given a 1% change in the provider's television advertising expenditures. The authors find no association between television advertising and overall category searches, concluding that television ads for financial services brands do not seem to expand the market by encouraging customers to enter the product category. Additionally, the results reveal few significant correlations between television advertising and consumer click-through behavior.

The study by Joo, Wilbur, and Zhu is novel in that it marks the first empirical study of the impact of television advertising on internet search, an area relatively untouched by previous literature. Here I will test their conclusions by applying a similar analysis to a different product category, studying specific metropolitan area advertising markets, and utilizing a more comprehensive online search data set from Google Insights.

B. Advertising Impact on Demand

There is a vast bank of literature analyzing the effectiveness of television advertising in generating demand, typically measured by sales, revenues or share prices and often narrowed in scope to focus on a specific industry or advertising technique. For example, Elberse and Anand (2005) examine the impact of televised pre-release movie advertising on demand for the film in theaters, concluding that the magnitude of the effect is greater with a high-quality movie. The current paper, as well as Joo, Wilbur, and Zhu (2010), build uniquely upon such literature by instead studying how television advertising impacts consumer online search, a crucial intermediate step between the advertisement and the final sale in many product categories.

Furthermore, this area of literature heavily references the Koyck distributed lag model, which will be leveraged in the interpretation of results in this paper. The model was originally contrived in Koyck's 1954 PhD thesis "An Econometric Study of the Time-Shape of Economic Reactions, with an Application to Investment Behavior" and is often used to illustrate both the current and carryover effects of advertising on sales, summed to equal the total or cumulative effect of advertising. In our analysis, however, the Koyck model will be applied to calculate the cumulative effect of advertising on daily Google searches.

C. Information Search

Secondly, this paper contributes new insight to the extensive field of information search, which has been an important aspect of economic study dating back to early publications such as George Stigler's "The Economics of Information" half a century ago (1961). In his paper, Stigler explains the value of information in consumer decision-making, demonstrating that the acquisition of such information requires a cost – sometimes in the form of money, but more often in the form of time. While some historic literature explores the impact of advertising on information search, it originates from an era in which consumer search was difficult to quantify and is therefore limited in its conclusions. For example, Newman and Staelin (1973) and Bettman and Park (1980) both explain that exposure to advertisements or other forms of prior product information leads to a more exhaustive information search. The current paper adds to such studies by using Google Insights search query data to empirically replicate these results for online information gathering.

The recent release of Google search query data has spurred new developments in the academic field of information search, largely focusing on the use of online search trends to predict current and future economic data or events. Ginsberg et all (2009) investigates how search data lack many of the time lags typical of other statistics, drawing implications for uses in health markets to create informed responses. Choi and Varian (2009) establishes a theoretical framework for the predictive use of search data, explaining that the interest measured by search queries may be correlated with current economic activity within an industry and therefore suggesting it might be helpful in predicting upcoming data releases. Furthermore, Askitas and Zimmerman (2009), Choi and Varian (2009), and Suhoy (2009) all study connections between search queries and macroeconomic trends such as unemployment. Azar (2009) uses Google Insights for Search weekly data as a representation of public interest, finding a negative relationship between oil prices and interest in electric cars. The current paper expands the use of Google search query data by focusing on the possibility that outside factors such as advertising could influence search queries.

D. Multimedia Advertising Synergies

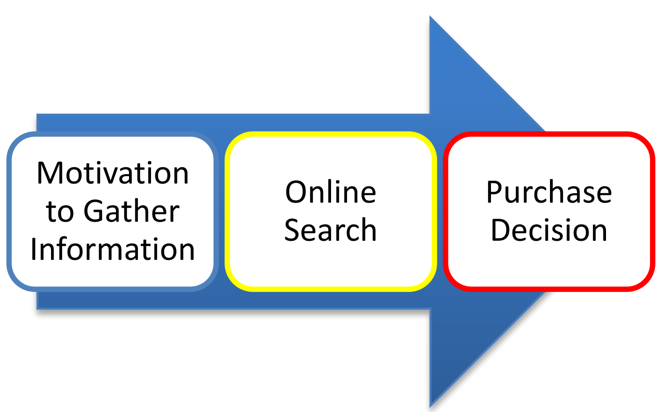
By suggesting possible synergies between offline and online media, this paper contributes to the body of literature which examines multimedia communications and the potential marketing complementarities that exist within the growing range of media outlets. Naik and Raman (2003) apply both empirical and theoretical analysis to validate the Integrated Marketing Communications (IMC) framework, which suggests that each advertising medium enhances the contributions of all others such that the collective impact of a multimedia platform is greater than the sum of its individual parts. Naik and Raman conclude with practical budget implications, suggesting that the existence of synergies should cause marketers to increase the total budget, allocating a greater portion of funds towards the less effective media activity. Naik and Peters (2010) confirm the existence of synergies both within media (i.e., intra-online) and across media (online/offline). Joo, Wilbur, and Zhu (2010), in combination with this study, add a new facet to this literature by addressing the influence that television advertising can have on the consumer’s pursuit of information online, empirically reaffirming the existence of cross-media synergies with exclusive focus on the interaction between television and internet.

E. Search Engine Marketing

The final source of related literature is the growing body of work on search engine marketing, specifically that which pertains to competition, advertiser strategy and keyword bidding techniques. Search engine marketing utilizes auction mechanisms known as generalized second price auctions, or GSP, which have been theoretically analyzed by Edelman, Ostrovsky, and Schwarz (2007), Varian (2007), and numerous others. Empirical analysis of advertiser strategy is prevalent in the literature as well. For example, Rutz and Bucklin (2008) explain that broad generic keywords, while often more expensive, tend to generate spillover effects as consumers begin with category searches and then narrow their scope to a branded search before purchasing. Shin (2009) discusses marketers' choice to advertise on their own branded keywords in an effort to deter rivals, while also advertising on the branded keywords of their competitors. However, despite the vast quantity of such papers on search engine marketing, the possibility of an advertiser's offline campaigns impacting consumer search choices online remains largely ignored. One example of a study that does take this possibility into account is an unpublished paper by Kim and Balachander (2010), who employ an analytical model to coordinate traditional media advertising with search engine advertising, drawing implications for optimal keyword bids. If television advertising can be shown to impact online search, there will be direct implications for the advertiser in its choices regarding search engine marketing.

III. Theoretical Framework

The online search process does not begin with a search query; rather, it begins with the source of the idea to gather information. There are a wide variety of possible motivations to search for more information on a telecommunications or cable provider: a residential relocation, a conversation with a friend, a magazine article, or, perhaps, a television advertisement by one of the providers. Some TV advertisements even encourage this



behavior; for example, a current Time Warner Cable advertisement concludes by declaring "call or go online now for more information."

After viewing a television advertisement, a consumer might choose to gather information online in one of two ways: firstly, the ad might prompt a user to search a category-related keyword, seeking to broadly gather information on the product, the providers available, or the technology involved. Secondly, the advertisement might improve brand salience, encouraging the user to search a branded keyword (i.e. "Verizon FiOS") rather than a generic category query (i.e. "internet providers"). This searching process might take place on the same day the advertisement is viewed, or it might not occur until a day or two later. This paper will combine daily local television advertising expenditure data with Google Insights for Search query data to determine if the effect of television advertising on branded search is significant in either the short term (the current day) or the long term, which considers the cumulative effect of advertising across multiple days as calculated by the Koyck model. To the extent possible, the empirical methodology will control for other potential causes for daily variation in search volume, such as other mediums of advertising or time fixed effects.

IV. Data

A. Product Category Selection

The product category selected for analysis is bundled Internet/TV/phone, a product offered by a number of providers nationwide based on specific geographic markets. Competitors include cable companies, such as Time Warner and Comcast, as well as telecommunications companies, such as Verizon and AT&T, as well as a number of smaller, regional players. In order to select this overall product for analysis, possible categories were evaluated based on the following series of criteria:

1. *The category must be one in which consumers actively search for information on both products and brands before buying*. Such "high involvement" categories tend to be products that are infrequently purchased, expensive, and exhibit high price dispersion. Consumers seek information before purchase because it is prohibitively challenging to experiment with various brands through product trial. In "The Economics of

Information," George Stigler notes that "the larger the fraction of the buyer's expenditures on the commodity… the greater the amount of search".[3] The selected product fits this criterion perfectly – consumers purchase once and then pay a large sum of money monthly. Furthermore, the new and exciting nature of the product category drives increased search interest by consumers.

2. *Brands within the category must use television advertising at the local metropolitan level to a significant degree*. Because service by each provider is only available in select metropolitan areas, frequent television advertising is conducted primarily on the local level. Furthermore, the category as a whole devotes over 60% of its advertising expenditure to television spot ads, followed by 18% newspaper and 16% online.

3. *The category cannot be subject to concerns of temporal endogeneity*. There are no obvious alternate explanations for a temporal correlation between television advertising of services and consumer search interest.

B. Television Advertising Data

Kantar Media's "Stradegy" database provides television advertising expenditure data from 2005 through the present. Kantar Media records paid television advertisements on national and local broadcast TV stations and cable networks. Analysts view each video file, classifying it by parent company, product, and category and assign it an estimated advertising cost. Each record is also labeled as belonging to one of a list of geographic markets which parallel those used to divide the online search data (see Table 1 in the Appendix). Subsequent encounters of the same advertisement are categorized in the same manner, albeit with some cases of mislabeling which need to be evaluated and combined as needed.[4] Because of the cost-prohibitive nature of obtaining ratings information to supplement the expenditure information, it

[3] Stigler, 219.

[4] For example, while some television advertisements are categorized by the parent company Time Warner Cable, Inc., others are labeled as Time Warner, Inc.

is common in the literature to assume that aggregate expenditures on television spot ads are correlated with audience and ratings.

C. Google Insights for Search Query Data

Google Insights for Search data tracks relative changes in Google search queries from January 2004 through the present, updated daily, and is available to the public for free download online. Results can be geographically filtered at the national, state, and metropolitan area level based on the originating IP address. The metro area classifications are those defined by Arbitron and correspond to the federal government definitions for metropolitan areas, as shown in Table 1 of the Appendix. Despite the fact that no other search engines have released similar search query data, Google's persistently dominant market share throughout the time period of consideration (rising from 56% in 2004 to 67% in 2010) suggests it is a reasonable proxy for total search query data (comScore).

To protect proprietary information pertaining to absolute query volumes, the data is first normalized and then scaled from 0 to 100, with each point divided by the highest point within the selected time period, which is assigned a value of 100. The normalization allows for comparison of data between regions with different absolute levels of search activity, as well as controlling for an increasing use of Google search overtime. Google labels this concept "query share," explaining that "query share can be understood as the ratio between the number of queries for that term and the total number of queries at a given time and location" (Insights Help). Therefore, if two regions display the same value for a given search term, this does not imply that both areas have the same absolute number of searches; rather, this indicates that individuals at IP addresses in both cities are equally likely to search for the term. Additionally, Google eliminates repeated queries from a single user over a short period of time so that interest levels are not artificially adjusted. Furthermore, Google Insights only shows results for search terms that receive a significant amount of traffic, enforcing minimum volume thresholds for inclusion. Instances below the minimum threshold were excluded from analysis in this paper.

Google Insights was designed "with the advertiser in mind" as a user-friendly and straightforward platform, emphasizing flexibility and functionality for practitioners (Inside AdWords Blog). Users first input their own query, location, and time frame into what seems like a “black box,” and Google returns a string of data on the spot, along with various illustrative graphics, as shown in a screenshot visual in Figure 2 of the Appendix. However, this emphasis on simplicity creates a number of limitations for academic research. Though Google provides a basic description of some aspects of their data processes, such as the normalization and scaling described above, it is evident that there is more going on than Google explains to users. Most important is the fact that, when a user inputs a query, Google Insights grabs data from only a sample percentage of the enormous overall search population, rather than basing numbers on all available information. This process was briefly acknowledged by Google Chief Economist Hal Varian in the conclusion of his 2009 paper “Predicting the Present with Google Trends,” recognizing that the process adds some additional noise to the data. The sampling method becomes evident when inputting the same data request repeatedly – rather than returning the exact same string of data each time, there is some variance in the results returned by the “black box.” This makes sense if we are to believe that Google is pulling from a different sample of the population each time. In order to evaluate how much the same string of data might vary when pulled on separate days, a series of examples were tested. Each version was found to have between 75% and 100% correlation with the others, as well as similar means and standard deviations. Because of this high level of similarity, each string of data was pulled only one time, rather than obtaining and averaging multiple versions. However, this issue sheds light on the overall research limitations presented by such simplified data, which are explored in detail by Tierney and Pan (2009). Future researchers should view the results with this weakness in mind, incorporating a healthy skepticism in their use of Google Insights data.

A second relevant limitation of the simplified data is that, if the user desires daily values for search behavior (as is necessary for this paper), the selected time range must be less than or equal to three months. If a longer range is selected, the data will instead be returned in weekly intervals. While it would theoretically be possible to obtain overlapping three-month strings of daily data and combine them by rescaling, it is not desirable to do so due to the fact that each string will be based on a different sample of the population, as described above. This means that the combined data string would not reflect a seamless trend of search behavior from the same population. Therefore, the combination of these two drawbacks of the Google Insights data limits the regression analysis to separate three-month periods of advertising expenditure and the corresponding search behavior. This limitation was confirmed by Tierney and Pan (2009) who conclude that the use of daily Google data was limited to a single quarter (three months), hindering study of long-run trends. In this paper, however, the separate three-month time periods will be pieced together, accounting for the quarterly breaks by using dummy variables in regressions.

D. The Construction of Branded and Category Search Phrases

In constructing a query in Google Insights, users can either enter their own search term (ex: "Verizon FiOS"), a combination of their own search terms, or use one of Google's categories and subcategories (ex: category = "Telecommunications", subcategory = "Providers"). When entering a combination of their own search terms, users design the wording in a number of ways, each specifying a different method of selecting the queries to be included:

1) **Verizon FiOS**: This is the default matching type and will be primarily used for analysis of brand-related search queries, combined with the supplementary techniques (2) – (5). The results include searches containing both "Verizon" and "FiOS," in any order, and possibly along with additional terms (ex: "Verizon FiOS availability," "FiOS TV Verizon," and "Verizon FiOS Durham" would all be included in the results). This does not include plural or singular forms of entered terms or spelling variations.
2) **"Verizon FiOS"**: Using quotation marks, results must include "Verizon FiOS" in that specific order and may also include words before or after the phrase, such as "Verizon FiOS availability" or "Verizon FiOS packages." This option will be used in combination with additional terms.
3) **Verizon + FiOS**: Using a plus sign indicates that either "Verizon" or "FiOS" must be included in the query, but not both.
4) **FiOS + "Verizon TV"**: This combination indicates that either "FiOS" or "Verizon TV" must be included in the phrase, but "Verizon" alone would be insufficient (therefore, a query like "Verizon wireless" would not be included).
5) **FiOS – wireless**: The use of a minus sign allows you to specifically exclude any queries containing a given term, such as "wireless". This allows you to ensure that certain unrelated queries are not included in the results.

These techniques will be combined to compose a specific phrase to search for each provider, differing intuitively based on characteristics of provider offerings and branding. Each of the branded phrases is listed in Table 2 of the Appendix. The terms to be included are determined through qualitative analysis of brand websites in combination with suggestions from the Google AdWords keyword selection tool and the related keywords section of Google Insights. The total number of words included in a phrase is limited to 30, which, in most cases, poses no troublesome limitation. Each branded phrase was entered into the Google Insights platform as shown in Figure 2 of the Appendix and the resulting observations for each brand were used for the $BRANDSEARCH$ variable.

The composition of provider-specific phrases, as described above, is more challenging for large telecommunications companies like Verizon and AT&T. While most providers included in the dataset offer only phone/TV/internet services, companies like Verizon and AT&T also provide unrelated services such as mobile phone service, which represents the largest share of their search volume. For example, for the US population between 2005 and 2010 (the years included in the advertising data), search queries specifically pertaining to FiOS represent about 9% of the total searches including "Verizon," whereas those pertaining specifically to wireless represent about 42%. Therefore, the inclusion of all terms that incorporate the brand "Verizon" would constitute a vast over-estimation of the search interest in Verizon FiOS, likely drowning out the effect of FiOS advertising. Taking this into account, the analysis will include only those searches that specifically pertain to the FiOS product. Despite this more narrow definition, there was still adequate search volume for Google Insights to return non-zero values.

E. Selection of Time Windows

Because the daily data from Google Insights is limited to three month periods, the analysis is conducted quarterly. The span of the advertising data allows for the potential study of 18 total quarters, from Q1 2006 thru Q2 2010. However, because the more recent data most closely aligns with the qualitative design of Google Insights phrases, only the most recent six quarters will be considered. For each of these quarters, the analysis will include each brand in each market that has sufficient advertising and search data. Sufficient data for the inclusion of brand *X* in market *Y* for a given quarter is defined as follows:

1) Brand *X* must have positive TV advertising expenditure in market *Y* on at least half of the days within the quarter.
2) Google Insights must have sufficient volume for brand *X* in market *Y* to provide non-zero values for all days in the quarter. If there is insufficient search data, which is sometimes the case for smaller companies in more rural areas, Google Insights will return a value of zero, and brand *X* in market *Y* must be excluded from analysis.

Using these selection criteria, the final data set encompasses 56,268 observations, with each observation representing a single day in a specific market.

V. Empirical Methodology

The data sources described in Section IV will be combined into a single pooled dataset of time series cross-sectional data: for each provider, there are observations on the three variables $BRANDSEARCH$, $TVADEXP$, and $NADEXP$ for each of n entities (metropolitan areas) at T time periods, defined as follows:

- $BRANDSEARCH$ = the relative search volume for brand-related queries, scaled and normalized by Google Insights, with values ranging from 0 to 100.
- $TVADEXP$ = the daily expenditure on television advertisements
- $NADEXP$ = the daily expenditure on newspaper advertisements

The number of entities (metropolitan areas) varies by provider, because each runs television advertisements only in those markets in which it operates, and not necessarily in all quarters. The final analysis encompasses 56,268 observations across 141 groups.

The models enumerated below use panel data analysis, which endows our regression analysis with both spatial and temporal dimensions. The spatial dimension of our panel pertains to the geographic markets, which represent the cross-sectional units of observation, while the temporal dimension is the daily observations across a defined time period (Q1 2009 – Q2 2010).

Rather than estimating *n* parameters (one for each market) with a fixed effects model, the panel regression is conducted using random effects, with each market-specific intercept seen as a random deviation from some mean intercept. Dummy variables will be included for each of the six quarters to account for the fact that they represent six separately normalized and scaled strings of search query data. The model begins as simply as possible, with each subsequent equation layering on additional parameters. The results of all 10 regressions are presented in Section VI.

(1) The first and simplest model is a regression of the brand-related search interest, $BRANDSEARCH$, on the television advertising expenditure, $TVADEXP$. Logarithmic transformations of search and television advertising are used to allow for interpretation of the results as elasticities. Additionally, μ represents the mean intercept across markets, while α_i pertains to the market-specific random deviation from μ, with e_{it} as the market and day-specific error. Dummy variables are included for each day of the week (Monday – Sunday), each brand, and each quarter (labeled 1-6), though these are not shown in the equations below.

$$\log(BRANDSEARCH_{it}) = \mu + \alpha_i + \beta_1 \log(TVADEXP_{it}) + e_{it}$$

(2-5) The second through fifth equations sequentially add first, second, third, and fourth lags of branded search. The lags of the dependent variable are included to account for habitual and dynamic effects, an inclusion that is common in time-series models of consumer demand (in this case, consumer demand for information):

$$\log(BRANDSEARCH_{it}) = \mu + \alpha_i + \beta_1 \log(TVADEXP_{it}) + \beta_2 \log(BRANDSEARCH_{i(t-1)}) + e_{it}$$

$$\log(BRANDSEARCH_{it}) = \mu + \alpha_i + \beta_1 \log(TVADEXP_{it}) + \beta_2 \log(BRANDSEARCH_{i(t-1)}) + \beta_3 \log(BRANDSEARCH_{i(t-2)}) + e_{it}$$

$$\log(BRANDSEARCH_{it}) = \mu + \alpha_i + \beta_1 \log(TVADEXP_{it}) + \beta_2\log(BRANDSEARCH_{i(t-1)}) + \beta_3\log(BRANDSEARCH_{i(t-2)}) + \beta_4\log(BRANDSEARCH_{i(t-3)}) + e_{it}$$

$$\log(BRANDSEARCH_{it}) = \mu + \alpha_i + \beta_1 \log(TVADEXP_{it}) + \beta_2\log(BRANDSEARCH_{i(t-1)}) + \beta_3\log(BRANDSEARCH_{i(t-2)}) + \beta_4\log(BRANDSEARCH_{i(t-3)}) + \beta_5\log(BRANDSEARCH_{i(t-4)}) + e_{it}$$

(6-7) The sixth and seventh equations add first and second lags of television advertising in order to measure the baseline relationship, if any, between search volume on day *t* and advertising levels on days *t-1* and *t-2*, indicating a delayed effect.

$$\log(BRANDSEARCH_{it}) = \mu + \alpha_i + \beta_1 \log(TVADEXP_{it}) + \beta_2\log(BRANDSEARCH_{i(t-1)}) + \beta_3\log(BRANDSEARCH_{i(t-2)}) + \beta_4\log(BRANDSEARCH_{i(t-3)}) + \beta_5\log(BRANDSEARCH_{i(t-4)}) + \beta_6\log(TVADEXP_{i(t-1)}) + e_{it}$$

$$\log(BRANDSEARCH_{it}) = \mu + \alpha_i + \beta_1 \log(TVADEXP_{it}) + \beta_2\log(BRANDSEARCH_{i(t-1)}) + \beta_3\log(BRANDSEARCH_{i(t-2)}) + \beta_4\log(BRANDSEARCH_{i(t-3)}) + \beta_5\log(BRANDSEARCH_{i(t-4)}) + \beta_6\log(TVADEXP_{i(t-1)}) + \beta_7\log(TVADEXP_{i(t-2)}) + e_{it}$$

(8-10) The eighth equation adds newspaper advertising expenditure, $NADEXP$. Because providers spend approximately 17% of their advertising budgets on newspaper ads, daily changes in newspaper ad expenditures might also be contributing to the changes in brand-related search queries. The ninth and tenth equations sequentially add first and second lags of newspaper advertising in order to measure the baseline relationship, if any, between search volume on day *t* and newspaper advertising levels on days *t-1* and *t-2*, indicating a delayed effect.

$$\log(BRANDSEARCH_{it}) = \mu + \alpha_i + \beta_1 \log(TVADEXP_{it}) + \beta_2\log(BRANDSEARCH_{i(t-1)}) + \beta_3\log(BRANDSEARCH_{i(t-2)}) + \beta_4\log(BRANDSEARCH_{i(t-3)}) + \beta_5\log(BRANDSEARCH_{i(t-4)}) + \beta_6\log(TVADEXP_{i(t-1)}) + \beta_7\log(TVADEXP_{i(t-2)}) + \beta_8\log(NADEXP_{it}) + e_{it}$$

$$
\begin{aligned}
\log(BRANDSEARCH_{it}) &= \mu + \alpha_i + \beta_1 \log(TVADEXP_{it}) + \beta_2 \log(BRANDSEARCH_{i(t-1)}) \\
&+ \beta_3 \log(BRANDSEARCH_{i(t-2)}) + \beta_4 \log(BRANDSEARCH_{i(t-3)}) \\
&+ \beta_5 \log(BRANDSEARCH_{i(t-4)}) + \beta_6 \log(TVADEXP_{i(t-1)}) \\
&+ \beta_7 \log(TVADEXP_{i(t-2)}) + \beta_8 \log(NADEXP_{it}) \\
&+ \beta_9 \log(NADEXP_{i(t-1)}) + e_{it}
\end{aligned}
$$

$$
\begin{aligned}
\log(BRANDSEARCH_{it}) &= \mu + \alpha_i + \beta_1 \log(TVADEXP_{it}) + \beta_2 \log(BRANDSEARCH_{i(t-1)}) \\
&+ \beta_3 \log(BRANDSEARCH_{i(t-2)}) + \beta_4 \log(BRANDSEARCH_{i(t-3)}) \\
&+ \beta_5 \log(BRANDSEARCH_{i(t-4)}) + \beta_6 \log(TVADEXP_{i(t-1)}) \\
&+ \beta_7 \log(TVADEXP_{i(t-2)}) + \beta_8 \log(NADEXP_{it}) \\
&+ \beta_9 \log(NADEXP_{i(t-1)}) + \beta_{10} \log(NADEXP_{i(t-2)}) + e_{it}
\end{aligned}
$$

VI. Results

A. Regression Results

Tables 4 and 5 (shown on the next two pages) present the coefficients and significance of each of the explanatory variables for each of the ten equations presented in Section V, as well as the R-squared values within markets, between markets, and overall for each equation. The equations build sequentially upon one another, such that equation (10) includes all explanatory variables. The interpretation of each of the beta coefficients for television or newspaper advertising would be that, as *X* varies across time and markets by 1%, branded search increases or decreases by β%. The final model (10) has reasonable explanatory power, with an R-squared value of 0.3211 within markets, 0.9745 between markets, and 0.4535 overall. The R-squared value between markets is largely irrelevant, however, because search tends to fluctuate around a given level within a market (say, 40 or 80). Therefore, the inclusion of lagged search variables from previous days would largely explain the difference between markets. Rather, we should focus on the within-market and overall R-squared values.

Table 4: Regression results for Equations 1-5

	(1) Includes just TV ad expenditure	**(2) Adds first lag of search**	**(3) Adds second lag of search**	**(4) Adds third lag of search**	**(5) Adds fourth lag of search**
$\log(TVADEXP_{it})$	-0.000156	0.0019618**	0.0015218**	0.0011959**	0.0011622**
Monday	0.0433732**	0.0699024**	0.0678369**	0.0546187**	0.0600527**
Tuesday	0.0258247**	0.0162648**	0.0322776**	0.0223079**	0.0244102**
Thursday	-0.0100835*	0.0036062	0.0048461	-0.0072358*	0.0009913
Friday	0.0183568**	0.0421167**	0.0451152**	0.0346059**	0.033876**
Saturday	0.0281242**	0.0334219**	0.042598**	0.0362435**	0.0370299**
Sunday	-0.025077**	-0.022831**	-0.018287**	-0.021950**	-0.018872**
$\log(BRANDSEARCH_{i(t-1)})$		0.5245647**	0.4249069**	0.3812766**	0.3608812**
$\log(BRANDSEARCH_{i(t-2)})$			0.2110467**	0.1738093**	0.1507761**
$\log(BRANDSEARCH_{i(t-3)})$				0.1529537**	0.1115249**
$\log(BRANDSEARCH_{i(t-4)})$					0.1190157**
$\log(TVADEXP_{i(t-1)})$					
$\log(TVADEXP_{i(t-2)})$					
$\log(NADEXP_{it})$					
$\log(NADEXP_{i(t-1)})$					
$\log(NADEXP_{i(t-2)})$					
R-sq: within	0.0428	0.2649	0.2968	0.3113	0.3211
R-sq: between	0.3813	0.8985	0.9449	0.9665	0.9741
R-sq: overall	0.1162	0.3862	0.4243	0.4434	0.4534

^ Significant at the 10% confidence level / * 5% confidence level / ** 1% confidence level

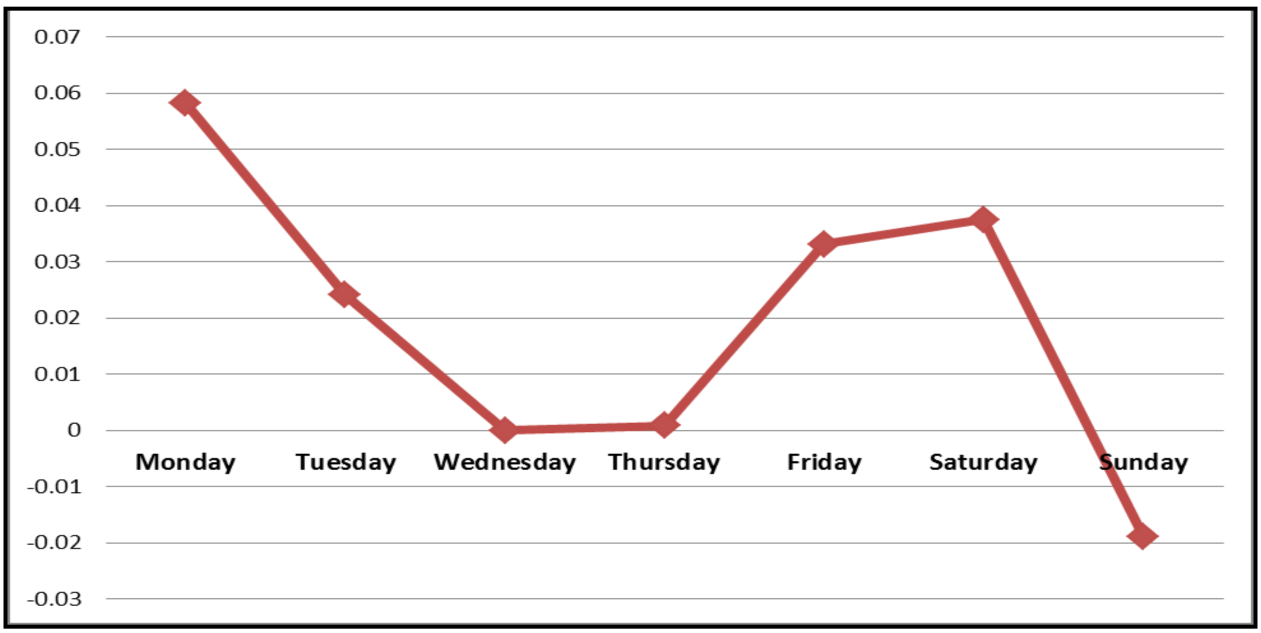
Table 5: Regression results for Equations 6-10

	(6) Adds first lag of TV exp.	**(7) Adds second lag of TV exp.**	**(8) Adds newspaper exp.**	**(9) Adds first lag of NP exp**	**(10) Adds second lag of NP exp**
$\log(TVADEXP_{it})$	0.0016278**	0.0015644**	0.0015167**	0.0015209**	0.0015051**
Monday	0.0586398**	0.0585657**	0.0587816**	0.0578097**	0.0581526**
Tuesday	0.0242758**	0.0246801**	0.0249657**	0.024823**	0.0240343**
Thursday	0.0010021	0.0009572	0.0011387	0.0007558	0.0008573
Friday	0.0333729**	0.0333322**	0.0335344**	0.033359**	0.033101**
Saturday	0.0374335**	0.0373492**	0.0377795**	0.0375788**	0.0374716**
Sunday	-0.0185006**	-0.0187415**	-0.019253**	-0.0190053**	-0.0190011**
$\log(BRANDSEARCH_{i(t-1)})$	0.3609087**	0.3609394**	0.3608937**	0.3608106**	0.3607386**
$\log(BRANDSEARCH_{i(t-2)})$	0.1508511**	0.1508292**	0.1507602**	0.1507367**	0.1506909**
$\log(BRANDSEARCH_{i(t-3)})$	0.1114706**	0.1114521**	0.1113941**	0.1113125**	0.111312**
$\log(BRANDSEARCH_{i(t-4)})$	0.1191911**	0.1191643**	0.1113941**	0.11905**	0.118975**
$\log(TVADEXP_{i(t-1)})$	-0.0008019^	-0.000929^	-0.0009242^	-0.0009777*	-0.0009621*
$\log(TVADEXP_{i(t-2)})$		0.0002444	0.0002381	0.0002429	0.0002012
$\log(NADEXP_{it})$			0.0007022^	0.0005609	0.0004561
$\log(NADEXP_{i(t-1)})$				0.0008038*	0.0006911^
$\log(NADEXP_{i(t-2)})$					0.0007523*
R-sq: within	0.3212	0.3212	0.3211	0.3211	0.3211
R-sq: between	0.9739	0.9740	0.9742	0.9744	0.9745
R-sq: overall	0.4534	0.4534	0.4534	0.4535	0.4535

^ Significant at the 10% confidence level / * 5% confidence level / ** 1% confidence level

As we might intuitively expect, the dependent variable that has the strongest relationship is the first lagged value of search. The second, third, and fourth lags of search also have significant positive coefficients, but diminishing in magnitude (shown in models 2-5). This suggests that online search does not exhibit high volatility from one day to the next; rather, it appears to be sticky, such that the greatest predictor of search volume on a given day is search volume on the day before. Each of the weekday variables is also significant, save for Thursday, indicating that search activity is significantly tied to the day of the week, regardless of other factors. Relative search volume tends to be highest on Mondays and lowest on Sundays, which agrees with our intuitive understanding of search behavior, as shown in Figure 1 (below).

Figure 1: Baseline Tendency to Search by Weekday



In the first equation, the coefficient for television advertising is extremely small and negative but highly insignificant. However, once additional explanatory variables were added, the coefficient for television advertising became both positive and significant in all models. This indicates that television advertising does indeed have a positive relationship with searches conducted on the same day. On the other hand, the two lagged values of television advertising present quite a different picture (introduced in equations 6 and 7). The first lag of television advertising has a negative coefficient and is significant at either the 5% or 10% level, depending on the model. This may not necessarily indicate a negative relationship between the previous day's television advertising and search; rather, it may just be the result of wide fluctuations in television advertising, combined with a sticky pattern in search behavior. It is also possible that when there is television advertising on day *t*, those consumers who would have searched on the day *t+1* might instead search on day *t*. This is essentially saying that advertising might be causing day *t* to steal search volume from the following day. Combined with the fact that the second lag of television advertising is highly insignificant in all models, these results point to a relatively stronger contemporaneous effect of advertising on same day searches. Some portion of this could be the result of multitasking between television and internet, as found in the "American Media Multitasker Study" mentioned in the introduction. This also agrees with the conclusions about advertising carryover drawn in Joo, Wilbur, and Zhu (2010), which explains that associations between television advertising and search behavior persist for hours, rather than days.

Newspaper advertising, first incorporated in equation (8), initially has a positive coefficient, significant at the 10% level. However, as the first and second lags of newspaper advertising are added in equations (9) and (10), these lagged values become significant, while the current day newspaper advertising is not. This might suggest that newspaper advertising produces a delayed effect on its audience, improving brand salience and increasing searches over the subsequent days, but not contemporaneously with encountering the advertisement. This makes sense if we are to believe that consumers multitask often with television and internet, but rarely read the newspaper while online. Furthermore, newspaper advertising expenditure is highest on Sundays, yet the weekday dummy variables reveal that online search for this product category is lowest on Sundays and highest on Mondays, which might contribute to the positive sign and significance of a first lag of newspaper expenditure.

Additionally, six brands both large and small (AT&T, Brighthouse, Cablevision, Charter, Comcast, Cox) were tested in a vacuum, using OLS regressions on just a single quarter at a time, for two separate quarters (Q1 and Q2 2010). Out of these twelve separate regressions, eight of them showed the coefficient of television advertising to be positive and significant. Those that did not were those providers operating in fewest markets (Brighthouse, Cablevision, etc.) For smaller providers operating in only one or two markets, there were as few as 90 observations total. To test whether these smaller brands might be biasing the overall panel regression results, equation (10) was replicated, incorporating only the top 7 brands (AT&T, Verizon, Comcast, Cox, Charter Communications, Qwest, and Time Warner Cable). The results were virtually identical to those presented above, and are displayed for reference in Table 3 of the Appendix.

B. Koyck Model Estimation of Cumulative Advertising Impact

The Koyck distributed lag model is based upon a geometric decay of the impact of advertising, measuring advertising goodwill as a weighed function of current and past advertising.[5] An autoregressive explanatory variable is included because of the aforementioned assumption that the effect is distributed across multiple time periods:

$$S_t = \mu + \beta A_t + \lambda S_{t-1} + u_t$$

S_t, A_t, and u_t represent sales, advertising, and a random disturbance in time t, respectively. The regression parameters of interest are μ, β, and λ. $0 \leq \lambda \leq 1$ is interpreted as the geometric decay rate of advertising. According to the model, the total effect of advertising is calculated in the following manner:

$$\epsilon = \frac{\beta}{1-\lambda} = \frac{0.001962}{1-0.524565} = 0.00413$$

The coefficients are substituted from regression equation (2), the version that incorporates only one lag of search. The value 0.00413 represents the cumulative, or long-term, impact of advertising on search. It is greater than twice the magnitude of the short-term impact of advertising on search (β), which is estimated in equation (2) to be 0.001962. The Koyck model calculation reveals that there is a positive total effect of television advertising on search, extending beyond the current day, even if it is not captured in the individual lagged television advertising regression coefficients.

[5] For more information on the Koyck model, see Morey, Raturi, McCann (1991) or Frances (2004).

VII. Conclusion

This paper presented an empirical investigation of the relationship between television advertising and online consumer search for a high-involvement product category. In contrast to the mature financial services product category considered in Joo, Wilbur, and Zhu (2010), the internet/phone/television product is constantly evolving, with new products often entering the market and brands periodically expanding coverage to new metropolitan areas.

The results indicate that television advertising does indeed have a positive and significant association with online search behavior on the same day. This outcome agrees with the findings of Joo, Wilbur, and Zhu (2010), who determine that television advertising is positively associated with the choice of branded keywords. Furthermore, the size of the cumulative effect of television advertising on Google search as calculated using the Koyck model is more than twice as large as the same-day effect. However, the descriptive analysis conducted in this paper only considers the relationship between the two variables; no claims can be drawn about causality. On the other hand, we can make a reasonable assumption that reverse causality is not occurring – companies are unable to base their television advertisement purchases on the same day search volume, because this data is not available until the day is over, and are unlikely to base purchases on search volume from the previous day.

The results present a number of avenues for future academic and industry research on this relatively unexplored topic. Additional product categories and datasets could be used to confirm the relationship. Researchers could shift from a broad scope to an individual lens, focusing on specific households, interviews, or surveys to isolate the effect. A parallel analysis could be conducted on a completely different area of advertising, such as political campaigns preceding an important election or awareness generated by public service announcements.

If we are to believe that television advertising encourages the pursuit of information online, the strategic implications for companies and marketers would be substantial as they seek to leverage the trend of simultaneous media consumption. Marketers could design television advertisements with multimedia synergies in mind, encouraging viewers who may be multitasking to search online for the product. Media buyers could better focus placement during those television programs and air times that best facilitate multitasking. Specific insight can be drawn from the "American Media Multitasker Study," which indicates that simultaneous media consumption of television and internet is greatest for the 18-30 age group and occurs least during scripted dramas and comedies. Furthermore, the results of this paper suggest consequences for the academic modeling and practical use of search engine marketing, an area of rapidly growing importance in marketing budgets. Keyword advertising on search engines such as Google could incorporate aspects of the brand's television advertising campaigns, leading to adjustments in keyword purchases and advertisement phrasing. Lastly, an established link between offline advertising and online information gathering would improve return on investment (ROI) calculations for both media, allowing for better optimization of marketing budgets.

The analysis presented in this paper is limited in both reliability and scope due to the nature of the Google Insights for Search query data. However, it provides valuable insight into both the benefits and limitations of daily data from Google Insights, which is largely ignored in the literature (the vast majority of existing papers utilize the weekly data option). The Google Insights platform presents a number of attractive qualities: a broad user base (majority of search engine market share), metropolitan area-specific refinement, customizable search query construction, a wide time span of data availability, and no cost to practitioners. However, its weaknesses are also undeniable. Most notably, the sampling technique employed in extracting data makes the coverage less powerful (based only on a portion of the overall searching population) and the output inconsistent. In the conclusion of his 2009 paper "Predicting the Present with Google Trends", Google Chief Economist Hal Varian explained: "Currently Google Trends is computed by a sampling method and varies somewhat from day to day. This sampling error adds some additional noise to the data. As the product evolves, we expect to see new features and more accurate estimation of the Trends query share indices."[6] Future iterations of the platform sound very promising for academic research, despite the shortcomings of the current version.

[6] Varian, Hal, and Hyunyoung Choi, (2009). Predicting the Present with Google Trends. *Google*, pg. 18.

Appendix

Figure 1: Yahoo! and Nielson Study: The American Media Multitasker[7]

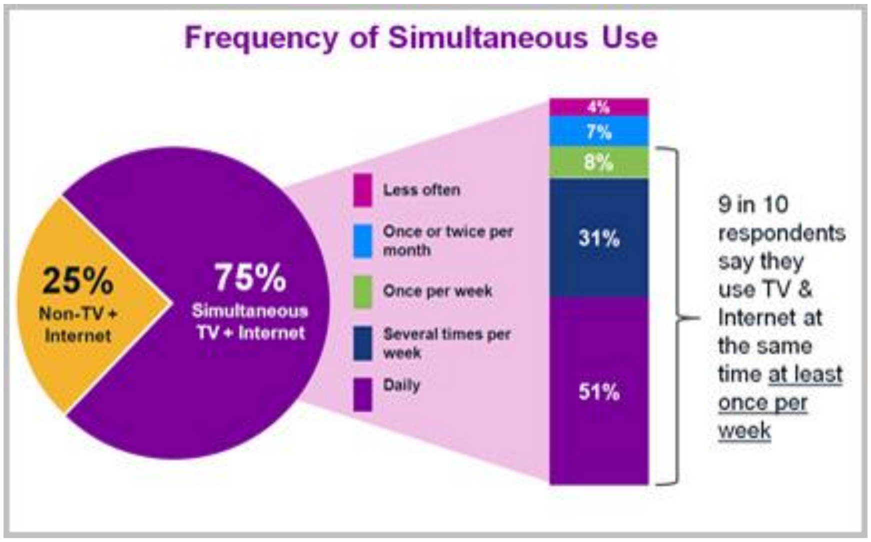
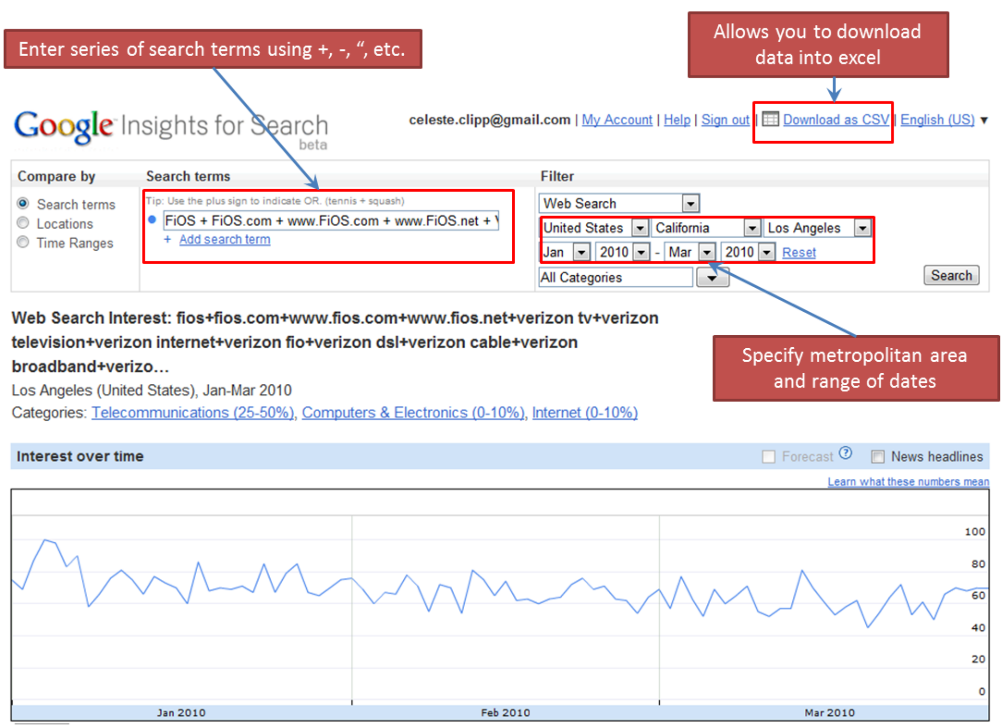


Figure 2: Visual demonstration of Google Insights for Search platform



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[7] Graphic taken from Yahoo! Advertising Blog

Table 1: Kantar Markets and Corresponding Google Insights Metropolitan Areas

	KANTAR MARKETS	GOOGLE INSIGHTS METROPOLITAN AREAS
1	ALBANY,NY	ALBANY-SCHENECTADY-TROY
2	ALBUQUERQUE	ALBUQUERQUE
3	ATLANTA	ATLANTA
4	AUSTIN	AUSTIN
5	BALTIMORE	BALTIMORE
6	BATON ROUGE	BATON ROUGE
7	BIRMINGHAM	BIRMINGHAM
8	BOSTON	BOSTON
9	BUFFALO	BUFFALO
10	BURLINGTON	BURLINGTON
11	CEDAR RAPIDS	CEDAR RAPIDS-WATERLOO
12	CHAMPAIGN	CHAMPAIGN-SPRINGFIELD-DECATUR
13	CHARLESTON,WV	CHARLESTON-HUNTINGTON
14	CHARLOTTE	CHARLOTTE
15	CHATTANOOGA	CHATTANOOGA
16	CHICAGO	CHICAGO
17	CINCINNATI	CINCINNATI
18	CLEVELAND	CLEVELAND
19	COLORADO SPRGS	COLORADO SPRINGS
20	COLUMBIA,SC	COLUMBIA
21	COLUMBUS,OH	COLUMBUS
22	DALLAS	DALLAS-FORT WORTH
23	DAVENPORT	DAVENPORT-ROCK ISLAND-MOLINE
24	DAYTON	DAYTON
25	DENVER	DENVER
26	DES MOINES	DES MOINES
27	DETROIT	DETROIT
28	EL PASO	EL PASO
29	EVANSVILLE	EVANSVILLE
30	FLINT	FLINT
31	FRESNO	FRESNO
32	FT MYERS	FT MYERS
33	GRAND RAPIDS	GRAND RAPIDS
34	GREEN BAY	GREEN BAY-APPLETON
35	GREENSBORO	GREENSBORO
36	GREENVILLE,SC	GREENVILLE-SPARTENBURG
37	HARRISBURG	HARRISBURG-LANCASTER-LEBANON-YORK

38	HARTFORD	HARTFORD
39	HONOLULU	HONOLULU
40	HOUSTON	HOUSTON
41	HUNTSVILLE	HUNTSVILLE
42	INDIANAPOLIS	INDIANAPOLIS
43	JACKSON,MS	JACKSON
44	JACKSONVILLE	JACKSONVILLE
45	JOHNSTOWN	JOHNSTOWN-ALTOONA
46	KANSAS CITY	KANSAS CITY
47	KNOXVILLE	KNOXVILLE
48	LAS VEGAS	LAS VEGAS
49	LEXINGTON	LEXINGTON
50	LITTLE ROCK	LITTLE ROCK-PINE BLUFF
51	LOS ANGELES	LOS ANGELES
52	LOUISVILLE	LOUISVILLE
53	MADISON	MADISON
54	MEMPHIS	MEMPHIS
55	MIAMI	MIAMI
56	MILWAUKEE	MILWAUKEE
57	MINNEAPOLIS	MINNEAPOLIS-ST PAUL
58	MOBILE	MOBILE
59	NASHVILLE	NASHVILLE
60	NEW ORLEANS	NEW ORLEANS
61	NEW YORK	NEW YORK
62	NORFOLK	NORFOLK-PORTSMOUTH
63	OKLAHOMA CITY	OKLAHOMA CITY
64	OMAHA	OMAHA
65	ORLANDO	ORLANDO
66	PADUCAH	PADUCAH
67	PHILADELPHIA	PHILADELPHIA
68	PHOENIX	PHOENIX
69	PITTSBURGH	PITTSBURGH
70	PORTLAND,ME	PORTLAND-AUBURN
71	PORTLAND,OR	PORTLAND
72	PROVIDENCE	PROVIDENCE
73	RALEIGH	RALEIGH-DURHAM
74	RICHMOND	RICHMOND-PETERSBURG
75	ROANOKE	ROANOKE-LYNCHBURG
76	ROCHESTER,NY	ROCHESTER
77	SACRAMENTO	SACRAMENTO

78	SALT LAKE CITY	SALT LAKE CITY
79	SAN ANTONIO	SAN ANTONIO
80	SAN DIEGO	SAN DIEGO
81	SAN FRANCISCO	SAN FRANCISCO
82	SAVANNAH	SAVANNAH
83	SEATTLE	SEATTLE-TACOMA
84	SHREVEPORT	SHREVEPORT
85	SOUTH BEND	SOUTH BEND
86	SPOKANE	SPOKANE
87	SPRINGFIELD,MA	SPRINGFIELD-HOLYOKE
88	SPRINGFIELD,MO	SPRINGFIELD
89	ST LOUIS	ST LOUIS
90	SYRACUSE	SYRACUSE
91	TAMPA	TAMPA
92	TOLEDO	TOLEDO
93	TRI CITIES	YAKIMA-PASCO
94	TUCSON	TUCSON
95	TULSA	TULSA
96	WACO	WACO-TEMPLE-BRYAN
97	WASHINGTON,DC	WASHINGTON
98	WEST PALM BCH	WEST PALM BEACH
99	WICHITA	WICHITA
100	WILKES BARRE	WILKES BARRE-SCRANTON
101	YOUNGSTOWN	YOUNGSTOWN-WARREN

Table 2: Provider-specific phrases for the selection of branded queries

AT&T	Uverse + “U verse” + uverse.com + uverse.net + www.uverse.com + www.uverse.net + AT&T TV + AT&T television + AT&T internet + AT&T dsl + AT&T cable + AT&T broadband + ATT TV + ATT television + ATT internet + ATT dsl + ATT cable	Must include “Uverse” or “U verse” or “uverse.com” or “uverse.net” or “www.uverse.com” or "www.uverse.net" or both “AT&T” and “TV” or both “AT&T” and “television” or both “AT&T” and “internet” or both “AT&T” and “dsl” or both “AT&T” and “cable” or both “AT&T” and “broadband” or both “ATT” and “TV” or both “ATT” and “television” or both “ATT” and “internet” or both “ATT” and “dsl” or both “ATT” and “cable”

Bright House Networks	Brighthouse + “Bright house” + brighthouse.com + brighthouse.net + www.brighthouse.com + www.brighthouse.net	Must contain “brighthouse” Or “bright house” Or “brighthouse.com” Or “brighthouse.net” Or “www.brighthouse.com” or “www.brighthouse.net”
Cablevision	Cablevision + “Cable vision” + cablevision.com + cablevision.net + www.cablevision.com + www.cablevision.net + Optimum + iO Cable	Must include “cablevision” Or “Cable vision” or “cablevision.com” or “cablevision.net” or “www.cablevision.com” or “www.cablevision.net” or “optimum” or both “iO” and “cable”
Centurylink	Centurylink + “century link” + Centurytel + “century tel” + Centurylink.net + Centurylink.com + Centurytel.net + Centurytel.com + www.centurylink.com + www.centurylink.net + www.centurytel.com + www.centurytel.net + embarq + embarq.com + embarq.net + myembarq.com + myembarq.net + www.embarq.com + www.embarq.net + www.myembarq.com + www.myembarq.net + embarqmail	Must include “centurylink” Or “century link” Or “centurytel” Or “century tel” Or “centurylink.net” Or “centurylink.com” Or “centurytel.net” Or “centurytel.com” or “www.centurylink.com” or “www.centurylink.net” or “www.centurytel.com” or “www.centurytel.net” Or “embarq” Or “embarq.com” Or “embarq.net” Or “myembarq.com” Or “myembarq.net” or “www.embarq.com” or “www.embarq.net” or “www.myembarq.com” or “www.myembarq.net” Or “embarqmail”
Charter Communications	Charter communications + Charter com + charter TV + charter television + charter internet + charter dsl + charter cable + charter broadband + charter.net + charter.com + www.charter.net + www.charter.com	Must include both “charter” and “communications” or both “charter” and “com” or both “charter” and “TV” or both “charter” and “television” or both “charter” and “internet” or both “charter” and “dsl” or both “charter” and “cable” or both “charter” and “broadband” or “charter.net” or “charter.com” or “www.charter.net” or “www.charter.com”

Cincinnati Bell	Cincinnati Bell + cincinnatibell + cincinnatibell.com + cincinnatibell.net + www.cincinnatibell.com + www.cincinnatibell.net	Must include both “Cincinnati” and “bell” Or “cincinnatibell” Or “cincinnatibell.com” Or “cincinnatibell.net” or “www.cincinnatibell.com” or “www.cincinnatibell.net”
Comcast	Comcast + comcastcom + comcast.com + comcast.net + www.comcast.com + www.comcast.net + Xfinity + X finity + xfinity.com + xfinity.net + www.xfinity.com + www.xfinity.net	Must include “Comcast” Or “comcastcom” Or “comcast.com” Or “comcast.net” Or “www.comcast.com” or “www.comcast.net” Or “Xfinity” Or both “X” and “finity” Or “xfinity.com” Or “xfinity.net” Or “www.xfinity.com” Or “www.xfinity.net”
Cox	Cox + coxcom + cox.com + cox.net + www.cox.com + www.cox.net	Must include “cox” Or “coxcom” Or “cox.com” Or “cox.net” Or “www.cox.com” or “www.cox.net”
Earthlink	Earthlink + earth link + earthlink.com + earthlink.net + www.earthlink.com + www.earthlink.net	Must include “earthlink” Or both “earth” and “link” Or “earthlink.com” Or “earthlink.net” Or “www.earthlink.com” or “www.earthlink.net”
Fairpoint	Fairpoint + fair point + fairpoint.com + fairpoint.net + www.fairpoint.com + www.fairpoint.net	Must include “fairpoint” Or both “fair” and “point” Or “fairpoint.com” Or “fairpoint.net” Or “www.fairpoint.com” or “www.fairpoint.net”
Frontier	Frontier communications + frontier com + frontier TV + frontier television + frontier internet + frontier dsl + frontier cable + frontier broadband + frontier fios	Must include both “frontier” and “communications” or both “frontier” and “com” or both “frontier” and “TV” or both “frontier” and “television” or both “frontier” and “internet” or both “frontier” and “dsl” or both “frontier” and “cable” or both “frontier” and “broadband” or both “frontier” and “fios”
Hawaiian Telecom	Hawaiian telecom + Hawaiian telcom	Must include both “Hawaiian” and “telecom” Or both “Hawaiian” and “telcom”

	+ Hawaiian tel + Hawaiiantel + Hawaiiantel.net + hawaiiantel.com + www.hawaiiantel.com + www.hawaiiantel.net + Hawaii telecom + Hawaiian communications + hawaiian com + hawaiian TV + hawaiian television + hawaiian internet + hawaiian dsl + hawaiian cable + hawaiian broadband	Or both “Hawaiian” and “tel” Or “hawaiiantel” Or “hawaiiantel.net” Or “hawaiiantel.com” Or “www.hawaiiantel.com” Or “www.hawaiiantel.net” Or both “Hawaii” and “telecom” or both “hawaiian” and “communications” or both “hawaiian” and “com” or both “hawaiian” and “TV” or both “hawaiian” and “television” or both “hawaiian” and “internet” or both “hawaiian” and “dsl” or both “hawaiian” and “cable” or both “hawaiian” and “broadband”
Insight Communications	insight communications + insight telecom + insight com + insight TV + insight television + insight internet + insight dsl + insight cable + insight broadband + myinsight.com + myinsight.net + www.myinsight.com + www.myinsight.net + insight-com + insight-com.com + www.insight-com.com	Must include both “insight” and “communications” Or both “insight” and “telecom” or both “insight” and “com” or both “insight” and “TV” or both “insight” and “television” or both “insight” and “internet” or both “insight” and “dsl” or both “insight” and “cable” or both “insight” and “broadband” or “myinsight.com” or “myinsight.net” or “www.myinsight.com” or “www.myinsight.net” or “insight-com” or “insight-com.com” or “www.insight-com.com”
Knology	Knology + knology.com + knology.net + www.knology.com + www.knology.net + myknology.com + myknology.net + www.myknology.com + www.myknology.net + connectwithknology + connectwithknology.com + connectwithknology.net	Must include “knology” Or “knology.com” Or “knology.net” Or “www.knology.com” or "www.knology.net" Or “myknology.com” Or “myknology.net” Or “www.myknology.com” or “www.myknology.net” or “connectwithknology” or “connectwithknology.com” or “connectwithknology.net”
Mediacom	Mediacom + "media com" + mediacomcc + mediacomcc.com + mediacomcc.net	Must include “mediacom” or “media com” or "mediacomcc" or “mediacomcc.com” or “mediacomcc.net”

	+ www.mediacomcc.com + www.mediacomcc.net	or “www.mediacomcc.com” or “www.mediacomcc.net”
Metrocast	Metrocast + metro cast + metrocast.com + metrocast.net + www.metrocast.com + www.metrocast.net	Must include “metrocast” Or both “metro” and “cast” Or “metrocast.com” Or “metrocast.net” Or “www.metrocast.com” or “www.metrocast.net”
North State Communications	North state telecom + northstate telcom + North state communications + northstate communications + northstate.net + www.northstate.net + north state com + northstate com + northstate TV + northstate television + northstate internet + northstate dsl + northstate cable + northstate broadband + north state TV + north state television + north state internet + north state dsl + north state cable + north state broadband	Must include “north” and “state” and “telecom” Or both “northstate” and “telcom” Or “north” and “state” and “communications” Or both “northstate” and “communications” Or “northstate.net” Or “www.northstate.net” or “north” and “state” and “com” or both “northstate” and “com” or both “northstate” and “TV” or both “northstate” and “television” or both “northstate” and “internet” or both “northstate” and “dsl” or both “northstate” and “cable” or both “northstate” and “broadband” or “north” and “state” and “TV” or “north” and “state” and “television” or “north” and “state” and “internet” or “north” and “state” and “dsl” or “north” and “state” and “cable” or “north” and “state” and “broadband”
Qwest	Qwest + qwest.com + qwest.net + www.qwest.com + www.qwest.net	Must include “qwest” Or “qwest.com” Or “qwest.net” Or “www.qwest.com” or “www.qwest.net”
RCN Corp	RCN + RCN.com + RCN.net + www.RCN.com + www.RCN.net	Must contain “RCN” Or “RCN.com” Or “RCN.net” Or “www.RCN.com” Or “www.RCN.net”
Suddenlink Communications	Suddenlink + “Sudden link” + suddenlink.com + suddenlink.net + www.suddenlink.com + www.suddenlink.net	Must contain “Suddenlink” Or “Sudden link” Or “suddenlink.com” Or “suddenlink.net” Or “www.suddenlink.com” Or “www.suddenlink.net”
Surewest Communications	Surewest + Sure West + surewest.com	Must contain “surewest” Or both “sure” and “west” Or “Surewest.com”

	+ surewest.net + www.surewest.com + www.surewest.net	Or “Surewest.net” Or “www.surewest.com” Or “www.surewest.net”
Time Warner Cable	Time Warner + TWC + Times Warner + tim warner + Warner cable + time cable + “Road Runner” + roadrunner + timewarnercable + timewarnercabl + timewarner.com + www.timewarner.com + timewarner.net + www.timewarner.net + timewarnercable.com + www.timewarnercable.com + timewarnercable.net + www.timewarnercable.net + twc.com + www.twc.com + twc.net + www.twc.net	Must include both “time” and “warner” Or “TWC” or both “times” and “warner” or both “tim” and “warner” or both “warner” and “cable” or both “time” and “cable” or “road runner” or “roadrunner” or “timewarnercable” or “timewarnercabl” or “timewarner.com” or “www.timewarner.com” or “timewarner.net” or “www.timewarner.net” or “timewarnercable.com” or “www.timewarnercable.com” or “timewarnercable.net” or “www.timewarnercable.net” or “twc.com” or “www.twc.com” or “twc.net” or “www.twc.net”
Verizon	FiOS + FiOS.com + www.FiOS.com + www.FiOS.net + Verizon TV + Verizon television + Verizon internet + Verizon fio + Verizon dsl + Verizon cable + Verizon broadband + Verizon triple play + Verizon double play + Verizon fiber optics + Verizon fiber optic	Must include “FiOS” or “FiOS.com” or “www.FiOS.com” or www.FiOS.net or both “Verizon” and “TV” or both “Verizon” and “television” or both “Verizon” and “internet” or both “Verizon” and “fio” or both “Verizon” and “dsl” or both “Verizon” and “cable” or both “Verizon” and “broadband” or both “Verizon” and “triple” and “play” or both “Verizon” and “double” and “play” or both “Verizon” and “fiber” and “optics” or both “Verizon” and “fiber” and “optic”
Winstream Corp.	Windstream + "wind stream" + windstream.com + windstream.net + www.windstream.com + www.windstream.net	Must contain “windstream” Or "wind stream" Or “windstream.com” Or “windstream.net” Or “www.windstream.com” Or “www.windstream.net”

Table 3: Regression Results of Only Top 7 Large Brands
(AT&T, Verizon, Comcast, Cox, Charter Communications, Qwest, and Time Warner Cable)

$\log(TVADEXP_{it})$	0.0013595**
Monday	0.0581134**
Tuesday	0.0238079**
Thursday	0.001016
Friday	0.0332531**
Saturday	0.0375455**
Sunday	-0.0192139**
$\log(BRANDSEARCH_{i(t-1)})$	0.3651135**
$\log(BRANDSEARCH_{i(t-2)})$	0.1539059**
$\log(BRANDSEARCH_{i(t-3)})$	0.1142803**
$\log(BRANDSEARCH_{i(t-4)})$	0.1220990**
$\log(TVADEXP_{i(t-1)})$	-0.0010604*
$\log(TVADEXP_{i(t-2)})$	0.0000836
$\log(NADEXP_{it})$	0.0004876
$\log(NADEXP_{i(t-1)})$	0.0007223^
$\log(NADEXP_{i(t-2)})$	0.0007862*
R-sq: within	0.3211
R-sq: between	0.9772
R-sq: overall	0.4516

^ Significant at the 10% confidence level / * 5% confidence level / ** 1% confidence level

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