Television and Digital Advertising: Second Screen Response and Coordination with Sponsored Search

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We consider the potential to improve the efficiency and efficacy of broader advertising efforts through cross-channel coordination. Past work has demonstrated a positive relationship between television advertising and online search activity. Here, we consider the types of devices on which search response predominantly manifests following TV advertisements, and the degree to which shifts in search activity can be used to evaluate the success of TV advertisers' targeting efforts. We leverage data on TV advertising around Microsoft Windows 10 and an Xbox app (NFL Game Day Evolution), in combination with large-scale proprietary search data from Microsoft Bing. Our identification strategies hinge on a combination of geographic heterogeneity in TV advertising exposure and continuous variation in the cost of TV advertisements (a proxy for TV audience size). We first demonstrate that search response peaks within three minutes of the airing of a TV advertisement, and that this manifests primarily via second-screen mobile devices. Our estimated elasticities indicate that a 20% increase in advertising spend equates to an approximate 2.5% (3.4%) increase in search volumes for Windows 10 (the Xbox app). Second, we show that, indeed, the demographic groups targeted by TV advertisements are those most likely to respond, and we thereby demonstrate that TV ad effectiveness can be usefully measured via online search data. Third, examining sponsored search clicks in our query-level data, for queries involving brand-related keywords, we demonstrate a significant increase in rank-ordering effects in searches that take place in the minutes immediately following a TV advertisement, which implies a complementarity between TV and sponsored search advertisements.

Key words: mobile; paid search advertising; search engines; search volumes; click-through rates; conversion rates; television advertising; differences in differences

1. Introduction

Television remains a dominant advertising medium in North America despite the massive growth of online search and display advertising over the last 20 years. The typical American home contains as many TVs as it does people, and Nielsen reports that as of Q4 2015, the average American spends nearly five hours each day watching television (Nielsen 2016). As a result, viewers are exposed to nearly 30 minutes of advertising content each day. In addition, online advertising has grown rapidly in recent years. Whereas a typical American spent just 30 minutes online each month in the late 1990s, this had grown to roughly 2.5 hours each day at end of 2015 (Nielsen 2016). Although online advertising formats vary widely, the most prominent is sponsored (paid) search. A typical Internet user in the United States employs a search engine 1.8 times per day and is accordingly exposed to sponsored search advertisements at the same frequency (Joo et al. 2014).

Recent research has demonstrated that television advertisements are associated with higher rates of online search for the advertised brands and products (Joo et al. 2014, Kitts et al. 2014, Lewis and Reiley 2013). This suggests significant potential for optimizing advertising effectiveness in online and offline settings through cross-channel coordination, an area that thus far remains untapped. Coordination of television and online advertising efforts remains particularly uncommon, with a majority of advertising agencies in the United States not offering any in-house television advertising services, and making no attempt to coordinate television and sponsored search advertisements for their clients (Joo et al. 2014). We therefore seek to address a number of open questions that have direct implications for cross-channel coordination of advertising, particularly with respect to television and online sponsored search. We consider the following: To what degree does search response manifest via second-screen (mobile) devices? Do sponsored search listings serve as complements or substitutes for television advertisements? Can we leverage online search data to assess the efficacy of targeting efforts in TV advertisements?

Recent work reports on the interactions between and within different advertising channels (Assael 2011). A few of these studies bear particular relevance to our research questions. First, in the sponsored search context, scholars have highlighted the importance of ranking effects for consumer click-through (Ghose and Yang 2009), the complementarity between sponsored and organic search listings (Yang and Ghose 2010), and the positive relationship between TV advertisements and online search response (Joo et al. 2014, Kitts et al. 2014, Lewis and Reiley 2013). To our knowledge, however, researchers have yet to consider the interaction between sponsored search listings and television advertisements, a logical next step and gap that we aim to address here.

There are a number of reasons we might expect sponsored search listings and TV advertisements to interact with one another, e.g., TV advertisements may drive amplified or attenuated ranking effects in sponsored search clicks either making searchers more sensitive to rank, or less. The importance of sponsored search listings may be amplified if search response is primarily attributable to mobile devices, because sponsored search links generally appear at the top of search results and mobile users are known to prefer items at the top of the screen (Ghose et al. 2013). This is notable, because recent industry reports indicate that second-screen response is particularly likely, with 87% of individuals reportedly using a second-screen device while they watch TV (Accenture 2015). Additionally, beyond the role of the searcher's device, research in social psychology discusses the mere exposure effect (Zajonc 1968, Fang et al. 2007), which suggests that consumers will exhibit a preference for something merely because it is familiar. Sponsored search advertisements related to a given product may therefore prove more attractive to users who initiate their search immediately following a TV advertisement. Sponsored search ranking may also prove to be less important following TV advertisements. This may be the case if the bulk of search response to TV advertisements is navigational in nature (Broder 2002), with consumers merely looking for the brand website to complete their product purchase or download. Thus, TV advertisements could serve as a either a complement or a substitute to sponsored search results. In either case, this would have direct implications for marketers, as it would suggest that they could benefit significantly from optimizing their keyword bidding around TV advertisements, in terms of timing, dollar amounts, and target device type.

To explore these ideas, we leveraged proprietary data on national television advertising related to the release of the Windows 10 software upgrade and an Xbox video game (hereafter referred to simply as Xbox). We paired this data with large-scale proprietary data on search queries from the Microsoft Bing search engine involving keywords related to each product. We explored i) how search volumes shifted dynamically in response to television advertisements, ii) differences in search volumes initiated by device type (i.e., desktop vs. mobile), iii) whether, conditional on making a search, queries were more likely to result in clicks on sponsored search listings, and iv) in any given query, whether rank ordering effects became more pronounced. We identified causal effects in search response via a relative time (minute) difference-in-differences estimation (Angrist and Pischke 2009, Autor 2003), exploiting plausibly exogenous geographic heterogeneity in TV advertising exposure.

This work makes a number of important contributions to the literature. First, beyond replicating past work (Kitts et al. 2014, Lewis and Reiley 2013), demonstrating that search response peaks within a matter of minutes following a TV advertisement, we show that search response manifested primarily via second-screen devices, namely smart phones, where estimated elasticities of search volumes with respect to advertising spend indicate that a 20% increase in spend equated to an approximate 2.5% (3.4%) increase in search volume in the case of Windows 10 (Xbox). Second, we show how online search data can be used to evaluate the efficacy of TV advertisers marketing efforts, demonstrating particular response amongst demographic subgroups, e.g., males for advertisements

aired during Sports shows. Third, conditional on search volume, we show that the volume of clicks on sponsored search listings increases significantly in the minutes immediately following TV advertisements. Finally, considering query-level data, we observe a significant increase in the strength of rank ordering effects amongst queries executed in the minutes immediately following a TV advertisement. Repeating these regressions conditional on device type (e.g., desktops only, or smartphone only), we observe no significant effects, which suggests that the aggregate result is driven by a relative increase in the proportion of mobile-initiated searches, and thus the greater ordering effects that mobile users are known to exhibit (Ghose et al. 2013).

In the following sections, we provide a brief review of the literature related to television, sponsored search, and mobile search. We then present our research design and identification strategy. Finally, we present our results, offer interpretations and discussion, and conclude by identifying a number of future research opportunities.

2. Literature Review

Our work is broadly related to the literature on marketing and information systems that addresses cross-channel interactions. A major focus of this body of work has been on the interaction between online and offline channels in retail. For example, Zentner et al. (2013) examined how video rental patterns changed as customers moved into a rental chains online channel and found that consumers became more likely to rent niche titles. Another example is the work by Forman et al. (2009), who demonstrated geographic heterogeneity in the use of online retail channels due to variation in the benefits of using this medium.

A few studies have also explored how advertising in one channel can influence activity in another (Assael 2011). For example, Lewis and Reiley (2014) showed via a massive randomized experiment in partnership with a major retailer that the majority of the effects of online advertising sales manifested offline. Conversely, Lambert and Pregibon (2008) demonstrated the effect of offline print advertisements on online sales. Most relevant to our work, however, are the few studies that have shown that television advertisements lead to short-term increases in the volume of online searches for associated brands (Joo et al. 2014, Lewis and Reiley 2013, Kitts et al. 2014). Television audiences whose interest is aroused by an advertisement may initiate an online search query, either to acquire the specific product mentioned (navigational search) or to learn more about it (informational search).

In this scenario, there are a number of reasons to expect that sponsored search listings will receive more attention from searchers. First, research in social psychology dating back nearly 50 years discusses the mere exposure effect, which holds that individuals exhibit a preference for something merely as a result of having been exposed to it previously (Zajonc 1968). Previously, this effect

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was shown as applicable in a variety of consumer decision-making contexts (Fang et al. 2007). If a television advertisement for a brand has just aired and is the reason a search was initiated, consumers should exhibit a natural preference for additional advertisements for the same brand rather than an organic link because the advertisements are more likely to be tied directly to the product being advertised on TV.

Second, online search response to television advertisements has been shown by multiple scholars to peak within minutes of the advertisement being aired (Lewis and Reiley 2013, Kitts et al. 2014). The quick response time suggests that consumers initiate searches using mobile, second-screen devices (e.g., smartphones and tablets). This is important because search costs have been shown to differ on mobile devices, with results displayed higher on the screen receiving more attention (Ghose et al. 2013).

Even on desktop computers, most users begin browsing from the top of search-result lists so higher-ranked items are likely to receive more attention, a phenomenon known as the primacy effect. The additional search costs imposed by mobile devices only exacerbate these effects. Moreover, Microsoft Bing, when viewed with a mobile browser, typically presents sponsored search listings at the top of the page, above any organic listings. Taken together, if consumers initiate searches from second-screen devices, we should observe a significant increase in the volume of clicks on sponsored listings.

3. Research Design

Microsoft is considered a large brand advertiser, spending over a billion dollars on advertisements across advertising channels per year. We studied television advertisements that were aired in the United States as part of three distinct Microsoft product marketing campaigns. The first campaign was for the launch of a major software product, Windows 10, which was the largest campaign in recent history for Microsoft. The campaign was truly global, reaching people from all across the world. The campaign was consistent across North America for both TV and sponsored search ads, a feature we will exploit later. The scale of the campaign, including the amount of search data that was generated by viewers, makes it a perfect testbed for TV advertising research.

The remaining two campaigns were significantly smaller. The second ad campaign was for the NFL Game Day Evolution App on the Xbox gaming console (which we henceforth refer to simply as Xbox), and the third is for a "back to school" campaign for Windows 10. Our television advertising data, obtained from Competitrack, includes all Microsoft TV advertisements from the period between July 20, 2015 and October 26, 2015 for the Windows 10 launch, the period between August 27, 2015 and October 26, 2015 for Xbox, and May 15, 2016 to September 25, 2016 for the Windows 10 "back to school" campaign. For each advertisement, we observed a unique code

l able 1	Timing & Density of Ad S	opend and Volu	me by Geog	graphic Scope	
Ad Campaign	Dates	National Ads	Local Ads	National Spend	Local Spend
Windows 10 Launch	7-20-2015 to 10-26-2015	0.88	0.12	0.99	0.01
Xbox NFL Evolution	8-27-2015 to 10-26-2015	0.74	0.26	0.97	0.03
Windows 10 Back to School	5-15-2016 to 9-25-2016	0.90	0.10	0.97	0.03

Table 1	Timing &	Density of	f Ad Spend	and Volume	bv	Geographic Scope
	0					

indicating the creative content (a specific advertisement, which may be aired repeatedly), the date and time the advertisement aired, what television channel aired the advertisement (e.g., Fox or NBC), the estimated cost of the advertisement, the name of the television program within which the advertisement was aired, and the length of the advertisement in seconds.

Microsoft often purchases National TV Ads, ads that are shown at the same time across the United States. However, Microsoft also purchases local TV ads that are targeted to a specific region, or Designated Market Area (DMA). DMAs are geographic regions defined by AC Nielsen, and have been used by TV networks to sell local advertising for decades. There are 210 DMAs in the United States and these DMAs vary in size based on the populations they cover. In our study, the Windows 10 Launch was largely a national campaign with 99% of AdSpend being National during the study period. Similarly, the Xbox campaign was 97% National. While the Windows 10 "back to school" campaign skewed towards National ads in the beginning, during the end of the campaign a significant number of ads were shown locally with only 5% being National in the dates between August 1, 2016 and September 25, 2016 (see table 1). There was not only heterogeneity in the amount of advertising spend per DMA; different locations were also shown different advertising creative. During this time Microsoft partnered with companies to highlight certain laptops (i.e., HP, Lenovo, Dell, MS Surface Pro). Some ads included a generic laptop, instead. We selected a small set of ad creatives to focus on for the third campaign. We selected ads that highlighted either Dell or generic laptop products in their messaging. This resulted in a total of four ad creatives. Two of the ad creatives aired primarily local ads in August and September 2016.

For national TV advertisements, we excluded those with an estimated spend below US \$35,000, for two reasons: i) these ads would likely have been viewed by a very small number of people, and ii) perhaps more importantly, excluding these ads leaves us with a set of treatments that do not overlap in time. The approach of focusing on relatively high-spend advertisements is similar to that used in a number of prior studies that have focused on advertisements during the Super Bowl (e.g., Lewis and Reiley 2013), which attracts the largest television audience for advertisements in a calendar year, and where the average advertisement costs approximately US $4,500,000^{1}$ At the same time, our consideration of a large number of advertisements over a long period of time enabled us to estimate the elasticity of dollars spent on television advertising. Our sample

¹ http://www.forbes.com/sites/alexkonrad/2013/02/02/even-with-record-prices-10-million-spot/

includes 439 national advertisements for Windows 10, 48 national advertisements for Xbox, and 87 National advertisements for the Windows 10 "back to school" campaign. Figure 1 presents a timeseries plot of total advertisement volume over time and the cumulative dollars spent on national television advertisements for Windows 10 over the period of first case study. The Windows 10 Launch campaign was by far the largest of the campaigns that we examined.



Figure 1 National TV Advertisement Volume Over Time for Windows 10.

We paired our data on television advertisements with proprietary data from Microsoft Bing on minute-by-minute search activity related to each product. Searches were identified as relevant to the product based on specific mentions of the product name in the search query (e.g., win 10, windows 10, etc., or Xbox, Xbox One, etc.). Given that both product names are unique, they are unlikely to confound other ambiguous search terms.

We included any searches that were initiated from a web browser or via Bing Mobile (the default non-browser search feature on older Windows phones); we excluded any searches that were initiated via Cortana, Siri, Yahoo, or other apps (e.g., the Bing app for iPhone), and in the case of the Windows 10 Launch, any searches initiated from a Windows 10 operating system, because we assumed known existing customers of Windows 10 would have different needs than potential customers, e.g., support requests. For each search, we observed the device type and operating system used to initiate the query. Notably, the searches in our sample for Windows 10 are predominantly from desktop devices, with the remainder of searches initiated from smartphones, tablets, and a variety of other devices, such as gaming consoles and portable media players. For Xbox, on the other hand, the proportion of searches originating from mobile devices is significantly higher, likely due to the younger consumer base. We also observed the general location of the user

initiating each search. Finally, in some cases, we observed user age and gender. Our dependent variable considers the number of unique searches over time by location and also by cohort (e.g., male, female, etc.).

In addition to logging searches, Bing records the URLs displayed to users as a result of a query, including organic results, sponsored listings, and answers, along with which links they click. Based on this information, we constructed an additional dependent variable: the volume of sponsored listings that were clicked amongst those displayed in search results (for queries related to the product), on a minute-by-minute basis. We recorded the volume of clicks for the first five ad results associated with every search. Figure 2 provides a visual example of how search results are presented to Microsoft Bing desktop users. Sponsored listings can appear in various locations on the page; if any of these are clicked, the measure of advertising clicks is incremented accordingly. Figure 3 provides a visual example of how search results are presented to Microsoft Bing smartphone users. Notably, sponsored listings are typically presented at the top of the screen, with organic links appearing below.





Figure 3 Microsoft Bing Mobile Search Results.



4. Methods

4.1. Identification Strategy: Simultaneous Substitution

To our knowledge, our work is the first to consider the impact of television advertising on online search while directly accounting for the endogenous timing and targeting of advertisements. As Joo et al. (2014) note, "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 account for this potential endogeneity, we began by considering a quasi-experimental setup derived from Canadian broadcasters practice of simultaneous substitution (Taylor 1993, Wagman 2013).² This repeated natural experiment allowed us to identify a conservative estimate of the effect of television advertisements on online search volumes across device types.

Wagman (2013, pg. 618) explained simultaneous substitution as Canadian television broadcasters' practice of purchasing the rights to American television programming and broadcasting this content to Canadian audiences in parallel via their own television feed (rather than directly supplying the American feed), enabling them to replace American advertisements with local advertisements and thus exploit their rights to American content to earn additional profit. Because the American content may attract a large audience, a company based in Canada or interested

² http://en.wikipedia.org/wiki/Simultaneous_substitution

in reaching the Canadian audience may wish to communicate through these broadcasts. Taylor (1993) estimated that in 1993, Canadian broadcasters earned the equivalent of US \$80 million in advertising revenue via this practice, an amount that would equate to US \$130 million today, and which would surely have increased in the intervening years. We should note, however, that simultaneous substitution is not comprehensively applied to all American advertisements. Some American content makes its way directly to Canadian consumers 'over-the-air' and via satellite. Additionally, although Canadian broadcasters maintain the rights to 'simsub', they do not always take advantage of the privilege. As such, some portion of American advertisements in our data will have been exposed to Canadian consumers as well. Any effects we identify are thus attributable to those instances where simultaneous substitution did in fact take place, and thus can be viewed as conservative estimates.

Our identification strategy is thus a typical differences-in-differences approach, similar to that employed by Card and Krueger (1994), Black (1999), and in other recent work that has sought to identify the effects of television advertising on offline retail sales (Shapiro 2015, Tuchman 2016). In contrast to these past studies, however, we estimated our models in a relative-time (minuteby-minute) manner (Angrist and Pischke 2009, Autor 2003). This enabled us to identify dynamic effects and the precise minute at which search volumes peak following the airing of a television advertisement.

Our analysis amounted to a consideration of multiple treatments over time, for repeated national TV advertisements. We structured our data such that we recorded 64 observations of search volumes around each product advertisement, with each observation reflecting a unique couple of country and relative (to advertisement air time) minute. Thus, we were left with pairs of panels of minute-by-minute search volumes in Canada and the United States over a balanced 32-minute window surrounding each TV advertisement (i.e., 16 minutes each for pre-advertisement and post-advertisement, for Canada and the United States, for each product).

4.1.1. Search Volume & Click-Through Rates We estimated the specification presented in Equation 1, where Y is the volume of unique individuals initiating a search on Microsoft Bing in country i at minute t for ad-run j. Our analysis was simplified by the fact that although the ads were aired across a number of broadcasters, none of the observation windows overlapped in their timing. We incorporated a vector of ad-run fixed effects, μ , which absorbs all static characteristics of a panel, including the effects of advertising creative, country, the television program in which the advertisement was embedded, and the product itself, among others. Here, USA is effectively our treatment indicator and is equal to 1 if the observation pertains to the United States and 0 if it pertains to Canada. Based on a continuous measure of the chronological distance, in minutes, from the ad air time, we constructed our vector of relative time dummies, *RelMin*. For example, the relative time dummy for $t\theta$ equals 1 only in those observations that pertain to the exact minute when advertisement j aired, and 0 otherwise. Similarly, the relative time dummy for t1 equals 1 only for observations that took place in the minute immediately following the start of a TV advertisement, and 0 otherwise. Finally, *AdSpend* captures the cost of a TV advertisement in US \$1,000.

$$\log(SearchVolume_{ijt}) = \alpha \cdot USA_i + \beta \cdot \sum_{\rho=-16}^{+15} RelMinute_{jt}^{\rho} + \gamma \cdot \sum_{\rho=-16}^{+15} RelMinute_{jt}^{\rho} \cdot USA_i + \delta \cdot USA_i \cdot \log(Aspend_j) + \lambda \cdot \sum_{\rho=-16}^{+15} RelMinute_{jt}^{\rho} \cdot \log(AdSpend_j) + \eta \cdot \sum_{\rho=-16}^{+15} RelMinute_{jt}^{\rho} \cdot USA_i \cdot \log(AdSpend_j) + \mu_j + \varepsilon_{ijt}$$

$$(1)$$

Our coefficients of interest are those reflected by η , which captures AdSpend moderated difference-in-differences estimates. We omitted the second minute prior to the recorded timestamp of an ad-run (t-2), treating it as the reference period. Our expectation was that we would observe no significant difference in the trend of search volumes between Canada and the United States in the minutes leading up to an advertisement, yet a significant, positive difference in the minutes immediately following. We estimated this specification twice, separately considering searches initiated from desktop devices and mobile devices. Incorporating AdSpend enabled us to recover elasticities with respect to the price of TV advertisements. Including this moderator, the lowerorder interaction term between USA and our RelMinutes dummies ceases to be of interest, as the associated coefficients reflect the difference-in-differences estimate when AdSpend is equal to 0, which is never the case.

We then considered the effects of TV advertisements on an alternative DV-the volume of sponsored result clicks-tying each click to the point in time when the associated search was initiated, as per Equation 2. Controlling for *Search Volume*, any significant shift in the volume of sponsored link clicks in the minutes following an advertisement could be interpreted as an increase in searchers' preference for sponsored search listings (or ordering effects, given that sponsored listings are primarily displayed at the top of the screen).

$$\log(SearchClicks_{ijt}) = \alpha \cdot USA_i + \beta \cdot \sum_{\rho=-16}^{+15} RelMinute_{jt}^{\rho} + \gamma \cdot \sum_{\rho=-16}^{+15} RelMinute_{jt}^{\rho} \cdot USA_i + \delta \cdot USA_i \cdot \log(Aspend_j) + \lambda \cdot \sum_{\rho=-16}^{+15} RelMinute_{jt}^{\rho} \cdot \log(AdSpend_j) + \eta \cdot \sum_{\rho=-16}^{+15} RelMinute_{jt}^{\rho} \cdot USA_i \cdot \log(AdSpend_j) + \phi \cdot SearchVolume_{ijt} + \mu_j + \varepsilon_{ijt}$$

$$(2)$$

As noted above, we also took this opportunity to explore heterogeneity in searches initiated by different demographic segments of the population, to demonstrate how online search activity may be used to assess the efficacy of TV advertiser targeting efforts. We showed, for example, that TV advertisements for Windows 10 that were aired during sports programs induced a response primarily among males. We assessed this by adding an additional interaction with a binary indicator, *Sports*, which equaled 1 for advertisements that were aired during the broadcast of sporting events (e.g., football games). We captured gender heterogeneity by first considering the subset of searches initiated by male users and then comparing our estimates with the subset of searches initiated by female users.

4.1.2. Query-Level Analysis We then considered the set of all queries that were initiated on Bing, using each keyword set, in the same window of time, again around national TV advertisements for a product. We constructed one observation for each sponsored search result (ad link), j, that was displayed to a user as a result of a given query, i. We once again estimated a relative time differencesin-differences specification, as expressed in Equation 3. Our outcome of interest, *AdClick*, was a binary indicator of whether the link was clicked by the user, thus we estimated a Linear Probability Model (LPM). Our independent variables once again included a vector of relative time dummies, *RelMinute*, equal to 1 in the relevant, relative minute with respect to when the TV advertisement began to air. Additionally, we once again interacted these dummies with our treatment indicator, *USA*. To measure the anticipated increase in ordering / ranking effects, we also included the ordinal ranking of the link in question as another moderator.

Because search response is shown to manifest primarily on mobile devices, we expected to see that ranking effects grew stronger in the USA in the minutes immediately following the TV advertisement airing. Thus, 2nd is an indicator of whether the search result ranking of a link observation was 2nd (versus 1st). We treat the top ranked result as the reference group in our estimation, so an ordering effect would manifest as significant negative coefficient on this rank dummy. We consider only the first two sponsored search results because our data indicates that mobile devices receive no more than two sponsored search results in the vast majority (more than 70%) of cases. Limiting our analysis to queries in which exactly two sponsored search results were displayed, regardless of device type, helps to ensure that all observations are homogeneous or 'comparable' in terms of advertising content. Nonetheless, to account for the possible endogeneity of link rank with respect to sponsored advertisement content (e.g., the text used in the description of a sponsored search result), we also included a vector of sponsored advertisement fixed effects, *URL*.

Finally, we also incorporated a query-level fixed effect, μ , which accounts for any static features of the search query, such as keyword choice, device type, or searcher intent. This query-level fixed effect subsumes the main effects of the *RelMin* dummies and *USA*, their two-way interactions, and any main effect of absolute query timing; thus, we observed only the main effects of our link rank dummy as well as its interactions with our time and country measures. Observing a negative interaction here would be consistent with a complementarity story, as it would suggest that in the minutes following a TV advertisement, it would be of greater importance for an advertiser to offer the highest bid on keywords related to the product, to ensure that their sponsored search result appears in the first ad position. Conversely, if we were to observe a significant positive interaction, this would be consistent with a substitution story, as it would indicate that obtaining the top sponsored result slot would be of lesser importance in the minutes immediately following a TV advertisement.

As noted earlier, our initial expectation is that we would observe a negative main effect from our rank dummy and, given our finding that the bulk of search response to TV advertisements manifests on smartphone devices, that its interaction with our difference-in-differences relative time dummies, η , will also have a negative and significant effect in the minutes immediately following a TV advertisement, bearing in mind the higher search costs that mobile users are known to experience (Ghose et al. 2013).

$$\begin{aligned} AdClick_{ij} &= \\ \alpha \cdot 2nd_j + \beta \cdot USA_i \cdot 2nd_j + \gamma \cdot \sum_{\rho=-16}^{+15} RelMinute_{jt}^{\rho} \cdot 2nd_j + \\ \eta \cdot \sum_{\rho=-16}^{+15} RelMinute_{jt}^{\rho} \cdot USA_i \cdot 2nd_j + \delta \cdot URL_{ij} + \mu_j + \varepsilon_{ijt} \end{aligned}$$
(3)

Following our primary set of analyses, we next consider the robustness of our results by exploring alternative identification strategies. These robustness checks follow.

4.2. Robustness Check 1: One Week Prior

In conducting our analyses of the advertising and search data of Xbox, it became apparent that unlike the global release of Windows 10, wherein online searchers were exposed to homogeneous sponsored search content (the vast majority of sponsored search links directed to just two websites, regardless of the user's geography), sponsored search advertisements for Xbox were targeted geographically (and largely domestically), such that the sponsored advertising content displayed between Canada and the United States exhibited almost zero commonality. That is, sponsored links to the main Xbox website appeared only to American users, and not Canadians. This lead us to consider a second identification strategy, which helps us to evaluate the robustness of our main results. In this alternative approach, we contrast Bing search and click activity in the United States, in the minutes around a TV advertisement, with the same activity observed in the United States exactly one week prior. We removed ads that had advertisements exactly one week apart. There were only 2 examples of this in our data.

Our estimations for this second identification strategy, which we apply to the Xbox data, closely mirror those outlined above with respect to Simultaneous Substitution. However, our treatment indicator now reflects whether the observations are *One Week* later versus earlier. That is, we replace our *USA* indicator throughout the various regression specifications with this alternative indicator.

4.3. Robustness Check 2: Designated Marketing Areas (DMAs)

In our analysis of the Windows 10 "back to school" campaign, we observed that the end of the campaign was primarily targeted to specific locations, in that specific advertisements were frequently shown only to selected DMAs. Prior research has exploited heterogeneous advertising expenditure between pairs of bordering counties that fall within neighboring DMAs (Shapiro 2015, Tuchman 2016). We thus consider a third identification strategy, of the same sort, which can be employed by marketers to evaluate the effects of local advertising efforts. Because we wish to maintain granularity in time, location and searcher demographics, for each TV ad spot that was aired at a particular time in a given program, we compare DMAs in a common timezone (for example Eastern Standard Time) that were shown the ad with other DMAs in the same timezone that were not. This DMA-based identification strategy allows us to compare locations within the United States that were shown different levels of advertising while allowing for the aggregation of search volume over all the relevant DMAs.

Our estimations for this third identification strategy, which we ultimately apply to the Windows 10 "back to school campaign" follow both the simultaneous substitution strategy and one week prior above. However, our treatment indicator, *DMA*, reflects whether the observations pertained

to a DMA where a TV advertisement was shown or not, within a common timezone. We once again replace our *USA* indicator throughout the various regression specifications with this alternative indicator.

5. Results

Before reporting our regressions, we present simple descriptives. Although we are unable to reveal data on raw search volumes, we provide information on the density distribution of average search activity in both Canada and the United States over time and, across devices, around the airing of TV advertisements for the Windows 10 Launch (see Figure 4). Here, we see that search volumes visibly spike in the minutes immediately following a TV advertisement, particularly on mobile devices.





In the following sections, we present analyses associated with our primary and secondary identification strategies, beginning with Simultaneous Substitution (i.e., USA vs. Canada), followed by the One Week prior strategy, and then finishing with the DMA-based strategy.

5.1. Main Results: Simultaneous Substitution

5.1.1. Search Volumes Our relative time-regression results with respect to unique users initiating searches over time in regard to Windows 10 are presented in Table 2. Each variable in the table reflects the log(Adspend) moderated difference-in-differences estimate for the indicated time period, where lower-order interactions and the main effects of our relative time dummies and country are omitted for the sake of brevity (that is, we report only estimates of η from Equation 1).

We limit our report to relative minutes -9 through +5, which represents a balanced range before and after our omitted (reference) period, t-2, again for the sake of brevity. Note that we treat t-2 as our reference period to allow for the possibility that the timestamps reflecting television advertisement air times may occasionally be recorded with a small degree of error (i.e., one to two minutes).

Variable	Desktop (1)	Mobile (2)
$RelMin_{t-9}$	0.019(0.064)	-0.041 (0.055)
$RelMin_{t-8}$	-0.002(0.069)	-0.033(0.050)
$RelMin_{t-7}$	-0.073(0.070)	-0.020(0.049)
$RelMin_{t-6}$	-0.021(0.070)	-0.052(0.051)
$RelMin_{t-5}$	$0.080 \ (0.063)$	0.027 (0.046)
$RelMin_{t-4}$	-0.040(0.061)	-0.056(0.050)
$RelMin_{t-3}$	0.068(0.058)	-0.012(0.044)
$RelMin_{t-2}$		
$RelMin_{t-1}$	-0.024(0.058)	-0.008(0.046)
$RelMin_{t+0}$	-0.091(0.070)	-0.043(0.055)
$RelMin_{t+1}$	-0.011(0.066)	$0.124^{st}(0.049)$
$RelMin_{t+2}$	0.033(0.071)	$0.115^{st}(0.051)$
$RelMin_{t+3}$	-0.021(0.065)	0.049(0.050)
$RelMin_{t+4}$	-0.045(0.071)	$0.035 \ (0.053)$
$RelMin_{t+5}$	-0.095(0.072)	-0.066(0.053)
Ad-Airing FEs	Yes	Yes
Advertisements	439	439
F-Statistic	7.94(127,438)	188.47 (126, 438)
Within \mathbb{R}^2	0.423	0.876

Table 2 Windows 10 Search Volumes – Sim. Sub. DV = Log(SearchVolume)

Robust standard errors in brackets; *** p<=0.001, ** p<=0.01, * p<=0.05

The coefficients returned from the log-log estimations can be interpreted directly as elasticities. Thus, we observed significant, positive increases in search volumes in the two to three minutes following a TV advertisement, but only on mobile devices. The coefficient estimates for our mobile regression are also presented graphically in Figure 5. The estimated elasticities indicate that a 20% increase in *AdSpend* around Windows 10 was associated with an approximately 2.5% increase in mobile search volumes in each of the two minutes after a TV advertisement first began to air. We observed no significant response for desktop searches. We considered the same regressions for search query volumes related to the Xbox; these are presented in Table 3, where we find similar results.

Figure 5 AdSpend Moderated Relative Time Estimates for Windows 10 Mobile Searches – Sim. Sub.



Table 3	Xbox Search Volumes – Sim. Sub.
	DV = Log(SearchVolume)

Variable	Desktop(1)	Mobile (2)
$RelMin_{t-9}$	-0.179 (0.173)	0.073(0.108)
$RelMin_{t-8}$	-0.060 (0.139)	-0.050(0.085)
$RelMin_{t-7}$	-0.020(0.101)	-0.175(0.103)
$RelMin_{t-6}$	-0.155(0.136)	$0.111 \ (0.099)$
$RelMin_{t-5}$	0.009(0.111)	$0.121 \ (0.085)$
$RelMin_{t-4}$	-0.039(0.131)	-0.047(0.103)
$RelMin_{t-3}$	-0.118(0.145)	$0.087 \ (0.082)$
$RelMin_{t-2}$		
$RelMin_{t-1}$	$0.028\ (0.117)$	$0.075 \ (0.082)$
$RelMin_{t+0}$	-0.058(0.142)	-0.003(0.096)
$RelMin_{t+1}$	-0.050(0.153)	$0.173^{st}(0.0.079)$
$RelMin_{t+2}$	-0.033(0.130)	$0.106\ (0.101)$
$RelMin_{t+3}$	-0.036(0.142)	$0.0185\ (0.098)$
$RelMin_{t+4}$	-0.020(0.143)	$0.123\ (0.099)$
$RelMin_{t+5}$	0.183(0.112)	$0.117 \ (0.105)$
Ad-Airing FEs	Yes	Yes
A dvertisements	48	48
F-Statistic	24.72(47,47)	$32.62 \ (47, \ 47)$
Within R^2	0.338	0.892

Robust standard errors in brackets; *** p<=0.001, ** p<=0.01, * p<=0.05

5.1.2. Click Through Rates Next, we re-estimated Equation 1, replacing search volumes with an alternative DV, the log of *TotalAdClicks*, which reflects the total volume of sponsored link clicks by individuals who initiated search queries at a particular point in time, relative to

the airing of a TV advertisement. We also incorporated *Search Volumes* as a control. Accordingly, these regressions amount to a rough analysis of sponsored search click-through rates. At the same time, we acknowledge that the approximation is imperfect because individuals may click on more than one link following any given search. Our estimates are presented in Table 4. Focusing on column 2, we observe that, conditional on search volumes, there was an increase in the number of advertisements that were clicked. This is particularly true among mobile users.

Variable	Desktop (1)	Mobile (2)
$RelMin_{t-9}$	0.032(0.038)	0.067(0.038)
$RelMin_{t-8}$	$0.048\ (0.038)$	-0.027(0.036)
$RelMin_{t-7}$	$0.026\ (0.038)$	-0.001(0.036)
$RelMin_{t-6}$	-0.003(0.037)	$0.058\ (0.039)$
$RelMin_{t-5}$	0.010(0.039)	$0.061 \ (0.036)$
$RelMin_{t-4}$	-0.007(0.037)	-0.005(0.034)
$RelMin_{t-3}$	0.012(0.033)	-0.005(0.038)
$RelMin_{t-2}$		
$RelMin_{t-1}$	-0.031(0.037)	$0.006 \ (0.037)$
$RelMin_{t+0}$	0.016(0.038)	-0.005(0.039)
$RelMin_{t+1}$	$0.038\ (0.037)$	$\boldsymbol{0.107}^{*}(0.041)$
$RelMin_{t+2}$	$0.024\ (0.039)$	$0.096^{*}(0.039)$
$RelMin_{t+3}$	$0.056\ (0.036)$	$0.062 \ (0.036)$
$RelMin_{t+4}$	$0.001 \ (0.035)$	$0.008\ (0.035)$
$RelMin_{t+5}$	-0.007(0.038)	$0.011 \ (0.041)$
SearchVolume	$0.010^{***}(0.001)$	$0.031^{***}(0.001)$
Ad-Airing FEs	Yes	Yes
Ad-Airings	439	439
F-Statistic	6.12(127, 438)	28.40(127,438)
Within \mathbb{R}^2	0.548	0.354

Table 4 Windows 10 Click-Through Rates – Sim. Sub. DV = Log(TotalAdClicks)

Robust standard errors in brackets; *** p<=0.001, ** p<=0.01, * p<=0.05

The fact that we observed increased clicks on advertisements, conditional on device type, suggests that the effects might not be entirely attributable to differences in form-factor. It may thus be the case that ordering effects grow stronger because of differences in user intent as well. For example, it may be that immediately following a TV advertisement, individuals who search for Windows 10 are significantly more likely to be be shown a relevant advertisement for Windows 10, e.g., download here. In contrast, at other points in time, it may be the case that advertisements for Windows 10 are irrelevant to a search user's interests (e.g., perhaps individuals performing queries with keywords such as *windows* are actually interested in learning about product features). Thus, it may be the case that search queries initiated as a result of the TV advertisement enable marketers

to better identify searcher intent; bidding on product-related keywords immediately following a TV advertisement may increase return on investment.

The Simultaneous Substitution identification strategy is not entirely appropriate when it comes to click-through from Xbox related searches. This is because, unlike Windows 10 sponsored search results, Xbox sponsored search results varies a great deal between the United States and Canada. In particular, the most common sponsored search advertisement related to Xbox search terms in the United States directs a user to the Xbox.com website. However, this particular sponsored link never appears for Canadian users in our sample. This is a primary reason that we explore alternative identification strategies in later sections.

5.1.3. Demographic Targeting We also explored heterogeneity in response to the TV advertisements by television programming content and gender in the Windows 10 campaign. In particular, we estimated two regressions (one for each gender), wherein we compared the gender-specific responses to ads aired during sports vs. non-sports related content. We constructed our indicator, *Sports*, such that it was set equal to 1 if the television program was a sporting event, and 0 if the television event fell into the categories of Prime Time or Morning Show (these are the top three most common day-part categories in our sample). Here, we focused in particular on the response from mobile devices, given our results above that illustrate that search response is only detectable on mobile devices. The results of the estimation are presented in Table 5. We see that male-initiated searches are significantly more likely to manifest when the host television program is sports related than otherwise, yet the same is not true of females.

5.1.4. Query-Level Analysis Having demonstrated the importance of second-screen devices in search response to TV advertisements, we next considered the implications for sponsored search advertisements. In particular, we considered the relative strength of ranking / ordering effects in consumers' click behavior in the minutes surrounding a TV advertisement for the keyword indicated brand, as per Equation 3. It is important to note that we only report this analysis for Windows 10-related advertisements. Once again, this is because Xbox sponsored search advertisements are geo-targeted.

In our Windows 10 sample, desktop searchers receive as many as five sponsored search results, yet for the vast majority of cases (more than 70% of queries), mobile users receive no more than two. As such, as an additional action to encourage homogeneity in the sponsored search content displayed to searchers, we limited our estimation sample to queries where exactly two sponsored search results were displayed, regardless of device type. This both ensures comparability across devices in terms of the advertising content displayed, and it excludes queries where only one sponsored result was displayed (i.e., queries that do not enable us to evaluate ordering effects).

Variable	Male - Mobile (1)	Female - Mobile (2)
$Sports \cdot RelMin_{t-9}$	0.074(0.100)	0.085 (0.106)
$Sports \cdot RelMin_{t-8}$	$0.070 \ (0.107)$	-0.075(0.110)
$Sports \cdot RelMin_{t-7}$	$0.112 \ (0.105)$	$0.006\ (0.108)$
$Sports \cdot RelMin_{t-6}$	$0.044\ (0.090)$	$0.059\ (0.110)$
$Sports \cdot RelMin_{t-5}$	$0.111 \ (0.106)$	0.108(0.101)
$Sports \cdot RelMin_{t-4}$	$0.008\ (0.100)$	$0.186\ (0.096)$
$Sports \cdot RelMin_{t-3}$	$0.065\ (0.106)$	$0.184\ (0.099)$
$Sports \cdot RelMin_{t-2}$		
$Sports \cdot RelMin_{t-1}$	-0.007(0.093)	$0.008\ (0.094)$
$Sports \cdot RelMin_{t+0}$	$0.086\ (0.108)$	0.110(0.108)
$Sports \cdot RelMin_{t+1}$	$0.159\ (0.104)$	$0.070\ (0.115)$
$Sports \cdot RelMin_{t+2}$	$0.209^{*}(0.105)$	$0.005\ (0.103)$
$Sports \cdot RelMin_{t+3}$	$0.088 \ (0.099)$	$0.052\ (0.123)$
$Sports \cdot RelMin_{t+4}$	-0.019(0.132)	$0.008\ (0.093)$
$Sports \cdot RelMin_{t+5}$	$0.116\ (0.099)$	-0.127(0.095)
$Ad-Airing \ FEs$	Yes	Yes
Ad-Airings	429	429
F-Statistic	724.92(164, 428)	285.24(164, 428)
Within R^2	0.783	0.401

 Table 5
 Windows 10 Gender Targeting – Sim. Sub. (Sports vs. Other)

 DV = Log(SearchVolume)

Robust standard errors in brackets; *** $p \le 0.001$, ** $p \le 0.01$, * $p \le 0.05$

We thus estimated a single rank dummy, which captures the relative difference in click-through probability between the second and first ad results. That is, we used the lowest rank (top position) as the reference category.

In column 2, we see clear evidence that the rank-ordering effect grows significantly stronger in the minutes immediately following a TV advertisement, before returning to 'normal'. That is, search users exhibit a stronger preference for the first link on the page, relative to the second, in the minutes immediately following a TV advertisement. For example, in the Windows 10 case, the probability that an average search user employing brand-related keywords will click the second link displayed becomes approximately 2-3% lower than the probability of clicking the first link shortly after a TV advertisement airs (effectively doubling the baseline ordering effect that exists at other points in time).

5.2. Robustness 1: One Week Prior

5.2.1. Search Volumes Because of the aforementioned issues around Xbox sponsored search results, i.e., geographic heterogeneity, we next revisited that sample of data and applied our alternative identification strategy, contrasting patterns of search in the United States around a national TV advertisement with activity in the same location one week prior. We report the results of the search volume regression first, in Table 7. As in our prior set of estimations, we observe significant

Variable	Order Effect (1)	Relative Time (2)
2^{nd}	$-0.039^{***}(0.0002)$	$-0.019^{***}(0.005)$
$RelMin_{t-9} \cdot 2^{nd}$		-0.003(0.007)
$RelMin_{t-8} \cdot 2^{nd}$		$0.005 \ (0.007)$
$RelMin_{t-7} \cdot 2^{nd}$		-0.002(0.008)
$RelMin_{t-6} \cdot 2^{nd}$		-0.007(0.007)
$RelMin_{t-5} \cdot 2^{nd}$		-0.005(0.007)
$RelMin_{t-4} \cdot 2^{nd}$		-0.003(0.007)
$RelMin_{t-3} \cdot 2^{nd}$		-0.004 (0.007)
$RelMin_{t-2} \cdot 2^{nd}$,
$RelMin_{t-1} \cdot 2^{nd}$		$0.014 \ (0.010)$
$RelMin_{t+0} \cdot 2^{nd}$		$-0.017^{*}(0.007)$
$RelMin_{t+1} \cdot 2^{nd}$		$-0.012^{*}(0.006)$
$RelMin_{t+2} \cdot 2^{nd}$		-0.005(0.008)
$RelMin_{t+3} \cdot 2^{nd}$		-0.005(0.007)
$RelMin_{t+4} \cdot 2^{nd}$		$0.003 \ (0.008)$
$RelMin_{t+5} \cdot 2^{nd}$		-0.011 (0.007)
Query FEs	Yes	Yes
$URL \; FEs$	Yes	Yes
F-Statistic	$45,379.48^{***}(1,X)$	$360.40^{***}(126, X)$
Within \mathbb{R}^2	0.037	0.037

Table 6 Windows 10 Ordering / Ranking Effects – Sim. Sub. DV = AdClick

Robust standard errors in brackets; *** $p \le 0.001$, ** $p \le 0.01$, * $p \le 0.05$; 2nd degrees of freedom measure excluded from F statistic reporting because raw query count is confidential.

effects only in searches initiated from smartphones, and not from desktops. We present the estimated mobile search volume response graphically in Figure 6. The estimated effects we observe are much stronger than those in Table 3, both in terms of magnitude and statistical significance. This can likely be attributed to the fact that the simultaneous substitution strategy only enables us to recover conservative estimates of the TV advertisements' effects on search response (again, because American advertisements are not substituted in every case and may occasionally be viewed by Canadian audiences).

5.2.2. Click-Through Rates With the One Week identification strategy, it is now possible for us to reliably estimate aggregate click-through rates. These results are reported in Table 8. Consistent with prior results, we once again observe increased rates of sponsored search clicks conditional on search volumes, once again primarily on smartphones (column 2). In particular, we observe significant increases in click-through in t+1, t+2 and t+4. Our estimates indicate that a 20% increase in advertising spend is associated with an approximate 5-6% increase in the rate of click-through.

5.2.3. Demographic Targeting To evaluate the robustness of our main findings, we once again explored heterogeneity in response to the TV advertisements by television programming

Variable	Desktop(1)	Mobile (2)
$RelMin_{t-9}$	0.099(0.106)	0.103(0.086)
$RelMin_{t-8}$	0.133(0.110)	$0.078 \ (0.088)$
$RelMin_{t-7}$	0.058(0.090)	$0.037 \ (0.068)$
$RelMin_{t-6}$	$0.045\ (0.093)$	0.115(0.081)
$RelMin_{t-5}$	0.082(0.089)	0.110(0.092)
$RelMin_{t-4}$	0.044(0.084)	$0.030 \ (0.086)$
$RelMin_{t-3}$	$0.048\ (0.109)$	$0.056\ (0.073)$
$RelMin_{t-2}$		
$RelMin_{t-1}$	-0.003(0.079)	$0.134\ (0.059)$
$RelMin_{t+0}$	$0.027 \ (0.091)$	$0.164 \ (0.094)$
$RelMin_{t+1}$	0.120(0.091)	$0.258^{stst}(0.080)$
$RelMin_{t+2}$	0.027(0.091)	$0.155^{st}(0.065)$
$RelMin_{t+3}$	0.000(0.090)	$0.189^{st}(0.095)$
$RelMin_{t+4}$	0.093(0.092)	0.104(0.078)
$RelMin_{t+5}$	$0.080 \ (0.082)$	$0.174^{st}(0.083)$
Ad – Airing FEs	Yes	Yes
Ad-Airings	48	48
F-Statistic	268.51 (47, 47)	123.61 (47, 47)
Within \mathbb{R}^2	0.159	0.345

 Table 7
 Xbox Search Volumes – One Week

 DV = Log(SearchVolume)

Robust standard errors in brackets; *** p<=0.001, ** p<=0.01, * p<=0.05

Figure 6 AdSpend Moderated Relative Time Estimates for Xbox Mobile Searches – One Week.



content and gender, this time in the Xbox advertising campaign. Once again, we estimated two regressions (one for each gender), wherein we compared the gender-specific responses to ads aired during sports vs. non-sports related content. We constructed our indicator, *Sports*, such that it

Variable	Desktop (1)	Mobile (2)
$RelMin_{t-9}$	-0.081(0.094)	-0.096 (0.140)
$RelMin_{t-8}$	-0.001(0.088)	0.109(0.107)
$RelMin_{t-7}$	-0.004(0.071)	-0.047(0.085)
$RelMin_{t-6}$	$0.021 \ (0.055)$	0.099(0.117)
$RelMin_{t-5}$	-0.001(0.061)	0.115(0.091)
$RelMin_{t-4}$	$0.099\ (0.089)$	$0.115\ (0.100)$
$RelMin_{t-3}$	$0.033\ (0.103)$	$0.117 \ (0.094)$
$RelMin_{t-2}$		
$RelMin_{t-1}$	-0.064(0.077)	-0.156(0.098)
$RelMin_{t+0}$	-0.014(0.064)	-0.002(0.115)
$RelMin_{t+1}$	0.069(0.063)	$0.021 \ (0.101)$
$RelMin_{t+2}$	$0.072 \ (0.065)$	0.128(0.113)
$RelMin_{t+3}$	-0.022 (0.079)	-0.067(0.079)
$RelMin_{t+4}$	-0.103(0.075)	$0.053\ (0.115)$
$RelMin_{t+5}$	-0.040(0.075)	$0.200^{st}(0.095)$
SearchVolume	$0.020^{***}(0.002)$	$0.027^{stst}(0.002)$
Ad – Airing FEs	Yes	Yes
Ad-Airings	48	48
F-Statistic	$356.61 \ (47, 47)$	76.87(47,47)
Within R^2	0.103	0.136

Table 8 Xbox Click Through Rates – One Week DV = Log(TotalAdClicks)

Robust standard errors in brackets; *** p<=0.001, ** p<=0.01, * p<=0.05

was set equal to 1 if the television program was a sporting event, and 0 if the television event fell into the categories of Prime Time or Weekend Daytime (once again the top three most common day-part categories in our sample). We focused on the response from mobile devices, as before, given our results above that illustrate that search response is only detectable on mobile devices. The results of the estimation are presented in Table 9. We again saw that male-initiated searches are significantly more likely to manifest when the host television program is sports related than otherwise, whereas the same was not true of females.

5.2.4. Query Level Analysis Finally, we repeat our analysis of ordering / ranking effects, this time in the Xbox data. The results of our estimations are reported in Table 10. Whereas we had observed a significant increase in ordering / ranking effects in the minutes following a Windows 10 advertisement, here we observe no such significant effects. It is possible that this is because a much larger proportion of searches for Xbox keywords are already on mobile devices to begin with, such that second screen response does not cause as substantial a shift in the prevalence of mobile initiated searches as in the case of Windows 10. Alternatively, it may be that our sample simply lacks power, given that the total volume of Xbox queries is approximately $1/50^{\text{th}}$ the volume of Windows 10 queries.

Variable	Male - Mobile (1)	Female - Mobile (2)
$Sports \cdot RelMin_{t-9}$	0.179(0.410)	-0.009(0.651)
$Sports \cdot RelMin_{t-8}$	0.179(0.520)	-0.071(0.604)
$Sports \cdot RelMin_{t-7}$	$0.069\ (0.521)$	$0.186\ (0.675)$
$Sports \cdot RelMin_{t-6}$	0.702(0.484)	$0.250\ (0.555)$
$Sports \cdot RelMin_{t-5}$	-0.528(0.609)	$0.941 \ (0.504)$
$Sports \cdot RelMin_{t-4}$	0.470(0.308)	-0.065(0.168)
$Sports \cdot RelMin_{t-3}$	$0.054\ (0.861)$	-0.358(0.345)
$Sports \cdot RelMin_{t-1}$	0.520(0.462)	0.024(0.572)
$Sports \cdot RelMin_{t+0}$	0.346(0.442)	0.512(0.434)
$Sports \cdot RelMin_{t+1}$	-0.189(0.591)	0.410(0.449)
$Sports \cdot RelMin_{t+2}$	$0.689^{st}(0.267)$	0.104(0.540)
$Sports \cdot RelMin_{t+3}$	$0.705^{*}(0.318)$	-0.077(0.585)
$Sports \cdot RelMin_{t+4}$	0.393(0.277)	0.296(0.334)
$Sports \cdot RelMin_{t+5}$	0.705(372)	0.209(0.567)
Ad-Airing FEs	Yes	Yes
Ad-Airings	48	48
F-Statistic	5.5e + 08(49, 47)	6.3e + 08(49, 47)
Within \mathbb{R}^2	0.442	0.159

Table 9 Xbox Gender Targeting – One Week (Sports vs. Other) DV = Log(SearchVolume)

Robust standard errors in brackets; *** p<=0.001, ** p<=0.01, * p<=0.05

In the next section, we explore the robustness of our results further by exploring our findings with the application of a third identification strategy, which is ideally suited to local advertisements.

5.3. Robustness 2: DMA-based

Search Volumes While local advertising spots comprise the minority of TV ads that 5.3.1. Microsoft purchases, a number of brand advertisers rely on local DMA-based advertising, in part because the cost of national advertising spots in prime time shows and major sporting events is prohibitive, but also because some advertisers seek to reach a particular local audience. Therefore, in this section, we demonstrate that we can measure search response to local DMA-based ads as well. We applied our approach to TV advertisements that once again pertained to Windows 10, this time as part of a "back to school" campaign that took place in the Summer and early Fall of 2016. Unlike the prior two TV advertising campaigns, where televised advertisements were limited to only one creative, the "back to school campaign" involved 5 very different ad creatives that aired within our period of observation, each of which highlighted a partner OEM laptop company. We focus on the most recent ads that featured either Dell computers or a Generic computer. We chose keywords once again associated with Windows 10, in addition to keywords associated with laptops. Investigating search response by the minute for a relatively small number of DMAs that were advertised to greatly limits the size of the television audience. As a result, total search response volumes are much smaller compared to the Windows 10 campaign we have reported on above, so

Variable	Order Effect (1)	Relative Time (2)
2^{nd}	$-0.049^{***}(0.002)$	$-0.072^{stst}(0.021)$
$RelMin_{t-9}$		0.011 (0.044)
$RelMin_{t-8}$		-0.035(0.040)
$RelMin_{t-7}$		$0.040\ (0.040)$
$RelMin_{t-6}$		-0.027(0.043)
$RelMin_{t-5}$		-0.015(0.043)
$RelMin_{t-4}$		-0.035(0.040)
$RelMin_{t-3}$		-0.017(0.041)
$RelMin_{t-2}$		
$RelMin_{t-1}$		$0.044 \ (0.038)$
$RelMin_{t+0}$		0.026(0.042)
$RelMin_{t+1}$		-0.012(0.044)
$RelMin_{t+2}$		-0.064 (0.046)
$RelMin_{t+3}$		0.008(0.038)
$RelMin_{t+4}$		0.078(0.044)
$RelMin_{t+5}$		-0.006(0.045)
Query FEs	Yes	Yes
$URL\ FEs$	Yes	Yes
F-Statistic	$418.86^{***}(1,X)$	$3.41^{***}(127,X)$
Within \mathbb{R}^2	0.042	0.051

Table 10 Xbox Ordering / Ranking Effects – One Week DV = AdClick

Robust standard errors in brackets; *** p<=0.001, ** p<=0.01, * p<=0.05; 2nd degrees of freedom measure excluded from F statistic reporting because raw query count is confidential.

our ability to undertake cohort analyses, e.g., search volumes by device, or gender, are constrained. Nonetheless, we are able to confirm that treated DMAs are more likely to exhibit an increase in searches in the minutes after a TV advertisement was aired and, additionally, conditional on search volumes, the volume of clicks on sponsored search advertisements also increases following a TV advertisement. Tables 11 and 12 present these results for search and click through rates, respectively, aggregated across all device types and demographics. Figure 7 presents the estimated search volume effects graphically.

6. Discussion

In this paper, we sought to measure cross-channel TV advertising effectiveness by asking the following questions: To what degree does search response manifest via second-screen (mobile) devices? Do sponsored search listings serve as complements or substitutes for television advertisements? Can we leverage online search data to assess the efficacy of targeting efforts in TV advertisements? This work makes a number of novel contributions to both the literature and practice on cross-channel coordination in advertising and marketing. Our work is the first to provide clear evidence that the majority of online search response to television advertisements manifests via second-screen mobile

Variable AllDevices	
$RelMin_{t-9}$ -0.021 (0.093)	
$RelMin_{t-8}$ 0.122 (0.099)	
$RelMin_{t-7}$ 0.148 (0.102)	
$RelMin_{t-6}$ -0.002 (0.089)	
$RelMin_{t-5}$ 0.059 (0.087)	
$RelMin_{t-4}$ 0.072 (0.122)	
$RelMin_{t-3}$ 0.141 (0.087)	
$RelMin_{t-2}$	
$RelMin_{t-1}$ 0.142 (0.086)	
$RelMin_{t+0}$ 0.053 (0.085)	
$RelMin_{t+1}$ 0.219 [*] (0.090)	
$RelMin_{t+2}$ 0.117 (0.075)	
$RelMin_{t+3}$ 0.008 (0.088)	
$RelMin_{t+4}$ 0.010 (0.105)	
$RelMin_{t+5}$ 0.195 ^{**} (0.060))
Ad-Airing FEs Yes	
Ad-Airings 87	
F-Statistic 159.85 (47,47)	
Within R^2 0.775	

Table 11 Windows 10 Back to School Search Volumes – DMA-Based DV = Log(SearchVolume)

Robust standard errors in brackets; *** p<=0.001, ** p<=0.01, * p<=0.05

Figure 7 AdSpend Moderated Relative Time Estimates for Back to School Searches – DMA-based



devices. We also show that people are much more likely to click on sponsored search ads when searching for products immediately after they are advertised on TV.

Variable	All Devices
$RelMin_{t-9}$	0.0813(0.058)
$RelMin_{t-8}$	-0.009(0.037)
$RelMin_{t-7}$	0.0263(0.041)
$RelMin_{t-6}$	$0.001 \ (0.0360)$
$RelMin_{t-5}$	-0.038(0.0360)
$RelMin_{t-4}$	0.053(0.043)
$RelMin_{t-3}$	-0.022(0.034)
$RelMin_{t-2}$	
$RelMin_{t-1}$	$0.026\ (0.046)$
$RelMin_{t+0}$	0.010(0.040)
$RelMin_{t+1}$	$0.096^{st}(0.043)$
$RelMin_{t+2}$	$0.054 \ (0.062)$
$RelMin_{t+3}$	-0.010(0.037)
$RelMin_{t+4}$	$0.020 \ (0.048)$
$RelMin_{t+5}$	$0.052\ (0.048)$
SearchVolume	$0.013^{***}(0.0004)$
Ad – Airing FEs	Yes
Ad-Airings	48
F-Statistic	42.24(47,47)
Within \mathbb{R}^2	0.874

Table 12 Windows 10 Back to School Click Through Rates – DMA-based DV = Log(TotalAdClicks)

Robust standard errors in brackets; *** $p \le 0.001$, ** $p \le 0.01$, * $p \le 0.05$

Our findings have implications for how advertisers should plan their digital advertising campaigns around TV advertisements. Consumers who are initially driven to conduct an online search by a television advertisement might easily be distracted and shift their focus to a competing brand. This is perhaps one reason for the observation that purchasing sponsored search listings is beneficial for a brand, even when that brand already appears in organic listings; if a brand can dominate (both organic and sponsored) search results, it can preclude consumers shift in focus to a competing brand (Yang and Ghose 2010). On a mobile device, after a TV ad, this concern may be even more pronounced, because the searcher is quite likely to place a great deal of focus on the top-ranked sponsored listing, which would possibly be the only item in view due to the small format of the device. Since we demonstrate that most people are using mobile second screens to respond to TV ads, channel coordination is very important for advertisers. Future work can explore the relative influence and interactions between sponsored and organic search-result ranking effects by device type in the minutes following TV advertisements.

This study hints at other opportunities to build on recent studies in the area of sponsored search as well. For example, Agarwal and Mukhopadhyay (2016) have recently reported evidence that click-through for a particular sponsored search listing can be influenced by competing sponsored listings appearing in neighboring positions, because consumers may infer the quality of a focal advertisement based on the quality of neighboring advertisements. Our results suggest that the influence of competing sponsored advertisements can also vary in the minutes following TV advertisements, again because of the spike in searches initiated from second screen devices. In particular, if users exhibit a growth in preference for lower rank sponsored listings, their consideration of competing ads may also decline.

From a practical standpoint, our work provides a number of important insights to marketers. Besides quantifying the precise relationship between ad spending and increased online searches and ad clicks, we measured the search response from specific intended TV audiences by gender and age (age results not shown due to space constraints). Our approach for doing so can be used in at least two ways: 1) to determine if the intended audience of a demographically targeted ad is responding and, if not, how can advertisers tweak their strategies by offering different creative or advertising during different TV shows and 2) to allow an advertiser to advertise more generally at first to determine who will respond to their product ads. This information, in turn, provides an opportunity to learn the audience and, as a result of the learning, tweak ad campaigns to be more targeted to the most appropriate audiences.

7. Concluding Remarks

The scale, geo-temporal granularity, and complexity of the data at hand provide many opportunities for future work. Our work already informs marketers on how they should coordinate their crosschannel advertising spend; they should work to ensure their ads show up first on mobile searches in the minutes after a TV ad is shown, thus when a company runs a TV advertisement, they should also advertise on mobile aggressively at the same time. However, there are a number of other possible avenues for future work that could help further inform marketers. First, we plan to move beyond searches and clicks and measure the longer-term effects on product sales. We also plan to explore the actual links that users are exposed to and click on, enabling us to study whether a searcher is more likely to click on product-related content as opposed to any click on an ad. Using these more detailed data, we can also explore interactions between TV ads and organic and sponsored search links for a given page of results. In addition, by coding searches by their intent, we have already found that navigational searches (to buy, download, or upgrade) for the product in our study significantly increase conditional on searching after a TV ad is shown.

In Figure 8, we show a combined list of the top 10 search queries about Windows 10 posed to Bing on mobile in the 3 minutes before ads (pre) compared to the 3 minutes after ads (post). We calculate the proportion of times the query appears over all queries in the given period and find that people are likely to be more direct, searching for "Windows 10" 71% of the time, compared





to 64% of the time in the pre period. In addition, we find that people are more likely to search for "Windows 10 commercial" in the post period, which provides validation that searchers are indeed responding to the ad. Going forward, we plan to take the search labeling further and ascertain whether we can measure the impact of TV advertising on consumers at different stages in the purchase funnel and on more active users. Finally, we plan to extend this work to other Microsoft products as well as those of its competitors.

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