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Immediate Responses of Online Brand Search and Price Search to TV Ads

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Abstract

This study aims to deepen the understanding of evaluating TV ad spots by their immediate effects on important online activities. The authors merged minute-by-minute brand search and price search data with spot-level TV advertisement data for the three leading pickup truck brands in the United States over an 11-month period. They presented a generalizable modeling framework and used it to estimate the size and variation of immediate online responses to TV ads. The average elasticity of brand search to a brand's own national ads is .09, and the average elasticity of price search to a brand's own national ads is .03. Given ad audience size, immediate search responses vary with ad creative characteristics, audience category interest, slot of the break, program genre, and time factors. Overall, the results show that ordinary TV ads lead to a variety of immediate online responses and that advertisers can use these signals to enrich their media planning and campaign evaluations.

Keywords

TV advertising, attribution, brand search, price search, programmatic

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Although TV ad spend in the United States was surpassed by digital in 2016, TV remains an important medium, accounting for approximately 37% of total ad spend (eMarketer 2017a). In 2020, advertisers in the United States are projected to spend $70 billion on TV advertising (eMarketer 2018). Digital advertising has overtaken TV and other offline media for many reasons; for example, the perceived ease with which digital advertisers can quantify the relative effectiveness of different ad insertions on the basis of behavioral responses such as click-throughs and conversions. Such a capability allows digital advertisers to have greater confidence in their selections of ad creative and media placements.

By contrast, with the exception of informercials and other direct-response-oriented ads, most traditional TV advertisers have not relied on behavioral response measures to determine the relative effectiveness of different ad copy or media placements. Instead, in evaluating ad creative, TV advertisers have relied on either "gut feel" or attitudinal measures collected through focus groups or sample surveys. In planning media placements, TV advertisers have long relied on program ratings and basic audience demographics such as age and gender.

Meanwhile, consumers' self-reported television usage has not fallen: it was reported at 2.77 hours per weekday per person in both 2013 and 2017 (American Time Use Survey 2013, 2017). So-called "second screening" behaviors, particularly during commercial breaks, have rapidly become pervasive, with 178 million Americans regularly using a second-screen device while watching TV (eMarketer 2017b). Ready access to a second screen empowers TV viewers to take immediate actions after seeing an ad, such as searching for product reviews, attributes, or prices; expressing opinions on social media; or placing an order on the advertiser's website. Given rampant ad blocking, ad fraud, and nontransparency in digital advertising markets, advertisers that aim to influence online actions may wish to continue advertising in offline media such as television. They may further wish to use detailed online response data to help refine media plans and campaign evaluations.

Both practitioners (e.g., Lewis and Reiley 2013; Zigmond and Stipp 2010, 2011) and researchers (e.g., Hill, Burtch, and Barto 2017; Liaukonyte, Teixeira, and Wilbur 2015) have recognized that TV ads can cause immediate—within minutes—post-ad spikes in various online activities (e.g., searches

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or app downloads for the advertised brand, visits to the advertiser's website). The prevalence and immediacy of such ad-driven online responses raise a tantalizing question: Can TV advertisers use post-ad spikes in online activities to assess the relative effectiveness of different ad spots? If the answer is affirmative, it would have the potential to dramatically improve how TV ad copy and media placements are chosen, which would ultimately lead to enhanced cost-effectiveness of TV as an advertising medium.

Indeed, recognizing such potential, many attribution vendors have introduced services that promise to link spikes in online activities to the individual TV ads that caused them, helping advertisers select ad copy and media placements to maximize immediate online response. We are aware of more than a dozen vendors that offer such services. For example, Google Analytics 360 TV Attribution pairs minute-level ad airing data with search and website traffic data and uses a machine learning algorithm to "accurately attribute digital activity to your TV ad spots . . . to help you make smart choices about your advertising investment."[1] Similarly, Neustar MarketShare's TV attribution application, in collaboration with comScore Rentrak, measures the impact of TV ad spots on website visits and inbound calls, which "shows why your ads work. Or don't. (Was it the network? Creative? Timing? A combination of those?)" TVSquared ADvantage claims to have helped more than 700 brands, agencies, and networks improve TV campaign effectiveness by tracking "how TV drives response via phone, app, mobile, web and SMS," thereby allowing advertisers to "understand spot-level and campaign-wide performance by day, daypart, network, genre, program, creative and audience."[2] In 2018, Adobe Advertising Cloud TV, a leading platform for programmatic TV ("automated, data-driven planning and buying of television advertising"; TVSquared 2018), launched a partnership with TVSquared ADvantage to allow advertisers to optimize national, cable, and local TV buys on the basis of spot-level online response.[3]

In addition to advertising attribution vendors, many start-ups and other digital-first marketers have developed similar capabilities in-house. Private conversations with practitioners indicate that many are using these practices to mechanically refine their TV ad creative and media schedules without a deeper understanding of the TV-to-online spillovers. It is against this backdrop that we conducted the current study, with the following intended contributions.

Methodologically, all the TV attribution vendors have kept the core algorithm behind their proprietary solution a trade secret, providing little detail to the public for an independent and impartial evaluation. Getting attribution right is notoriously difficult, even more so for mass media such as television. It is one matter to show that TV ads can cause statistically significant immediate post-ad spikes in online activities; it is another to measure spot-level responses with such precision that one can quantify the relative performances of different ad creative and media placements. We see many challenges that need to be adequately addressed:

- *Establishing a proper baseline at the minute level*. The baseline must be flexible enough to account for complex trend and seasonality (e.g., minute-of-hour, hour-of-day, day-of-week patterns). In addition, many other factors can influence the baseline and thus cause potential misattribution. For example, a portion of the post-ad spike in online activities could have been caused by the absence of programming content during a commercial break, as opposed to the presence of a particular ad spot. Alternatively, many correlated observables and unobservables can influence both the focal advertiser's ads and online activities. For example, a competitor's media schedule could be correlated with the focal advertiser's, and competitive ad spots could have an immediate spillover on the focal advertiser's online metrics.
- *Separating signal from noise*. Many online activities are inherently very noisy, and many TV ad insertions may produce subtle signals, especially when the number of impressions generated by a TV spot is small or the response rate per impression is low.
- *Assigning attribution across overlapping spots*. It is not uncommon that multiple spots of the same TV advertiser may be aired on different networks at approximately the same time—in the same minute or with overlapping durations (e.g., ad insertions by a heavy prime-time advertiser or during a blitz campaign). One therefore must be able to assign attribution across overlapping spots in a logically coherent manner.
- *Accounting for a multitude of moderating factors*. The amount of immediate online response to an ad spot is determined by the number of ad impressions and the response rate per impression. The former requires a reliable measure of ad audience size (as opposed to just the program rating or ad spend). The latter can be a function of ad creative characteristics, media placement, and audience composition. Because these moderating factors can be correlated with one another, one needs to account for them simultaneously to minimize omitted variable biases.

We aim to develop a rigorous, yet practical, approach to addressing these challenges. We propose a modeling framework that links ad insertions to minute-by-minute online metrics and illustrate it with "real-world" size data compiled from multiple sources. We intend to provide practitioners and researchers alike a transparent and replicable tool for TV attribution based on immediate online response. Advertisers, agencies, and networks can use our method as a benchmark in evaluating the proprietary solutions offered by attribution vendors.

[1] https://www.youtube.com/watch?v=bmnPtVXx43k (accessed October 2018).
[2] https://tvsquared.com/products/advantage/ (accessed October 2018).
[3] https://www.adobe.com/experience-cloud/topics/programmatic-tv.html (accessed October 2018).

In addition to making a methodological contribution, we intend to make a substantive contribution by answering the following empirical questions, which can potentially serve as reference points for future research in this area:

- What is the typical rate of immediate online response to a *regular* TV ad spot? How does the elasticity compare with those reported in prior studies?
- How long does the immediate response last? How does the response rate vary by minute after an ad insertion? Does it peak in the minute the ad is shown and then decay exponentially, or does it peak in the minute after the ad is aired and then fade away gradually?
- How is the response rate similar or different for brands from the same product category?
- Is there immediate online response to competitors' TV ads? Are competitive spillovers positive or negative? How do spillovers between brands compare with own-brand effects? Are spillovers asymmetric between leader and follower brands?
- How is the immediate online response affected by ad creative quality? All else being equal, is there more immediate online response to ads that are deemed as more informative? What about ads that are rated as more likable, or ads that make the advertised product more desirable?
- How do media placement factors affect the rate of immediate online response to an ad spot? All else being equal, how much higher is the response rate for the first slot in a commercial break? What about prime time versus non–prime time, broadcast versus cable, live sports versus other programs, weekend versus weekdays?
- How does audience category interest affect the rate of immediate online response?
- How may answers to the previous questions vary depending on the nature of the online activity in question (e.g., brand search vs. price search)?

As the empirical context for our study, we focus on three top pickup truck brands in the U.S.—Ford F-Series, Chevy Silverado, and Ram Trucks—for four key reasons. First, car shoppers engage in various online activities before making a purchase, with a purchase funnel that can last for weeks or months (J.D. Power and Associates 2017). Car shoppers are exposed to numerous ads and promotions from a myriad of online and offline sources. These exposures make it nearly impossible to quantify the impact of any regular TV ad spot on sales or brand attitudes (Du, Joo, and Wilbur 2019). This, in turn, makes the automotive industry highly relevant for testing the potential of refining TV media planning and campaign evaluation by using immediate online responses to TV ads.

Second, these three pickup truck brands represent a set of well-defined direct competitors, allowing us to compare and contrast effect estimates to identify similarities and differences as well as to quantify the direction and degree of competitive spillovers. According to *Motor Intelligence*, Ford F-Series had a market share of about 31% in 2016, followed by Chevy Silverado at 22% and Ram Trucks at 18%, continuing a 33-year trend of stable market share rankings in a $40 billion category (Xu, Wilbur, and Silva-Risso 2018).

Third, these three brands offer a fertile ground for investigating how various ad creative–, media placement–, and audience-related factors may moderate the rate of immediate online response to TV ads. During the period under study (a span of 493,920 minutes), the three brands ran 27,562 ad spots on national TV, deploying 169 distinct pieces of creative and spanning a wide range of dayparts, pod positions, broadcast and cable networks, and program genres. This allows us to quantify immediate online response to TV ad insertions under a wide variety of conditions. Furthermore, we have access to ad audience data and a measure of audience interest in the pickup truck category for each national spot. This allows us to separate, for the first time in research in this area, the effects of ad creative and media placements from those of audience characteristics.

Fourth, these three brands present a conservative test of our modeling framework for quantifying the immediate online response attributable to individual ad spots. Ford F-Series, Chevy Silverado, and Ram Trucks are all mature brands that are well known to U.S. consumers (in contrast to newer or lesser known brands, for which ad viewers may exhibit a stronger tendency to respond immediately by searching online). Furthermore, many prior studies in this area have examined ad spots in "must-see" TV programs that had tens of millions of viewers (e.g., the Super Bowl, the Olympic Games). The average and median audience per spot for the "ordinary" national TV ads included in our study are .5 million and .2 million, respectively. In addition, no prior study has examined local TV ads, which tend to have a much smaller audience per spot, presumably causing a much smaller and thus harder-to-detect post-ad spike in online activities. Unlike national spots, we do not directly observe the audience size for each local spot. As a result, we use the spend estimate of each local spot as a proxy. In our study, the three pickup truck brands had in total 750,672 local ad insertions, with an average (median) spend of $348 ($159) per spot. The upshot is that the empirical context of our study enables us to test whether our modeling framework is sensitive and reliable enough to quantify immediate online response to ordinary national and local TV ads, thus making our findings more generalizable to everyday circumstances encountered by the majority of TV advertisers.

Before proceeding, it is important to acknowledge that while it is useful and insightful to model how and when TV ad spots can drive immediate brand and price searches, such midfunnel performance metrics are only part of a bigger picture because advertisers are ultimately interested in driving bottom-line performance metrics such as sales. Although it is beyond the scope of the current study, more research is needed in linking the former with the latter.

The rest of the article consists of the following. The next section discusses how our study relates to and extends the existing research. We then present the proposed modeling

Table 1. Literature on Online Response to Offline TV Ads.

Research	Response Variables	Time Window/Unit of Analysis	Moderating Effects	Competitive Spillovers	Ad Content Data	Ad Audience Data
Zigmond and Stipp (2010)[a]	Online search (Google)		No	No	No	No
Hu, Du, and Damangir (2014)	Online search (Google) and sales	Monthly	No	No	No	No
Laroche et al. (2013)	Online search	Weekly	No	No	No	No
Tirunillai and Tellis (2017)	Online chatter	Daily	No	No	No	No
Chandrasekaran, Srinivasan, and Sihi (2018)	Online search (Google)	Three-day window	Yes	No	Yes	No
Joo et al. (2014)	Online search (Google)	Hourly	No	No	No	No
Joo, Wilbur, and Zhu (2016)	Online search (AOL)	Hourly	Yes	No	Yes	No
Guitart and Hervet (2017)	Customer conversions	Hourly	No	No	No	Yes
Lewis and Reiley (2013)	Online search (Yahoo!)	Minute	No	No	No	No
Liaukonyte et al. (2015)	Brand website traffic on desktop and laptop (direct and search engine referrals), and online purchases on desktop and laptop	Two-minute window	Yes	No	Yes	No
Fossen and Schweidel (2017)	Online WOM	Two-minute window	Yes	No	Yes	No
Kitts et al. (2014)	Web traffic	Five-minute window	No	No	No	No
Hill et al. (2016)	Online search (Bing)	Minute	No	No	No	No
He and Klein (2018)	Online sales	Minute	No	No	No	Yes
Current research	Online brand search (Google) and online price search (car shopping websites)	Minute	Yes	Yes	Yes	Yes

[a]Zigmond and Stipp (2010) published several case studies with only data visualizations and no formal econometric analysis.

framework and the data used to illustrate it. We report the empirical findings and results from what-if analyses. We conclude with a discussion of the managerial implications and directions for future research.

Relationship to Prior Literature

As the second-screen phenomenon during television advertising has become more prevalent, a growing body of research has documented some of its effects on various online metrics. Table 1 provides an overview of this stream of research and identifies the key dimensions that distinguish the current study from prior work.

Zigmond and Stipp (2010, 2011) published the first case studies that documented large post-ad spikes in Google search for the advertised brands following TV ads during the opening ceremonies of the 2008 and 2010 Olympic Games. Since then, several studies have found a similar positive effect of TV ads on online search (Chandrasekaran, Srinivasan, and Sihi 2018; Hill, Burtch, and Barto 2017; Joo et al. 2014; Joo, Wilbur, and Zhu 2016; Laroche et al. 2013; Lewis and Reiley 2013). Further research has shown that TV ads lead to other online responses as well, including brand website traffic (Kitts et al. 2014; Liaukonyte, Teixeira, and Wilbur 2015), online word of mouth (WOM; Fossen and Schweidel 2017; Konitzer et al. 2019; Tirunillai and Tellis 2017), and online conversions (Guitart and Hervet 2017; He and Klein 2018). These results stem from various types of analyses using monthly, weekly, daily, hourly, or minute-level data. Given that over 90% of TV ad spots are shorter than one minute, the most granular analysis at the minute level is more desirable because a smaller data interval could better eliminate potential aggregation bias (Tellis and Franses 2006). We therefore focus on comparing the current research with previous studies that have also conducted analyses at the minute level (see Table 1).

Even though there seems to be a broad consensus that television advertising leads to a variety of behavioral responses online, only a handful of previous studies have investigated how factors related to ad creative and media placements moderate those effects. Liaukonyte, Teixeira, and Wilbur (2015) found that the effects of TV ads on brand website traffic and subsequent online purchases vary depending on whether the ads have an action, information, emotion, or imagery focus. Fossen and Schweidel (2017) showed that featuring a hashtag or the web address in the call to action increases subsequent online brand WOM for ads that air in the first slot of a commercial break, but featuring a phone number reduces subsequent online chatter.

Both articles used innovative ad content measures—Liaukonyte, Teixeira, and Wilbur (2015) employed research assistants to code content, and Fossen and Schweidel (2017) brought in data produced by a firm called iSpot by analyzing advertisement videos. We expand this small number of studies by examining how consumer attitudinal responses to ad creative (collected by a firm called Ace Metrix from large panels of survey respondents) moderate immediate online brand and price search response, in addition to other media- and audience-related moderators. Therefore, the moderating effects of ad content enter the analysis as ad creative quality ratings, rather than specific content elements within individual ad creatives. Given the large and diverse nature of stimuli encoded within TV ads, it is possible that these summary evaluations are both more parsimonious and more complete measures of content than prior studies were able to access.

More broadly, the current study contributes to the literature in five notable ways. First, it is the first article to study the effect of television advertising on price search (i.e., requesting price quotes at car shopping websites), and it further allows for direct comparison of those effects to the effects of TV ads on brand search from Google. By differentiating between brand search and price search, it helps improve our understanding of how TV-to-online spillovers vary across different stages of the purchase funnel. The answers can influence brands' media planning and buying practices to reach targeted audience at the "right" moment of the shopping journey.

Second, most of the existing studies measured advertising exposure using either ad expenditures (Hill, Burtch, and Barto 2017; Hu, Du, and Damangir 2014; Joo et al. 2014; Joo, Wilbur, and Zhu 2016; Laroche et al. 2013) or ad gross rating points (Guitart and Hervet 2017; He and Klein 2018), which are typically measured at the telecast or quarter-hour level. To the best of our knowledge, we are the first to use spot-level ad audience size data in quantifying the rate of immediate online response to regular TV ads. This is important because consumer ad avoidance varies throughout commercial breaks and sharpening the resolution of the number of viewers exposed to each ad spot facilitates greater statistical power and estimation precision.

Third, we were able to gain access to an important measure at the spot level—namely, the proportion of viewers who were contemporaneously in the market for a new pickup truck. It seems likely that TV-to-online spillovers will be strongly influenced by the proportion of viewers who are category shoppers, but this has never been quantified in any similar context. The possibility was previously tested in the TV/YouTube context by Draganska, Hartmann, and Stanglein (2014), who showed that accurate evaluation of ad effects depends critically on viewers' preexisting brand knowledge. As far as we know, we are the first to quantify how audience interest in the advertised category affects viewers' immediate online search response after seeing a TV ad.

Fourth, the current study contributes to the literature on advertising competitive spillovers. Perhaps the most similar paper from this literature is Sahni (2016), who found that advertisements for restaurants increased phone referrals to competing restaurants. Our results complement a larger literature showing positive/negative/no competitive spillovers, including Anderson and Simester (2013) in catalog retailing, Joo, Wilbur, and Gauri (2017) in cruises, Shapiro (2018) in prescription drugs, Lewis and Nguyen (2015) in online display advertising, Fong (2017) and Fong et al. (2019) in targeted promotion, and Seiler and Song (2017) in brick-and-mortar store feature advertising. The direction and degree of competitive spillovers have not been reported in the context of TV ads and online responses. The current research aims to uncover how TV ads spill over to brand and price search for competitors' products and further to quantify possibly asymmetric effects between competitors.

Finally, we offer a generalizable modeling framework that should prove useful to brands that want to quantify the immediate online behavioral consequences of their TV ad creative, the programs during which the ads run, and the people who view the ads.

Model

In this section we present a framework for modeling online activities at the minute level, which is decomposed into the sum of a baseline, an immediate response caused by TV ads, and an error term. The baseline is allowed to have, among other things, an hourly fixed effect and a within-hour trend that can vary by hour of the week. The immediate response to an ad spot is modeled to have a duration and a flexible decay pattern that are determined empirically. The immediate impact of each ad on online activity is modeled as the product of the ad audience size (or cost, when audience data are not available) and a response rate, which in turn depends on the characteristics of the ad creative, media placement, and audience. The error term is serially correlated, with the pattern determined empirically. Although parts of the model are tailored to the automotive industry (e.g., we separate ad spots into own national, competitor national, own local, and dealers associations), the framework is readily adaptable to other empirical contexts.

Let us assume online activity $l \in \{\text{brand search, price search}\}$ for brand b in minute t, S^l_{bt}, consists of the following components:

$$S^l_{bt} = \tau^l_{bt} + \sum_{i=0}^{M}\left[\phi^l_{bt,\,t-i}NA_{b,\,t-i}\right] + \sum_{i=0}^{N}\sum_{c=1}^{C_b}\left[\chi^l_{bct,\,t-i}NA_{c,\,t-i}\right] + \sum_{i=0}^{N}\left[\psi^l_{bt,\,t-i}LA_{b,\,t-i}\right] + \sum_{i=0}^{N}\left[\omega^l_{bt,\,t-i}DA_{b,\,t-i}\right] + \epsilon^l_{bt}, \quad (1)$$

where

- τ^l_{bt} denotes the baseline of activity l for brand b in minute t (i.e., what would have been the volume of brand or price search if there had been no TV ads), which we specify as a function of fixed hour effects, within-hour trends that can vary by hour of the week, and the volume of search for a control keyword ("SUV") in minute t, as described in more detail subsequently;
- $NA_{b,\,t-i}$ and $NA_{c,\,t-i}$ denote the total audience (in millions) exposed to national TV ads in minute $t-i$ for, respectively, brand b and each of its competitors $c \in C_b$;
- $\phi^l_{bt,\,t-i}$ and $\chi^l_{bct,\,t-i}$ denote the rates at which ad audiences $NA_{b,\,t-i}$ and $NA_{c,\,t-i}$, respectively, respond to an ad exposure at minute $t-i$ with online activity l for brand b in minute t;

- $LA_{b,\,t-i}$ and $DA_{b,\,t-i}$ denote the spend (in \$10,000s) on local TV ads by, respectively, brand b and its dealers associations in minute $t-i$[4];
- $\psi^{l}_{bt,\,t-i}$ and $\omega^{l}_{bt,\,t-i}$ denote the rates at which ad spend $LA_{b,\,t-i}$ and $DA_{b,\,t-i}$, respectively, generate, after an i-minute delay, online activity l for brand b in minute t; and
- ϵ^{l}_{bt} denotes the error term, which is given a moving-average representation, $\epsilon^{l}_{bt} = e^{l}_{bt} + \sum_{i=1}^{59} \rho^{l}_{bi} e^{l}_{b,\,t-i}$ with $e^{l}_{bt} \sim$ i. i. d. $N(0, \sigma^2_{l,\,b})$, to allow for a flexible pattern of serial correlation.

Of key interest is $\phi^{l}_{bt,\,t-i}$—that is, for every one million exposures to a national TV ad of brand b in minute $t-i$, the number of online responses of type l in minute t, which we specify as

$$\phi^{l}_{bt,\,t-i} = \alpha^{l}_{natl,\,bi} \exp\left(\gamma^{l}_{b}\,\text{week}(t) + \sum_{j=1}^{J} \beta^{l}_{j} X_{bj,\,t-i}\right), \quad (2)$$

where $\alpha^{l}_{natl,\,bi}$ denotes a baseline rate of i-minute delayed response, γ^{l}_{b} captures a long-term trend in viewers' tendency to respond immediately to brand b's national TV ads, and β^{l}_{j} captures the moderating effect of the jth "lift factor," $X_{bj,\,t-i}$, which characterizes brand b's TV ads in minute $t-i$. There are three broad types of factors that can moderate the rate of immediate online response to a TV ad spot: those related to the ad creative, the media placement, and the audience.[5] For minutes with overlapping ads (i.e., spots aired in the same minute but on different networks), $X_{bj,\,t-i}$ is calculated as the audience size-weighted average. Note that the exponential formulation implies that the jth lift factor has a multiplier effect—all else being equal, for one unit increase in $X_{bj,\,t-i}$, the response rate would be scaled by a multiple of $\exp(\beta^{l}_{j})$.[6]

Compared with the rate of immediate response to a brand's own national TV ads ($NA_{b,\,t-i}$), we adopt a simpler specification for the rate of immediate response to competitors' national ads ($NA_{c,\,t-i}$) to obtain a more parsimonious investigation of the competitive spillover of TV advertising on immediate online response. Due to the lack of data on all three types of moderating factors, we model the rate of immediate response to own local ads ($LA_{b,\,t-i}$) and own dealers association ads ($DA_{b,\,t-i}$) in a similar fashion:

$$\chi^{l}_{bct,\,t-i} = \alpha^{l}_{natl,\,bci},\ \psi^{l}_{bt,\,t-i} = \alpha^{l}_{loc,\,bi},\ \text{and}\ \omega^{l}_{bt,\,t-i} = \alpha^{l}_{dealer,\,bi}. \quad (3)$$

It is critical to specify the baseline flexibly to avoid conflating advertising effects with correlated unobservables. To minimize such concerns, we formulate τ^{l}_{bt} as follows:

$$\tau^{l}_{bt} = \mu^{l}_{b,\,hour(t)} + \lambda^{l}_{b,\,hour\ of\ week(t)}\,t + \kappa^{l}_{b}\,SUV_t, \quad (4)$$

where

- $\mu^{l}_{b,\,hour(t)}$ denotes a fixed effect for the specific hour containing minute t, accounting for the average baseline activity in each given hour of the sample period.
- $\lambda^{l}_{b,\,hour\ of\ week(t)}$ denotes a fixed effect that accommodates a distinct local trend in baseline activity for each hour of the week (i.e., Monday 12 A.M., Monday 1 A.M., . . . , Sunday 11 P.M.). It is included to control for unobservables that have within-hour trends and may correlate with within-hour TV ad insertion patterns.[7]
- SUV_t denotes the number of searches containing the keyword "SUV" in minute t, which serves as a control for consumers' general tendency to search for large automobiles in any given minute of the sample period.

In summary, we see three main ways in which endogeneity could bias the estimates of immediate online response to TV ad insertions. In Web Appendix A, we discuss these main threats and explain how we alleviate those concerns through a combination of model specification and data richness.

To calibrate the model described in Equations 1–4, we first take the difference between pairs of consecutive minutes within each hour, canceling out the hour-of-sample fixed effects $\mu^{l}_{b,\,hour(t)}$. This relieves us of the need to estimate these fixed effects, which are numerous but not of primary interest. Formally, by applying the first-difference operator (i.e., $\Delta x_t = x_t - x_{t-1}$), we can transform the original model into the following mathematically equivalent representation:

$$\begin{aligned}\Delta S^{l}_{bt} = {} & \lambda^{l}_{b,\,hour\ of\ week(t)} + \kappa^{l}_{b}\,\Delta SUV_t \\ & + \sum_{i=0}^{M} \alpha^{l}_{natl,\,bi} \Big\{ \exp\Big[\gamma^{l}_{b}\,\text{week}(t) + \sum_{j=1}^{J} \beta^{l}_{j} X_{bj,\,t-i}\Big] NA_{b,\,t-i} \\ & - \exp\Big[\gamma^{l}_{b}\,\text{week}(t-1) + \sum_{j=1}^{J} \beta^{l}_{j} X_{bj,\,t-1-i}\Big] NA_{b,\,t-1-i} \Big\} \\ & + \sum_{i=0}^{N} \sum_{c=1}^{C_b} \alpha^{l}_{natl,\,bci}\,\Delta NA_{c,\,t-i} + \sum_{i=0}^{N} \alpha^{l}_{loc,\,bi}\,\Delta LA_{b,\,t-i} \\ & + \sum_{i=0}^{N} \alpha^{l}_{dealer,\,bi}\,\Delta DA_{b,\,t-i} + \Delta e^{l}_{bt} + \sum_{i=1}^{59} \rho^{l}_{bi}\,\Delta e^{l}_{b,\,t-1}.\end{aligned} \quad (5)$$

We estimate Equation 5 using nonlinear least squares with serially correlated residuals. For all three brands, brand search response becomes statistically undetectable nine minutes after

[4] The average cost of one local TV ad exposure is approximately \$.01, so \$10,000 approximates one million ad exposures (Quora 2016).

[5] One could also posit interactions among these factors, but such interactions would require substantially more data for robust identification.

[6] An alternative to the exponential formulation would be linear, which leads to qualitatively the same results but slightly inferior goodness-of-fit in our empirical analyses.

[7] Instead of hour of the week, we have also tried 30-minute and two-hour fixed effects to account for alternative local trends in baseline search. The empirical results are essentially the same.

the start of own national TV ads (i.e., M = 9), and five minutes after the start of competitor national ads, own local ads, and dealers association ads (i.e., N = 5). Price search response becomes indistinguishable from zero after six minutes for own national ads (i.e., M = 6) and four for competitor national, own local ads, and dealers association ads (i.e., N = 4).

Data

For each of the three pickup truck brands, we compiled a rich set of data from multiple sources, from February 15, 2015, through January 23, 2016, a span of 493,920 minutes, avoiding Super Bowl outliers to focus on regular TV spots. The rest of the section describes data from each source and how we merged them for our empirical analyses.

Brand search. We obtained minute-by-minute brand search volume data by combining extracts from Google Trends and AdWords Keyword Planner.[8] Google Trends provides brand search indices by week-within-sample period, hour-within-each-week, and minute-within-each-hour. Google AdWords Keyword Planner provides monthly total brand search volume estimates. We apportioned Keyword Planner's monthly total brand search volume estimates according to Google Trends' brand search indices to obtain, sequentially, brand search volume estimates for each week, each hour within each week, and finally, each minute within each hour.

Price search. We obtained minute-by-minute price search volume data from Autometrics (www.autometrics.com), which has agreements with major car shopping websites in the United States to process records of car shoppers requesting online price quotes from local dealerships. Each record consists of the time stamp of an online price quote request, the car shopping website through which the request was made, the brand and the model of the vehicle requested, and the zip code entered by the car shopper who made the request. We are able to access these records aggregated by brand and minute, thus forming the price search data used in this study. Private conversations with Autometrics and automotive executives indicate that the amount of online price quote requests is a common key performance indicator in the industry, often used as a proxy for the number of car shoppers who are close to the end of the purchase funnel.

SUV search. Using the same method we used to obtain minute-by-minute brand search volume data for the three pickup truck brands, we obtained the number of Google search queries containing the word "SUV" in each minute. The purpose of collecting this data was to improve baseline search volume estimates for each focal truck brand by using SUV search volume as a control for factors that vary by the minute and may influence online searches for large automobiles such as SUVs and pickup trucks (e.g., the presence of a TV commercial break).

Ad audience size for national spots. During the sample period, the three focal truck brands ran a total of 27,562 ad spots on national TV at a cost of $210 million. For each of these national spots, we obtained audience size data from comScore's "TV Essentials" database. ComScore collects TV viewing data passively from 52 million digital set-top boxes in 22 million households. ComScore has nearly a thousand-fold advantage over Nielsen's sample size of 26,000 households,[9] enabling it to provide reliable audience size estimates for "long-tail" television networks and programs. By having a reliable estimate of the actual audience size of each ad spot (as opposed to using program ratings or cost estimates as proxies), we are in a position to quantify, for the first time in the literature, the amount of immediate online response to TV ad spots on a per impression basis (analogous to click-through rates of display ads).

Ad creative scores for national spots. We obtained ad creative scores from Ace Metrix, a provider of competitive intelligence on advertising content. Ace Metrix identifies new national TV ad creative and, within 24 hours of its first airing, exposes each creative to 500 online panelists and records their attitudinal responses through a standardized survey. The panelists were asked to indicate their level of agreement with a battery of statements about the ad creative in question on a scale of 0–100 (0 = "Not at all," and 100 = "Very much"). We were able to obtain survey ratings from Ace Metrix for ad creatives that accounted for 92% of the national TV impressions in our sample. Three scores are of particular interest: AdInfo (how informative an ad creative is), AdLike (how likable an ad creative is), and AdDes (how much an ad creative has made the advertised brand desirable), which map roughly into the three broad stages in the hierarchy of effects—cognitive, affective, and conative (Lavidge and Steiner 1961). The survey statements used to generate these three scores are, respectively, "I learned something," "I like this ad," and "I want that! (whatever you think the commercial is about)."

Media placements for national spots. For each national TV ad insertion in our sample, we obtained media placement data

[8] Search volume data were collected for all queries containing "f150," "f 150," "f-150," "f250," "f 250," "f-250," "f 350," "f 350," "f-350," "silverado," "dodge ram," "ram trucks," ram 1500," "ram 2500," "ram 3500," "ram truck." To construct minute-by-minute search indices, we set the time window for each Google Trends inquiry to one hour. We then obtained hour-by-hour search indices by setting the time window for each inquiry to one week. Finally, we obtained week-by-week search indices by setting the time window to the whole sample period. The Google Trends server limited the number of queries served daily, so several months were required to collect the sample analyzed in this paper. The time cost of data collection is the primary reason that nonbranded keywords are not analyzed, as the number of relevant nonbranded keywords likely exceeds the number of relevant branded keywords, and nonbranded search volume has previously been found to be less likely to respond to branded TV ads (Joo et al. 2014). According to Google Correlate, the branded keywords correlate highly across competing brands, but few generic keywords correlate highly with the branded keywords.

[9] http://www.thevab.com/national-tv-measurement/ (accessed September 2017).

from Kantar Media's "Stradegy" database, a comprehensive source for competitive advertising intelligence that covers all ad spots run on major national networks and local broadcast stations. For each national spot, we observe the date, start time, duration (30 seconds for 99% of ads in the sample), advertised brand, ad creative identifier, pod position, TV network, program genre, and a cost estimate.

Ad audience category interest for national spots. Polk Automotive Intelligence (Polk, hereinafter) collects data on all new automobile registrations in the United States. In partnership with comScore, for each national TV ad spot, Polk uses proprietary algorithms to estimate what fraction of the ad's audience was contemporaneously a potential purchaser or lessee of a new pickup truck.[10] We obtained these spot-level estimates and refer to them as AudienceCategoryInterest, the sample averages of which are 17.2% for Ford's ad audience, 16.7% for Chevy's, and 17.7% for Ram's.

Ad spend for local spots. During the sample period, the three focal truck brands ran a total of 750,672 ad spots (318,238 from manufacturers and 432,434 from dealers associations) on local TV stations at a cost of $261 million, with $106 million spent by manufacturers and $155 million spent by dealers associations. For each of these local spots, we obtained from Kantar Media's "Stradegy" database the date, start time, duration, advertised brand, and a cost estimate. Unfortunately, comScore's "TV Essentials" database does not cover local spots. As a result, we used spot-level cost estimates as a proxy for spot-level audience sizes. In addition, neither Ace Metrix nor Polk covers local TV ad spots, preventing us from having ad creative scores or ad audience category interest estimates for these local spots.

Merging spot-level data by minute. In our proposed modeling framework, national ad audience sizes, local ad spend, and national ad lift factors are minute-level measures. To convert spot-level data to minute-level measures and merge them across sources, we do the following.

For national spots that straddled consecutive minutes, we assume a constant number of viewers at each second of the spot's duration. For example, for a 30-second spot that started at 19:50:45 and had an audience size of 1 million, we assume it generated 15 million impression-seconds from 19:50:45 to 19:50:59 and 15 million impression-seconds from 19:51:00 to 19:51:14. For each minute, we aggregate impression-seconds from all the national spots that had exposures during any second of that minute. We then divide the total impression-seconds in each minute by 60 to arrive at our minute-level measure of average national ad audience size (i.e., $NA_{b,\,t}$ and $NA_{c,\,t}$ in Equation 5).

[10] Admittedly we do not have detailed information on how this fraction is calculated. However, our empirical results suggest a way to validate the usefulness of such proprietary data.

Table 2. Descriptive Statistics of Minute by Minute Brand and Price Search Data.

	Ford	Chevy	Ram
Total number of minutes	493,920	493,920	493,920
Total number of brand searches (million)	35.7	21.2	19.3
Number of Brand Searches Per Minute			
Mean	72	43	39
SD	40	26	12
Minimum	1	1	3
25th percentile	38	20	32
Median	71	41	39
75th percentile	102	62	46
Maximum	722	504	490
Total number of price searches (million)	8.1	6.6	2.7
Number of Price Searches Per Minute			
Mean	16	13	6
SD	10	9	5
Minimum	0	0	0
25th percentile	9	7	2
Median	15	12	4
75th percentile	22	18	8
Maximum	153	613	330

For local spots that straddled consecutive minutes, we split the cost estimate of each spot into each minute, proportional to the number of seconds run in each minute. We then aggregate the costs by minute to arrive at our minute-level measure of local ad spend (i.e., $LA_{b,\,t}$ and $DA_{c,\,t}$ in Equation 5).

Finally, for minutes with exposures from multiple national ad spots, we calculate our minute-level lift factors (i.e., $X_{bj,\,t}$ in Equation 5) by taking the weighted averages across all the ad spots that had any exposures in each minute, with the weight being the impression-seconds each spot had in each minute.

Table 2 presents descriptive statistics of the minute-by-minute brand and price search data. Overall, the variation in brand and price searches across brands conforms to the three brands' relative position in market share. During the sample period, Ford F-Series was searched 36 million times on Google (or 72 times per minute) and 8 million times on major car shopping websites (or 16 times per minute); Chevy Silverado was searched 21 million times on Google (or 43 times per minute) and 7 million times on major car shopping websites (or 13 times per minute); Ram Trucks was searched 19 million times on Google (or 39 times per minute) and 3 million times on major car shopping websites (or 6 times per minute).

Table 3 presents descriptive statistics of the spot-level advertising data. During the sample period, Ford F-Series spent $191 million on television advertising, 42% of which on 1,777 national manufacturer spots, 8% on 39,229 local manufacturer spots, and 50% on 264,488 dealers association spots. Chevy Silverado spent $135 million on television advertising, 47% of which on 12,653 national manufacturer spots, 26% on 112,209 local manufacturer spots, and 27% on 125,885 dealers association spots. Ram Trucks spent $145 million on television

Table 3. Descriptive Statistics of Spot-Level Advertising Data.

	Ford	Chevy	Ram
Total spend on television advertising (million)	$191.0	$135.1	$145.0
National Manufacturer Ads			
Total spend (million)	$80.9	$63.8	$65.4
Total number of spots	1,777	12,653	13,132
Total number of spots straddling consecutive minutes	866	6,327	6,531
Total number of impression-minutes (million)	1,379	2,421	2,585
Total number of unique ad creative	30	72	67
Avg. number of seconds per spot	30.0	30.4	30.0
Avg. number of impression-minutes per spot (million)	.8	.2	.2
Avg. spend per spot	$45,540	$5,042	$4,982
Avg. spend per 1,000 impression-minutes	$58.7	$26.4	$25.3
Local Manufacturer Ads			
Total spend (million)	$14.5	$34.5	$57.3
Total number of spots	39,229	112,209	166,800
Total number of spots straddling consecutive minutes	18,724	55,778	81,512
Avg. number of seconds per spot	28.7	30.0	29.6
Avg. spend per spot	$371	$307	$343
Local Dealers Association Ads			
Total spend (million)	$95.5	$36.9	$22.3
Total number of spots	264,488	125,885	42,061
Total number of spots straddling consecutive minutes	128,401	62,299	20,782
Avg. number of seconds per spot	29.4	29.8	30.0
Avg. spend per spot	$361	$293	$530

advertising, 45% of which on 13,132 national manufacturer spots, 40% on 166,800 local manufacturer spots, and 15% on 42,061 dealers association spots. During the sample period, Chevy Silverado aired 72 unique pieces of national ad creative, followed by Ram Trucks with 67 and Ford F-Series with 30.

Table 4 presents descriptive statistics of the minute-level advertising data that was merged across sources and used in model estimation.[11] Ford F-Series had far fewer minutes with national ads (2,562) than Chevy Silverado and Ram Trucks (each with more than 18,000) but much larger audiences per ad minute (540,000 vs. 13,000–14,000, on average). This is because Ford's national spots were far more concentrated in broadcast networks, especially during professional football games, which also tend to be more expensive on a per impression basis, leading to a much higher average spend per national spot for Ford (about $45,000) than Chevy (about $5,000) and Ram (about $5,000). Ace Metrix data indicate that Ford ads were rated as the most informative and likable on average and Chevy ads induced the most desire to purchase. Median audiences per ad minute were far smaller than the averages, with the

[11] Web Appendix B presents visualizations of the minute-level data used in model calibration.

Table 4. Descriptive Statistics of Minute-Level Advertising Data.

	Ford	Chevy	Ram
Number of minutes with national manufacturer ads	2,562	18,036	18,651
Number of minutes with exposures from multiple national manufacturer ads	239	1,035	1,071
Number of minutes with local manufacturer ads	43,130	100,078	134,052
Number of minutes with exposures from multiple local manufacturer ads	26,840	57,398	64,947
Number of minutes with local dealers association ads	176,214	105,490	51,218
Number of minutes with exposures from multiple local dealers association ads	83,081	70,824	39,113
Audience Size Per National Manufacturer Ad Minute (Million)			
Mean	.54	.13	.14
SD	1.21	.34	.38
25th percentile	.04	.02	.02
Median	.15	.06	.06
75th percentile	.44	.15	.13
Maximum	14.38	18.40	14.44
Avg. spend per local manufacturer ad minute	$337	$344	$427
Avg. spend per local dealers association ad minute	$542	$349	$435
Avg. ad informativeness score (AdInfo)[a]	.74	.32	−.73
Avg. ad likability score (AdLike)[a]	.42	.28	−.29
Avg. ad desirability score (AdDes)[a]	.31	.52	−.42
% of ad audience interested in pickup truck category	17.2	16.7	17.7
% of Ad Audience Exposed to Ads That Are Placed In…			
First slot	44.5	32.9	33.5
Prime time	40.5	39.8	39.6
Broadcast networks	57.3	13.8	19.3
Pro football	25.7	2.9	3.7
Weekend	68.0	49.5	53.5

[a]The three Ace Metrix scores are standardized across ad creative.

medians ranging from about 60,000 for Chevy and Ram to 150,000 for Ford, underscoring the "ordinary" TV ad spots that predominate the sample.

Figure 1 visualizes the patterns of minute-by-minute brand searches for three one-hour periods—for each focal brand, we zoomed in on the hour containing ad insertions that had the highest spend in the sample period, which all occurred during nationally televised professional football games. Each gray bar in Figure 1 depicts a commercial break during the telecast, and each dash vertical line indicates an ad insertion by a focal brand.

In Figure 1, Panel A, we see two ad insertions for Ford F-Series. The first began at 9:16:20 PM, lasted for 30 seconds, and had a middle pod position and an average audience of 21.9 million. In the minute before the ad insertion, there were 152 own-brand searches; in the minute after the ad insertion, there were 664 own-brand searches, a 4.4-fold spike. A back-of-the-envelope calculation suggests that the immediate own-brand

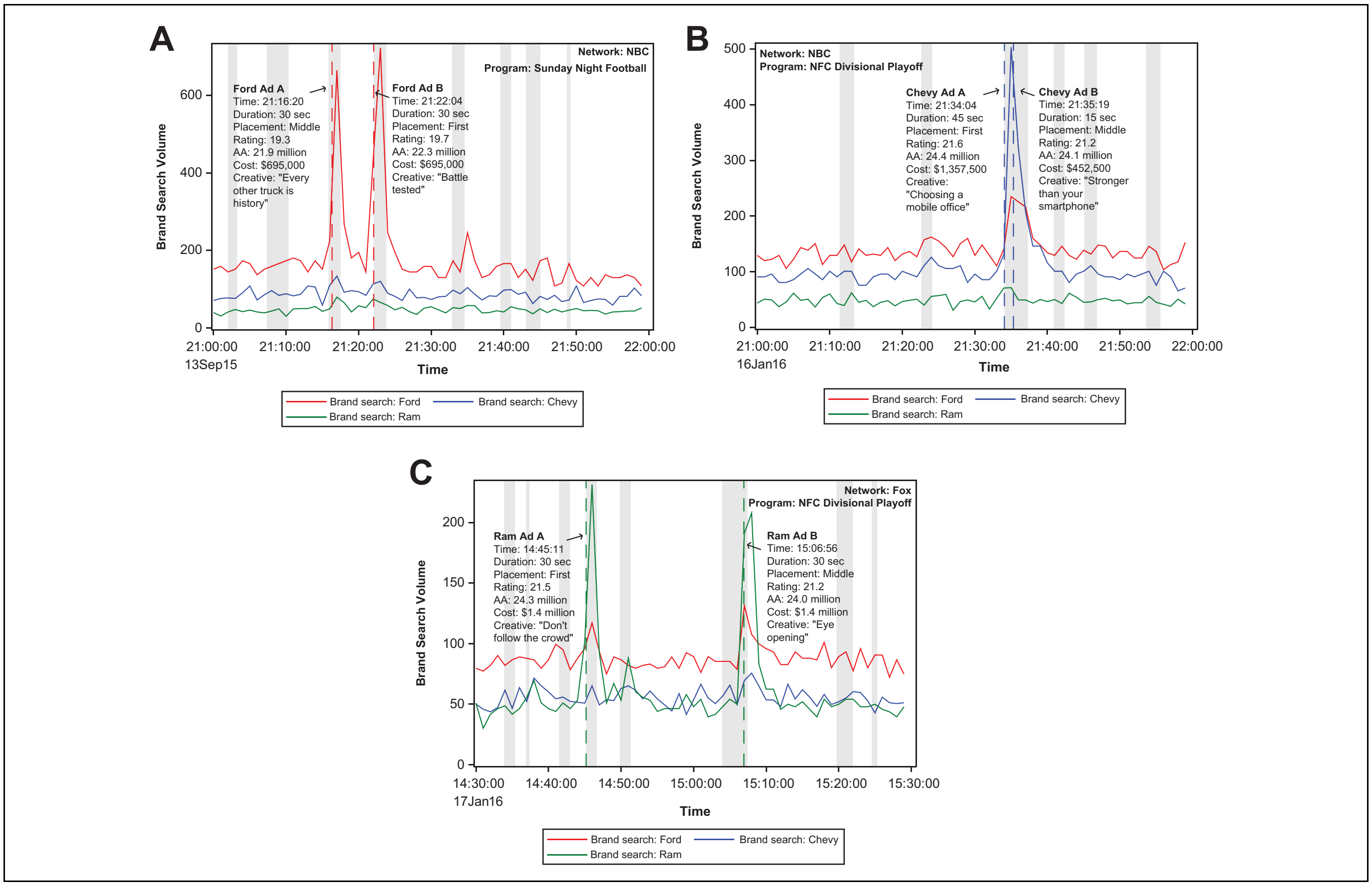

Figure 1. National TV ads and post-ad brand search spikes.

Notes: The panels present three one-hour windows that contain national TV ad insertions with the largest audience size for each of the three brands. In all three panels, gray bars indicate the time windows for commercial breaks. Dashed vertical lines mark the starting time of the ad insertions for a focal brand.

search response rate, one minute after the ad insertion, could be approximately 23 per million [= (664 − 152)/21.9].

The second Ford ad insertion, with different creative, began at 9:22:04 PM, lasted for 30 seconds, had a first pod position and an average audience of 22.3 million. The volume of own-brand searches had a five-fold spike, from 144 in the minute before the ad insertion to 722 in the minute after, suggesting an immediate own-brand search response rate of roughly 26 per million [= (722 − 144)/22.3]. From Figure 1, Panels B and C, we see spikes of similar magnitudes in minute-by-minute brand searches for Chevy and Ram, after their respective ad insertions.

Besides the immediate post-ad spikes in searches for the advertised brands, there are several other patterns in Figure 1 that are remarkable. First, all the focal ad insertions (especially the ones by Chevy and Ram) seem to have preceded spikes in brand searches for their direct competitors (Ford in particular), suggesting positive competitive spillover in immediate online response to TV advertising. Second, we see no noticeable spikes in searches for the three focal brands during commercial breaks that did not have any of their ad insertions. This suggests that the brand search spikes are caused mainly by the presence of the focal brands' TV ads, rather than by the absence of the game. Third, brand search volume reverted to its pre-ad baseline within five minutes or less. Finally, no noticeable dips appear below the pre-ad baseline following the post-ad spikes, which might imply that the ads produced truly incremental search rather than accelerating search that would otherwise have occurred a few minutes later.

The striking visualization presented in Figure 1 offers clear but anecdotal evidence of immediate online response to TV ads. The patterns we observe in Figure 1 could prove to be the exception rather than the rule, because the vast majority of ad spots have audiences that are two orders of magnitude smaller. Can one reliably quantify the immediate online response to regular TV ads and how the response rate may be moderated by various lift factors? The next section presents our empirical findings by applying our proposed modeling framework to the comprehensive data we have managed to stitch together from multiple sources.

Results

This section presents the parameter estimates for the main effects ($\alpha^1_{natl,\ bi}$, $\alpha^1_{natl,\ bci}$, $\alpha^1_{loc,\ bi}$, and $\alpha^1_{dealer,\ bi}$) and the moderating effects (β^1_j) based on Equation 5, the estimating equation. It concludes with what-if analyses based on the calibrated model. Web Appendix C presents the parameter estimates

Table 5. Main Effects of Own National Spots.

Minute After Ad Insertion	Brand Search Response Per One Million Impression-Minutes			Price Search Response Per One Million Impression-Minutes		
	Ford	Chevy	Ram	Ford	Chevy	Ram
0	4.46*	4.78*	1.99*	−.15	−.08	−.20
1	23.70*	18.83*	10.47*	1.11*	.34	−.06
2	6.72*	5.49*	3.30*	1.41*	.39*	.20
3	2.39*	2.53*	1.46*	1.26*	.06	.32*
4	.89*	1.47*	.96*	1.11*	.59*	.22*
5	.20	.45	.10	.86*	.46*	.26*
6	.72*	.49*	−.05	.64*	−.10	−.19
7	.88*	.23	−.16			
8	.12	.02	.02			
9	.15	−.53*	−.29			
Total incremental search	40.24*	33.76*	17.80*	6.24*	1.65*	.55*
Average elasticity	.22	.10	.06	.20	.02	.02
Median elasticity	.07	.05	.02	.05	.01	.01

*$p < .01$.

related to the baseline ($\lambda^1_{b,\ \text{hour of week}(t)}$, κ^1_b, and ρ^1_{bi}), which are not of primary interest but are important from the standpoint of model calibration.

Main Effects of Own National Spots

Table 5 reports the main effect estimates of own national TV ads ($\alpha^1_{\text{natl},\ bi}$), averaged across spots by minute following an ad insertion. In terms of own-brand search response, from the minute the ad was aired to the ninth minute afterward, one million ad impression-minutes (i.e., an average ad audience of one million over a span of 60 seconds) would generate, on average, 40.2 immediate brand searches for Ford F-Series, 33.8 for Chevy Silverado, and 17.8 for Ram Trucks, following the order of the brands in total brand search volume and market share. These effect estimates indicate that the rate of immediate own-brand search response per viewer is, respectively, .0040% for Ford, .0034% for Chevy, and .0018% for Ram, which are smaller than the typical click-through rates for online display ads (.05%) (Chaffey 2019). That said, given the large number of total national ad impression-minutes (1,379 million for Ford, 2,421 million for Chevy, and 2,585 million for Ram), the total number of immediate own-brand searches attributable to national TV ad spots are still substantial (about 55,000 for Ford, about 82,000 for Chevy, and about 46,000 for Ram).

In terms of price search response, from the minute the ad was aired to the sixth minute afterward, one million ad impression-minutes would generate, on average, 6.2 immediate price searches for Ford, 1.7 for Chevy, and .6 for Ram, following the order of the brands in total price search volume and market share. These effect estimates indicate that the rate of immediate price search response per viewer is much lower than the rate of brand search response: .0006% for Ford, .0002% for Chevy, and .0001% for Ram. This is not surprising, in that there tend to be more shoppers at the upper funnel, who are more likely to conduct brand searches, than shoppers at the lower funnel, who are more likely to conduct price searches. Nevertheless, because the total number of ad impression-minutes is large, the total number of immediate price searches attributable to national TV ads is nontrivial: about 8,600 for Ford, about 4,000 for Chevy, and about 1,400 for Ram. It is also a testament to the power of the data and modeling framework in detecting weak signals.

How do these effect estimates compare with what has been reported in the literature? To facilitate comparison, we report at the bottom of Table 5, summarized across all the ad minutes and by brand, the average and median elasticities of minute-level brand and price searches to national TV ads. We see heterogeneity across the brands and between the types of search response. Following the order in market share, the average elasticities of brand search are, respectively, .22 for Ford, .10 for Chevy, and .06 for Ram. The average elasticities of price search are, respectively, .20 for Ford, .02 for Chevy, and .02 for Ram.

Across all the ad minutes and brands, the average elasticities of brand search and price search are, respectively, .09 and .03, which are comparable to the average elasticity of sales to advertising (.12) reported by Sethuraman, Tellis, and Briesch (2011) and those that have been reported in the literature of online response to offline TV ads. For example, Hu, Du, and Damangir (2014) find that the average elasticity of brand search to advertising (across 21 vehicles) is .04; Joo et al. (2014) report an average elasticity of .17; Joo, Wilbur, and Zhu (2016) report an average elasticity of .07 for less established brands; Guitart and Hervet (2017) find that the elasticities of conversion to advertising range from .05 to .11 in car insurance, health insurance, and banking industries; and Hill, Burtch, and Barto (2017) report elasticities of mobile search between .13 and .17.

Figure 2 plots the percentages of total immediate search response realized by minute following an ad insertion. For own-brand search, on average about 12% of the cumulative

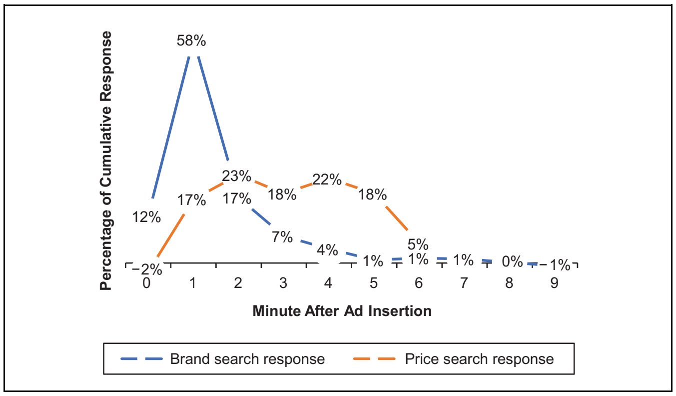

Figure 2. Percentage of cumulative search response to own national ads by minute after ad insertion (averaged across brands).

effect is realized in the minute the ad is aired, followed by approximately 58% in the following minute and 17%, 7%, and 4% in the second, third, and fourth post-ad minutes, respectively. For price search, the vast majority of response occurs between the first and the fifth post-ad minutes, with each of the five minutes accounting for about 20% of the cumulative effect. These temporal patterns suggest that (1) for both brand search and price search, nearly all of the immediate response takes place within five minutes of a TV ad insertion, and (2) brand search response arises and dissipates more quickly than price search response, which is intuitive because, on average, it takes more time to conduct a price search through a car shopping website than a brand search through Google.

Table 6. Moderating Effects of Lift Factors.

		Brand Search Response/ Elasticity Multiplier[a]	Price Search Response/ Elasticity Multiplier[a]
Ad creative–related factors	Informativeness[b] ("I learned something")	119%*	143%
	Likability[b] ("I like this ad")	108%*	80%
	Desirability[b] ("I want that!")	110%*	69%
Media placement–related factors	First slot (vs. other pod positions)	122%*	154%*
	Prime time (vs. other dayparts)	123%*	111%
	Pro football (vs. other programs)	155%*	127%
	Broadcast (vs. cable networks)	88%*	154%*
	Weekend (vs. weekday)	91%*	164%*
Audience-related factors	Audience category interest[c]	102%*	108%

*$p < .01$.
[a]The multipliers are calculated as $\exp(\beta_j^l)$.
[b]The scores are standardized to have a standard deviation of one.
[c]AudienceCategoryInterest is measured in percentage points.

Moderating Effects of Lift Factors for National Spots

In addition to quantifying the average effects of ad spots, TV advertisers are equally interested, if not more so, in quantifying how contextual factors may moderate immediate online response, which can help them assess the relative effectiveness of different ad creative, media placements, and audience targeting criteria. We allow the contextual factors (i.e., $X_{bj,\,t}$ in Equation 5) to moderate the response rate multiplicatively. Thus, all else being equal, for one unit increase in $X_{bj,\,t}$, the response rate and the elasticity are expected to be lifted by $\exp(\beta_j^l)$ times. In other words, one can interpret $\exp(\beta_j^l)$ s as the multiplier effects of the contextual factors, whose estimates we report in Table 6. A multiplier significantly different from 100% indicates that the corresponding factor has a significant impact on immediate brand or price search response.

Ad creative–related factors. In terms of brand search response, the multipliers associated with the three ad creative scores (standardized to have a standard deviation of one) are all significantly greater than 100%, suggesting that, all else being equal, ad creative deemed by viewers as more informative ("I learned something from the ad"), likable ("I like this ad"), or desirable ("I want that!") generates more immediate brand searches. This is reassuring in the sense that advertisers selecting ad creative on the basis of either traditional survey-based copy testing scores or immediate brand search response would make similar choices. The estimated multipliers (119% for informativeness, 108% for likability, and 110% for desirability) indicate that, on average, one standard deviation of improvement in an ad creative's attitudinal response could lead to approximately 10% to 20% improvement in brand search response.

In terms of price search response, the multipliers associated with the three ad creative scores are further away from 100%, but none are significant at the 99% confidence level. We see two potential explanations. It could simply mean that the signal-to-noise ratio is not high enough to reliably quantify the moderating effects of ad creative scores on immediate post-ad price search. An alternative explanation could be that price search is more likely a lower-funnel behavior, whereas national TV ads are more often used to further upper-funnel goals, which makes the creative scores of national TV ads a less reliable predictor of immediate price search response.

The contrast between the results for brand search and price search suggests that advertisers should be cautious in relying on any single online response measure in assessing the relative effectiveness of ad creative. Although it appears that ads with more favorable attitudinal response are associated with more immediate post-ad brand searches, they do not seem to generate more immediate price searches. Thus, it is important to ascertain (1) whether the signal-to-noise ratio is high enough to reliably quantify the moderating effects of ad creative–related factors and (2) how critical favorable attitudinal response is in generating the behavioral response the marketer seeks.

Media placement–related factors. For both brand and price search, all else being equal, spots run in the first slot of a commercial break generate significantly higher rates of immediate online response (+22% and +54%, respectively). Note that we obtain these strong effects after controlling for the audience size of each ad spot. In other words, these effects are not due to the fact that more viewers may have watched the first ad in a commercial break before they changed channels. We speculate that these positive first-slot effects resulted because ad viewers are more attentive during the first ad in a commercial break, before their cognitive capacity is depleted by subsequent ads in the break. It could also be the case that viewers have more time to conduct online searches after watching the first ad in a commercial break, having to worry less about missing the TV programming after the break. In short, our results are consistent between brand and price search and suggest that the first slot in a commercial break could be worth a double-digit premium due to a more attentive/responsive audience.

Similar to the first-slot effect on brand search response, we observe that ad spots run during prime time or a professional football game generate significantly more immediate brand searches (+23% and +55%, respectively), after having controlled for ad audience size. The positive lift of prime time could be due to the fact that viewers are more attentive to the commercials and TV programming during the daypart that is typically associated with TV viewing. Another intuitive explanation is that the second-screening phenomenon is the strongest during prime time because more TV viewers have ready access to their mobile devices, enabling them to conduct immediate post-ad search online. It could also be that prime time coincides with when most car shoppers conduct online research for cars and are thus more likely to respond to car ads. The strong positive lift of professional football games is also intuitive. We suspect that viewers are more attentive to the commercials during live sports programming.

The effects of prime time and professional football on price search response are also positive (+11% and +27%, respectively), but not significant at the 99% confidence level. The lack of statistical significance is another sign that the signal-to-noise ratio in the price search data may not be high enough to reliably quantify the moderating effects of some lift factors.

Unlike the effects of first slot, prime time, and professional football, which are directionally consistent between brand search and price search, the effects of broadcast and weekend diverge between the two types of online response. Ad spots run on broadcast networks generate significantly fewer immediate brand searches per viewer (−12%) and significantly more immediate price searches per viewer (+54%). We speculate that these divergent effects occur because broadcast viewers are, on average, less affluent than cable viewers and are therefore more price sensitive, which makes broadcast viewers (relative to cable viewers) more likely to conduct price searches and less likely to conduct brand searches.

Ad spots run on weekends generate significantly fewer immediate brand searches per viewer (−9%) and significantly more immediate price searches per viewer (+64%). We speculate that these divergent effects occur because car shoppers are more likely to visit dealerships and make purchases on weekends than on weekdays. As a result, relative to weekdays, car shoppers are, on average, more likely to conduct price searches (operationalized as requesting price quotes from local dealerships in our study) and less likely to conduct brand searches on weekends.

The divergent broadcast and weekend effects on brand versus price search show that media placements that can generate more of one type of online response may generate less of other types of digital activity. This cautions TV advertisers against relying on any single immediate online response metric in selecting media placements, as there is unlikely a media plan that can optimize all types of online response. That said, if the advertiser does have one type of online response that it intends to focus on for a particular campaign, large lifts in performance and cost effectiveness can accrue from quantifying the multiplier effects of various media placement factors and then making media buys accordingly.

Audience-related factors. All else being equal, for every one-percentage-point increase in AudienceCategoryInterest, the number of immediate brand searches per ad viewer increases by 2%, which is significant at the 99% confidence level. The amount of immediate price searches per ad viewer also increases but the increase is not significant. To put the effect size of AudienceCategoryInterest on brand search response into perspective, consider an ad spot with AudienceCategoryInterest at, say, 27%, which is ten percentage points above the average of 17%. Our effect estimate ($\beta^1_j = .16$) indicates that, all else being equal, one would expect to see a brand search response rate that is 17% higher [$= \exp(.016 \times 10) - 1$] than the average. This finding suggests that spot-level audience characteristics data furnished by third-party vendors (e.g., Polk, comScore, Acxiom, Datalogix, Experian, Nielsen) can be validated through their correlation with immediate post-ad online response. In our empirical context, the spot-level audience category interest estimates have demonstrated strong face validity, which is reassuring for TV advertisers that increasingly rely on rich audience data for targeted media buys.

Main Effects of Competitor National Spots

Table 7 reports the effect estimates of competitor national TV ads ($\alpha^1_{\text{natl, bci}}$) on focal brand search and price search, averaged across spots by minute following an ad insertion. In terms of total brand search response (cumulative from the minute the ad was aired to the fifth minute afterward), we see positive and significant spillover across all six directional dyads. These significant and consistent effect estimates suggest that TV ads can trigger not only immediate searches for the advertised brand

Table 7. Main Effects of Competitor National Spots.

Minute After Ad Insertion	Brand Search Response Per One Million Impression-Minutes						Price Search Response Per One Million Impression-Minutes					
	Chevy ↓ Ford	Ram ↓ Ford	Ford ↓ Chevy	Ram ↓ Chevy	Ford ↓ Ram	Chevy ↓ Ram	Chevy ↓ Ford	Ram ↓ Ford	Ford ↓ Chevy	Ram ↓ Chevy	Ford ↓ Ram	Chevy ↓ Ram
0	.40	.81*	.60*	.07	.64*	.53	−.15	.19	.05	.42*	.21*	−.21
1	4.85*	2.31*	2.59*	.33	2.15*	1.54*	.01	.02	.14	.18	.06	−.04
2	2.18*	.54*	.69*	.10	.94*	.63*	−.41*	.15	−.05	.60*	.22*	−.07
3	.42	.87*	−.01	.09	.50*	.15	.21	−.18	−.13	−.12	.20*	−.23*
4	.83*	−.32	−.04	.37	−.01	.70*	−.56	−.15	.21	−.53*	.28*	.55*
5	−.48	.13	.42*	.13	−.04	.29						
Total	8.20*	4.35*	4.25*	1.09*	4.18*	3.84*	−.91	.03	.23	.55*	.98*	−.01
Avg. elasticity	.01	.01	.04	.003	.05	.01	−.01	.0003	.01	.01	.12	−.0004

$^*p < .01$.

but also its competitors. We speculate that this occurs because TV ads can remind viewers of alternatives to the advertised brand, which in turn could spur them to search the competitor brand for comparison. It also might be that TV ads remind consumers of category needs, thereby leading consumers interested in competing brands to search those brands directly, without a comparison.

In terms of magnitude, the estimated main effects on own brands are much larger than competitive spillovers. For one million impression-minutes, an average Ford spot generates 40.2 Ford searches versus 8.4 Chevy/Ram searches, an average Chevy spot generates 33.8 Chevy searches versus 12.0 Ford/Ram searches, and an average Ram spot generates 17.8 Ram searches versus 5.4 Ford/Chevy searches. It is remarkable that the data and modeling framework reliably quantified the sizes of competitive spillovers, even though the competitor brand search response rate is extremely low: .0008% for Ford, .0012% for Chevy, and .0005% for Ram. The implied average elasticities of brand search to competitor national TV ads range from .003 to .05.

Ford receives the most competitive spillovers (8.2 from Chevy and 4.4 from Ram). This suggests, unsurprisingly, that the category leader is probably the default or the reference option in most shoppers' consideration set. As a result, it receives the most comparison searches.[12]

Finally, in terms of competitive spillovers in price search response, we find mostly insignificant effect estimates. This could be another sign that the signal-to-noise ratio in the price search data may not be high enough for our model to reliably quantify immediate post-ad competitor price search. It could also be that, as car shoppers approach the end of the purchase funnel, they are less likely to comparison shop between brands and more likely to comparison shop between local dealerships of the same brand for the best price.

[12] Yoo and Mandhachitara (2003) investigated the differentiating effects of a focal brand's advertising on its rival brand's sales between the "market leader" and "market challenger" and found similar patterns of results.

Main Effects of Local Spots

Table 8 reports the effect estimates of local manufacturer ads ($\alpha^1_{\text{loc, bi}}$) and dealers association ads ($\alpha^1_{\text{dealer, bi}}$), averaged across spots by minute following an ad insertion. In terms of brand search response, from the minute the ad was aired to the fifth minute afterward, local manufacturer/dealers association ads costing about \$10,000 would generate, on average, 8.1/7.0 immediate brand searches for Ford, 6.4/8.7 for Chevy, and 6.4/−1.2 (insignificant at the 99% confidence level) for Ram. Averaged across the three brands, the implied elasticity of brand search to local manufacturer ads and dealers association ads are, respectively, .002 and .001. In terms of price search response, the effects are, respectively, 6.3/2.0 for Ford, −2.2/2.8 for Chevy, and .6/1.0 for Ram. Averaged across the three brands, the implied elasticities of price search to local manufacturer ads and dealers association ads are, respectively, .0002 and .002.

Several aspects of the results are worth noting. First, because the total spend on local ads is large (\$110 million for Ford, \$71 million for Chevy, and \$80 million for Ram), the total number of immediate searches attributable to local TV ads is substantial: about 78,000 for Ford, about 54,000 for Chevy, and about 37,000 for Ram in brand searches; and about 28,000 for Ford, about 10,000 for Chevy, and about 6,000 for Ram in price searches. Summed across the three brands, there was a total spend of \$261 million on local ads, which generated about 169,000 immediate post-ad brand searches and about 44,000 price searches.

It is also instructive to compare the immediate post-ad searches attributable to local spots with those attributable to national spots, which are presented in Table 9. Relatively speaking, in terms of generating immediate brand search response, national spots are the most cost effective (on average 8.7 per \$10,000 spend), followed by local manufacturer spots (6.6 per \$10,000 spend) and local dealers association spots (6.4 per \$10,000 spend). The opposite is true when it comes to generating immediate price search response: local dealers association spots are the most cost effective (on average 2.1 per

Table 8. Main Effects of Local Spots.

Minute After Ad Insertion	Brand Search Response Per One Million Impression-Minutes						Price Search Response Per One Million Impression-Minutes					
	Local Manufacturer Ads			Local Dealers Association Ads			Local Manufacturer Ads			Local Dealers Association Ads		
	Ford	Chevy	Ram	Ford	Chevy	Ram	Ford	Chevy	Ram	Ford	Chevy	Ram
0	1.85*	2.96*	.82*	2.62*	2.00*	−.26	1.86*	−.18	−.16	.53*	1.57*	.13
1	3.90*	1.99*	3.00*	3.10*	3.80*	.68	1.80*	−1.05*	.26*	−.04	−.40	.37
2	1.16	1.04*	1.97*	.78*	1.75*	.19	.85	−.45	.38*	.88*	.30	−.01
3	.59	.92*	−.08	.47	.14	−.24	.69	−.78*	−.27*	.39*	.19	.53*
4	−.17	.08	.36	−.33	−.12	−.55	1.06*	.24	.35*	.22	1.18*	.02
5	.76	−.56	.33	.33	1.15*	−1.02*						
Total	8.09*	6.43*	6.41*	6.96*	8.71*	−1.20	6.26*	−2.21*	.56*	1.99*	2.84*	1.04*
Avg. elasticity	.0004	.001	.003	.003	.002	−.0002	.002	−.002	.002	.005	.003	.002

*$p < .01$.
Notes: It is a bit counterintuitive that the immediate price search response rate for Chevy local manufacturer ads is negative and significant (−2.21). It could simply be a type I error. Or it could be that Chevy local manufacturer ads have already provided sufficient information that it makes price search unnecessary.

Table 9. National Versus Local Spots in Immediate Post-Ad Search Response (Averaged Across All Insertions).

	Brand Search Response	Price Search Response	Sum of Brand and Price Search Response	Ratio between Price and Brand Search Response
National Spots				
Per $10,000 spend	8.7	.7	9.4	1 vs. 13.1
Per 1 million impression-minutes	28.7	2.2	30.9	1 vs. 13.1
Local Manufacturer Spots				
Per $10,000 spend	6.6	1.2	7.8	1 vs. 5.7
Local Dealers Association Spots				
Per $10,000 spend	6.4	2.1	8.4	1 vs. 3.1

$10,000 spend), followed by local manufacturer spots (1.2 per $10,000 spend) and national spots (.7 per $10,000 spend).

This reversal of relative cost effectiveness in generating brand versus price search has an intuitive explanation in that the content of TV ads for these three truck brands typically varies systematically between national and local spots. National spots are purchased exclusively by the manufacturers and, according to a content analysis by Xu et al. (2014), typically carry brand-oriented messages with relatively few price-oriented messages. Local TV spots are purchased by both manufacturers and local dealers associations, with both parties designing ads that extensively communicate current market-specific pricing and promotion terms. As a result, TV viewers respond accordingly: the ratio between price and brand search response is the highest for price-focused local dealers association spots (1:3) and the lowest for brand-focused national spots (1:13). We view this intuitive finding as another testament to the face validity of our effect estimates and, in turn, the power of the data and modeling framework.

Finally, it is worth remembering that, unlike national spots, we do not have access to reliable audience measures for local spots, which requires us to rely on spot-level cost estimates provided by Kantar Media as a correlate of local ad audience size. As a result, we can only quantify immediate search response rate on a per impression-minute basis for national spots. To the extent that the same amount of spend can purchase more impressions on local TV than on national TV, the amount of immediate search response per viewer is likely lower on local TV than on national TV. That said, because there is likely greater measurement error in local ad exposure than in national ad exposure, our local spot effect estimates are likely to have more downward error-in-variable bias than their national counterparts.

What-If Analysis

How can TV advertisers leverage our modeling framework and the resulting effect estimates to assess the relative effectiveness of different ad spots and thereby refine their selection of ad creative and media placements? This subsection presents several what-if analyses to demonstrate the potential usefulness of our approach in practice.

Given the calibrated model, we can simulate the amount of incremental brand and price searches if the TV advertiser were to have a different allocation of ad spend across media placements, target audiences, and ad creative. Because media placement factors and target audiences tend to be correlated with one another, for simplicity, we focus our what-if analyses on ad creative selection. We simulate what could have happened to immediate search response if Ford had reallocated its national

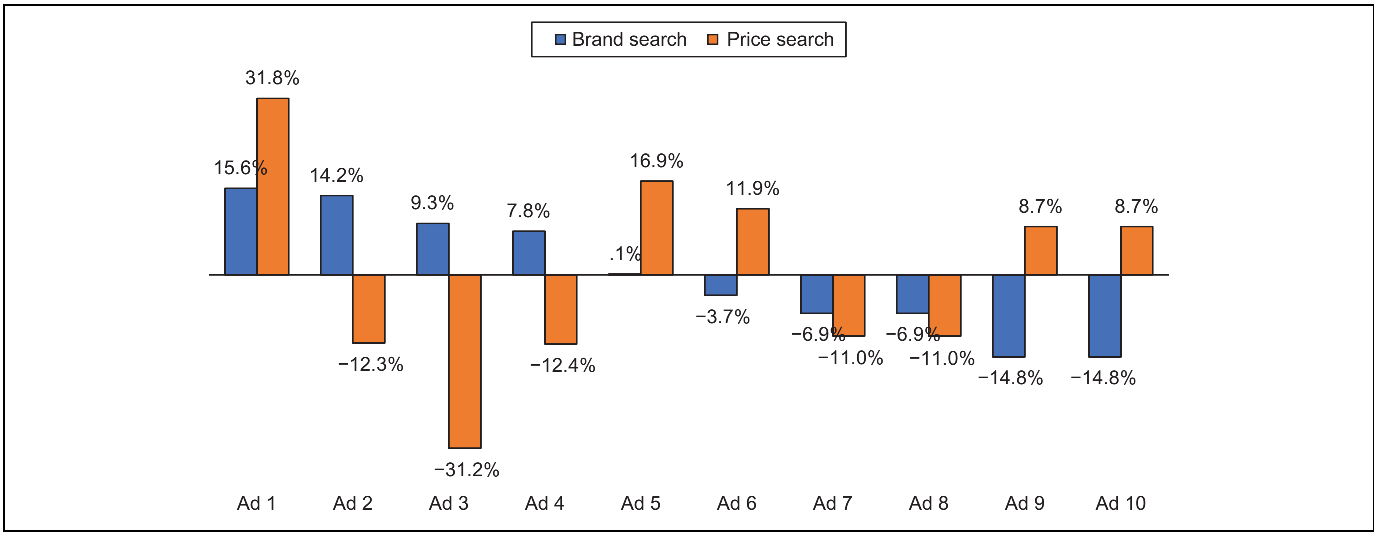

Figure 3. Percentage difference in search response if Ford had used only one ad copy for national TV.
Notes: Each bar represents the percentage difference (relative to the average across the ten pieces of Ford ad copy for which we observe ad creative scores) in generating brand/price searches if 100% of the national TV ad impression minutes that accrued to the ten pieces of ad copy had been allocated to just one of them.

TV impression-minutes across ad creative while maintaining the allocation across media placements and target audiences.

For the ten pieces of Ford ad copy with creative scores, we simulate the immediate search response under the scenario in which 100% of the national TV ad impression-minutes that accrued to the ten pieces of ad copy had been allocated instead to only one piece of ad copy. Figure 3 presents, for each of the ten pieces of ad copy, the percentage differences (relative to the average across the ad copy) in generating immediate brand and price searches. The first ad copy from the left, which has the highest score in informativeness and below-average scores in likability and desirability, could have generated 15.6% more brand searches and 31.8% more price searches. However, none of the other nine pieces of ad copy could have generated more of one type of search without generating less of the other. This exercise again highlights a key takeaway: TV advertisers should be cautious if they rely on only one particular type of online response in evaluating and selecting ad creative, because it can be difficult for any single piece of ad creative to excel in driving all types of online response. Rather, TV advertisers should monitor a variety of online activities and align the performance metric with the specific objective of each campaign (e.g., brand building vs. price promotion).

To make the previous simulation more realistic, we consider an alternative scenario: What would have happened if Ford had allocated 20% of the national TV ad impression-minutes to each of the five top-performing pieces of ad creative (out of the ten)? When we use immediate brand search response as the selection criterion, the top five pieces of ad copy could have generated 9.4% more brand searches while producing only 1.5% fewer price searches. When we use immediate price search response as the selection criterion, the top five pieces of ad copy could have generated 12.5% more price searches while producing only 3.5% fewer brand searches. These simulations demonstrate that substantial gains could be made by applying our proposed modeling framework in ad creative selection. Equipped with additional information in real world applications, TV advertisers could conduct similar what-if analyses in refining their plans of media placement and audience targeting.

Conclusions and Future Directions

Compared with digital media, most TV advertisers have traditionally been unable to access behavioral response measures at the spot level, frustrating efforts to select ad creative or media placements on the basis of their relative effectiveness in achieving particular behavioral objectives. Thanks to the increasing prevalence of the second-screening phenomenon, a new class of attribution vendors has emerged, promising that TV advertisers can measure immediate post-ad spikes in online activities and use those measures to assess the relative effectiveness of ad spots.

It is against this backdrop that we conducted our study. We focused on three top pickup truck brands, for which we compiled a rich data set by stitching together information from multiple sources, covering a span of nearly half a million minutes. We focused on two types of online activities: brand search and price search. We observed 27,562 ad spots on national TV and 750,672 spots on local TV. By merging the spot-level ad data with the minute-level search data, we built a comprehensive testing ground to demonstrate the worth and insights available from estimating the linkage between TV ad spots and immediate online response.

Our research offers several key takeaways. First, for both brand search and price search, there is a detectable spike immediately after a regular ad insertion, be it on national or local TV. The rate of response follows the order of the brands in total search volume and market share. We believe our focal brands offer a conservative setting because they are decades old and many, if not most, category consumers are intimately familiar with them. We suspect that brands that are newer or lesser known, or transact primarily online, would likely see even greater responses.[13]

Second, nearly all of the immediate response occurs within five minutes of an ad insertion, with brand search response peaking in the minute after the ad is aired and then dissipating quickly, while price search response is spread out more evenly over the five post-ad minutes.

Third, in addition to generating immediate own-brand searches, national TV ad insertions also lead to significant competitor-brand searches. The category leader receives larger positive competitive spillovers than its rivals. For price search, however, we detected little competitive spillover, probably because as car shoppers approach the end of the purchase funnel, they are less likely to comparison shop between brands and more likely to comparison shop between local dealerships of the same brand for the best price.

Fourth, relatively speaking, national spots appear to be more cost effective in generating immediate brand search response, whereas local spots appear to be more cost effective in generating immediate price search response. Although this reversal of relative cost effectiveness is a novel finding, it is intuitive in the sense that the three focal brands' national spots are typically more brand-oriented, whereas their local spots are mostly focused on price promotions.

Fifth, ad creative with more favorable attitudinal response seems to be associated with more immediate post-ad brand searches. On average, a one-standard-deviation improvement in ad creative quality (as measured by survey-based ratings of ad informativeness, likability, and desirability) could result in a 10% to 20% improvement in post-ad brand search response. However, the moderating effects of ad creative characteristics are muted when it comes to generating immediate price searches. This suggests that TV advertisers should be cautious in replacing survey-based creative ratings with any single online response measure, especially when the indicator pertains to a lower-funnel activity such as online price quote requests.

Sixth, media placement factors and audience category interest can also moderate the rate of immediate search response. TV ads (1) placed in the first slot of a commercial break, (2) aired during prime time, and (3) aired during professional football games cause more immediate brand and price searches. Ad spots run on broadcast networks or weekends generate significantly fewer immediate brand searches but significantly more immediate price searches. A one-percentage-point increase in audience category interest leads to a 2% increase in immediate brand search, providing support for the practice of TV advertisers relying on increasingly rich audience characteristics data for targeted media buys.

Managerially, our findings about positive lifts of certain media placements (e.g., first slot, prime time, live sporting event) and audience category interest suggest that when TV advertisers intend to focus on maximizing one particular type of online response, large gains in effectiveness could accrue from quantifying and balancing the multiplier effects of various media and audience factors against their cost differentials. That said, the findings about divergent effects of broadcast/cable, weekend/weekday, national/local, and ad creative characteristics on brand versus price search caution advertisers against relying on any single immediate online response metric in assessing media placements and ad copy, as there is unlikely to be a media plan or ad creative that would be optimal for all types of online response.

Practically, unlike the proprietary methods used by advertising attribution vendors, our proposed framework for modeling behavioral response at the minute level is transparent and readily replicable. The brand search data used to estimate the model are accessible to any brand, both for itself and for its competitors. The price search data represent a type of online response that has not been studied in the prior literature. Admittedly, because our sources for search data (Google and Autometrics) are unlikely to capture all the relevant search responses, our estimates of response rates are likely downward biased. The estimates of elasticities and moderating effects should be more robust to the fact that our data are unlikely a census of brand and price searches.

TV advertisers could further extend our modeling framework to include website traffic, online transactions, social media activities (as in Fossen and Schweidel [2017]) or other important behavioral indicators that vary at the minute level. We suspect that the reliability of spot-level attribution will depend on the signal-to-noise ratio. The strength of the signal will depend on the size of the ad audience and the tendency of ad viewers to respond immediately, which can be weaker, for example, for brands that compete in low-involvement categories. The level of noise shall depend on variability, relative to the mean, of minute-by-minute online activity. One way to overcome a low signal-to-noise ratio is to include a large number of ad spots over an extended period of time, as we demonstrated in the current study.

Directions for Future Research

A deeper understanding of immediate online response to TV ad spots opens up multiple areas for further research. While advertisers may ultimately care about the impact of advertising on sales, it remains a challenge for many TV advertisers, such as the ones in the current study, to quantify the impact of any

[13] In Web Appendix D, similar to Figure 1, we visualize the patterns of minute-by-minute brand searches for two newly introduced daily fantasy sports brands—Draft Kings and Fan Duel—during a one-hour telecast of a professional football game, wherein each brand ran two spots. All four spots were followed by an immediate multifold spike in both own- and competitor-brand searches (no noticeable spikes during commercial breaks without the daily fantasy sports ads). A back-of-the-envelope calculation suggests that the average one-minute post-ad own-brand search response rate could be around 420 per million ad viewers, which would be an order of magnitude greater than what we observed for the three pickup truck brands.

regular TV spot on sales because consumers can be exposed to a myriad of ads and promotions from both online and offline sources over weeks or even months. To close the attribution loop, following immediate online responses through to purchases or other types of transactions is a critically important step forward. Future research needs to address the question of whether the rate of immediate online response is positively correlated with the amount of online and offline response accrued over time and, ultimately, with incremental sales attributable to a single spot. If such positive correlation could be established, TV advertisers could be more confident in the validity of using the relative sizes of immediate online response to assess the relative effectiveness of different ad spots.

Besides driving sales in the near term, TV campaigns often have long-term brand-building goals. Although our study has examined the correlation between three survey-based attitudinal measures and immediate search response, it remains a fertile ground to systematically investigate the relationship between an ad's efficacy in changing various mindset metrics (e.g., awareness, value and quality perception) and its efficacy in generating different online activities.

Methodologically, the current study relies solely on a time-based identification strategy to detect the immediate effects of TV ads on online search. A powerful direction for future research would be to combine time-based identification with a spatial identification strategy, as exemplified by Hartmann and Klapper (2018). This seems applicable to national advertisements, as exogenous variation across time zones may allow for even more accurate predictions of counterfactual online response. Similarly, dividing online response by geographic origin and merging local response with local ad exposure may greatly enhance the signal-to-noise ratio.

The dependable and sizable influence of TV ads on online brand and price search cautions marketers against the use of simplistic "last-touch" attribution strategies, as they may overestimate the effect of search engine marketing and underestimate the generative influence of TV advertising. Traditional and digital advertising budgets are still commonly divided between siloed agencies with little or no coordination between them. The TV-to-online spillover observed in this study renews the call for holistic integration and evaluation of ad campaigns and cross-media synergies (e.g., Kim and Hanssens 2017; Naik and Peters 2009).

To conclude, our study contributes to a larger effort to understand how measurable funnel actions correspond to the reach, placement, and content of TV advertising. It could be fruitful to extend the current literature on TV-to-online spillovers to other broadcast media, such as radio, where the same fundamental challenge of spot-level ad performance assessment and attribution exists. We are confident that the drive for marketing accountability will continue and that multitaskers' immediate online response to traditional advertising will be prominently featured as marketers refine their understanding of how advertising affects the customer journey.

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