TV Ad Viewability: How Viewer Tuning, Presence and Attention Respond to Ad Content*

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March 2021

Abstract

Can TV ads effectively "cut through the clutter?" New measurement technology quantifies TV viewer tuning, presence and attention, enabling new distinctions between TV ads that are viewable and TV ads that are actually viewed. We use broadcast networks' verifiably quasi-random ordering of ads within commercial breaks to identify causal effects of ads on viewing behaviors among 4.26 million advertising exposures. We supplement ad metadata with three sets of machine-coded ad content features for 6,650 frequent ads. Recreational product ads preserve audience tuning and presence. Prescription drug advertisements decrease tuning and presence, with larger audience losses during drug ads treating more prevalent and severe conditions. Viewer attention decreases with ad duration and during the first three slots in the break. Effects of ad content on viewer attention are near zero, calling into question whether advertisers can use ad content to attract audience attention.

*We thank TVision Insights, especially Tristan Webster, Yan Liu, and Dan Schiffman, for enabling this research and providing valuable feedback. We also thank Thales Teixeira at Decoupling.co for connecting us with TVision and seminar participants at Bocconi, BU, Cornell, Delaware, Georgetown, Indiana, Minnesota, UCSD, UT-Dallas, Virginia Tech, Western Ontario and Wisconsin for helpful suggestions. An earlier version dated July 2019 was called "Watching People Watch TV." Mistakes, omissions and opinions are ours alone.

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1 Introduction

This paper asks two questions about TV advertising viewing. How does traditional tuning compare to new TV viewer presence and attention metrics? How does viewing respond to ad content?

We investigate novel viewing behavior measurements produced *in situ* in a sample of 3,659 viewers in 1,155 households over 12 months. Cameras, microphones and algorithms measure viewer tuning, presence and attention passively and continuously. Viewers are absent from the room during 30% of the ads that play on their TV during active viewing sessions. In the remaining 70% of ad exposures, viewers remain present for 85% of ad seconds. Younger viewers are less likely to change channels during ads, but more likely to leave the room or divert their visual attention.

To answer the second question, we use machines to measure three sets of ad content features in 6,650 frequent ad videos. We verify and exploit broadcast networks' practice of quasi-random ordering of ads within breaks to identify causal effects of ad content on tuning, presence and attention. Viewer tuning and presence during ads fall less during recreational product category ads. Prescription drug ads reduce tuning and presence more than average. A second-stage analysis shows that drug ad audience losses are larger for more severe and more prevalent treated conditions. Attention falls with ad duration, and in the first three ad slots in a break, and with ad duration, but does not otherwise respond much to ad content.

Next we discuss how the paper builds on and extends the scientific literature on advertising. Section 2 introduces and describes the new measures of ad viewing and ad content. Section 3 specifies the model and causal identification strategy. Section 4 presents the findings and Section 5 extends them by relating drug ad estimates to treated condition attributes. Section 6 concludes with limitations and possible extensions.

1.1 Relationship to Previous Literature

The current paper follows and extends four related literatures: advertising avoidance, advertising content, advertising attention and advertising sequence externalities.

Advertising-supported media rely on consumer attention to ads to finance programs, but the exchange is non-contractual and consumers exercise agency (Tuchman et al., 2017). Ad avoidance has proven to be a moving target for scholars as ads, media and distribution technologies have changed frequently in recent decades. Danaher (1995) pioneered the television advertising avoidance literature, using people meter data to show that tuning fell during commercial breaks by 5% on average, depending on program genres and commercial break durations. Siddarth and Chattopadhyay (1998) linked ad "zapping" behavior to household purchase data, showing that advertising avoidance falls with household category purchases and differentiating messages in ads. Wilbur (2008) extended earlier work on viewer choice of television programs (see, *e.g.*, Shachar and Emerson 2000, Goettler and Shachar 2001) to quantify how much total ad time reduced TV program audiences. Bronnenberg et al. (2010) analyzed a field experiment in which digital video recorders were provided to households, finding a tight null treatment effect of ad-avoidance technology on package goods purchases, likely because consumers only fast-forwarded 6.5% of all ad exposures. Schweidel and Kent (2010) analyzed a year of live set-top box usage data, finding that commercial break audiences were 10% lower than program audiences on average. Teixeira et al. (2010) found consumers avoided ads more when brand logos appeared for longer durations or in central screen locations. Wilbur (2016) studied viewing behaviors following 5-minute periods of inactivity, finding that viewers changed tuning during 27% of commercial breaks, and that ad avoidance varied across networks, break durations and weather conditions. Deng and Mela (2018) studied advertising avoidance in a large panel of individual program, advertisement and product consumption choices. Individual viewer factors dominated other explanations for ad avoidance decisions, so micro-targeted TV ads would be far more profitable than traditional program-targeted ads. The current paper contributes to the ad-avoidance literature in several ways, most notably by supplementing traditional ad tuning data with new measures of advertising avoidance that previously were only available to ethnographers in small samples (Jayasinghe and Ritson, 2013; Voorveld and Viswanathan, 2015).

The second literature quantifies advertising content and how it impacts markets. Advertisers design ad content to inform, persuade and sell, but advertised products often appeal to a small minority of the audience. Therefore, most consumers experience most ads as a "bad" - an implicit attentional price bundled with desired media content, with more enjoyable ads imposing lower prices. Resnik and Stern (1977) were the first to operationalize and investigate the informational content of advertisements. More recently, Liaukonyte et al. (2015) content-coded TV advertisements and showed that TV ad content predicted post-ad patterns in brand website traffic and sales. Anderson et al. (2013) developed a framework to model the information-persuasion tradeoff in ads, and Anderson et al. (2016) focused on comparative advertising and estimated an equilibrium model of firms' advertising content choices. Some recent studies measure ad content using machines or combinations of humans and machines. Tucker (2015) constructed experimental estimates of video ad persuasiveness, finding that more persuasive ads were generally less likely to "go viral," except when they attracted large numbers of comments. Lee et al. (2018) combined human judges and natural language processing algorithms to content-code over 100,000 Facebook ads, finding that brand personality content tends to increase ad engagement (likes, comments and shares) whereas directly informative content without brand personality content tends to reduce ad engagement. Tsai and Honka (2021) quantified content in a large corpus of car insurance ads, finding that brand-focused, funny and entertaining content is most effective in increasing brand recall. We seek to contribute to the ad content literature by constructing three sets of machine-coded ad content measures in a sample of 6,650 videos and estimating causal effects of those measures on viewing behaviors.

The third literature models how advertising affects consumer attention directly, often measuring eye tracking within experimental settings. For example, Zhang et al. (2009) showed that print ad features that boost sales–such as larger ads, more prominent placements and more colors–also attracted longer consumer gaze durations. Teixeira et al. (2012) used facial recognition algorithms to measure moment-by-moment viewer surprise and joy reactions to ads, finding that both the levels and trajectories of viewer emotions help to predict attention to ads. Liu et al. (2018) studied how movie trailers predict viewers' moment-by-moment emotional responses, and in turn how viewers' reactions could be used to optimize clip content and predict increases in subjects' stated purchase intentions as well as movie revenue data. Related to this stream, TVision Insights attention data have also been studied by Liu et al. (2020), who quantified how suspense and surprise during baseball games affect viewer attention during the game and commercial breaks. They found that in-game suspense distracts consumer attention from commercials, whereas in-game surprise enhances attention to commercials.

Finally, scholars have studied how ads presented in linear sequences interfere with each other. Webb (1979) found that "clutter"—longer strings of consecutive commercials—decreased average attention paid to ads and unaided recall of advertised brands. Burke and Srull (1988) found that exposure to ads for competing brands interfered even more, and also confused consumers about which competitor's ad made which claims. Standard television network ad sales contracts promise advertisers that competitors' messages will not be placed in the same break, although competitive interference effects were later disputed (Brown and Rothschild, 1993). More recent studies have found evidence of externalities between consecutive ads in television advertising (Wilbur et al., 2013; Kar et al., 2015; Joo et al., 2020), in-app mobile advertising (Rafieian and Yoganarasimhan, 2020) and search advertising (Gomes et al., 2009). A rare finding of positive externalities is Fossen et al. (2020), who found that political TV ads pique viewer engagement and deliver larger audiences to subsequent advertisements. We seek to contribute to this literature by estimating which ads disrupt which natural viewing behaviors, using what we believe to be the largest set of video advertisement features studied to date.

2 Data

2.1 Ad Viewing

Viewer tuning, presence, and attention data are provided by TVision Insights, an analytics firm founded to modernize television audience measurements. The data were drawn from TVision's panel of 1,155 consenting households between July 2016 and June 2017.

TVision installs cameras and microphones on each household's primary TV. Initial set-up includes training facial recognition algorithms on each household member. Infrared sensors measure depth and aid detection in low light conditions. Image data are processed in real time at the frame level five to six times per second on average. Images are not stored or transmitted outside of the home.

TVision combines audio data with industry-standard automated content recognition (ACR) services to measure television *tuning*, i.e., the television network and timestamp of the audio stream. Viewers change channels, mute or turn off the TV during commercial breaks, so changes in tuning may indicate a behavioral response to an ad.

TVision software detects human bodies – sets of heads, shoulders, and arms – in the cameras' field of view, based on standard person detection algorithms. Person detection technology is similar to real-time face and body recognition algorithms used in smartphone apps, e.g. Instagram filters. For each face, the software either identifies the household member or assigns a unique guest identifier. *Presence* is the detection and recognition of a particular viewer in the room. Viewers often leave rooms during ad breaks, so presence is another viewing behavior that may be related to ad exposure.

TVision software measures when viewers' eyes are open and infers head orientation based on the relative sizes, positions and angles of facial features. *Attention* is the co-occurrence of eyes-open and "eyes-on-screen" inferences. Ads may attract or deter viewers' visual attention, so this is a third viewing behavior that may be related to ad exposure.

TVision equipment measured tuning, presence and attention behaviors continuously and then sampled one measurement for each viewer-ad second. The data provided to us report average behaviors across viewer-seconds within each viewer-ad combination. So, viewing behaviors within 30-second ad exposures are based on 30 underlying measurements per viewer.

We note the possible limitation that average visual attention is only one possible measure of attention. For example, one viewer may actively process ad audio while looking away from the screen. Another viewer may stare at the screen yet be entirely absorbed in other thoughts. A third viewer may focus on a program but blinking or saccade behaviors may lead to average visual attention well below 100%. Still, visual attention seems particularly important to advertisers as it indicates potential perception of ad video.

2.1.1 Comparisons to Extant Advertising Audience Measurements

Nielsen and TVision both measure tuning continuously and passively. However, unlike Nielsen, TVision also measures viewer presence continuously and passively. Nielsen has no analogue to TVision's attention data.

Traditional television audience measurements are based on digital devices—mostly smart TVs and set-top boxes—and Nielsen "People Meters." Digital devices measure tuning passively and continuously in millions of households, but do not measure which household members are watching at which times, or whether anyone is watching at all. People Meters measure tuning passively and continuously in representative samples of tens of thousands of households, and they additionally measure viewer presence in an intrusive and intermittent fashion. People Meters use a red light to prompt Nielsen panelists to "log in" on a special remote control at the start of each viewing session and once every 15-45 minutes thereafter. Nielsen combines viewer presence data with tuning data to determine audience demographics and infer when viewing sessions may have concluded.

Television media buyers have long known that Nielsen audience estimates overstate advertisement audiences. Ephron (2006) argued that,

> "commercial-minute data... show losses of audience of about 2 to 10 percent during commercials compared to programs... Researchers, who read the fine print, qualify a Nielsen commercial exposure as 'an opportunity to see' a commercial. And given the opportunity, it's obvious the probability is a lot less than one. So the Nielsen commercial-minute audience is an overstatement of people seeing commercials."

In contrast, TVision's passive and continuous presence measurements avoid disrupting natural viewing behaviors. TVision data are precise enough to measure differences in "opportunities to see" (OTS) between consecutive ad slots, and further distinguish OTS from actual ad exposures.

In what follows, we define an *Opportunity to See (OTS)* as a viewer's television tuned to an ad insertion for at least two seconds, for any commercial break in which the viewer is present for at least two seconds in the first ad slot of the break. Selecting viewers present at the start of the break focuses on audience retention and removes inactive viewing sessions from the sample. The two-second threshold is inspired by the Media Rating Council's definition of a "viewable impression" in which 100% of an ad's pixels play on a screen for at least 2 seconds (Knauer, 2019).

The definition of a "viewable impression" does not require a human to be impressed by the ad. Industry reports estimate that 10-30% of digital ad spend is lost to ad fraud, often because ads are served to machines instead of to humans (Gordon et al., 2021). For example, an analysis by the IAB Tech Lab indicated that only 59.8% of ad clicks could be confirmed as human traffic (Swant, 2019). In March 2021, the top four Google search results for "buy youtube views" listed prices from $2.80-$5.99 per 1,000 views. TVision presence data may offer the first passive, continuous human detection data in the history of mass media advertising.

We define an *ad exposure* as any OTS in which a viewer is detected as present for at least two seconds. An example can illustrate how ad OTS differ from ad exposures. Suppose a viewer watches a program that goes to an ad break. The break starts with a Coca-Cola ad, then a Geico ad, then follows with 5 other ads. The viewer leaves the room halfway through the Geico ad in the second slot and does not return until after the break ends. The viewer has had 7 opportunities to see ads and two ad exposures (Coca-Cola and Geico).

The other major advantage of TVision data is attention measurement. Advertisers invest millions to address the age-old imperative to "cut through the clutter" and attract viewer attention with their ads. TVision provides the first continuous, passive measurements of television viewers' ad attention in natural viewing environments. Television viewers increasingly use smartphones or tablets at the same time as television, so attention data can help advertisers understand how viewer attention varies across time, programs and demographic groups, and how attention responds to advertising content.

2.1.2 Ad Viewing Descriptives

Viewer presence during an ad requires TV set tuning for the ad to play on the screen. Viewer attention to an ad requires viewer presence in the room during the ad. Tuning has been studied for decades. Is tuning a reliable proxy for presence or attention? We compare tuning, presence and attention behaviors in samples of ad OTS and ad exposures. The following graphics focus on viewers with at least 50 ad exposures and commercial breaks on top-4 broadcast networks between 7:00 A.M. and 1:00 A.M.

Figure 1, Panel A, graphs histograms of viewers' average tuning, presence and attention behaviors during OTS. The average viewer's television remains tuned to 96.3% of viewable TV ad seconds. However, the average viewer remains present for only 54.6% of all ad seconds during OTS, with substantial heterogeneity in average viewer presence resulting in a 10-90th percentile range of 28.2% to 76.7%. Further, the average viewer only pays attention to 7.7% of ad seconds during OTS. In fact, 7.2% of viewers disregard 99% or more of all viewable ad seconds on average. Ignoring the distinction between OTS and exposures underestimates ad viewing because 29.8% of the observations occur when ads play to empty rooms.

Figure 1, Panel B, shows the distributions in the subsample of ad exposures only. The tuning distribution changes little, with an average of 96.2% during ad exposures. However, average viewer presence increases from 54.6% to 85.3% and variation across viewers in average presence falls by about half after filtering out non-exposures. Average viewer attention increases from 7.7% to 11.7%. Only 3.1% of exposed viewers disregard more than 99% of all ad seconds.

Figure 2 depicts covariation among average viewing behaviors at the individual level. Each point plots an individual viewer's average of two viewing behaviors among all ad exposures observed. All three panels show diffusion around strong central tendencies, indicating that the three behaviors are correlated yet still quite distinct. For example, within the subset of viewers who average 95% tuning, average presence tends to range from 75% to 94%. Within the subset of viewers who average 85% presence, average attention tends to range from 1% to about 22%. In sum, people engage in different ad viewing behaviors at quite different rates. Thus tuning is an incomplete proxy for presence or attention, and controlling for viewer heterogeneity is important.

Next, we illustrate how tuning, presence and attention behaviors vary across the viewer demographic categories that traditionally mattered most for linear TV ad pricing. Figure 3 displays averages of each behavior by demographic group within the OTS and exposure samples.

Tuning is similar between genders and slightly higher among younger demographic groups in both samples. However, presence insights again change dramatically between the OTS and ad exposure samples. The OTS sample shows large differences in viewer presence across demographic groups, with older females showing the highest average presence at 67.3% and younger males showing the lowest average presence of 50.6%. However, the ad exposure sample shows muted variation with mean presence ranging from $85.8\% - 90.8\%$ across demographic groups. Therefore, nonpresence is about 3-4 times more common during ad exposures than tuneaway.

Like presence, attention to ads increases with viewer age within both genders. However, unlike presence, removing non-exposures from the OTS sample does not change variation across groups much; instead, it mostly induces a level shift in mean attention. The level shifts imply that people leave the room during ads they are unlikely to have watched otherwise. Overall, patterns of tuning, presence and attention during ad exposures are consistent with a theory that older viewers are more likely to avoid ads by changing channels and younger viewers are more likely to avoid ads by leaving the room or diverting their visual attention.

Next, we examine how viewing behaviors change across ad slots within commercial breaks. Figure 4 graphs mean tuning, presence and attention by ad slot, based on OTS and exposures, for all breaks with the modal length of 7 slots. Note that the changes across slots would be smaller in all three panels if they incorporated viewers who join commercial breaks after the first slot. OTS data show that, after the second ad slot, average tuning gradually rises as ad-averse viewers select out of the break. However, average presence falls rapidly from 86.2% in the first slot down to 71.0% in the seventh slot, and attention falls from 12.8% in the first slot down to 10.1% in the seventh slot.

The exposure data paint a similar picture in terms of average tuning, but a different picture in presence and attention. Average presence rises uniformly after the first slot. Surprisingly, average attention is nearly constant at 13.5% after the first slot. Together, these findings suggest that exposed viewers who leave early during a commercial break are generally less attentive than viewers who do not leave, and that passive measurements of viewer presence and attention offer richer information about viewing behaviors than tuning alone.

2.2 Sample Selection, Ad Features and Preliminary Evidence

TVision ad insertion data document the ad environment – network, date, air time, program, genre and episode. Ad metadata provide the ad creative name, product name, brand name, product category, and ad duration.

We checked the TVision ad insertion data against the official advertising schedule for Super Bowl 51 and against Kantar Media, a reliable commercial source of ad insertion data. The TVision ad data contained all 63 national ads in the correct order. The average insertion time difference was 4.9 seconds, consistent with standard asynchronies in local broadcast affiliate streams. We also found a very high correspondence between TVision ad insertion data and Kantar data in other program data.

Figure OA1 ("OA" refers to Online Appendix) shows that ad exposures and attention build throughout the day and peak during the evening "prime time" hours. The estimation sample selects ad insertions between 7:00 AM and 1:00 AM on the four major broadcast networks (ABC, CBS, FOX, NBC) from July 2016 to June 2017. We further limit the sample to viewers with at least 50 ad exposures. In total, we observe 4,257,112 exposures of 3,659 unique viewers to 6,650 unique ad creatives in 167 product categories. Regular panelists—defined as viewers with at least

50 active viewing days—view 22.49 sample ads per person per day, and pay attention to ads for an average of 1.13 out of 8.93 minutes of exposures.

2.2.1 Ad Features

The three most general sets of ad features are ad creative identifiers, brand identifiers and product category identifiers. An ad creative identifier summarizes all content in a unique ad creative and bounds the behavioral variation ad content could explain. We create an "Other" identifier for all ads with fewer than 50 exposures in the viewing sample, covering 1.95% of all exposures.

Advertised product categories describe things like beer, cancer drugs, or pick-up trucks. Product categories capture stylistic and thematic similarities across ads, such as humor and good times in beer ads or images of toughness and trucks in pick-up truck ads. They also reflect regulatory requirements about ad content, such as pharmaceutical brands describing approved drug use, generic drug name, and potential side effects (FDA, 2020). We supplement these data with three sets of ad features.

First, a TV advertising measurement company called iSpot.tv provides an online database of TV ads. We algorithmically downloaded ad videos from iSpot covering 85% of exposures to national ads in the estimation sample. We also scraped ad content features from iSpot webpages. For each ad, we observe a Tagline identifier, a sentiment score ranging from zero to one based on the positivity of the words in the audio transcript, a promotion identifier, a commercial Music identifier, a Movie identifier, an "engagement rating" based on the volume of digital activity related to the ad creative, and a professional actors indicator. iSpot also classifies the "mood" of each ad as active, emotional, funny, informative, or sexy.[1]

Second, we constructed a set of machine-coded ad content features using machine learning

[1] [Link: Doritos ad example.]

algorithms collated by Schwenzow et al. (2021). We retained measures with precision and recall scores of at least 50%, including number of scene transitions; average colorfulness, saturation, and luminosity; and percentages of ad video seconds showing facial expressions of Surprise, Neutral emotion, or Happiness. Table OA1 presents the summary statistics for all iSpot and machine-coded features.

Finally, we created a third set of ad features using the Google Cloud Vision (GCV) Application Programming Interface to tag recognized images within ad videos. GCV identifies over 1,000 common image tags in 70 categories, based on a large validation set of human-tagged images and videos. Blanchard et al. (2020) provides a detailed overview of the video coding platform and finds that image tags help to predict new product adoption. Kubany et al. (2020) found GCV performs well compared to competing image recognition services. We took two steps to filter out tags likely to be inaccurate or redundant. First, we sought to limit errors in variables by only retaining tags that describe concrete nouns and verbs, as indicated by asterisks in Table OA2. Second, we sought to limit collinearity by retaining only those 32 tags for which 50% or more of variance remained unexplained in a regression of the tag on product category, iSpot and machine-coded ad features. Table OA2 displays retained image tags and their frequencies in bold.

Ad content features carry three important caveats. First, ad content feature coding will always be incomplete. Ad content varies greatly across ad creatives, and no current method can fully characterize video content in interpretable ways. Unobserved features may correlate with coded features and complicate interpretation of feature coding results. Second, classical errors-in-variables issues may bias ad content feature parameter estimates toward zero. Third, ad videos were unavailable for 15% of sample exposures, so all ad content features implicitly interact video availability with feature measurement.

2.2.2 Linking Ad Viewing to Ad Features

Figure 5 shows how ad viewing changes with ad environment and ad features. Broadcast networks with lower average tuning tend to have higher average attention, a pattern that repeats when comparing prime time to other dayparts. Program genres show some different patterns. For example, ads during Football games have both the highest tuning and highest average attention whereas Drama ads have the lowest average tuning with moderate average attention.

Shorter ads retain more viewers and attention than longer ads on a per-second basis. Comparing 15-second ads to 30-second ads, mean tuning per ad second falls from 98% to 94%, mean presence falls from 94.1% to 85.6%, and mean attention falls from 13.5% to 12.5%.

Advertised product category also correlates with ad viewing. Figure 5 provides mean viewing behaviors for the 10 most-tuned and the 10 least-tuned advertised product categories. Casinos & gambling is both the most-tuned and most-attended ad category. Entertainment & games ads are highly tuned but attended much less, perhaps because they are more likely to generate second-screening behaviors. Eight of the ten least-tuned ad categories are for prescription drugs, and those eight drug categories all have lower mean attention than the remaining two least-tuned product categories.

Table OA3 presents variance decompositions of ad viewing behaviors on individual sets of viewer, break and ad features. Viewer identifiers are the best predictors of presence and attention, explaining 53 times more variation in attention than the traditional targeting variables of age and gender. This finding congrues with prior research quantifying the profitability of individually targeted advertising (Deng and Mela, 2018). It remains unclear how much of the correlation between viewer IDs and ad viewing behaviors accrues from advertisers' targeting strategies as opposed to individual viewer preferences and habits, but it highlights the importance of controlling for viewer heterogeneity. Ad environment variables also correlate with viewing behaviors, including slot within the break, network and program genre. Like viewer identifiers, it remains unclear how much the commercial break factors affect ad viewing directly as opposed to correlating with advertisers' and viewers' self-selection into commercial breaks.

The ad features correlate weakly with presence but explain less variation in tuning and remarkably little variation in attention. One of the strongest correlates is ad duration, explaining 4.6% of presence and 1.6% of tuning, but just .08% of attention. Another is ad category, which explains 1.0% of presence, 0.5% of tuning and 0.05% of attention. In summary, the variance decompositions presage difficulty in detecting effects of ad content on advertising attention.

3 Empirical Framework

3.1 Model Specification

We develop an empirical model in the "causal effects" paradigm described by Chintagunta and Nair (2011). The model explains tuning, presence, and attention behaviors as functions of ad features, slot and time-within-break features, and viewer-break interaction effects. b indexes ad breaks, each of which is a set of consecutive ads inserted into a specific network-program-date-time combination. Each ad slot within a break is indexed with s, so every (b, s) combination identifies a unique insertion of the particular ad creative that was aired in slot s of break b.

Let y^j_{ibs} be viewing behavior j for viewer i exposed to the s^{th} advertisement in ad break b. Ad viewing behavior is modeled as follows:

$$y^j_{ibs} = x'_{bs}\boldsymbol{\beta}^j + g(1_s, l_{bs}, t_{bs}; \Theta^j) + \delta^j_{ib} + \varepsilon^j_{ibs} \quad (1)$$

x_{bs} is a vector of ad features, such as ad creative fixed effects, product category fixed effects, and ad content features. $\boldsymbol{\beta}^j$ represents how ad characteristics change mean viewing behaviors.

The function $g(1_s, l_{bs}, t_{bs}; \Theta^j)$ estimates average changes in viewing behaviors during commercial breaks. The slot-specific indicator variables 1_s capture typical changes in viewing behaviors across ad slots. Ads in the sample range from 15 to 120 seconds, so it is also important for g to accommodate differences in advertisement durations, denoted l_{bs}, as well as the total time elapsed since the beginning of the break, t_{bs}.

δ^j_{ib} captures heterogeneity across viewers, breaks, and viewer-break combinations. δ^j_{ib} is an interaction effect that inherently nests: i) viewer-specific effects including viewer habits or viewing environment idiosyncrasies; ii) break-specific effects including time, program or network shocks, *e.g.* the program in which the break occurs, how much time has passed since the last break, the season of the year or the time of day; and iii) viewer-break interaction effects, such as how engaged viewer i is with the program or whether the viewer is watching the break during time-shifted programming. The flexibility of δ^j_{ib} comes from its high dimensionality given that there are 994,186 (i, b) combinations in the estimation sample.[2]

The error term, ε^j_{ibs}, captures any remaining omitted factors, such as measurement error relating to the viewer-detection equipment and algorithms.

3.2 Causal Identification: Theory and Evidence

A small but growing literature has recently established that advertising endogeneity problems can be severe. Lewis and Rao (2015) showed that small model specification errors can overwhelm true effects of digital banner ads on sales in observational work. Gordon et al. (2019) found that observational methods failed to recover experimental treatment estimates of Facebook ads on sales, even in huge samples with numerous covariates. Shapiro et al. (2021) found that careful endogeneity controls estimated smaller effects of TV ads on packaged good sales than correlational

[2]We decided against using a discrete choice model because (i) response behaviors are continuous and (ii) choice sets are unobserved but vary across viewers and viewing sessions, *e.g.* during live or time-shifted viewing.

approaches.

The ideal experiment to identify ad content effects on viewing behaviors would randomize ads across audiences, brands, ad breaks and slots. However, we know that advertisers and viewers both self-select into commercial breaks (Tuchman et al., 2017). Therefore, we assume x_{bs} correlates with δ^j_{bs} in the *causal* models and estimate the δ^j_{bs} parameters. For comparison, we also report results of *descriptive* models in which the δ^j_{bs} parameters are treated as unobservables.

We then rely on broadcast TV networks' quasi-random ordering of ads within breaks, which implies x_{bs} is uncorrelated with ε^j_{ibs}. The television industry has long known or assumed that viewing behaviors change across ad slots within the commercial break, as confirmed in Figure 4. However, broadcast networks do not sell specific ad slots to advertisers. Advertisers purchase ad insertions based on networks, dates and quarter-hours, typically months in advance and without guarantees of what program the ad will be inserted into. The exclusion of ad slots from standard ad contractual terms can be explained by observing that Nielsen audience estimates do not vary meaningfully between consecutive ad slots, likely due to the relative imprecision of People Meter presence measurements. Instead, standard TV ad sales contracts promise to rotate ads across slots on an "equitable" basis across commercial breaks (Mandese, 2004).

Quasi-random ordering of TV ads within commercial breaks is verifiable. If networks assign ads to slots using independent random draws, then the distribution of ad creatives' average slots should be Normal, by the Law of Large Numbers. To check, we define each ad insertion's position within its break as $\frac{s-1}{S_b-1}$, where S_b is the number of slots in break b. Thus, every ad position lies in [0,1] and the measure is comparable across various ad and break durations.

Figure 6, Panel A, plots the empirical distribution of average ad positions for the 1,384 advertised products with at least 50 ad insertions on broadcast networks.[3] The distribution appears approximately Normal. Panel B compares the empirical distribution of average ad positions to quantiles of a Normal distribution with the same mean and variance. There is a remarkably close correspondence. All 8 of the largest positive outliers are ads for sports programs that were probably house ads run by program producers (e.g., NFL Online, USGA Organization, FedEx Sponsored Event, etc.). Overall, ad positions are verifiably consistent with networks' contractual promises of quasi-random ad ordering.

Quasi-random ordering does carry an important caveat. Some cable networks price ads by slot. In fact, average cable network ad slots depart meaningfully from quasi-random placement, as shown in Figure OA2. Therefore we excluded cable networks from the sample. Quasi-random ordering is also unlikely in addressable TV or other programmatic ad sales contexts.

Numerous papers rely on quasi-random ordering of TV ads within breaks to identify causal TV ad effects. Those include studies of TV ad avoidance (Wilbur et al., 2013); brand website visits and sales (Liaukonyte et al., 2015; He and Klein, 2018; Meder et al., 2019); social media chatter (Fossen and Schweidel, 2019); brand search and price search (Du et al., 2019); subsequent TV ads' audience and resulting digital chatter (Fossen et al., 2020); and brand awareness, consideration and purchase (Tsai and Honka, 2021). However, to the best of our knowledge, no prior study has empirically confirmed quasi-random assignments of ads to slots. We therefore hope the confirmation of a common extant identification strategy is a contribution to methodologically similar studies.

[3]The ads exclude promotions for network programs, as these often appear either before or after commercial breaks. Promotions are identified in the data as advertised product names that include the name of a national TV network. The data are drawn from the population of ad insertions measured by Kantar; they are not restricted to the set of ad exposures observed in the TVision panel.

4 Findings

We present ad creative, ad category, and machine-coded feature effects on viewing behaviors, followed by duration, slot and time effects, then show the robustness of the ad category results to alternate model specifications.

4.1 Ad Creative Results

Figure 7 depicts six distributions of ad creative effects: one each for the descriptive and causal models, within each of the tuning, presence, and attention regressions. Each distribution characterizes 6,650 parameter estimates. We demean the distributions to focus on their shapes.

All six distributions are unimodal and nearly symmetric. The causal effect distributions vary less than their descriptive counterparts, with the greatest compression observed in the attention estimates. Specifically, the standard deviation of the causal tuning distribution is 12% smaller than in the descriptive tuning distribution, 20% smaller for presence, and 37% smaller for attention.

The greater variation in the descriptive distributions shows that ad effects on viewing behaviors covary with factors that predict ad assignments to highly-viewed breaks, such as viewer factors, break factors and viewer-break factors. Simply put, "better" ads are more likely to show up in "better" viewer-breaks and vice versa. The only difference in the models that generate the different results is whether the δ_{ib}^{j} parameters are estimated jointly with the ad creative effects or treated as unobservables as part of the error term.

Still, despite the compression within the causal effect distributions, the tails of those distributions contain some surprisingly large ad creative point estimates. For example, 5% of the point estimates in the causal tuning distribution exceed .039 in absolute value, more than the difference between tuning's average and its upper bound (.963 and 1.0, respectively). 5% of the presence point estimates exceed .048 in absolute value, and 5% of the attention point estimates exceed 0.030

in absolute value, both of which are surprisingly large compared to average viewing behaviors (e.g., .129 for attention), especially when considering that the regression separately accounts for slot effects and time-into-break effects.

We sought to better understand how individual ad creative estimates relate to sample sizes. Figure 8 turns the causal distributions on their side, showing how creative estimates covary with log(exposures). The x axis runs from e^4 to e^9, indicating that the range of exposures per ad creative runs from 50 to 5,076. The trend lines show that the creative estimates are nearly uncorrelated with the number of exposures. The outlying estimates are all infrequent ads; the most frequently viewed ad creative estimates are more concentrated around zero.

It is possible to bootstrap ad creative standard errors, but we prefer not to risk interpreting noise. We also investigated replacing the ad creative fixed effects with the 1,504 brand fixed effects, but again found a pattern quite similar to Figures 7 and 8, suggesting that they too may be underpowered and therefore uninformative. We focus instead on a model which shrinks the ad creative effects toward product category identifiers and machine-coded ad content features.

4.2 Ad Category Results

Figure 9 depicts the causal and descriptive distributions of product category effects. These distributions are unimodal with the causal distributions again being tighter than their descriptive counterparts. However, the degree of compression is similar across the three viewing behaviors. We observe 22%, 26%, and 21% decreases in standard deviations between the descriptive and causal models for tuning, presence, and attention, respectively ($SD^T_{Desc} = 0.0010$, $SD^T_{Caus} = 0.008$; $SD^P_{Desc} = 0.013$, $SD^P_{Caus} = 0.009$; $SD^A_{Desc} = 0.009$, $SD^A_{Caus} = 0.007$). Ad category effect distributions are tighter than ad creative effect distributions: 5% of the point estimates in the causal tuning distribution exceed 0.015 in absolute value, 5% of the presence point estimates exceed 0.017 in absolute value, and 5 of the attention point estimates exceed 0.011 in absolute value.

Table 1 shows evidence that product category estimates contain reliable signals. A 5% error rate predicts 8.35 false positives among the 167 category effects in any of the six regressions due to random chance alone. Descriptive models produce high proportions of significant correlational results. The causal model results indicate 32 significant category effects on Tuning, 20 significant effects on Presence, but only 8 significant effects on Attention. Therefore we report but do not really interpret the category effects in the Attention regression.

Figure 10 shows that ad category parameter significance is not driven by low-powered outliers. The majority of significant results do not occur among the lowest-powered coefficients. The tuning and presence panels show concentrations of both significant positive and significant negative category causal effects.

Figure 11 unpacks the results presented in Figure 10, highlighting the 40 highest and lowest ad category fixed effects as ranked by tuning estimates. Many of the largest category effects relate to recreation, including Hunting & Fishing; Casinos & Gambling; Wine, Alcohol & E-Cigarettes; Dating; Sports; Movies; and Airlines, whose television ad content promotes leisure travel. Many of the most negative category effects relate to prescription drugs, including drug categories treating Cancer; Depression, Bipolar & Insomnia; Alzheimers & Multiple Sclerosis; Psoriasis, Skin & Nails; Osteoporosis & Arthritis; Varied conditions; Bladder & Gastrointestinal; and Stroke, Cholesterol & Heart Disease.

The presence regression estimates mostly align with the tuning results, but exhibit larger standard errors. The categories that reliably increase viewer presence include Wine, Alcohol & E-Cigarettes; Underwear; Car Rental; Sports; Clothing; Speakers & Headphones; Movies; Legal Services; and Shoes & Socks. On the other end, 6 of the 7 largest significant negative findings again feature prescription drugs. We will investigate drivers of the drug category results in the next section.

Category effects on attention are mostly null results, with 66 of the 80 category confidence intervals lying entirely between -2% and 2% of ad seconds.[4] The null results on attention surprised us. Attention requires both tuning and presence, by definition, so we expected attention results to resemble tuning and presence results. It is possible that ingrained habits drives viewer attention more than on-screen ad content. Another possibility is that ad content is polarizing: if some content reliably attracts attention from viewers interested in the product market, it may simultaneously lead uninterested viewers to divert their attention, change channels or leave the room.

4.3 Ad Feature Results

We measured ad content because ad viewing behaviors may respond to stimuli displayed on television screens. However, we interpret ad feature results with caution, given the caveats about unobserved features, feature measurement error and feature availability.

Figure 12 presents iSpot and machine-coded ad feature causal effects on tuning, presence and attention. As before, tuning and presence results are more precisely estimated than attention, but all of the effects are small on an absolute basis. Sales-related content like taglines and promotions reduce tuning and presence, similar to fidings in Teixeira et al. (2010). Surprisingly, a higher sentiment score reduces tuning, and professional actors reduce both tuning and presence. It seems plausible that brands try to make unattractive ad messages more palatable by hiring professional actors or more positive scripts.

Another surprise is that the movie dummy reduces tuning and presence, given that the movies product category effect increases ad viewing. We investigated this more carefully by examining

[4]These limited absolute changes could still be appreciable on a relative basis given that average attention is near 13%.

the overlap between the movies category dummy and the iSpot movie classifier. The iSpot variable indicates both theatrical movie trailers and also the presence of theatrical movie brands in co-branded advertisements, such as for consumer packaged goods, cars, fast food and retail chains. If we drop the movie category dummy, then the iSpot movie effect becomes positive and significant. Therefore, it appears that movie ads increase viewing behaviors, but movie co-branding in non-movie ads reduces tuning and presence.

The engagement variable measures ad traffic across iSpot's video, social and search channels, and increases ad viewing behaviors. Ads classified by iSpot as having a "sexy" mood reduce tuning, but other mood variable effects are estimated imprecisely, perhaps because of measurement error in the features.

Two of the machine-coded features have significant effects. The number of scenes within an ad reduces tuning and presence, as does the duration of neutral facial expressions shown on screen. Other machine-coded features generally have point estimates near zero.

Figure 13 presents the effects of Google Cloud Vision features on viewing behaviors. The confidence intervals are again quite small but the large majority of feature labels do not have significant effects. Further, those few features that do have significant effects resist easy interpretation. For example, one might have predicted that Infant or Party might have increased viewing behaviors, but Infant is near zero and Party is negative. We again recall the caveat that labeled features may correlate with important unlabeled features, such as when brands pair less attractive selling messages with more attention-grabbing stimuli.

4.4 Duration, slot and time effects

Ad duration, slot and time-elapsed effect estimates are relatively precise and show some interesting patterns. We summarize the effects here and report full results in Table OA4.

Figure 14 shows how ad durations change viewing behaviors. 30-second ads reduce tuning by an absolute 2.7%, presence by 5.6%, and attention by 0.7%. The absolute change in attention is the smallest, but accounts for a 5.4% decrease relative to the average attention of 12.9%, similar to the relative 6.2% decrease in presence.

60-second ad duration effects are approximately double the absolute 30-second duration effects, per ad second. 60-second ads reduce tuning by an absolute 5.5%, presence by 10.9%, and attention by 1.5%. In fact, all common ad durations cause similar relative changes in presence and attention, and those relative changes are all approximately double the relative changes in tuning.[5]

Next we look at slot and time-elapsed effects. The modal ad break contains 7 slots and the modal ad duration is 30 seconds. Figure 15 graphs slot and time-elapsed effects on viewing behaviors for a hypothetical break consisting of 7 30-second ads. Standard errors of the combined effects are calculated by bootstrapping out of the joint asymptotic distribution of the parameter estimates, including off-diagonal terms. Confidence intervals widen throughout the break because audience calculations in later slots involve more parameter estimates.

Tuning decreases across slots with changes driven primarily by the time-elapsed variables. Presence shows a similar absolute decrease but is significantly impacted by both slot effects and time-elapsed variables.

Attention shows a different pattern. Slot effects significantly reduce attention, but unlike tuning and presence, the time-elapsed variables are not significant predictors of attention. Attention decreases from the first slot to the second, and from the second slot to the third, but confidence intervals overlap from positions 3-7. Therefore, despite the moderate reductions in tuning and presence through the course of the break, we cannot reliably say that average attention falls after the third slot.

[5]The lone exception is 105-second ads, but these are rare, as seen in the wider confidence interval.

4.5 Robustness of Ad Category Effects

We view the ad category results as the most interesting set of causal effects, so we investigate how stable they are to alternate model specifications. Figure OA3 overlays the category findings with similar category effects from a restricted model that excludes the three sets of ad content features. The restricted model retains the ad category identifiers; the duration, slot and time effects in the $g()$ function; and the δ_{ib}^{j} person-break interaction terms.

The restricted model results are nearly identical to the full model. Remarkably, none of the 480 depicted category point estimates falls outside the other model's confidence interval. The unusual stability of the ad category estimates suggests that imperfections in the ad content data did not bias the product category estimates. It is not possible to rule out whether inclusion of additional ad content data would change the category estimates, but this exercise suggests that the category findings may be highly reliable.

5 Further Analysis of Prescription Drug Category Results

Pharmaceutical drug advertisements tend to cause viewers to tune away and leave the room. Moreover, the most negative effects relate to serious conditions such as cancer, depression and Alzheimer's. We quantify how drug category attributes relate to ad effects on viewing behaviors.

5.1 Background

Previous research has found that pharmaceutical advertising tends to increase drug category consumption (Iizuka and Jin, 2005, 2007). Sinkinson and Starc (2018) found that anti-cholesterol drug ads promote category consumption and increase social welfare overall. Shapiro (2018) found that antidepressant drug ads increased category revenues and calibrated a supply-side model suggesting that the category was underadvertising in equilibrium. Shapiro (2020) quantified how patients' labor supply reacted to antidepressant drug ads, finding that the marginal effects of drug ads on total wages exceeded ad costs by a factor of 24.

If drug advertising enhances general welfare, then we should care about factors that may influence drug ad pricing. Digital ad sellers Facebook and Google typically include some element of consumer acceptance or rejection of ads in their advertising pricing algorithms, as earlier ads affect attention paid to subsequent ads. Broadcast television networks do not publish ad pricing algorithms, but it is possible that they also use audience reaction in ad pricing. Here we seek to quantify what drug category factors correlate with larger or smaller audience losses during drug ads.

Viewers may seek to avoid pharmaceutical ads for two distinct but related reasons. First, drug ads may present viewers with unpleasant reminders of prevalent adverse health conditions.[6] Second, advertised drugs may present viewers with unpleasant reminders of particularly severe health conditions.

5.2 Data

We collected objective measures of treated condition prevalence and severity for each pharmaceutical category. Prevalence is measured as the case rate, or the percentage of US residents who experience the disease or condition in a year. Severity is measured in Disability-Adjusted Life Years (DALYs), which estimates years of life lost due to premature death and years of healthy life lost due to poor health or disability, reflecting both mortality and morbidity in a single measure.[7]

Prevalence and severity measures mostly come from U.S. data compiled by the Institute for

[6] Alternatively, drug ads for more prevalent conditions may be more relevant to a wider set of viewers, but we question whether those viewers would prefer to receive such messages during television program consumption.

[7] https://www.who.int/data/gho/data/themes/mortality-and-global-health-estimates

Health Metrics and Evaluation's Global Burden of Disease studies.[8] Table OA5 presents the category prevalence and severity data. The two measures correlated at -0.2 at the category level. A few categories have both high prevalence and high severity (e.g., stroke, cholesterol and heart disease; depression, bipolar and insomnia). Most other categories have either high prevalence and low severity, or low prevalence and high severity.

5.3 Model and Results

We run a second stage regression of pharmaceutical category effect estimates from Equation 1 on disease prevalence and severity using Equation 2.

$$\hat{\beta}_k^j = \alpha^j + \gamma_1^j \text{PREV}_k + \gamma_2^j \text{SEV}_k + \varepsilon_k^j \tag{2}$$

$\hat{\beta}_k^j$ is the causal effect estimate of prescription category k ads on viewing behavior j (tuning, presence, or attention); PREV_k and SEV_k are the prevalence and severity of drug category k.

We account for first-stage estimation error using the estimated asymptotic joint distributions of the point estimates. Specifically, we estimate Equation 2 using Generalized Least Squares (GLS) with the estimated variance-covariance matrix, $\hat{\Omega}_{Rx}^j$, where $\hat{\Omega}_{Rx}^j$ is the relevant subset of the variance-covariance matrix of the parameters estimated in the first stage regression, covering only the pharmaceutical category effects, including the off-diagonal terms. Intuitively, estimating Equation 2 via GLS gives more weight to the more precise drug category estimates.

Table 2 presents the estimation results from Equation 2. The table also shows restricted models that contain each predictor individually, and OLS versions of all three models for comparison. We view the GLS results in Column 3 as the most informative specification. We interpret the results as

[8] http://ghdx.healthdata.org/. We use data from 2010 to ensure that data would not be subject to revisions. Prevalence and severity data did not change significantly between 2010 and 2017, when the viewer sample was collected.

descriptive as drug firms choose ads strategically and no instruments are available for unobserved category attributes.

Drug category prevalence and severity are both associated with more negative category effects on TV ad tuning and presence. The point estimates show increasing drug category severity by one million DALYs is associated with a 0.07% decrease in tuning and a 0.05% decrease in presence. Increasing drug category prevalence by 1% of the population correlates with a 0.05% decrease in tuning and a 0.5% decrease in presence.

5.4 Discussion

These second stage results are correlational but we think they are useful for three reasons. First, they point to underlying factors that predict viewer response to advertisements, helping to make some logical sense of the many disparate ad category results. Second, the US regulates direct-to-consumer advertising, but is one of the only two developed economies that allows it. Drug ads remain controversial (Sheehan, 2013), so quantifying the general market's response to drug TV ads may help to inform ad content regulations. Third, we speculate that TV networks may charge more to drug advertisers that treat more severe and more prevalent conditions. Prior literature has found that drug ads increase socially desirable outcomes and that drug brands under-advertise relative to the social optimum. It is possible that television ad pricing policies may restrict positive public health outcomes by further limiting the reach of drug ads.

6 Conclusion

This paper shows that new measures of TV ad viewer presence and attention differ meaningfully from tuning and offer the first precise measurements of TV ad viewability and exposures. We constructed ad features and used a verifiably quasi-experimental identification strategy to estimate how ad features influence ad viewing. We found that TV ads for recreational product categories tend to increase tuning and presence. Prescription drug ads tend to reduce tuning and presence, especially for more prevalent and severe conditions. Viewer attention falls during longer ads and early in commercial breaks, but does not respond reliably to advertised product categories or ad content features.

The current paper has several important limitations, as does all research. It is possible that our reliance on exclusively quasi-random variation in ad ordering may have over-controlled for endogeneity, though we prefer to be conservative in estimating causal effects rather than risking misinterpreting correlations. We were surprised that a full year of advertising exposures for 3,659 viewers would be insufficient to estimate nonzero ad content effects on viewer attention. It remains unclear whether null effects of ad content on ad attention result from noisy content effect measurement, highly variable attention behaviors or other data limitations. It is also possible that true effects are near zero, perhaps because broadcast networks pre-screen advertisements effectively prior to airing them, or because television viewers' ad-avoidance habits are deeply ingrained and not reactive to ad content. Finally, we presume that consumers often divert attention during ads because of second screening behaviors, but we are not yet able to measure such behaviors directly. Therefore, we are not able to quantify potentially positive effects of TV ads on consumer attention, such as online brand search, traffic or sales (*e.g.*, Liaukonyte et al. 2015).

Several extensions are possible. First, field experiments could exogenously manipulate video advertising content to get better estimates of how ad content influences viewing behaviors, as relatively few television advertising field experiments have been reported in the scientific literature. Second, no one has previously quantified how presence or attention predict ad effectiveness, *i.e.* the extent to which increasing presence or attention correlate with changes in ad viewers' propensity to purchase or consume a product. If attention indicates brand preference or purchase intention, attention measurements may offer a readily available intermediate proxy for ad effects. Third, the presence and attention findings condition on a specific measurement definition used in industry at the time of the sample. There may be better approaches available and measurement changes may produce different findings.

In summary, technology offers new measurements of viewing behaviors and advertising content in large samples. A major implication of the current paper is to question the conventional wisdom that advertisers and agencies can hope to use content to "cut through the clutter" and increase viewer attention to TV ads. Still, combining new measures with new analytical approaches should help advertisers and ad sellers better understand market response and improve ad viewer experiences. We hope this study offers a step on that path.

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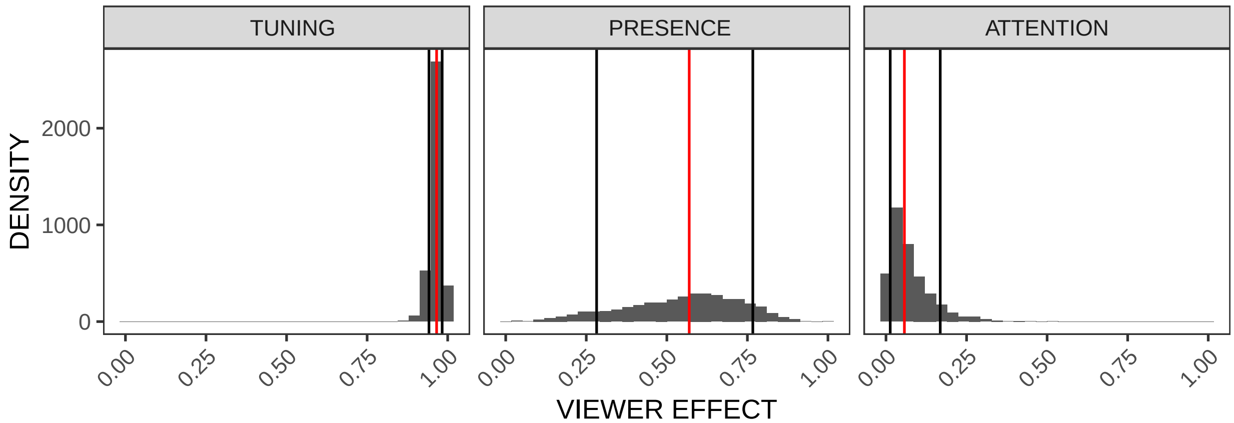
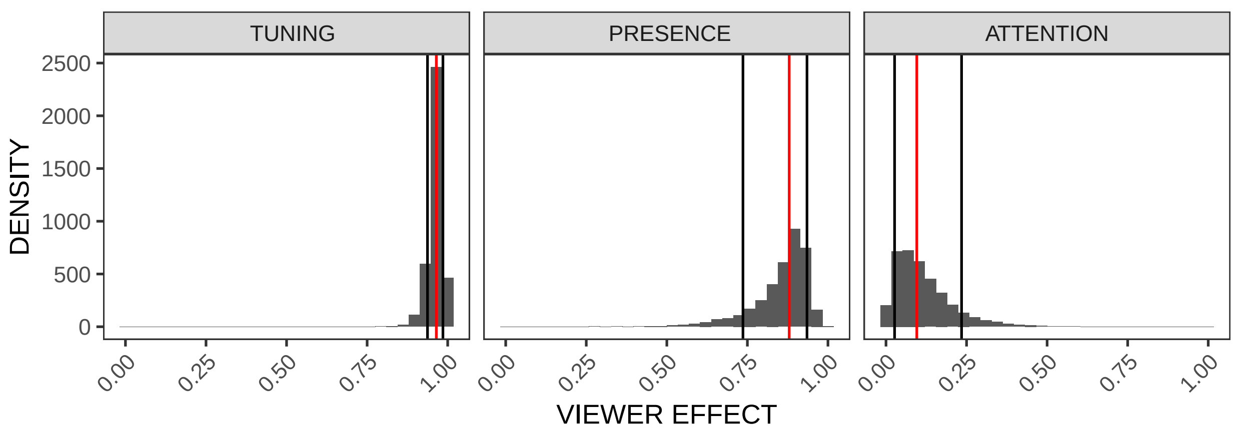
Figures

Figure 1: Viewer-Level Average Viewing Behaviors

A. Opportunities to See (OTS)

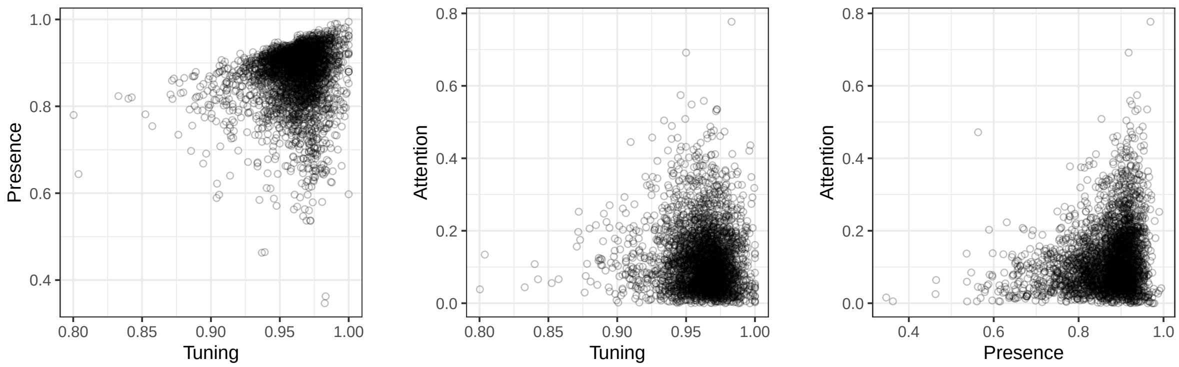


B. Exposures



Notes: Opportunities to see are defined as ads which are tuned for at least two seconds, during breaks when the viewer was present for at least 2 seconds in the first slot of the break. Exposures are defined as any ad during which the viewer is both tuned and present for at least two seconds during the ad's slot. Red lines denote the sample average. Black lines are the 10^{th} and 90^{th} percentiles.

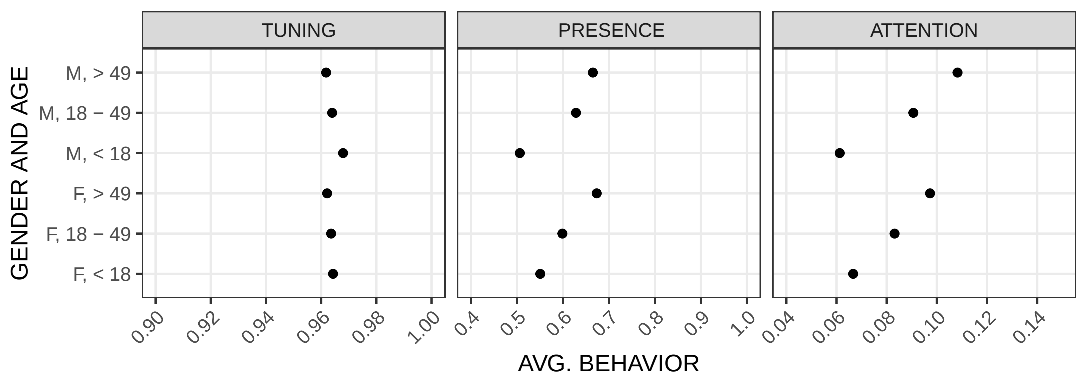
Figure 2: Viewer-Level Tuning, Presence, and Attention Averages



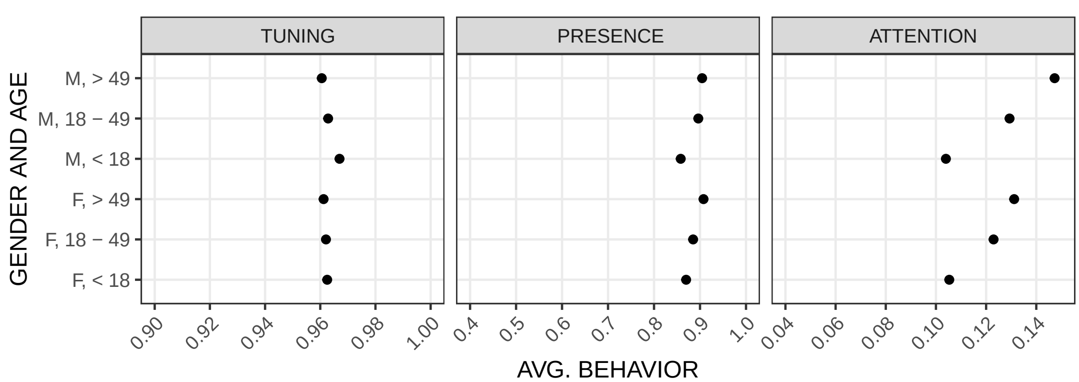
Notes: Each point plots a viewer according to their average tuning, presence and attention behaviors during advertising exposures.

Figure 3: Ad Viewing by Viewer Gender and Age

A. Opportunities to See (OTS)



B. Exposures



Notes: Opportunities to see are defined as ads which are tuned for at least two seconds, during breaks when the viewer was present at the start of the break. Exposures are defined as any ad during which the viewer is both tuned and present for at least two seconds.

Figure 4: Average Viewing Behaviors in all 7-Slot Breaks

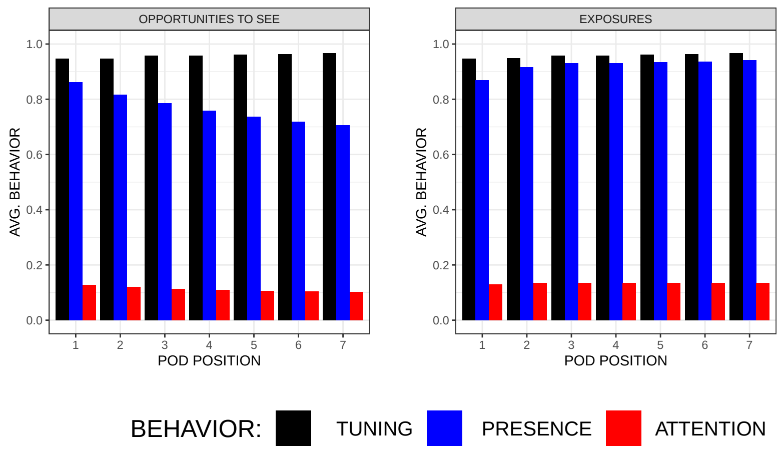


Figure 5: Viewing Behaviors during Ad Exposures by Break and Ad Characteristics

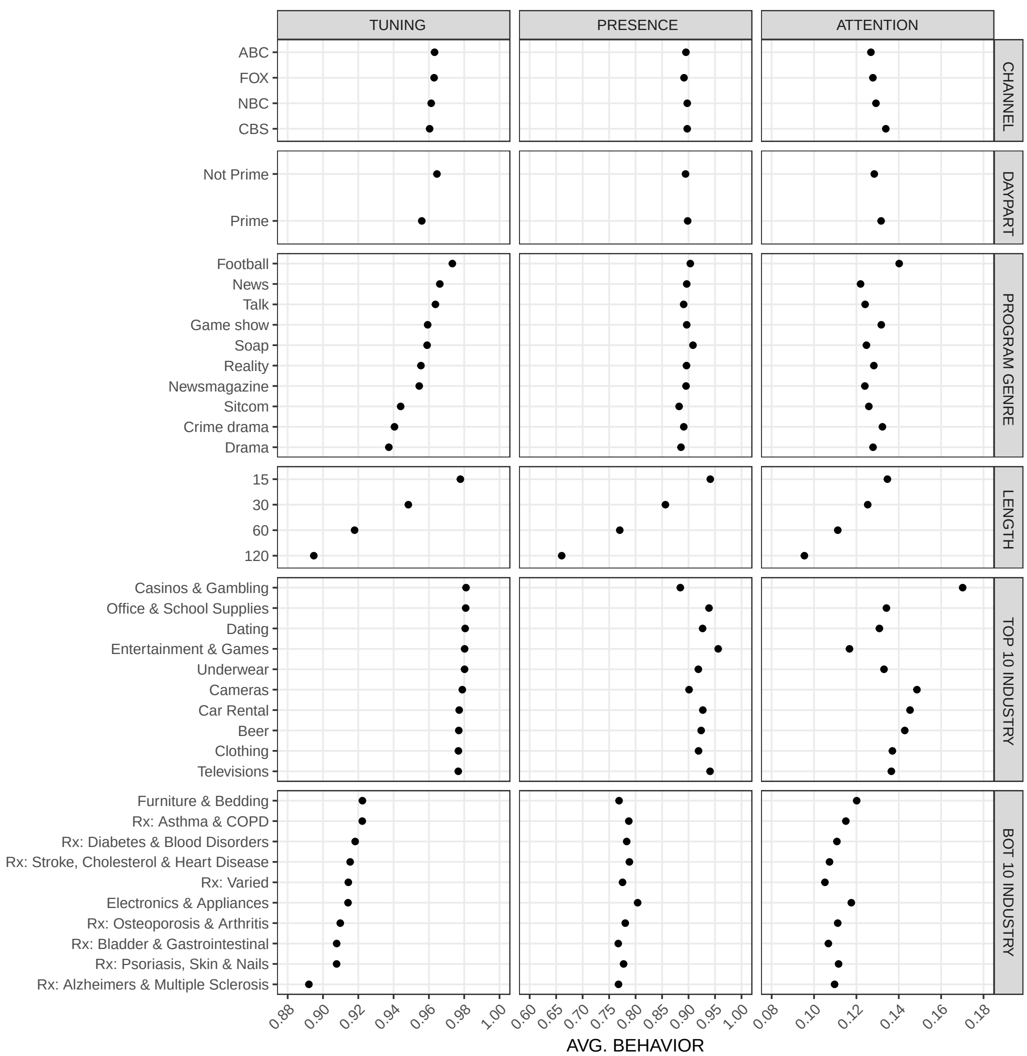
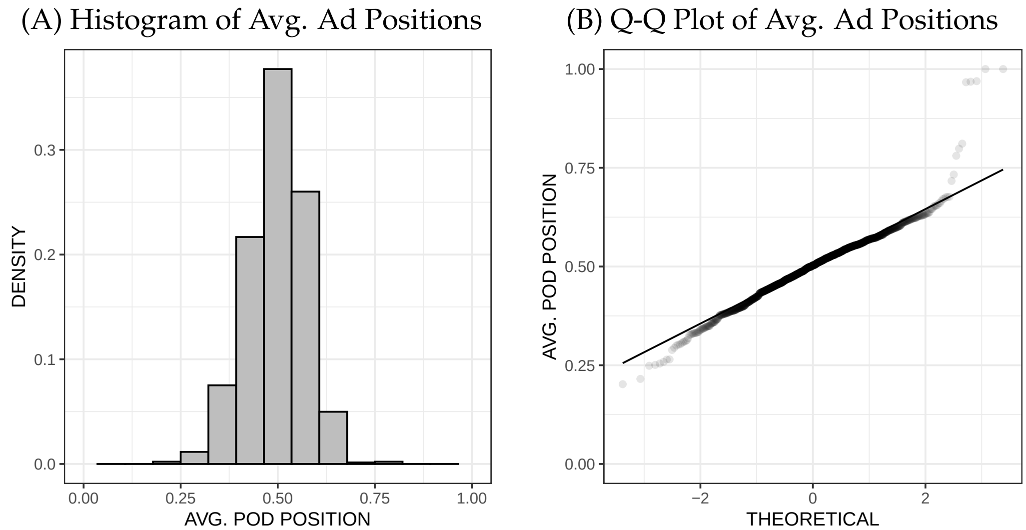
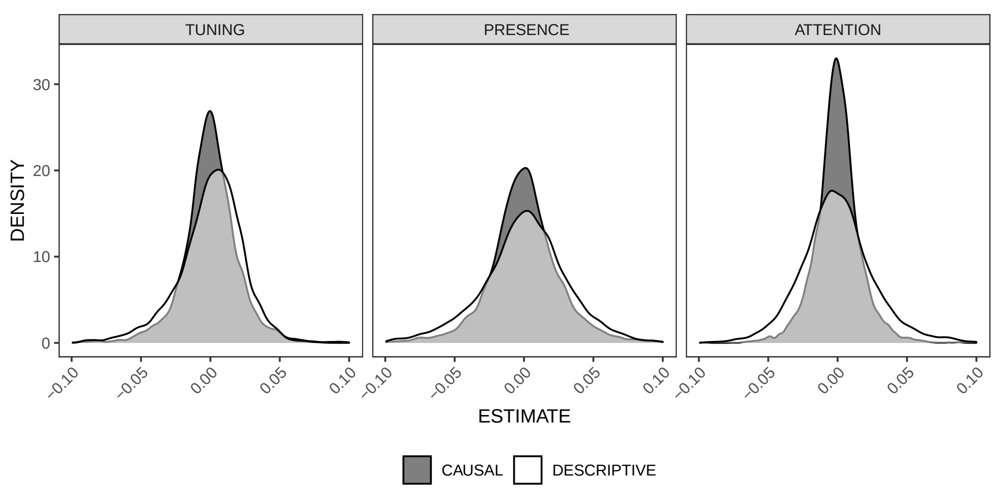


Figure 6: Randomization Check



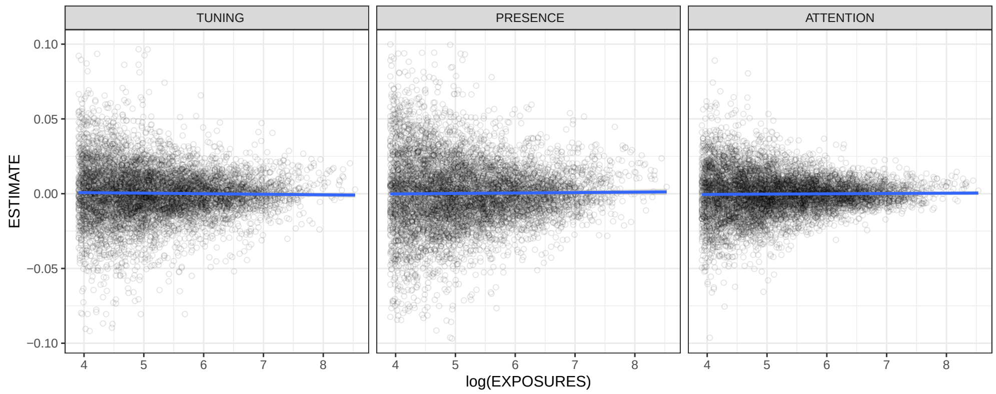
Notes: Panel A shows the empirical distribution of average ad position during broadcast network commercial breaks for the estimation sample of 1,384 advertised brands with at least 50 ad exposures. Panel B compares the empirical distribution of average ad positions to quantiles of a Normal distribution with the same mean and variance.

Figure 7: Distributions of Ad Creative Estimates



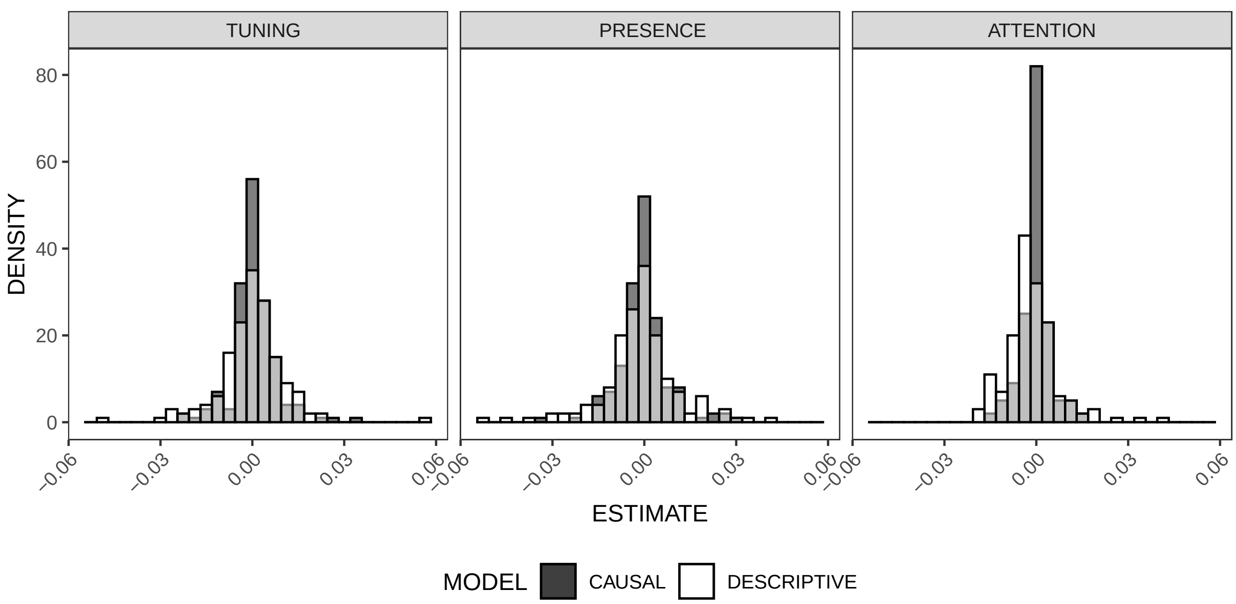
Notes: The three panels show distributions of 6,650 ad creative fixed effect estimates on Tuning, Presence, and Attention from the descriptive and causal models. Distributions are demeaned to aide comparisons across models and outcomes.

Figure 8: Ad Creative Estimates by Sample Size



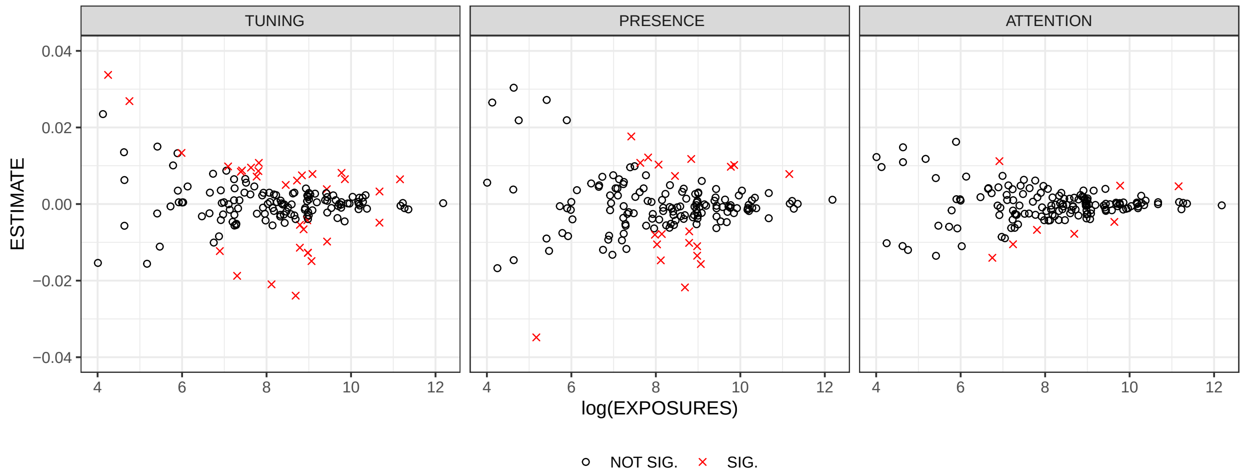
Notes: The three panels show scatterplots of causal ad creative estimates versus log exposures for each ad creative. Distributions are demeaned to aide comparisons across models and outcomes. The blue trend-line shows linear fit.

Figure 9: Distributions of Ad Category Estimates



Notes: The three panels show distributions of 167 ad category estimates on Tuning, Presence, and Attention from the descriptive and causal models. Distributions are demeaned to aide comparisons across models and outcomes.

Figure 10: Ad Category Estimates by Sample Size

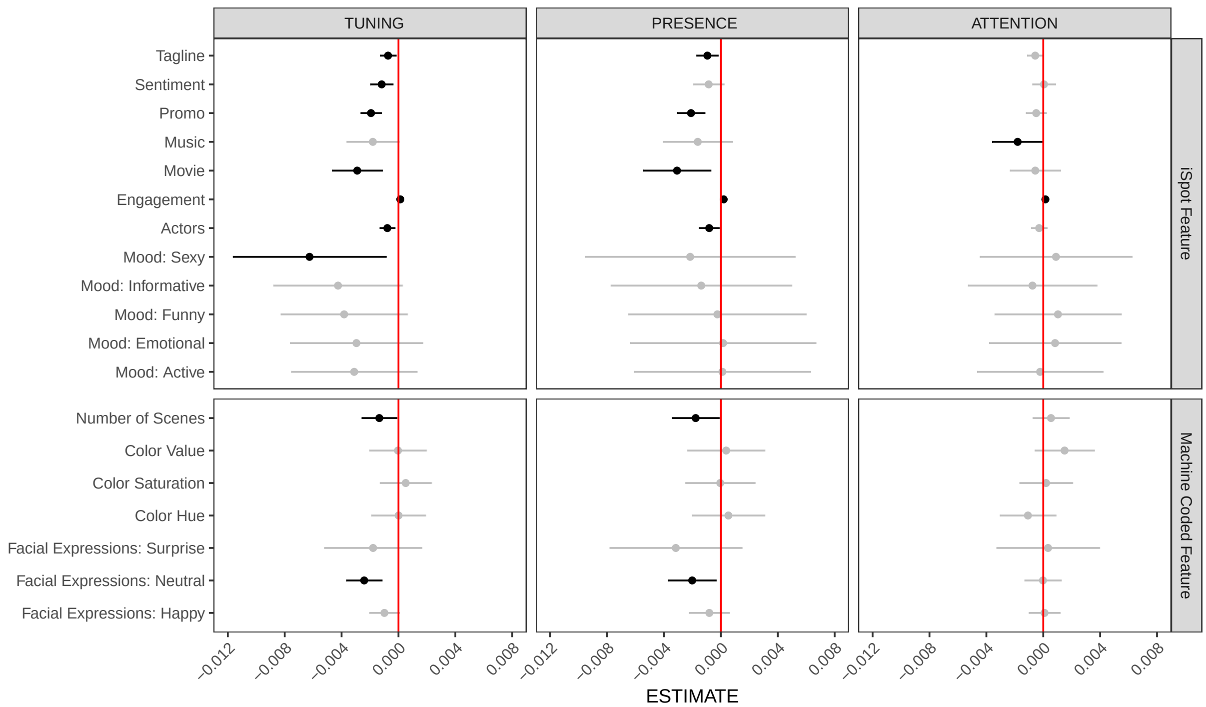


Notes: The three panels show scatterplots of causal ad category estimates versus the logged number of exposures. Distributions are demeaned to aide comparisons across models and outcomes. Red marks indicate statistical significance at the 95% confidence.

Figure 11: Top and Bottom 40 Ad Category Causal Effects

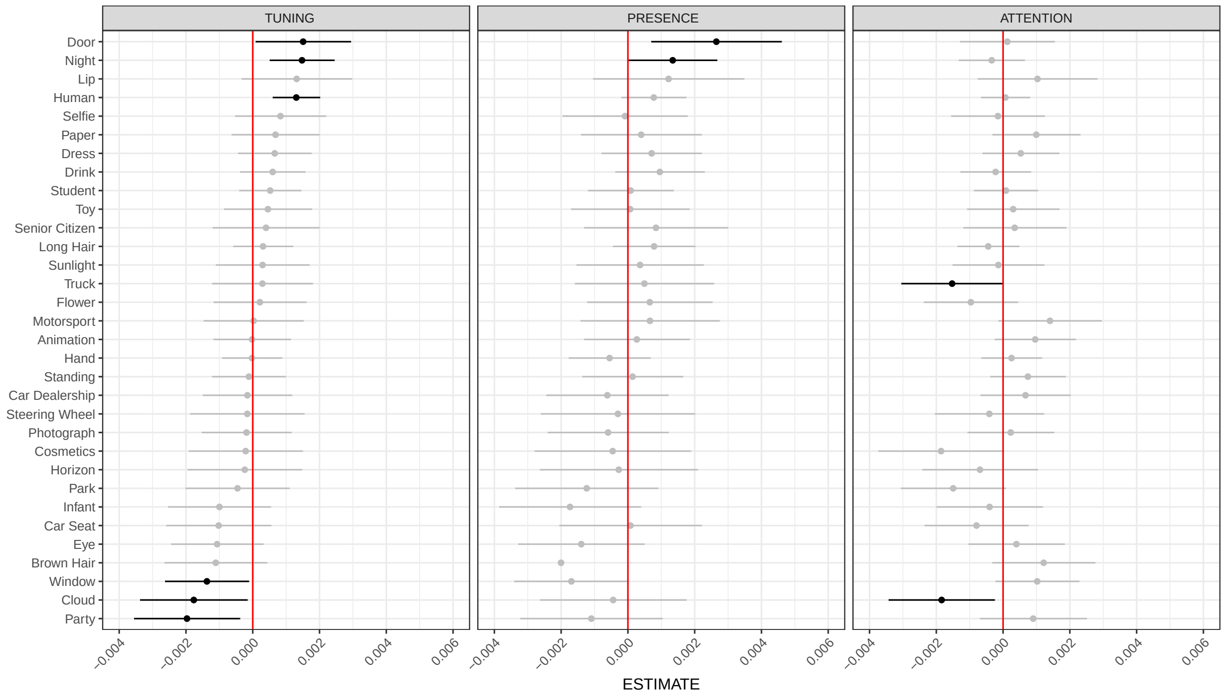
Notes: Each panel presents the top 40 and bottom 40 ad category causal effects, ranked by tuning point estimates. Whiskers represent 95% confidence intervals. Black indicates statistical significance at 95% confidence.

Figure 12: Machine-coded Ad Feature Causal Effects



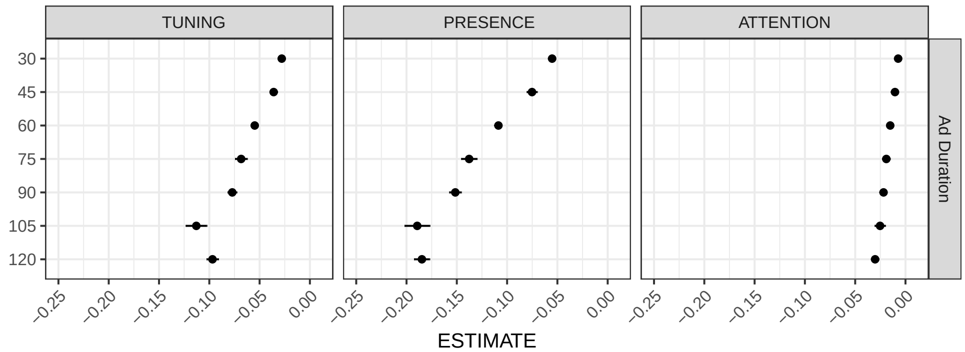
Notes: Whiskers represent 95% confidence intervals. Black indicates significance at 95% confidence.

Figure 13: Google Cloud Vision Ad Feature Causal Effects



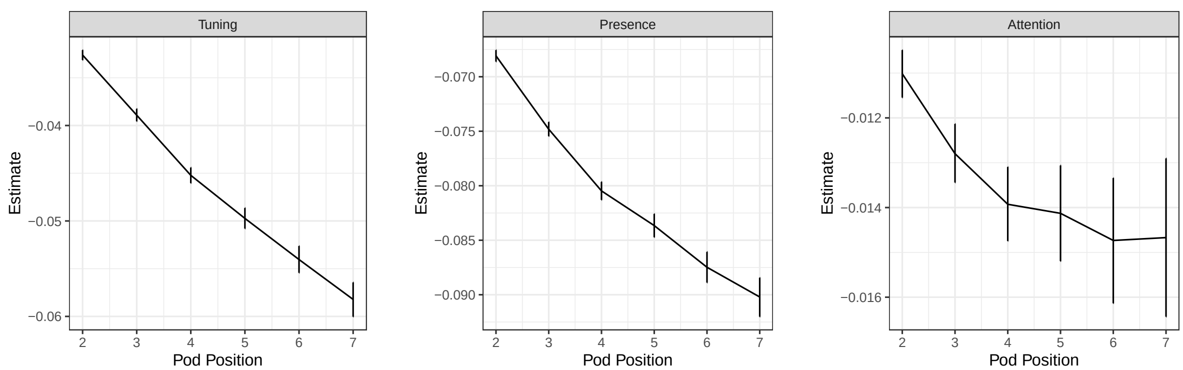
Notes: Features are tags created by Google Cloud Vision based on ad creative videos. Whiskers represent 95% confidence intervals. Black indicates statistical significance at 95% confidence.

Figure 14: Ad Duration Effects



Notes: Ad durations are measured in seconds. Whiskers represent 95% confidence intervals. Black indicates significance at 95% confidence.

Figure 15: Position and Time-Elapsed Effects in a Modal Break



Notes: The figure combines pod position and time-elapsed effects for a hypothetical break consisting of 7 30-second ads. Whiskers represent 95% confidence intervals. Black indicates significance at 95% confidence.

Table 1: Counts of Significant Ad Category Estimates

Model	Tuning	Presence	Attention
Descriptive	68	45	33
Causal	32	20	8

Notes: Table entries count how many of the 167 ad category estimates are statistically significantly different from the average ad at the 95% confidence level. A 5% Type I error rate predicts 8.35 false positive results in expectation.

Table 2: Descriptive Regressions of Pharmaceutical Category Causal Effects on Category Severity and Prevalence

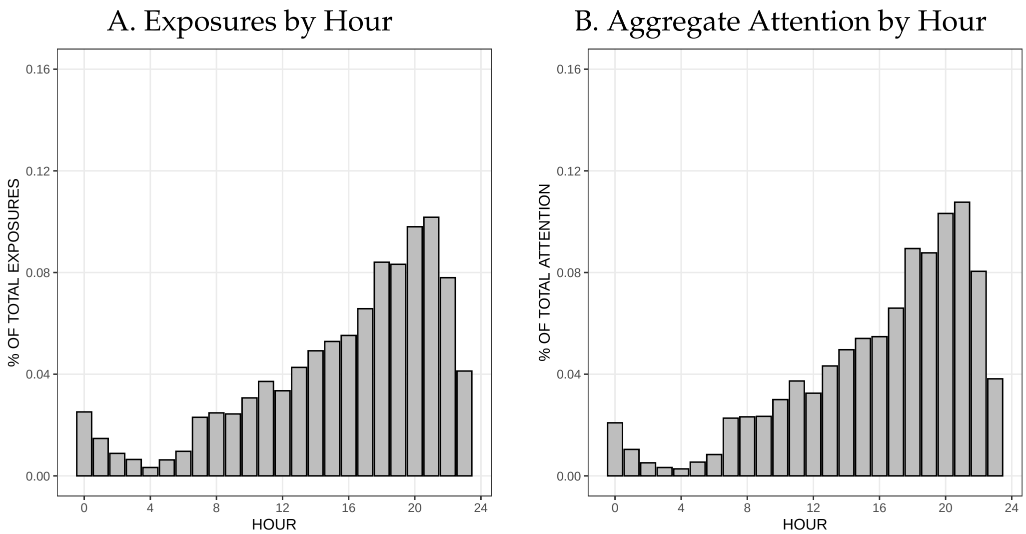
Generalized Least Squares	Tuning (1)	Tuning (2)	Tuning (3)	Presence (1)	Presence (2)	Presence (3)	Attention (1)	Attention (2)	Attention (3)
Constant	-0.00454 ***	-0.00731 ***	-0.00389 ***	-0.00177 ***	-0.00333 ***	-0.00098 ***	-0.00075 ***	-0.00127 ***	-0.0001 ***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00000)	(0.00000)	(.00000)
Severity	-0.00071 ***		-0.00072 ***	-0.00046 ***		-0.00048 ***	-0.00012		-0.0027 ***
	(0.00000)		(0.00000)	(0.00000)		(0.00000)	(0.00000)		(.00001)
Prevalence		-0.00037 ***	-0.00459 ***		-0.00262 ***	-0.00564 ***		0.00018 ***	-0.0037
		(0.00005)	(0.00003)		(0.00005)	(0.00004)		(0.00001)	(.00000)

Ordinary Least Squares	Tuning (1)	Tuning (2)	Tuning (3)	Presence (1)	Presence (2)	Presence (3)	Attention (1)	Attention (2)	Attention (3)
Constant	-0.00622 *	-0.01163 ***	-0.00820 **	(-0.00231)	-0.00654 ***	-0.00396	-0.00036	-0.00183 **	-0.0007 *
	(0.00212)	(0.00214)	(0.00209)	0.00183	(0.00181)	(0.00181)	(0.00050)	(0.00049)	(.00045)
Severity	-0.00078 *		-0.00066 *	(-0.00059)		-0.00050	-0.00019 *		0.0027
	(0.00032)		(0.00026)	0.00028		(0.00023)	(0.00008)		(.00119)
Prevalence		0.01169	0.00804		0.00946	0.00672		0.00360 *	-0.0032
		(0.00668)	(0.00519)		(0.00567)	(0.00449)		(0.00152)	(.00091)

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Online Appendix

Figure OA1: Ad Exposures and Attention by Hour of the Day



Notes:

Figure OA2: Randomization Check Using Average Ad Positions on Cable Networks

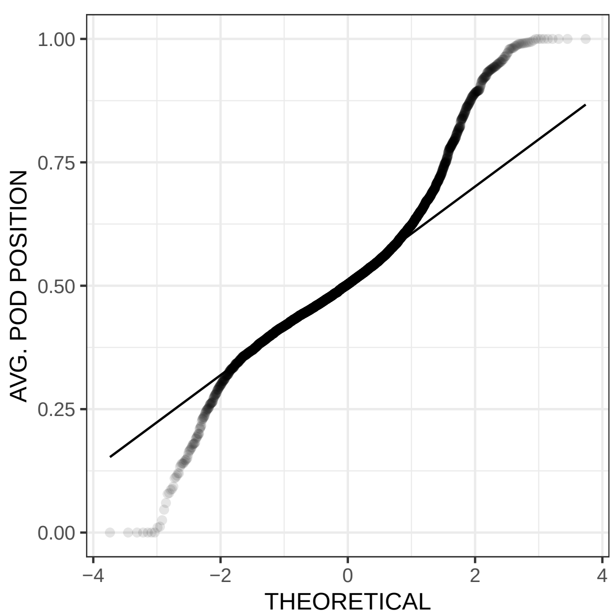
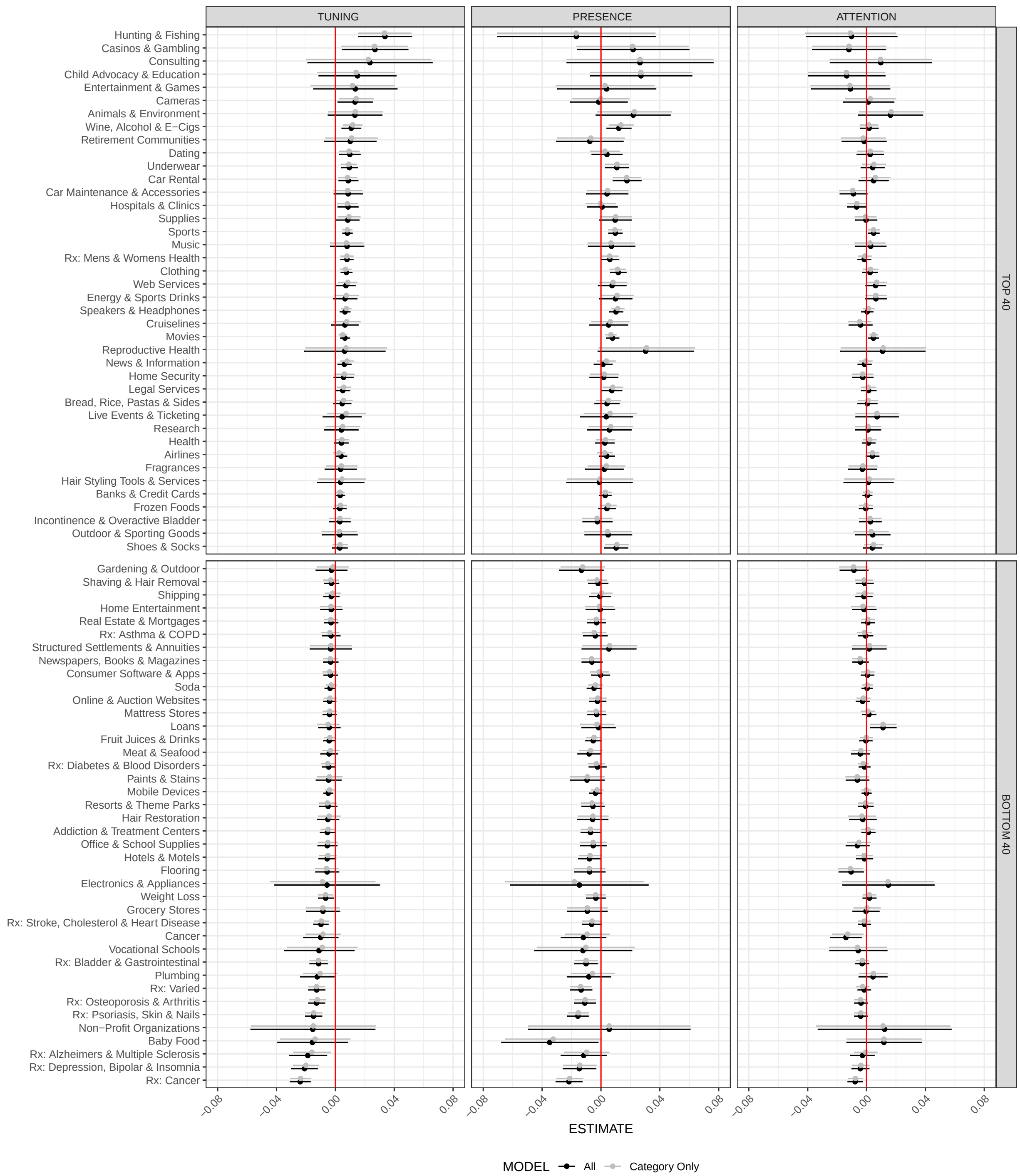


Figure OA3: Category Estimates with and without Ad Content Features



Notes: Black indicates category 95% confidence intervals from the full causal model. Gray indicates 95% confidence intervals from a model that excludes ad content feature data (iSpot features, machine-coded features and GCV features).

Table OA1: Summary of iSpot and Machine-Coded Ad Content Features

Ad Content	Mean	SD
iSpot Features		
Actors	0.483	0.500
Engagement	4.047	2.986
Promo	0.220	0.415
Tagline	0.583	0.493
Movie	0.032	0.177
Music	0.018	0.132
Sentiment	0.422	0.398
Mood == Active	0.583	0.493
Mood == Emo	0.024	0.154
Mood == Funny	0.203	0.402
Mood == Info.	0.046	0.211
Mood == Sexy	0.008	0.089
ML Coded Features		
Colorfulness	0.280	0.169
Saturation	0.420	0.235
Luminosity	0.357	0.188
Happy	0.187	0.236
Surprise	0.024	0.063
Neutral	0.182	0.197
Scene Frequency	0.425	0.271

Table OA2: Google Cloud Vision Feature Tag Frequencies

GCV Feature	% Exposures	GCV Feature	% Exposures	GCV Feature	% Exposures
Logo *	0.143	Mid Size Car	0.025	Downtown	0.014
Graphics	0.135	Transport	0.025	Summer	0.014
Text *	0.116	Ball Game	0.025	Residential Area	0.014
Conversation	0.106	Stage	0.024	**Cloud** *	0.014
People	0.104	Performance Art	0.024	Forest *	0.014
Smile *	0.101	Games	0.024	Town	0.014
Interaction	0.101	Pet *	0.024	Humour	0.014
Human *	0.090	Plant *	0.024	Television *	0.013
Vehicle	0.087	Bottle *	0.024	Formal Wear *	0.013
Facial Expression	0.087	Compact Car	0.024	**Steering Wheel** *	0.013
Song	0.087	Online Advertising	0.024	**Flower** *	0.013
Individual Sports	0.086	Telephone	0.024	**Truck** *	0.013
Sitting	0.084	**Standing** *	0.024	Classroom *	0.013
Car *	0.075	Windshield *	0.024	Junk Food	0.013
Fun	0.073	Lighting	0.024	Mountain *	0.013
Social Group	0.070	Symbol	0.023	Neighbourhood	0.013
Motor Vehicle	0.068	Professional	0.023	**Motorsport** *	0.013
Graphic Design	0.067	House	0.023	Structure	0.013
Food *	0.062	Website *	0.023	Architecture	0.012
Presentation	0.059	Street	0.023	Drinking	0.012
Brand	0.057	**Dress** *	0.023	Snack	0.012
Land Vehicle	0.056	Sport Utility Vehicle *	0.023	Romance	0.012
Emotion	0.055	Team Sport	0.023	**Senior Citizen** *	0.012
Long Hair *	0.054	Urban Area *	0.023	Soccer *	0.012
Mode of Transport	0.053	Dish *	0.022	**Lip** *	0.012
Nature	0.049	Meal	0.022	Music Venue	0.012
Animal *	0.049	Light	0.021	Retail	0.012
Sports	0.045	Cuisine	0.021	Foot *	0.012
Advertising	0.044	Media	0.021	Label	0.011
Driving *	0.044	Pedestrian *	0.021	Glass	0.011
Crowd *	0.044	Automotive Exterior	0.021	Education	0.011
Community	0.042	Furniture *	0.021	Machine	0.011
Tree *	0.041	Dog *	0.021	**Park** *	0.011
Performing Arts	0.040	**Animation** *	0.020	Property	0.011
Performance	0.040	Product	0.020	Metropolis	0.011
Hand *	0.039	Backyard	0.020	**Infant** *	0.011
Happiness	0.038	Lawn *	0.020	Ball *	0.011
Night *	0.038	**Car Dealership** *	0.020	**Horizon** *	0.011
Mobile Device	0.037	**Window** *	0.020	Choreography	0.011
Speech	0.037	Physical Fitness	0.020	Sunglasses	0.011
Font	0.037	Physical Exercise	0.019	**Cosmetics** *	0.011
Singing *	0.037	Portable Communications Device	0.019	**Party** *	0.011
Gadget	0.036	Sport Venue *	0.019	Sandwich *	0.011
Technology	0.035	Television Advertisement	0.019	Hair	0.011
Visual Effects	0.035	Electronics	0.019	Finger	0.011
Mobile Phone	0.035	Learning	0.019	Orator	0.011
Smartphone	0.035	**Photograph** *	0.018	Personal Computer	0.011
Black and White *	0.034	Luxury Vehicle	0.018	Off Road Vehicle	0.011
Sky *	0.034	Leisure	0.018	Concert	0.011
Play *	0.033	City	0.017	Woodland	0.011
Display Device	0.033	Ceremony	0.017	Musical Instrument	0.011
Television Program	0.033	Outdoor Recreation	0.017	Metropolitan Area	0.011
Glasses *	0.032	**Selfie** *	0.017	Terrain	0.011
Dance *	0.032	**Sunlight** *	0.017	Action Game	0.011
Student *	0.032	**Toy** *	0.017	Living Room	0.011
Audience *	0.031	Document *	0.017	Company	0.010
Fashion	0.031	Writing *	0.016	Sports Car	0.010
Grass *	0.031	Wilderness *	0.016	Body of Water	0.010
Automotive Design	0.030	**Eye** *	0.016	Footwear	0.010
Public Space *	0.030	Emblem	0.016	Signage	0.010
Home *	0.030	Yard	0.016	Chair	0.010
Electronic Device	0.030	Special Effects	0.016	Flora	0.010
Liquid *	0.029	Sedan	0.016	Facial Hair	0.010
Drink *	0.028	Player	0.016	Banner	0.010
Eyewear	0.028	Communication	0.015	Rural Area	0.010
Black *	0.028	Suit *	0.015	Kitchen	0.010
Public Speaking *	0.028	Plastic Bottle	0.015	Sign	0.010
Film	0.027	**Paper** *	0.015	Monochrome	0.010
Consumer Electronics	0.027	Landscape *	0.015	Glass Bottle	0.010
Road *	0.027	Compact Sport Utility Vehicle	0.015	Sea	0.010
Recreation	0.026	**Car Seat** *	0.015	Cheering	0.010
Cooking *	0.026	**Brown Hair** *	0.015	Uniform	0.010
Communication Device	0.026	**Door** *	0.015	Shoe	0.010
Eating *	0.026	Web Page	0.014	Nightclub	0.010
Building *	0.026	Fast Food	0.014	Hill	0.010

Table OA3: Variance Decompositions of Viewing Behaviors on Viewer, Break, Ad Features

		Tuning		Presence		Attention	
Variable	*df*	R^2	F	R^2	F	R^2	F
Viewer Characteristics							
Viewer ID	3659	0.00848	9.9	0.04635	**56.5**	0.15125	**207.2**
Viewer Age and Gender	6	0.00012	**105.8**	0.00387	**3,306.1**	0.00287	**2,446.8**
Ad Environment							
Pod Position	18	0.00153	**384.5**	0.00228	**572.4**	0.00004	9.0
Channel	4	0.00007	**95.4**	0.00010	**136.0**	0.00015	**211.1**
Program Genre	104	0.00539	**224.0**	0.00156	**64.6**	0.00201	**83.1**
Ad Characteristics							
Ad Len	8	0.01550	**9,574.5**	0.04658	**29,710.6**	0.00080	**486.6**
Ad Industry	167	0.00481	**124.0**	0.01068	**276.9**	0.00051	13.1
Ad Title	6650	0.01381	9.0	0.02076	13.6	0.00332	2.1
iSpot Features							
Actors	2	0.00008	**150.2**	0.00032	**565.9**	0.00001	9.0
Eng	2	0.00001	11.5	0.00001	14.1	0.00005	**88.8**
Promo	2	0.00015	**257.9**	0.00010	**184.6**	0.00001	20.2
Tagline	2	0.00022	**389.3**	0.00065	**1,162.0**	0.00001	9.5
Movie	2	0.00000	3.4	0.00001	14.4	0.00002	30.6
Music	2	0.00000	6.9	0.00001	14.1	0.00000	2.9
Actors	2	0.00008	**150.2**	0.00032	**565.9**	0.00001	9.0
Sentiment	2	0.00028	**505.5**	0.00053	**947.7**	0.00000	4.1
Mood	6	0.00092	**328.2**	0.00251	**893.3**	0.00018	**64.8**
All	13	0.00191	**283.7**	0.00464	**690.4**	0.00023	34.3
ML Ad Coded Features							
Colorfulness	2	0.00007	**115.4**	0.00032	**502.3**	0.00000	1.4
Saturation	2	0.00001	9.8	0.00007	**104.9**	0.00005	**70.8**
Value	2	0.00007	**103.9**	0.00017	**269.6**	0.00001	12.6
Emotion	4	0.00003	13.2	0.00011	**56.6**	0.00001	2.7
Scenes	2	0.00042	**655.9**	0.00127	**1,961.4**	0.00009	**142.7**
All	9	0.00071	**136.8**	0.00238	**461.8**	0.00012	23.1
Google Cloud Vision							
GCV Selected Features	33	0.00069	38.1	0.00182	**101.3**	0.00010	5.6

Notes: Each entry reports a separate variance decomposition of an ad viewing behavior on the set of viewer, break or ad features described in the row header. Bold indicates statistical significance at 95% confidence.

Table OA4: Slot, Duration and Time-Elapsed Parameter Estimates

Variable	Tuning	Presence	Attention
Pod Position == 2	0.00049	-0.00816 ***	-0.00352 ***
	(0.00036)	(0.00048)	(0.00040)
3	-0.00068	-0.01024 ***	-0.00509 ***
	(0.00056)	(0.00076)	(0.00067)
4	-0.00185 *	-0.01123 ***	-0.00603 ***
	(0.00075)	(0.00101)	(0.00090)
5	-0.00124	-0.00976 ***	-0.00602 ***
	(0.00093)	(0.00125)	(0.00110)
6	-0.00042	-0.00891 ***	-0.00643 ***
	(0.00108)	(0.00145)	(0.00129)
7	0.00053	-0.00700 ***	-0.00617 ***
	(0.00122)	(0.00164)	(0.00146)
8	0.00194	-0.00632 ***	-0.00658 ***
	(0.00135)	(0.00182)	(0.00162)
9	0.00128	-0.00675 ***	-0.00763 ***
	(0.00148)	(0.00199)	(0.00178)
10	0.00163	-0.00586 **	-0.00689 ***
	(0.00161)	(0.00217)	(0.00195)
11	0.00125	-0.00609 *	-0.00827 ***
	(0.00175)	(0.00236)	(0.00214)
12	0.00407 *	-0.00356	-0.00783 ***
	(0.00190)	(0.00258)	(0.00235)
13	0.00363	-0.00574 *	-0.00845 **
	(0.00208)	(0.00283)	(0.00261)
14	0.00223	-0.00916 **	-0.00974 ***
	(0.00231)	(0.00315)	(0.00291)
15	-0.00025	-0.00844 *	-0.00908 **
	(0.00262)	(0.00356)	(0.00336)
16	-0.00640 *	-0.01139 **	-0.01059 **
	(0.00313)	(0.00418)	(0.00383)
17	-0.01824 ***	-0.02730 ***	-0.00937 *
	(0.00406)	(0.00530)	(0.00457)
18	-0.04495 ***	-0.05422 ***	-0.01302 *
	(0.00622)	(0.00774)	(0.00622)
Ad Duration == 30	-0.02798 ***	-0.05526 ***	-0.00730 ***
	(0.00018)	(0.00025)	(0.00019)
45	-0.03603 ***	-0.07523 ***	-0.01044 ***
	(0.00197)	(0.00268)	(0.00163)
60	-0.05485 ***	-0.10864 ***	-0.01517 ***
	(0.00070)	(0.00094)	(0.00056)
75	-0.06833 ***	-0.13772 ***	-0.01904 ***
	(0.00313)	(0.00403)	(0.00198)
90	-0.07718 ***	-0.15149 ***	-0.02182 ***
	(0.00235)	(0.00307)	(0.00155)
105	-0.11291 ***	-0.18936 ***	-0.02527 ***
	(0.00535)	(0.00643)	(0.00272)
120	-0.09683 ***	-0.18470 ***	-0.03020 ***
	(0.00303)	(0.00396)	(0.00197)
Time Elapsed	-1.749e-04 ***	-1.624e-04 ***	-7.167e-06
	(1.216e-05)	(1.647e-05)	(1.424e-05)
Time Elapsed^2	1.330e-07 ***	2.339e-07 ***	1.601e-08
	(3.267e-08)	(4.625e-08)	(4.339e-08)

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table OA5: Prescription Drug Category Characteristics

Category Name	Prevalence (%)	Severity (MM DALY/year)
Allergies	18.5	0.0
Alzheimer's & Multiple Sclerosis	1.4	1.9
Asthma & COPD	8.0	5.4
Bladder & Gastrointestinal	25.9	0.4
Cancer	3.7	14.2
Depression, Bipolar & Insomnia	16.4	7.2
Diabetes & Blood Disorders	6.3	1.3
Mens & Women's Health	10.0	0.0
Osteoporosis & Arthritis	13.4	1.7
Psoriasis, Skin & Nails	28.1	2.4
Stroke, Cholesterol & Heart Disease	10.9	15.0
Varied	0.5	0.3