Advertising Content and Television Advertising Avoidance

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Abstract

This paper proposes a new measure of television advertising avoidance, the "Passive/Active Zap" (PAZ), as an occurrence of a set-top box switching channels during a commercial break after at least five minutes of inactivity prior to the break. 27% of eligible commercial breaks are interrupted by a PAZ. A proportional hazards model is applied to a unique dataset to estimate the impact of advertising content and commercial break characteristics on PAZ behavior. The results show that advertising avoidance is negatively associated with movie ads and positively associated with advertising for websites, auto insurance and women's clothing. Ad avoidance also tends to rise with repeated exposures to the same ad creative, advertising aired on general-interest television networks, later hours of the evening, and rainfall.

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1 Introduction

The average American watches about five hours of traditional television each day (Nielsen 2014).[1] This statistic can be approximately replicated with viewing data passively collected from television set-top boxes (STBs). The implication is that most Americans are exposed to large numbers of television advertisements each day, and that television advertising exposures are probably more common than ads in any other medium.

Motivated by the frequency of advertising exposure, economic theorists have built several models to predict different ways in which viewers respond to advertisements. The most famous of these models are based on the assumption that consumers actively choose which advertisements they will view or avoid. For example, Becker and Murphy (1993) predict that consumers choose their advertising exposures based on the utility provided by advertisements and complementarities between product and advertisement consumption. Anderson and Coate (2005) base their welfare analysis of broadcasting on the assumption that consumers value programs more than advertisements, and that increasing advertising levels will result in marginal viewers choosing to leave the audience.

There is substantial experimental support for the assumption that viewers actively choose whether to continue or stop consuming an advertisement, and that such choices are influenced by commercial content. For example, Woltman Elpers, Wedel and Pieters (2003) found that viewers choose to stop watching commercials that have little entertainment content or high information content. Teixeira, Wedel and Pieters (2010) reported that viewers choose to stop watching commercials that feature focal deviations from the main elements in the ad storyline.

However, econometric studies of television viewing data have provided mixed findings about whether advertising avoidance is intentional or not. Prior studies measured television advertising avoidance with "zapping," the act of changing channels during a commercial in a live television program. Danaher (1995) investigated zapping using People Meter data in New Zealand. He found that program ratings dropped by just 5% during ad breaks and that switching was more related to ingrained habits than advertising content. He concluded that "the characteristics of the commercial break...have an effect on the ad break ratings, but they are not substantial." However, the television industry in New Zealand at the time featured three

[1] 90% of viewing is live, with the remaining 10% directed toward time-shifted programs. Television usage rises with age and falls with income, but mean usage differs by less than 20% across demographic groups.

dominant networks and frequently synchronous commercial breaks, limiting the viewer's benefits of zapping and raising the question of whether this result would generalize to a more fractured media environment. Van Meurs (1998) analyzed Dutch People Meter data and included several additional control variables in his model. He found that "product and campaign characteristics do not exert any influence on the switching behavior during commercial breaks." Siddarth and Chattopadhyay (1998) analyzed a split-cable dataset, producing many interesting findings; among which, they reported that the presence of a brand differentiating message in a commercial causes a decrease in zapping, but that the effect is small.

More recently, Zigmond et al. (2009) examined commercial audience retention by running large-scale field experiments and analyzing STB data. They found that "creatives themselves do influence advertising viewing behavior in a measurable way," but that differences in audience retention across ad creatives were rather small. Schweidel and Kent (2010) used STB data to estimate a model of audience retention, showing that dramas retain viewers better than other program genres and that longer commercial breaks lose more viewers. Wilbur, Xu and Kempe (2013) estimated ad-specific effects of 25 national commercials on zapping in a large STB dataset. They found that, holding audience and environmental factors constant, tune-away rates ranged from about 4% for a T-Mobile ad featuring the cast of the television program *Saturday Night Live* to about 11% for a depression medication called Pristiq.

In sum, there is mixed econometric evidence about whether advertising content influences the rate at which viewers avoid ads. Given television's prevalence, and the role of advertising in financing television, it is important to understand whether and how television viewers respond to advertising content.[2] Networks may be incentivized to offer preferential treatment to advertisements that retain audiences disproportionately, such as by charging lower prices or offering more prominent positions, in order to retain and monetize more viewers throughout the commercial break (Wilbur, Xu and Kempe 2013). In principle, a more efficient selection of advertisements may improve viewer welfare, enlarge the audiences available for advertisers'

[2] The current paper focuses on live viewing. Digital Video Recorders (DVRs) were present in 39.6% of American households in May 2011, up from 30.0% in May 2009 (TVB 2011). However, DVR households continue to watch live television: live programs account for 43% of all viewing in TiVo households (source: TiVo StopWatch data). Advertising avoidance in recorded programming raises a host of different issues and therefore is beyond the scope of the current paper. The interested reader is referred to Bronnenberg, Dube and Mela (2010) or Wilbur (2008) for further discussion.

messages, and influence networks' incentives to make further investments in programming.[3]

The current paper attempts to add to this debate in several ways. First, I present some model-free evidence about how viewers watch television. Unlike previous datasets, the data indicate whether each individual television was powered on at the time of each commercial.[4] The patterns in the data motivate a new measure of commercial avoidance, the "Passive/Active Zap" (PAZ), defined as a zap that occurs during a commercial break preceded by at least five minutes of uninterrupted channel viewing. This measure improves the signal to noise ratio in STB viewing data by filtering out channel changes that occur shortly after a viewer tunes to a channel. It is argued that such zaps are more likely to be motivated by the absence of a desirable program than by the presence of undesirable advertising content.

A proportional hazards model is developed and applied to a novel STB viewing dataset. The model is specified to allow for STB-specific baseline hazard rates, which are then partialled out in a semiparametric econometric approach. The model is estimated using a large dataset of live television viewing with several novel features and covariates. The data are drawn from the "Prime Time" daypart (8 p.m.-11 p.m.) when advertising viewing and prices both peak.

The empirical results agree with several recent studies (e.g., Anderson, Ciliberto and Liaukonyte 2013, Liaukonyte 2015, Liaukonyte, Teixeira and Wilbur 2015) that advertising content has important effects on consumer behavior. Movie ads are avoided less frequently than other product categories, whereas advertisements for websites, auto insurance, and women's clothing are avoided more often. There are also indications that some individual advertisers' campaigns and common advertising content elements are

[3] A second motivation to study this question relates to an intriguing finding by Zufryden, Pedrick and Sankaralingam (1993). These authors investigated household-level zapping of yogurt commercials and yogurt consumption. They found a positive relationship, hypothesizing that heightened attention during avoided commercials may increase commercial recall. If advertising avoidance is related to advertising effectiveness, television advertisers may start to see zapping decisions as a good rather than a bad.

[4] The ability to observe whether the television is powered on is particularly important in measuring advertising avoidance. Viewers frequently power televisions off while leaving STBs powered on; unpublished industry estimates posit that about 30% of households *never* power off their STBs. Analyses of STB viewing data that do not indicate television power status may include many advertising exposures that were never actually viewed and therefore could not have been zapped, biasing measures of advertising avoidance toward zero and dampening estimates of advertising content's impact on ad-avoidance. However, it is important to note that any measure of commercial avoidance may be incomplete if the data do not indicate the times at which viewer attention is directed toward the television.

associated with systematic deviations from mean PAZ rates.

The analysis also shows that a number of commercial break factors are important predictors of viewer demand for advertising. Sports and niche-oriented television networks are generally associated with lower rates of commercial avoidance, whereas general interest networks experience more ad avoidance. Animated programs experience substantially less commercial avoidance than average, whereas sports magazine programs display substantially more. Commercial breaks on Sundays and Tuesdays, in the final hour of Prime Time, or starting in the final few minutes of the hour are more likely to be avoided. Ad avoidance increases with precipitation but is not apparently related to ambient temperature.

The next two sections present model-free evidence about television viewing behavior and motivate the PAZ measure used in the empirical analysis. Section 4 defines the sample, describes the data, and presents some preliminary investigations motivating the analysis. Section 5 specifies the model and estimation strategy, with results presented in section 6.

2 Typical Television Viewing Patterns

STB viewing data consist of live viewing "events." Each event includes an anonymous STB identifier, a callsign (e.g., ESPN or KNBC), a start time and an end time.

Figure 1 shows that, among all events shorter than one hour, the distribution of event duration is highly skewed toward zero. The average event duration is *eight* times larger than the median event duration.

Although most events are brief, Figure 2 shows that the distribution is much less skewed above the five-minute mark. In fact, viewing time is concentrated among the longer sessions. Figure 3 displays the cumulative distribution function of total viewing time by event duration. Events shorter than 5 minutes account for 78% of all observations with duration less than one hour but contain just 15% of total viewing time.

Viewers typically engage in long periods of passive viewing interspersed with short bursts of activity. Figure 4 shows, for all pairs of contiguous live viewing events within a STB, the likelihood that an event of duration x minutes is immediately followed by an event of duration y minutes or fewer. For example, an event that lasts 30 minutes is about 70% likely to be immediately followed by an event that lasts five minutes or less. An event of *any* duration has better than a 50% chance to be followed by an event shorter than one minute.

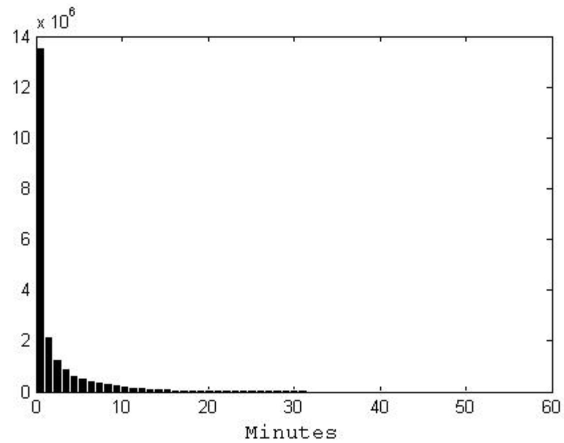


Figure 1: Histogram of Viewing Events by Duration (0-60 Minutes)

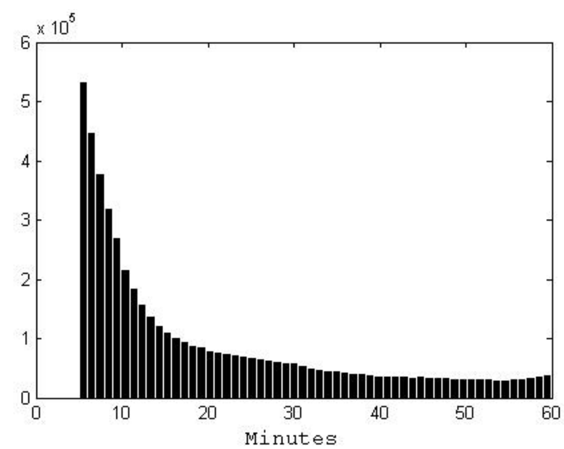


Figure 2: Histogram of Events by Duration (5-60 Minutes)

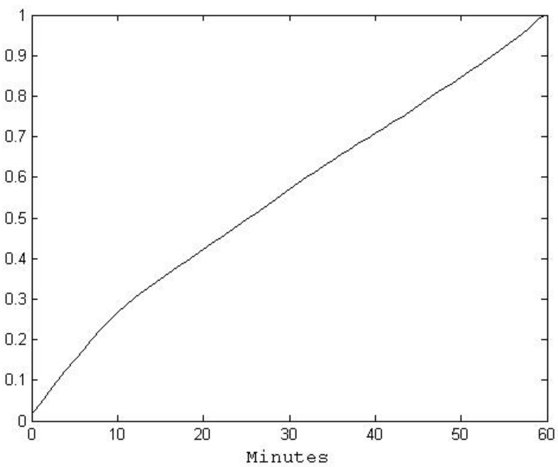


Figure 3: CDF of Total Viewtime by Event Duration (Minutes)

The figure shows that the influence of the first event's duration on the second event's duration is quite weak. This means that the tendency to alternate between short and long viewing events is not driven by STB heterogeneity. If, for example, one segment of households usually engaged in short viewing events while another segment of households usually engaged in longer viewing events, we would see a stronger positive relationship in Figure 4.

3 The Passive-Active Zap (PAZ)

For most viewers, the activity of watching television is typically a passive behavior. For example, televisions are often placed in commercial waiting areas as a means of occupying customers and reducing complaints. In fact, TV has been found to be so effective in pacifying viewers that televisions were available to inmates in two-thirds of America's jails and prisons (Springen 1992).

Although watching television is primarily a passive activity, a viewer sometimes enters an active state and switches television channels one or more times. Such switching behavior is typically motivated either to find a different program or to avoid an advertisement.

Entering the active state requires a modest effort. The viewer typically needs to locate a remote control, pick it up, point it at the television, and

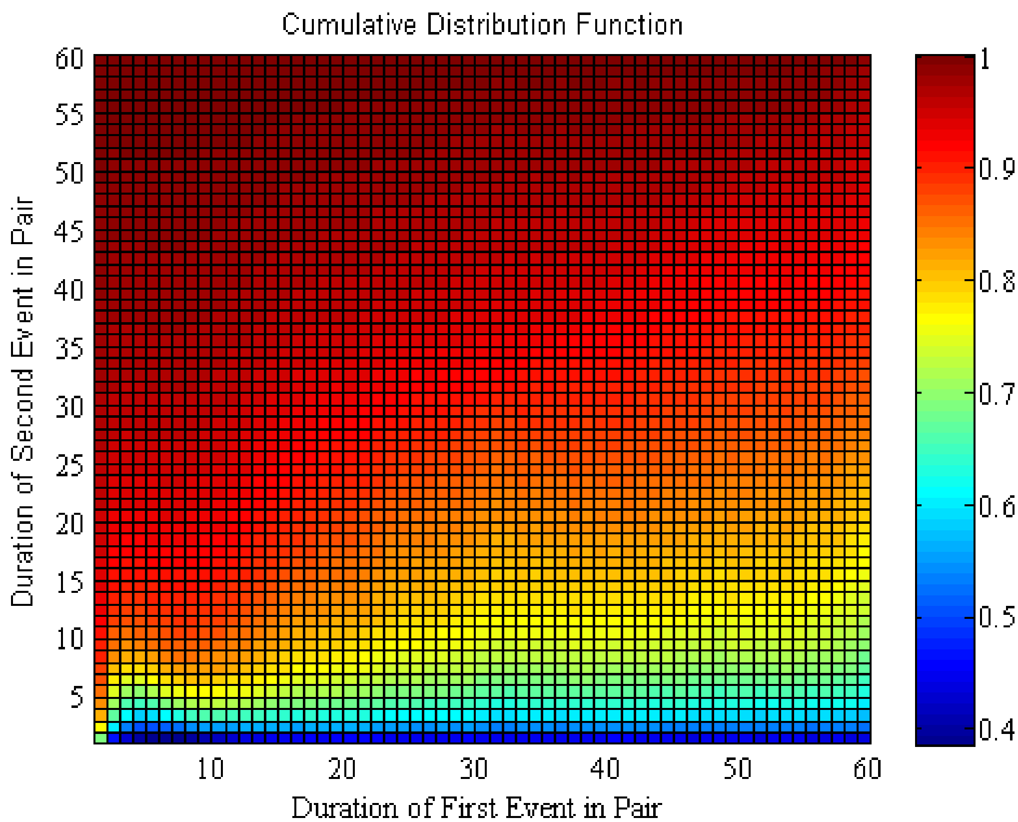


Figure 4: Empirical likelihood that an event of duration x minutes is immediately followed by an event of duration y minutes or fewer (best viewed in color)

decide on a new channel to select. She probably leans forward and concentrates briefly while doing this. She may then execute a series of one or more channel changes. When she encounters an acceptable program she is likely to lean back and return to the passive state.

The initial zap in a break is the most important event in a sequence, because it marks the beginning of the active state. It is the action most likely to be induced or delayed by advertising content. Channel changes after the initial zap are more likely related to finding a new program than to acceptance or rejection of the advertisement presented on the screen.

The "Passive-Active Zap" (PAZ) is proposed as a zap or a power-off action that occurs during a commercial break after the viewer has been watching the channel for at least five minutes prior to the commercial break. By focusing our model and estimation on the PAZ, instead of the zap, we filter out the noise associated with brief viewing events which are unlikely to be related to advertising content. In the data described below, approximately 27% of eligible commercial breaks are interrupted by a PAZ.

A thought experiment illustrates the advantage of the PAZ over the zap as a measure of commercial avoidance. Suppose a viewer starts watching channel 2 at 8:00:00 PM. Then, during the fifth slot of a commercial break, at 8:18:42 PM, she switches to channel 3 and encounters another commercial. After 5 seconds, she switches to channel 4, where she finds yet another commercial. After 3 more seconds, she switches again and then watches channel 5 until 9:00:00 PM.

In this example, the viewer has zapped three commercials, but the second and third zaps are likely related to the absence of programs rather than the advertisements presented on the screen. This viewer produced three observations of zapping behavior, but only the first zap is likely to be related to advertising content. Therefore, as the present article focuses on the effects of advertising content on advertising avoidance, we adopt the PAZ as our measure of advertising avoidance.[5]

[5]Google used "Initial Audience Retained" (IAR) to measure TV advertising avoidance when it sold television commercials (Zigmond et al. 2009). IAR is defined as the fraction of audience at the start of the ad which is subsequently exposed to the entire commercial. The PAZ is conceptually similar to IAR but more stringent in its requirement of at least five minutes of uninterrupted viewing prior to the commercial break.

4 Data

4.1 Data Sources

Viewing data were collected from a sample of anonymous set-top boxes (STBs) receiving signals from a satellite television system. For each STB, the data recorded all live tuning and TV power on/off events in Prime Time (8 p.m.-11 p.m. Eastern) during the four-week May 2011 "sweeps" period.

The viewing data were supplemented with advertising data on major broadcast and cable networks collected by Kantar Media. Kantar uses computers to continuously monitor and record all paid national advertisements on major networks. The Kantar data record the advertised product category, the television network, and the start and end time of each ad. They also provided the estimated cost of each ad insertion and a downloadable video file of each ad.

Video files were downloaded for the top 1,000 distinct ad creatives by expenditure, accounting for 81% of observed advertising revenues. These videos were analyzed by 22 content classifiers originally developed to characterize the content of unknown videos uploaded to YouTube. Each classifier was based on a machine learning algorithm trained on a specific dataset; for example, the "Pets" classifier identified ad content elements that are similar to its training set of YouTube pet videos. The output was a set of indicator variables identifying the presence within each ad creative of elements such as "Fashion," "Cooking," or "Cell phone."

Local weather conditions (temperature and rainfall) are included as control variables.[6] Weather information is included because it may affect the utility of non-television activities and because it is truly exogenous to the system.

4.2 Sample Selection

The unit of observation is the incidence of a commercial break served to a STB. Five criteria were used to select an estimation sample in accordance with the paper's main goal to investigate the influence of advertising content on commercial avoidance.

[6]The data were collected from a variety of sources and accessed through a Mathematica interface. For each STB and break, weather data were taken from the the most recent available report from the largest airport in that STB's local television market. The median difference between break start time and weather reporting time was about ten minutes. No time difference exceeded one hour.

First, the sample includes breaks that occurred between 8:00 p.m. and 11:00 p.m. Eastern time. We apply this criterion to focus on a set of national advertisements aired simultaneously in all local markets. Advertising prices and viewing both peak during this "Prime Time" daypart, making it the most important for television networks and viewers alike.

Second, the sample only includes STBs located in the Eastern time zone. This geographic criterion ensures that national programming is constant across all STBs in the sample, simplifying the procedure of matching ads to viewing events.

Third, the sample is limited to television sets that were connected to the STB by an HDMI cable and powered on at the time of the break. Because HDMI cables report the current power status of the television connected to the STB, this restriction includes only those commercials that were verifiably served to a television that was powered on, and therefore potentially viewable by consumers.

Fourth, the sample is limited to live viewing events whose duration did not exceed 60 minutes. The selection of a maximum viewing event duration is motivated by the inability to observe whether viewers are watching television at the time an advertisement is displayed; some viewers may leave the room without powering off the television, resulting in a viewing event with an inaccurately long duration.

The selection of a maximum event duration requires a trade-off: a larger maximum includes more commercial breaks in the sample, but this may come at the cost of including advertisements which were not actually viewed. Such choices are common in media audience measurement. In internet advertising, the maximum time threshold is normally set at 30 minutes, at which point an event is said to end in a "bounce." Our understanding is that television firms often employ thresholds between two and three hours; however, such a choice may be longer than optimal if it might be influenced by the desire to inflate audience estimates and increase advertising prices.

Figure 5 presents the distribution of all live viewing events up to three hours in length. 92% of all events lasted one hour or less; 95% of events lasted less than two hours; and 96% of all events lasted less than three hours. The fact that the change in cumulative frequency between the two-hour and three-hour thresholds is just 1%, whereas four times as many events lasted three hours or more, gives some support to the concern about including inactive events in the sample. In an attempt to guard against including inactive viewing sessions, while not eliminating too many commercial break exposures, we chose 60 minutes as the maximum event duration for analysis.

The fifth and final sample selection criterion is the minimum event dura-

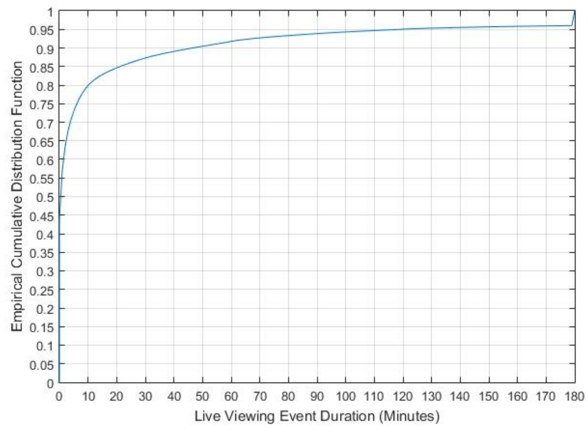


Figure 5: Empirical CDF of Live Viewing Event Durations (up to 3 hours)

tion threshold prior to the serving of a commercial break, which was chosen to be five minutes. The mean PAZ rate, after applying these five sample selection criteria, is 27.4%. If we were to replace the five-minute minimum pre-break viewing time criterion with a 3-, 7-, or 10-minute minimum, then the mean PAZ rate would change to 25.7%, 28.1%, or 24.3%, respectively.

4.3 Descriptive Statistics

After applying all five selection criteria, the dataset included 25,065 distinct commercial breaks carried on 84 television networks. On average, each network aired 5.1 commercial breaks per hour. The average commercial break was 2.6 minutes, with a standard deviation of 1.4 minutes.[7]

Figure 6 shows the average PAZ rate obesrved within each of the first 180 seconds of all breaks lasting 180 seconds or longer.[8] As one might expect, the likelihood of a PAZ spikes early in the break, at about the 15-second mark. However, the fact that PAZ probability is not monotonically decreasing supports the idea that there may be a small cost of entering an active state to switch the channel.

[7]These figures exclude time given to promos (also called "tune-ins"), as they were not reported by Kantar.

[8]The pattern is nearly identical if it is drawn over the first 60 seconds of all breaks lasting 60 seconds or more, or the first 120 seconds of all breaks lasting 120 seconds or more.

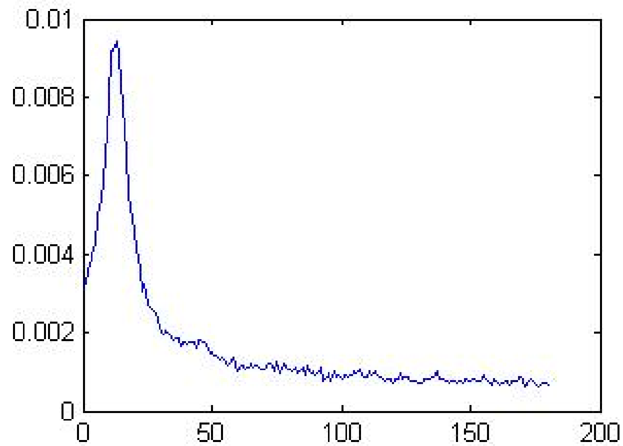


Figure 6: Empirical PDF of a PAZ in the First 180 seconds of a Commercial Break (for breaks of 180 seconds or longer)

Figure 6 also shows that the PAZ probability remains positive and nearly constant throughout the second and third minutes of the break. One might expect that viewers would become less likely to PAZ near the end of a break, since leaving the channel at a later point increases the risk of missing the return of the program. The presence of such apparently nonstrategic tuning behavior reinforces the idea that some PAZ decisions might be motivated by advertising content.

Figure 7 displays the corresponding empirical CDF of PAZ decisions by second within the break. It shows that the number of PAZ decisions before the 30-second mark of a 3-minute break is approximately equal to the number of PAZ decisions between the 30-second and 3-minutes marks.

In the final estimation dataset, 58,281 of 212,515 eligible commercial breaks served to powered-on STBs were PAZed. Figure 8 shows the histogram of STBs by observed PAZ tendency. Virtually no STBs PAZed all breaks and nearly all STB PAZed at least one break. The distribution of STB-specific PAZ tendencies has a small mass point at zero, and it has a right-hand tail, but the distribution seems to have multiple interior peaks and its density is not uniformly decreasing in the tail. This odd empirical distribution motivated us to specify a model that allows for an arbitrary pattern of STB heterogeneity in PAZ tendencies (as opposed to imposing a more regular distributional assumption, e.g. Normal, as a means to describe

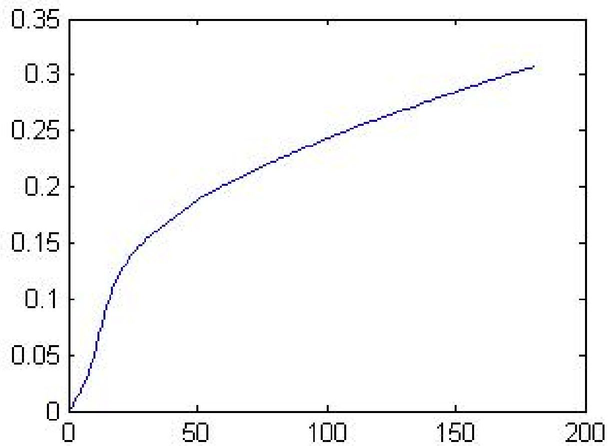


Figure 7: Empirical CDF of a PAZ in the First 180 Seconds of a Commercial Break (for breaks of 180 seconds or longer)

heterogeneity).

4.4 Preliminary Investigations

A preliminary analysis was performed to determine whether PAZ behavior can be predicted by four prominent features of the data: the STB identifier, the ad creative identifier, an identifier for any 5-second slot of the break during which an ad was displayed, and a break identifier subsuming all network, break, time and program characteristics. The goal of these preliminary regressions was simply to indicate whether each of these factors, either independently or in conjunction, is important in predicting PAZ behavior.

When analyzed at the intersection of a STB, commercial break, and a five-second slot of a break during which a PAZ may occur, this analysis can become expensive. For example, the data contain 73,026 unique STBs and 9.7 million observations of 5-second windows during which a PAZ may occur, so a regression of PAZ behavior on a full set of STB dummies would require the manipulation of a matrix consisting of 9.7 million rows and 73,026 columns. In order to reduce computational costs, the preliminary regressions investigated a random 1% subsample of all data and employed linear probability models, rather than a more expensive choice such as logit

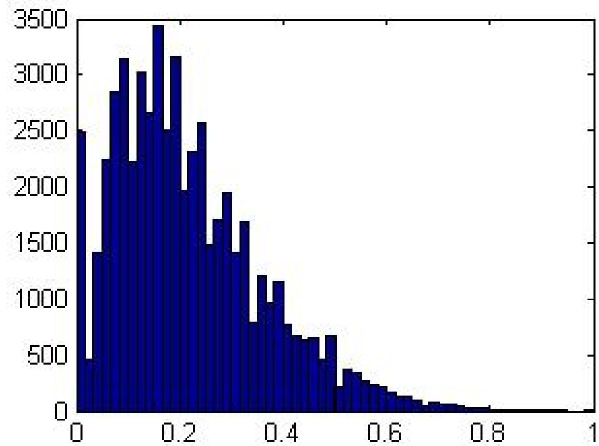


Figure 8: Histogram of STBs by PAZ Tendency (min. 9 breaks/STB)

or probit. These sacrifices allowed for an examination of the predictive power of each set of fixed effects with manageable computational costs.

Three sets of preliminary regressions were run: one set analyzed each group of fixed effects in isolation, another included all four groups of fixed effects, and the third analyzed *all but* each group of fixed effects. The results are reported in Figure 9. The regression statistics indicate several things. First, each of these four groups of fixed effects is highly significant in predicting PAZ behavior, either in isolation or in combination with the others. Second, break characteristics-which subsume such factors as television network, program genre, date, hour of the evening, etc.-explain the largest share of variation in PAZ behavior. Third, individual heterogeneity, as captured by STB dummy variables, are the next most important predictor of PAZ behavior after break characteristics. Fourth, ad creative and slot fixed effects explain smaller proportions of variation in PAZ behavior, and are roughly equal in importance. To restate this final finding in other words, it appears that PAZ behavior depends approximately as much on the content of the advertisement as the slot during which the ad appears.[9]

With these preliminary results in mind, the model specified in the next section is designed to partial out the STB and slot main effects, and any

[9]Although the STB identifiers are the second-most important factor in predicting PAZ rates, they seem to be less interesting than the effects of ad content and therefore are not the focus of the paper.

Figure 9: Preliminary Investigations

Linear Probability Regression Diagnostics of PAZ on…

STB Fixed Effects	x				x		x	x	x
Ad Fixed Effects		x			x	x		x	x
Slot Fixed Effects			x		x	x	x		x
Break Fixed Effects				x	x	x	x	x	
RMSE	.120	.125	.125	.108	.101	.106	.102	.102	.119
Adj. R-sq.	.101	.019	.016	.273	.366	.292	.350	.346	.109
F-stat.	28.7	27.6	90.2	38.7	42.3	39.6	42.6	42.3	31.1
P-Value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
AIC	-53,695	-52,308	-52,266	-57,124	-59,309	-57,550	-58,936	-58,819	-53,841

potential interactions between them without estimating those main effects and interactions. The remainder of the paper focuses on characterizing how ad creative and commercial break factors influence common PAZ tendencies.

5 Model and Estimation

The primary challenge in predicting PAZ behavior is that ad-avoidance habits vary substantially across viewers, as shown in the previous section and by Danaher (1995). Further, viewers are not randomly assigned to programs and ads. Therefore, audience heterogeneity may contaminate estimates of ads' effects on advertising avoidance.

A proportional hazards model is used to separate each PAZ decision into an individual STB-specific component and a set of advertisement content and placement factors.[10] The model is estimated using a semiparametric partial-likelihood approach.[11] This allows for individual STB-specific ad-avoidance habits but does not require that those individual habits be estimated.

The proportional hazards model is widely understood but this application is unusual due to the large volume of data available for each STB. In conventional hazard model applications, each member of the sample has a common baseline hazard rate and is observed to "die" just once. However, in the current application, a "death" is the end of a viewing event. There are many viewing events for every STB, so the model is designed to allow for STB-specific baseline hazard rates which then cancel out of the partial likelihood function so that they need not be estimated. Therefore, the baseline hazard rate is actually STB-specific, rather than common across all viewers.

5.1 PAZ Model

Let commercial break b be divided into $t = 1, ..., T_b$ five-second slots. The probability that STB i PAZes during slot t of commercial break b is written as a proportional hazard rate

[10] An alternate approach might be to estimate a probit based on individual PAZ decisions. However, any such approach must recognize the dependence inherent in consecutive PAZ decisions; a PAZ in slot $t+1$ may only occur if no PAZ occurred in slot t. It then becomes challenging to distinguish between state dependence and individual heterogeneity.

[11] Cox (1972) introduced hazard rate analysis. Cox (1975) proved that the properties of maximum likelihood estimators apply to partial likelihood estimation of the proportional hazards model. Helsen and Schmittlein (1993) discussed hazard rate model applications in marketing.

$$h_i(t|z_{ibt}) = h_{i0}(t)\phi(z_{ibt}\beta) \tag{1}$$

where

- $h_{i0}(t)$ is STB i's baseline tendency to PAZ at slot t of any break.
- ϕ is a proportional shift in the PAZ probability common to all STBs

$$\phi(z_{ibt}\beta) = \exp(z_{ibt}\beta) \tag{2}$$

where z_{ibt} is a vector of control variables described in section 5.3 and β represents their effects on PAZ probability.[12]

5.2 Estimation

Let B_i be the set of breaks served to STB i which could have been PAZed, let δ_{ib} be an indicator function which equals one if STB i PAZed break b and zero otherwise, and let B_{it} be the subset of breaks in B_i which were *not* PAZed by STB i prior to slot t. The semiparametric partial likelihood that STB i PAZed break b at slot t_{ib} is

$$L_{ib}(t_{ib}) = \frac{h_i(t_{ib}|z_{ibt_{ib}})}{\sum_{k\in B_{it_{ib}}} h_i(t_{ik}|z_{ikt_{ib}})}. \tag{3}$$

After substituting in for h_i, the STB-specific baseline hazard rate $h_{i0}(t_{ib})$ drops out, so expression 3 simplifies to

$$L_{ib}(t_{ib}) = \frac{\exp(z_{ibt_{ib}}\beta)}{\sum_{k\in B_{it_{ib}}} \exp(z_{ikt_{ib}}\beta)}. \tag{4}$$

Assuming that PAZ decisions across STBs and breaks are independent conditional on the observables, the likelihood associated with STB i is

$$L_i = \prod_{b\in B_i} (L_{ib}(t_{ib}))^{\delta_{ib}} \tag{5}$$

and the full likelihood function is $L = \prod_i L_i$.[13]

[12]The exponential function ensures non-negative hazard rates without requiring parameter constraints in the estimation.

[13]The model was estimated on a random subset of 10,000 of the 73,026 eligible STBs to reduce computation time. Because one of the control variables is the number of times STB i has been exposed to the commercial in slot t_{ib} in the previous seven days, and this variable could not be calculated for the first week of the sample, the first week of data was held out of estimation.

5.3 Covariates

The vector of control variables z_{ibt} includes two sets of advertising content characteristics: fixed effects for the advertised product category, and the ad content indicators created by the YouTube machine learning classifiers.[14]

The model also includes fixed effects for numerous commercial break characteristics, including the television network on which the break appeared, the genre of the program which the break interrupted, time effects (day of the week, hour of the evening, and the minute of the hour[15] during which the break started), and program tenure, defined as the number of minutes of uninterrupted programming prior to the placement of the commercial break.

Finally, the model included several controls for observable characteristics that were specific to the STB at the time of the commercial break:

- Number of times STB i saw the ad in slot t of break b within the past week,
- Viewing tenure, defined as the number of consecutive minutes STB i watched the network prior to the start of the break,
- Precipitation, and
- Temperature.

The first variable controls for ad wearout and the second for the length of time during which the STB has been inactive. Local weather conditions proxy for the current desirability of non-television activities.

Fixed effects were defined for each attribute level associated with at least 300 observations in the estimation dataset. Temperature, viewing tenure and program tenure were modeled as quadratic effects.

6 Findings

This section reports the empirical results. Given the large number of parameters estimated, we approach the results without strong priors and look for patterns that might increase our understanding of what drives PAZ behavior, as opposed to testing specific theories.

[14] All advertising content fixed effects are defined at the level of the ad creative, meaning that they apply to all five-second slots during which the ad aired.

[15] Some channel switching decisions may be motivated by program schedule changes on competing channels, so the minute of the hour at which the break starts is likely to predict tuneaway.

The effect of control variable z_{itb}^{l} is reported as the 95% confidence interval of $exp(\beta_l)$, the proportional effect of the variable in question on PAZ probability. When the upper bound of the confidence interval is less than one, the control variable reduces PAZ probability. When the confidence interval contains one, the control variable has no statistically significant effect on ad avoidance (using a two-tailed test). When the confidence interval lies entirely above one, the control variable increases advertising avoidance. The width of the confidence interval is inversely related to the precision of the parameter estimate.

6.1 Advertisement Characteristics

6.1.1 Advertised Product Category

51 product category fixed effects met the minimum threshold of 300 observations for inclusion, accounting for 54% of all advertising expenditures observed in the sample.

Figures 10 and 11 show the 95% confidence intervals for advertised product category effects on ad-avoidance. Five product categories were found to reduce ad-avoidance: quick service restaurants, domestic hybrid automobiles, family clothing stores, pizza products and movies. The movies category is the most intuitive, as movie ads offer consumers free samples of new products with wide appeal. Also, the movies product category featured 116 distinct advertisements, resulting in a relatively precise parameter estimate. The other four categories were dominated by single brands, as McDonald's, Ford Fusion, Old Navy and Pizza Hut spent far more on advertising than their competitors.

At the other end of the scale, seven of the 51 product categories were associated with above-normal PAZ tendencies. Three of these categories featured multiple large advertisers, including Online (Bing, Kayak, Priceline, Weight Watchers, Etrade, Autotrader, etc.), Auto Insurance (Nationwide, State Farm, Geico, Progressive) and Women's Clothing (Victoria's Secret, TJ Maxx, H&M). The other four product categories were dominated by small numbers of advertised products: Wireless Phones (iPhone 4), Seafood Restaurants (Red Lobster), Osteoarthritis (Cymbalta) and Ebook Readers (Kindle, NookColor).

Overall, the results strongly suggest that advertising avoidance may be influenced both by specific product category and specific advertising campaigns. Movies are generally associated with reduced advertising avoidance. Ads for websites, auto insurance and women's clothing are associated with

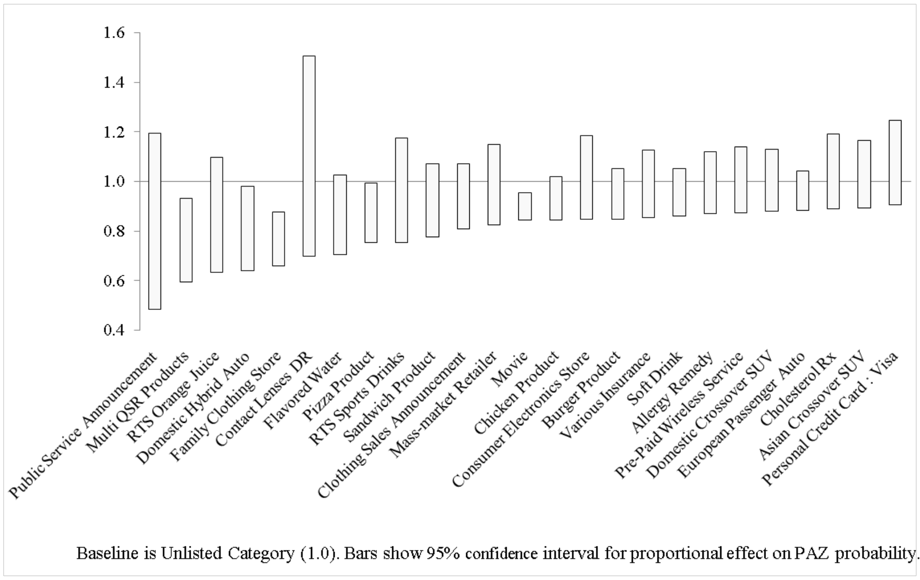


Figure 10: Advertised Product Category (Low Range)

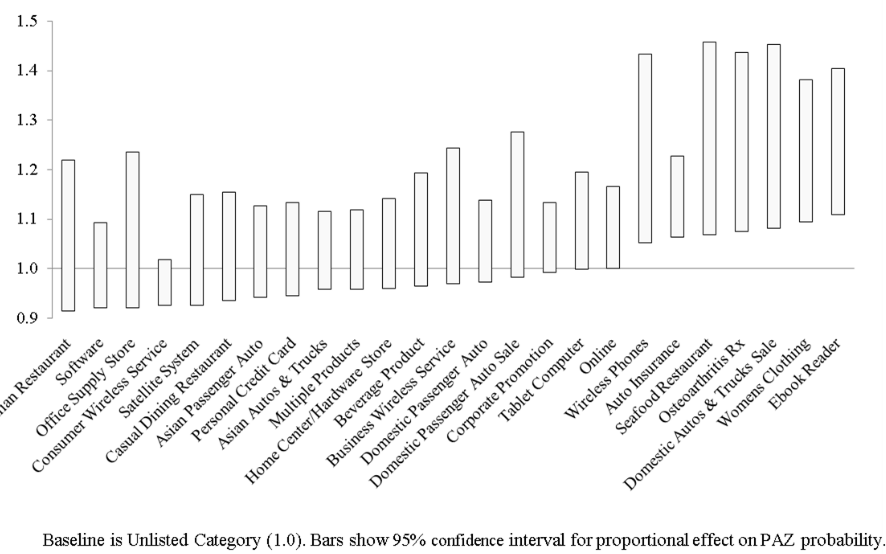


Figure 11: Advertised Product Category (High Range)

above-normal advertising avoidance.

6.1.2 Ad Content Elements

Figure 12 shows that six of the 22 advertising content classifiers had statistically significant associations with advertising avoidance. Ads that contained cellphones were associated with slightly less switching than average, while ads that were classified as containing news, pets, mobile devices, vlog or fashion content were associated with more switching than average.

In order to gauge the reliability of these results, the ads identified by each classifier were watched by the researcher. There was some variation in classifiers' accuracy.

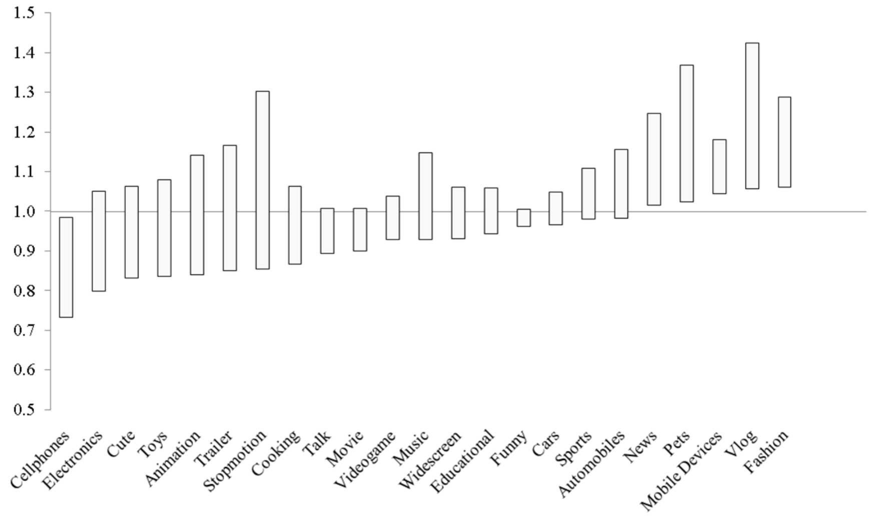
The cellphones classifier identified eight ad creatives, including six for the iPhone. All eight ad videos included cellphones. Combined with the wireless phones product category result reported above, one might conclude that iPhone ads that show the phone to a greater degree are associated with less switching than average, while ads that do not show the phone as much are associated with more switching than average.[16]

Mobile Devices and fashion classifiers were associated with above-normal advertising avoidance and seemed to be fairly accurate. The ads flagged by the vlog classifier featured extended waist-up shots of consumers speaking directly into the camera, and were also associated with greater ad avoidance than average. Mobile Devices flagged many more ad creatives than the cellphones classifier, including ads for the iPad, Blackberry, and many other ads that contained mobile devices. Fashion correctly identified numerous make-up and women's clothing and apparel products.

The News and Pets classifiers were also associated with higher-than-normal advertising avoidance. However, a review of the ads identified by those classifiers did not reveal any consistent pattern of ad contents that were associated with News or Pets. These variables were created by machine learning algorithms, leaving no clarity about why they contained so many false positives.

Overall, these results suggest that it may be possible to predict advertising avoidance by training machine learning algorithms on ad creative video

[16] These results should be interpreted with caution, as the fixed effects for the wireless phones product category and for the Cellphones content classifier had a correlation of 0.7. However, multicollinearity would normally inflate the standard errors for Cellphones and wireless phones parameter estimates, whereas here we have found both to be significant. The correlation between the Electronics content classifier and the wireless phones product category was 0.6; none of the other correlations between product category fixed effects and ad content classifiers exceeded 0.5.



Bars show 95% confidence interval for proportional effect on PAZ probability.

Figure 12: Advertisement Content

files. An intriguing possibility would be to combine PAZ data with advertising content to train a new machine learning algorithm to classify ad creatives according to PAZ probability.

6.2 Break Characteristics

6.2.1 Television Network

Figures 13, 14 and 15 show how advertising avoidance differs across TV networks. 14 of 62 networks displayed markedly less advertising avoidance than the excluded reference network (FOX, whose baseline PAZ rate was 23.8%). Some of these networks are unusually differentiated in the content they offer (Cartoon Network, Game Show Network, Fox News, Nickelodeon, Women's Entertainment, Weather Channel). It also appears that sports (ESPN, ESPN2, Golf, Versus), movies (A&E, AMC, Lifetime Movie Network) and instructional (Cooking Network, DIY, HGTV) networks reduce advertising avoidance.

It is interesting that some networks whose audiences are known to skew young (e.g. ESPN and ESPN2) actually are shown to be associated with lowered rates of advertising avoidance. This may underscore the importance

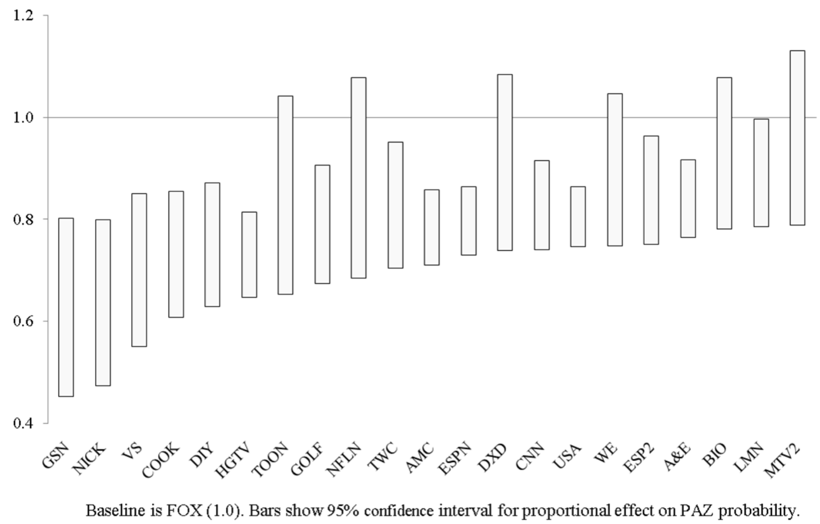


Figure 13: Network (low range)

of controlling for audience heterogeneity, TV network and program genre in estimating models of advertising avoidance behavior. For example, it may be that certain types of programming may be more frequently watched in groups of people, and that watching in groups changes viewers' preferred advertising avoidance strategies.

At the other end of the range, six of 62 networks feature significantly more advertising avoidance than the baseline: MSNBC, CBS, Lifetime, NBC, Discovery and G4. Viewers' PAZ tendency is 6-18% higher when watching CBS than when watching FOX, and 13-27% higher when watching NBC than when watching FOX. G4 features the highest advertising avoidance estimate; this network mostly airs programs about video games. Because the model partials out STB-specific baseline hazard rates, this finding is likely due to the program format and content seen on this network and not due to audience factors.

6.2.2 Program Genre

Figure 16 shows that program genre, as classified by Kantar, significantly impacts advertising avoidance. 16 of 24 genres had statistically significant effects on PAZ probability. Viewers were much less likely to avoid ads during

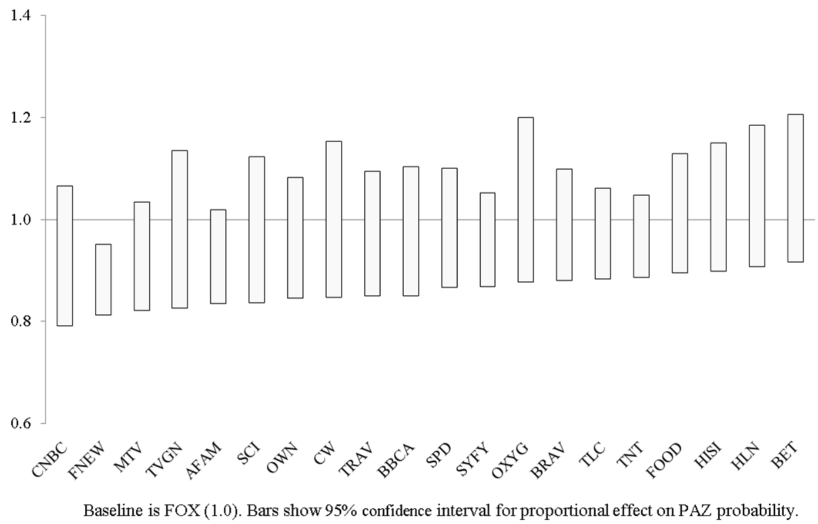


Figure 14: Network (middle range)

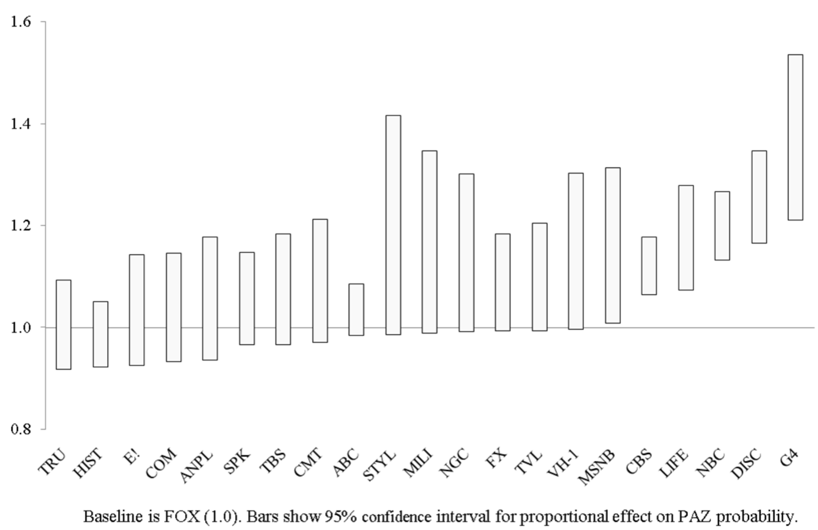
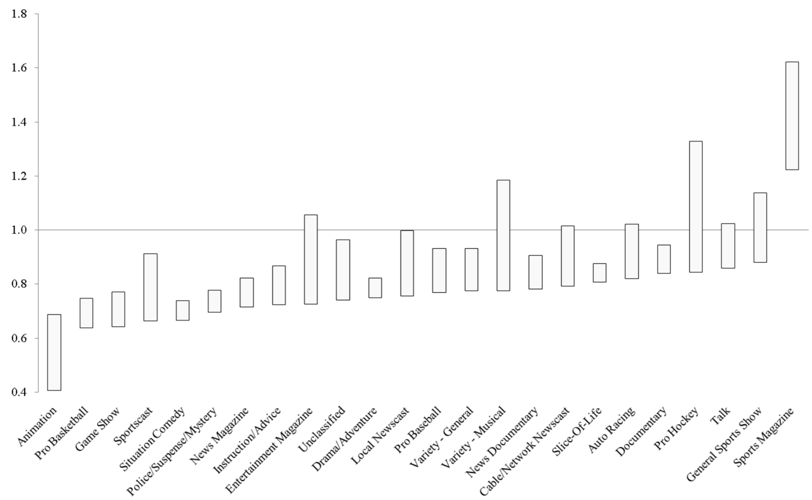


Figure 15: Network (high range)



Baseline is Feature Film (1.0). Areas show 95% confidence interval for proportional effect on PAZ probability.

Figure 16: Program Genre

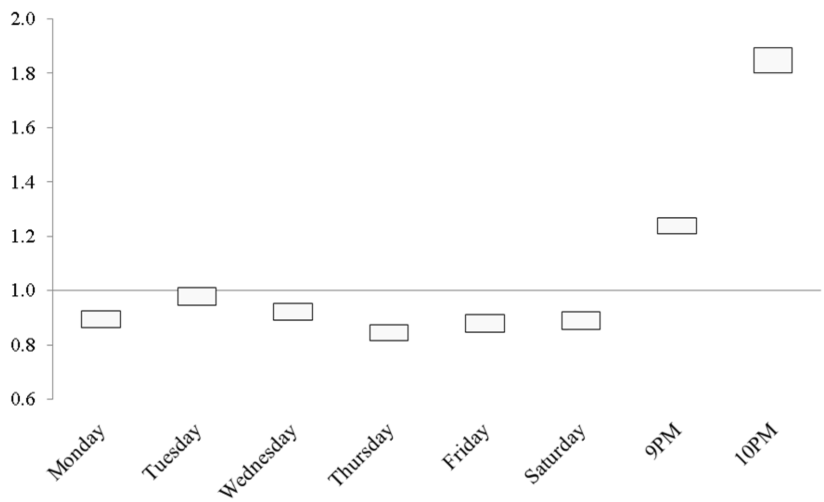
animated programs (31%-59%), followed by professional basketball (25%-36%), game shows (23%-36%) and situation comedies (26%-33%). Echoing Danaher (1995), PAZ tendency was lower during Police/Suspense/Mystery and Drama/Adventure programs.

Overall, the baseline program genre, feature films, encourages advertising avoidance relative to most other genres. Combined with the earlier movies network results, this suggests that movies on non-movies networks inspire significantly higher ad avoidance than normal. The only genre with a higher PAZ rate is Sports Magazine programming.

6.2.3 Weekday and Hour

Figure 17 shows that advertising avoidance is significantly lower on Monday, Wednesday, Thursday, Friday and Saturday than the excluded weekday (Sunday). Although the estimates are fairly precise, there is no apparent difference between Sunday and Tuesday.

Commercial avoidance rises rapidly throughout the evening. Ads in the 9-10 p.m. hour are 21%–27% more likely to be PAZed than ads in the 8:00 hour. Ads airing between 10 p.m. and 11 p.m. are 80%-90% more likely to be PAZed.



Weekday baseline is Sunday. Hour baseline is 8PM.
Areas show 95% confidence interval for proportional effect on PAZ probability.

Figure 17: Weekday and Hour

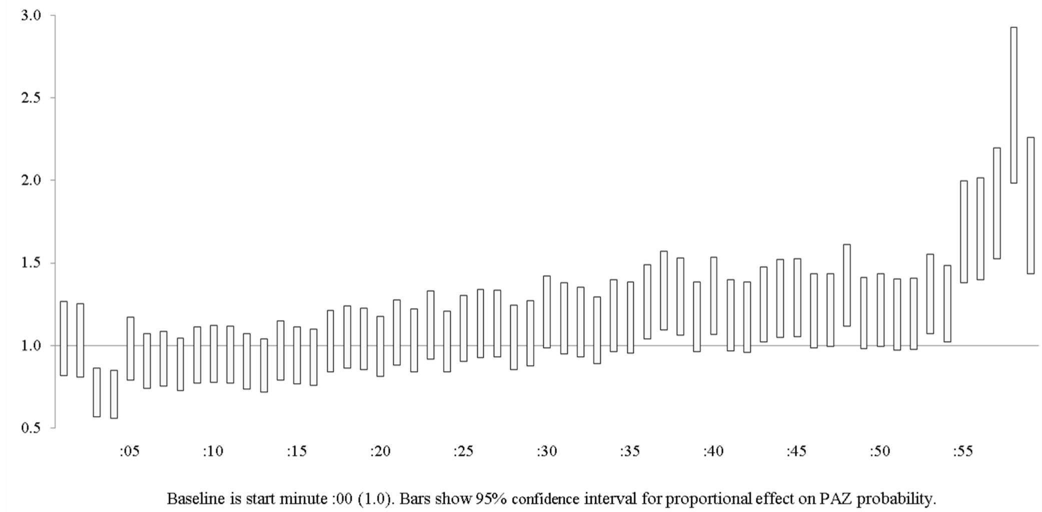


Figure 18: Break Start Minute

6.2.4 Break Start Minute

The model included dummy variables for each clock-minute within which a break could start. Figure 18 shows that breaks that start three or four minutes after the hour have about 15%-45% less ad avoidance than normal. Breaks that start in the :36-:40 range are slightly more likely to be PAZed. Breaks that start in the final few minutes of the hour have the highest PAZ rates by far, peaking at 98%-193% for breaks that start in the 58th minute of the hour. This pattern might be explained as the result of program changes on competing networks and perhaps also by the resolution of hour-long programs during their closing minutes.

6.2.5 Program Tenure

Figure 19 shows that advertising avoidance increases slightly when the commercial break follows a longer program segment. It may be that more uninterrupted program content prior to the break increases viewer engagement with the program, resulting in advertising becoming a more disruptive interruption because the viewer is more engaged with the program.

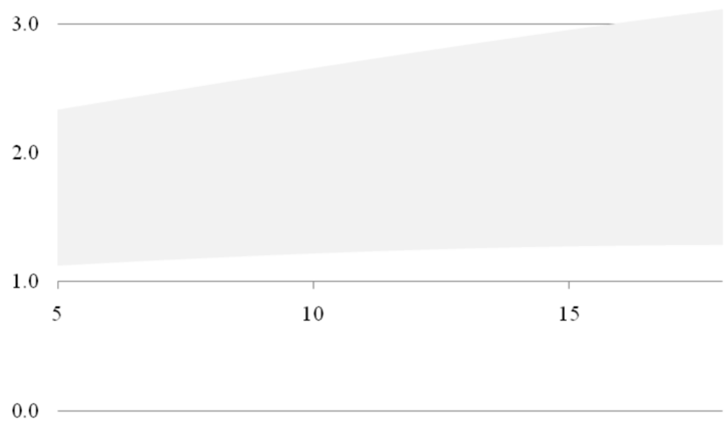


Figure 19: Minutes of Programming Preceding the Commercial Break

6.3 STB-Level Factors

6.3.1 Previous Exposures to the Ad

Figure 20 shows that PAZ probability rises 3-11% on the second viewing of an advertisement. Beyond that, previous exposure estimates become relatively imprecise. However, if one-tailed tests were employed, they would reject the null hypothesis that repeated exposures reduce ad-avoidance at the 90% confidence level.

6.3.2 Viewing Tenure

Figure 21 shows that advertising avoidance is "U"-shaped in viewing tenure. PAZ probability falls for the first 30-35 minutes of a viewing session, followed by a slight upward drift after the 40-minute mark.

6.3.3 Local Weather Conditions

Precipitation increases advertising avoidance, with one inch of rain associated with a 2%-24% higher PAZ probability. It may be that rain reduces the utility of non-television options, for example by making outdoor activities less attractive and driving more dangerous, and that such a change affects PAZ behavior. Although this seems like an intriguing finding, the current

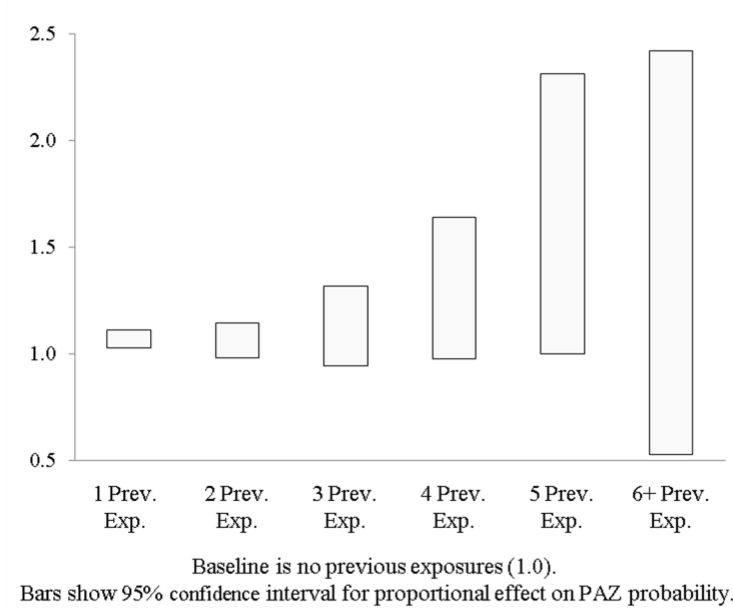


Figure 20: Number of Exposures to the Ad in the Past Week

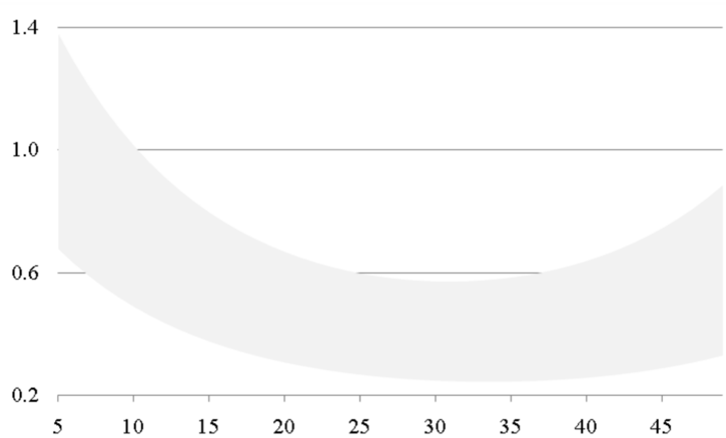


Figure 21: Viewing Tenure, i.e. Event Duration prior to Break Start

econometric design is not the ideal approach to determine the underlying cause of the effect.

Advertising avoidance does not have any statistically significant relationship to ambient temperature, though this average effect could mask geographical heterogeneity in response to temperature.

7 Conclusion

Given the importance of advertising in financing television networks, this paper seeks to understand the incidence and drivers of television advertising avoidance. It motivated and proposed a new measure of advertising avoidance, the Passive/Active Zap (PAZ). The core idea is that filtering out uninformative zaps improves the signal to noise ratio available in advertising avoidance data. It further specified a proportional hazards framework that allows for STB-specific advertising avoidance habits of arbitrary form without requiring these habits to be estimated. This model will be widely applicable to any set-top box viewing dataset. Model parameters were estimated using a large dataset with several unique characteristics.

The results show that advertising content does indeed influence advertising avoidance. Movie ads decrease advertising avoidance while auto insurance, website and women's clothing ads increase switching. Commercial avoidance varies systematically with automated measures of advertising content.

In addition, there are individual and commercial break factors that are important in predicting commercial avoidance. Advertising avoidance increases with just the second exposure to an ad in the previous week. Networks whose programming is highly differentiated, sports-oriented or instructional show lower rates of advertising-avoidance whereas general-interest networks are associated with more ad avoidance. Advertising avoidance is lowest on Thursdays, highest on Sundays and Tuesdays, and increases rapidly throughout Prime Time. Temperature does not apparently affect advertising avoidance but precipitation increases it.

As in all research, the current analysis contains a number of limitations which suggest opportunities for further inquiry. Perhaps the most compelling opportunity would be to allow advertising avoidance to depend on sequences of commercials rather than simply modeling contemporaneous effects of ad content. Another idea would be to use variation of advertising content within ad creatives to predict how tuneaway rates vary over time within each commercial. It might be interesting to describe how advertising avoidance varies across dayparts and geographic television markets, and the effects of weather could be allowed to vary across geographic television markets.

Overall, we hope that the insights into the drivers of advertising avoidance produced here will facilitate television networks' efforts to find a more efficient allocation of advertisements to viewers. We also hope to stimulate further careful study of how viewers respond to advertisements, both in television and in other media.

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