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How Much Does Ad Sequence Matter? Economic Implications of Consumer Zapping and the Zapping-Induced Externality in the Television Advertising Market

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ABSTRACT

It is well documented that TV viewers avoid advertisements by switching channels during commercial breaks ("zapping"). Ads with lower audience retention ability lead to more consumer zapping. Given that several ads are sequentially broadcast during a commercial break, an ad with a low retention rate will negatively affect the viewership of subsequent ads by decreasing their opportunities to be exposed to viewers. In this case, the ad imposes a negative externality on subsequent ads in the same commercial break. This externality is typically not priced in the TV advertising market; however, it may substantially affect the TV network's profit. Based on a large and rich data set on TV viewing and advertising, we build a comprehensive model of consumer zapping and conduct various simulation studies to quantify the impact of the zapping-induced externality on the network's revenue. Results show that our focal network may increase gross revenue up to 19.38% by reordering ads during a commercial break so that the negative impact of this externality is minimized.

Although modern consumers spend much of their time online, television remains one of the most popular media options for advertisers seeking to reach a mass audience (Koblin and Maheshwari 2017; Wilbur, Xu, and Kempe 2013). Spending on global TV advertising was up to USD 176.3 billion in 2019 (Guttmann 2020).[1] There are multiple reasons for this continued interest in TV advertising, which Koblin and Maheshwari (2017) summarize as follows: "Television still reaches more people, provides a reliable way for an ad to be seen on a full screen with sound, and there is a limited amount of inventory, in contrast to the fragmented reach of the web." In addition, TV advertising contains a negligible level of fraudulence in comparison with online advertisements (Davies 2017). Therefore, TV is expected to remain an attractive vehicle for advertisers for the foreseeable future.

A major concern for advertisers in the TV advertising market is consumer channel-surfing behavior, or consumer "zapping", where consumers switch to different channels during a commercial break to avoid advertisements. Given that ads are broadcast sequentially during a commercial break, consumers who zap an ad will also miss the subsequent ads. As a result, ads with a low retention rate (e.g., that are unattractive or irrelevant) impose negative externalities on subsequent ads in the same commercial break. Given the spillover effect across slots, the cumulative impact of the externality on the whole commercial break could be substantial.

Producing ads with a high customer retention rate seems to be a way of solving the problem. However, advertisers may not always have an incentive to produce ads with high audience retention ability. For example, in 2006, the parent company of HeadOn, a headache-relieving product, launched a television advertisement in which the tagline "HeadOn: Apply directly to the forehead" was quickly repeated three times in succession. Consumers viewing the ad were annoyed and likely to switch away, yet they could not

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forget the ad. As a result, the sales of HeadOn went up by 234% nearly overnight after the debut of this ad (Pilcher 2011), at the cost of loss of audience of the subsequent ads in the same commercial break. On media advertising platforms, it is common for annoying ads to have poor ability to retain viewers while simultaneously achieving high communication effectiveness in terms of attracting viewer attention and inducing memory (Stourm and Bax 2017). Yet this externality is typically not addressed in the pricing of the TV advertising market (Wilbur, Xu, and Kempe 2013) to deter advertisers from producing aversive ads.

Despite the consequences, the negative externality due to the spillover effect across TV advertisements within the same commercial break is rarely studied, mostly due to the lack of data that allow researchers to capture viewership at the ad-slot level. To the best of our knowledge, Wilbur, Xu, and Kempe's (2013) study is the first to explore the topic of zapping-induced externality in the TV advertising market. Their article is prescriptive, with a focus on developing an algorithm for the TV network to select, order, and price ads for each commercial break to correct the zapping-induced externality; the method assumes a hypothetical practice where ad prices are paid according to the realized audience sizes after the ads are broadcast. Our article is descriptive and differs from Wilbur, Xu, and Kempe's (2013) work by examining the magnitude of this externality's impact on a network's revenue; the procedure is based on common industry practices such that ad prices are charged according to estimated program ratings before the ads are broadcast.

Given the different focus of the two articles, the two studies—Wilbur, Xu, and Kempe's (2013) and ours—have different data requirements. As the main focus of Wilbur and colleagues (2013) is to demonstrate the performance of the focal algorithm in itself and relative to alternative algorithms, the requirements for data are less strict. For example, to calculate advertisers' willingness to pay for additional audience, they use estimated prices at the TV program level that do not vary across advertisements and commercial breaks, instead of using the actual price paid by each advertiser for the purchased advertisement. Also, due to a lack of ad content data, Wilbur, Xu, and Kempe (2013) measure the audience retention rate of each ad by including the ad-specific fixed-effect term in the consumer zapping model, the estimation of which becomes less feasible when the numbers of ads are large. As a result, they estimate advertisers' willingness to pay and audience retention rate for the 25 most aired ads.

However, our data requirements are more comprehensive, as the main focus of our article is to quantify the zapping-induced externality and provide a precise measure of its impact on the TV network's revenue. Therefore, accurately predicting the consumer zapping decision becomes the priority of our work. We achieve this by leveraging a large and comprehensive data set that includes not only the actual price paid by advertisers for each ad but also important factors such as ad content and individual viewer involvement level for all advertisements broadcast during prime time (8 pm to 12 am). We first build a comprehensive model of viewers' zapping behavior at the commercial-slot level. Simulations are then conducted based on parameter estimations to assess the impact of the zapping-induced externality on the network's revenue. Our work thus complements the work of Wilbur, Xu, and Kempe (2013) by quantifying the magnitude of the negative impact of zapping-induced externality on the TV network's revenue. Our study also goes beyond the large extant body of literature on consumer zapping that focuses on its determinants. We study the economic implications of consumer zapping in the presence of an externality that affects ads within the same commercial break.

To achieve our objectives, we first conduct an exhaustive literature review of consumer zapping and propose a binary choice model with a rich specification for individual viewers' zapping decisions. In terms of estimation, we predict consumers' advertisement-level zapping decisions and aggregate them to be matched with minute-to-minute consumer viewing observations in the data. In addition, we adopt a latent class approach to address consumer heterogeneity using an expectation-maximization (EM) algorithm. Upon completion of the model estimation, we conduct various simulation studies with the goal of quantifying the impact of the externality by comparing various sequences of ads. The core feature common to all simulation studies is how many viewers (hence monetary value) an ad would gain or lose if it were assigned to different slots within the same commercial break. Based on our empirical analysis for a major TV network in Hong Kong, our simulation studies show that the zapping-induced externality has a substantial impact on the TV network's revenue and the slot position interacts with the ad audience retention rate differently in leading to the externality problem.

The rest of the article is organized as follows. In the next section, we review the relevant literature. Then, we describe the data sources for our empirical analysis and note important data patterns. Next, we present a comprehensive model of consumer zapping behavior and its estimation. Then, we conduct various simulation studies to quantify the impact of the zapping-induced externality on the network's revenue and demonstrate the relevant importance of different slot positions in affecting the size of the impact. We conclude this article and discuss the theoretical and managerial implications in the final section.

Related Literature

Externality in Media Advertising

In the past decade, researchers started to investigate the impact of externalities on media advertising and to propose solutions to internalize the externality for profit maximization purposes. The earliest study in this area concerns sponsored search advertising. The externality is considered to be common and significant for advertised links/landing pages (Gomes, Immorlica, and Markakis 2009). Google has already taken this externality into account by letting the rank of sponsored ad links depend not only on the bid price but also on the click-through rate (Ghose and Yang 2009). A major search engine for high-technology consumer products studied by Yao and Mela (2011) adopts a similar method to mitigate the negative impact of the externality. Many researchers examine optimal rank allocation in the presence of the externality for ad links on a search engine (e.g., Aggarwal et al. 2008; Kempe and Mahdian 2008). Abrams and Schwarz (2007) investigate how to incorporate the externality into the generalized second price (GSP) auction used in a search engine to maximize efficiency.

Externalities exist as well in other types of online advertising. In the presence of an externality, Ieong, Mahdian, and Vassilvitskii (2014) provide a theoretical approximation algorithm for the optimization problem in a typical context of online stream ad advertising. Based on the cascade model, Kar, Swaminathan, and Albuquerque (2015) propose a mechanism to allocate nonskippable online in-stream video ads while addressing the potential negative externality whereby low-quality ads may lead viewers to exit the video session and miss subsequent ads. In the context of online display ads, Stourm and Bax (2017) consider the negative impact of an ad on other ads to be the "hidden cost" of the media platform; they study how media platforms can limit this hidden cost by incorporating a charge for the negative impact as a criterion for ad selection and pricing.

In the TV advertising market, Wilbur, Xu, and Kempe (2013) introduce the concept of audience externality to depict the impact of an ad imposed on subsequent ads in the same TV commercial break. They argue that the unpriced audience externality in the current commercial airtime selling system limits the TV network's profitability. They propose the audience value maximization algorithm (AVMA) to correct the audience externality during the dynamic process of selecting, ordering, and pricing advertisements for each commercial break. The performance of AVMA is validated using digital set box data on the 25 most aired ad creatives. Based on a rich data set that includes the performance of a large number of ad creatives and the actual price paid to the network by each advertiser, our article offers a framework for quantifying the potential monetary benefit for the TV network of minimizing audience externality and discusses managerial implications.

Consumer Zapping

A comprehensive review of potential factors that influence consumer zapping is crucial for this study, as our individual-level zapping model will be heavily guided by the main findings from previous research. A substantial amount of literature in this research stream shows that consumer zapping behavior is significantly affected by the advertisement broadcasting context, such as the associated program's broadcast duration, popularity, and frequency; the number of concurrent commercial breaks (Schweidel and Kent 2010); the advertisement's broadcast channel and broadcast time (day of the week, hour); and whether the advertisement is aired in between-program commercial breaks (e.g., Heeter and Greenberg 1985; Kaplan 1985; Danaher 1995; Danaher and Green 1997; Siddarth and Chattopadhyay 1998; Wilbur 2008; Yao, Wang, and Chen 2017).

Advertising content is also an important impact factor for consumer zapping. Prior research reports significant impacts of advertising content on both viewer zapping propensity (Wilbur 2016) and advertisement viewing time (Olney, Holbrook, and Batra 1991). Woltman Elpers, Wedel, and Pieters (2003) show that both the information and the entertainment value have a strong multiplicative effect on a consumer's likelihood of zapping. Siddarth and Chattopadhyay (1998) report that advertisements with brand-differentiating information are less likely to be zapped and that the advertising viewing probability increases with initial exposure but decreases afterward, following the notion of wear-in and wear-out in Pechmann and Stewart (1988). In addition, advertisement duration (Gustafson and Siddarth 2007), advertised product category (e.g., Deng and Mela 2018), audiovisual representation of brands (Teixeira, Wedel, and Pieters 2010), product placement in the program (Schweidel, Foutz, and Tanner 2014), and consumer brand purchase amount (Tuchman, Nair, and Gardete 2018) are other powerful predictors of consumer zapping. Gustafson and Siddarth (2007) further show that the first few seconds of an ad are critical for attracting and retaining viewers.

Prior literature demonstrates that the congruity (in terms of content, induced mood, and so on) between advertising and the associated program affects viewers' commercial recall (e.g., Horn and McEwen 1977), commercial liking and purchase intention (Kamins, Marks, and Skinner 1991), and consumer response in sports programs (Hart, Schiavone, and Stipp 1998). Other variables that could affect a consumer's evaluation of advertisements include a brand sign-off (e.g., Stewart and Furse 1987), endorser (e.g., Macinnis, Moorman, and Jaworski 1991), sex appeal (e.g., Olney, Holbrook, and Batra 1991), comparative claims (e.g., Pechmann and Stewart 1990; Grewal et al. 1997), authenticity (Becker, Wiegand, and Reinartz 2019), and the mode of advertisement delivery (e.g., Phillips and McQuarrie 2010; Kim, Ratneshwar, and Thorson 2017). Although the aforementioned behavioral research focuses on consumer responses to or evaluations of advertisements conditional on complete viewing of commercials, we conjecture that the same variables can potentially affect consumer zapping behavior and thus are valuable to be included in our individual-level zapping model.

Another stream of consumer behavioral research investigates aspects of consumers' program involvement that may affect zapping. Norris and Colman (1993) find that viewers rate the advertisement higher when they are more involved in the associated program. Lynch and Stipp (1999) argue that higher liking or involvement with the associated program reduces viewers' probability of tuning out during embedded commercial breaks. In other words, consumers' high involvement levels in preceding program segments are expected to reduce zapping propensity for the advertisement that follows. Anand and Shachar (2011) report that audiences show an elevated level of viewing persistence when their involvement levels with the associated program are high. That is, for fear of missing upcoming program segments, more engaged viewers are more likely to stay tuned during commercial breaks. Reflecting this finding in behavioral research, we include consumers' immediate and cumulative involvement levels with the associated program in our empirical model. The immediate involvement level reflects the viewer's engagement with the current program episode, and cumulative involvement level measures a consumer's viewing history of all past episodes of a target program.

Prior literature has also investigated the role of viewer demographics as explanatory variables for viewers' heterogeneous zapping behavior. For instance, Speck and Elliott (1997) report that age and income are the best demographic predictors across media, while Zufryden, Pedrick, and Sankaralingam (1993) show that zapping is more likely to occur in households with college-educated members. Based on these findings, we build a comprehensive model to estimate consumer zapping behavior, and the results form the basis for our simulation studies.

Data

Consumer TV Viewing and TV Broadcasting Data

The data set used for our empirical analysis comes from multiple sources. The first data source is AC Nielsen, Hong Kong (HK), which provided consumer TV viewing data for all networks in Hong Kong from January 1, 2005, to July 24, 2005. Similar to AC Nielsen in other countries, participants are invited to take part in a people-meter system in which they agree to press their assigned number on the handset of the people meter each time they start viewing and press it again when they stop viewing. Therefore, AC Nielsen's data allow us to observe complete individual-specific, minute-to-minute viewing histories of participating households. Consumers' demographic information is also available in the data. In addition, we have access to broadcasting information for the channels, such as program genre, program broadcasting time, commercial broadcasting time, and TV program ratings (TVRs). Although there were four free-to-air TV networks in Hong Kong at the time of the data collection, the combined share of two Chinese-language channels (hereafter channels P and Q) exceeded 80% of the market. Therefore, we narrow our analysis to these two channels and, further still, their prime time (8 pm to 12 am).

Table 1. Summary statistics of advertisements and programs.

Variables	Characteristics	*M*	*SD*	Freq. (%)
Characteristics of advertisements				
Between-program breaks	% of ad instances aired in between-program breaks			41.2
Slot number	Number of slots in a commercial break	7.53	3.16	
Ad duration	Ad duration in seconds	19.45	14.87	
Price information	% of ads that contain price information			10.93
Product information	% of ads that contain product information			43.54
Endorser	% of ads conveyed by one or more endorsers			16.64
Narrative	% of ads in a narrative form			18.51
Comparative	% of ads that contain comparative information			4.9
Repeat air times	Repeated air times of ad creatives	15.07	30.87	
Simultaneous commercials	% of ad instances that air when the competing channel also airs commercials			43.61
Characteristics of programs				
Channel	% of ad instances on channel P			49.62
Program duration	Program episode duration in minutes	20.64	17.85	
Number of pods	Number of breaks in a program episode	2.16	1.51	
TVR	TV rating of program episodes	10.47	10.57	
	TV rating of program episodes on channel P	22.47	9.22	
	TV rating of program episodes on channel Q	3.92	2.16	
Program genre	% of ad instances in drama programs			50.88
	% of ad instances in entertainment programs			13.88
	% of ad instances in documentary/religious/education programs			8.76
	% of ad instances in news/current affairs/sports programs			14.49
	% of ad instances in other programs			11.99

Additional Advertisement Data

Our second data source is Hong Kong's largest TV network (channel P). In HK, commercial slots are sold before they are broadcast, and the prices advertisers pay to the TV network mainly depend on the expected rating of programs in which the commercial break will be embedded. These prices will not be adjusted by the realized audience size, and there is no rating guarantee provided by the TV networks. The second data set contains the actual prices paid by advertisers for each ad during the time window that overlaps with the AC Nielsen data. These data give us some core aspects of advertisements, such as advertiser, ad duration, and ad product category.

Our third data set comes from a large boutique advertising services company that records the details of TV ads. In the data set, in addition to basic advertiser information, we have a text description of every advertisement creative, and we hired two trained coders to read the description of each ad and record its characteristics. To use the ad creatives as part of our zapping model, the two coders independently coded all ad creatives as follows: whether the ad has price information (e.g., Olney, Holbrook, and Batra 1991); whether the ad contains product information (e.g., Resnik and Stern 1977; Woltman Elpers, Wedel, and Pieters 2003); whether there is an endorsement from a celebrity or an expert (e.g., Macinnis, Moorman, and Jaworski 1991); whether the ad is conveyed in a narrative story (e.g., Phillips and McQuarrie 2010); and whether the ad contains a comparative message between the focal product and other products (e.g., Pechmann and Stewart 1990; Grewal et al. 1997). The Krippendorff's alphas of these five coded dummy variables are 0.83, 0.75, 0.84, 0.72, and 0.79, respectively, suggesting a good interrater reliability. Correlations among the five variables are reported in Supplemental Online Appendix A. Using each ad's broadcasting time and channel as unique identifiers, we match the records of advertisement data in this subsection with their corresponding records in the consumer viewing data from AC Nielsen.

In our data, sometimes more than one person is watching TV. Both the median and mean number of simultaneous viewers is 2, while the maximum value reaches 11. As a way to address the multiple-viewer issue (Yang, Narayan, and Assael 2006), we define the main viewer in a household as the one who consumes the most prime-time TV programs throughout the entire sample period, and focus our study on these main viewers. In our final sample, we observe 479 viewers and their minute-level viewing histories over a seven-month period, amounting to 4.8 million records. During this period, there are 299 unique TV programs, 6,862 commercial breaks, and 982 advertisers with 3,431 unique ad creatives. The total number of ad instances is 51,697. Therefore, an average ad creative was repeatedly broadcast about 15 times with a standard deviation of 31 in our sample period.

Descriptive Statistics

Table 1 shows the summary statistics of ads and TV programs. In our data, an average program episode

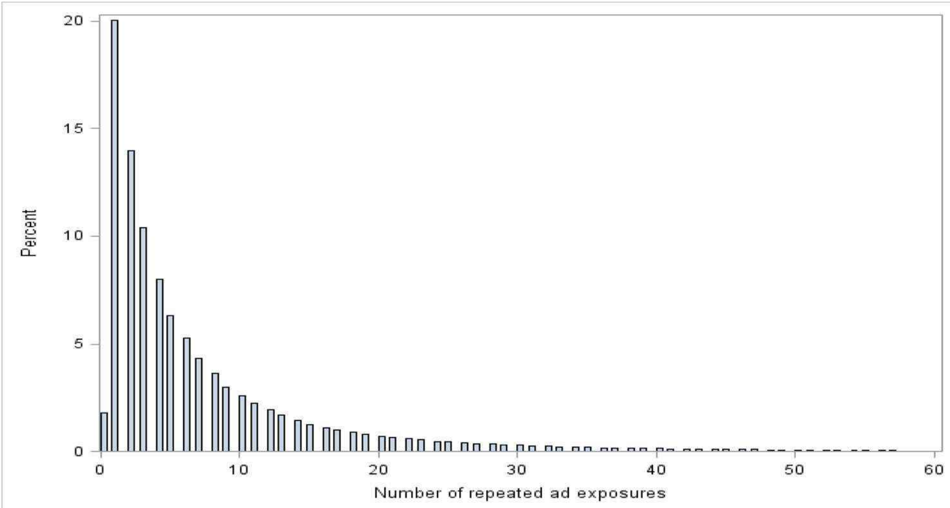


Figure 1. Distribution of repeated ad exposures across viewers and advertisements.

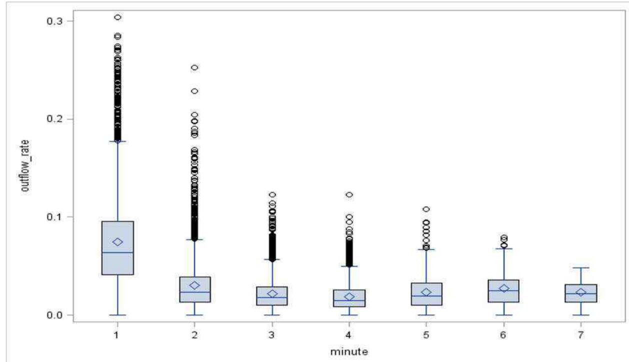
lasts 21 minutes (excluding embedded commercial time) and contains two commercial breaks. An average commercial break contains eight slots. The mean (standard deviation) of the ad's duration is 19 (15) seconds. In addition, 70% of ads last under 30 seconds, 27% last exactly 30 seconds, and only 3% exceed 30 seconds. In terms of advertising content, 11% contain price information and 44% contain product information. Moreover, 17% of ads involve endorsers, 19% of ads' content is delivered in narrative form, and 5% include comparative messages. On the consumption side, an average viewer is exposed to an average ad eight times, with a standard deviation of 14. Figure 1 shows the distribution of number of repeated ad exposures across viewers and advertisements, with extreme records in the upper 1% quintile excluded.

To keep the estimation at managerial level, we group 230 product categories into 11 broad categories. The top three advertised product categories are services, household goods, and foods, which account for 16%, 15%, and 8% of all advertisement instances, respectively. Comparing advertising costs across product categories, we see that electronics (HKD 7,269), real estate (HKD 7,092), and public, in other words, ads from government and nonprofit organizations (HKD 6,857) have the highest average unit cost per second. (Category description, broadcasting frequency, and price information on ad product categories are shown in Supplemental Online Appendix B.) We compute the average cost per second across all ads as HKD 5,873, and minimum and maximum costs per second are HKD 408 and HKD 25,070, respectively. An average advertiser purchases 31 placements in commercial breaks for a total cost of HKD 4 million during the sample period.

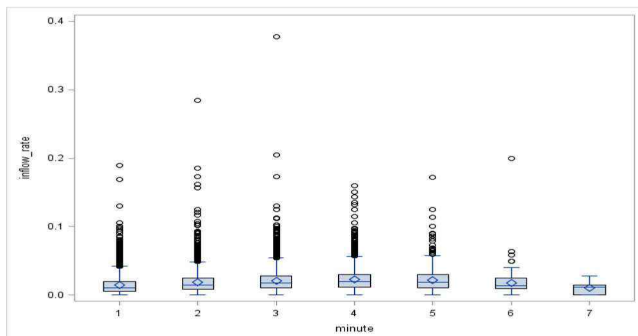
Next, we show viewer outflow and inflow rates at each minute in Figure 2(A) and (B), respectively. The outflow (inflow) rate is defined as the ratio of the number of viewers who stayed with the focal (other) channel at $t-1$ but switched away (in) at t to the total audience size at the beginning of the commercial break. Figure 2 is conditional on commercial breaks, the longest of which lasts seven minutes. We note that the average viewer outflow rate (i.e., zap rate) and its variance are highest in the first minute, drop sharply in the second minute, and remain relatively stable thereafter. In summary, the net outflow rate is subject to a high degree of variation across minutes, and an average advertisement loses about 7% of the initial audience size at the start of the commercial break. In contrast, the average inflow rate and its variance fluctuate marginally throughout the minutes. Similar patterns are obtained when we plot Figure 1 separately for within-program and between-program breaks.

Model

In this section, we aim to develop a model with a high predictive capability for our simulation studies. For program viewers (i.e., viewers who have watched the preceding program content), we first specify the utility function at each advertisement and then link this utility to the observed consumer zap incidences at the minute level.



(A) Outflow rate across 7 minutes



(B) Inflow rate across 7 minutes

Figure 2. Inflow and outflow rates at each minute.

Consumer Zapping for an Advertisement

Consumer i's utility of watching the j^{th} advertisement placed between minute $t-1$ and t is as follows:

$$U_{itj} = \alpha_i + Y_t^{'} \cdot \beta_i + O_{tj}^{'} \cdot \gamma_i + W_{it}^{'} \cdot \delta_i + V_{itj}^{'} \cdot \mu_i + \varepsilon_{itj}. \tag{1}$$

The consumer-specific intercept term α_i captures consumer i's intrinsic utility of watching an advertisement. Based on our review of prior literature on consumer zapping, we carefully choose the covariates. Some variables (such as authenticity and whether the ad includes a brand sign-off) are not included due to lack of data. Finally, in our model the vector Y_t is a collection of broadcasting characteristics at minute t, such as broadcasting channel, day of the week, hour of the day, whether minute t belongs to a between-program commercial break or not, pod of the commercial break (i.e., position of the commercial break in a program episode), genre of the preceding program, and the characteristics of subsequent programs and competitive factors (e.g., program genre and TVR) from programs on the other channel. Characteristics of subsequent programs are measured only when the ad is aired in the between-program commercial break. Coefficients of variables included in Y_t are represented by vector β_i.

The vector O_{tj} represents the characteristics of advertisement j at minute t. Entries in this vector include characteristics of the ad itself (e.g., duration, product category, and content information) and ad-slot positions within the break. We also include higher-order interaction between ad product category and program genre to partly control for the potential congruity between ads and the associated program. The vector γ_i is the corresponding coefficient.

The vector W_{it} captures the interaction between viewer i and broadcasting characteristics at minute t, such as consumer i's immediate involvement with the preceding programs, cumulative involvement with the upcoming programs on the channel, and interactions of these involvement levels with program genres. The immediate involvement level is measured by the viewer's viewing length of the preceding program segment normalized by the segment's duration. The cumulative involvement level is the viewer's cumulative historical program-segment viewing incidences of the program to which the subsequent program segment belongs. In addition, we include the number of viewers watching the TV program together with consumer i at minute t. The column vector δ_i represents the coefficients corresponding to W_{it}.

The last vector V_{itj} in the utility specification captures viewers' interactions with the advertising characteristics of j at minute t. Entries in this vector include interaction terms between viewer i's program involvement levels and ad positions in the break, as well as viewer i's cumulative exposure levels to advertisement j. The corresponding coefficients are collected by the column vector μ_i.

The random error term ε_{itj} captures the error term on the viewer's utility for factors that are observed by viewers but unobserved by researchers. Such unobserved factors may include the viewer's intrinsic interest in the advertised products and exposure to the product through other media formats. We assume that ε_{ijt} is a random variable from an i.i.d. type I extreme value distribution and that the mean utility of the outside option is normalized to zero. Full descriptions and operationalization of all covariates in Equation (1) are found in Supplemental Online Appendix C.

In our binary choice setting, the probability of consumer i zapping during the j^{th} ad between minute $t-1$ and t is

$$\Pr\left(Z_{itj}=1|\boldsymbol{X},\ \boldsymbol{\Theta}\right)=\Pr\left(U_{itj}<0|\boldsymbol{X},\boldsymbol{\Theta}\right) \tag{2}$$

where $\boldsymbol{X} = \{Y_t,\ O_{tj},\ W_{it},\ V_{itj}\}$ are data and $\boldsymbol{\Theta} = \{\alpha_i,\ \beta_i,\ \gamma_i,\ \delta_i, \mu_i\}$ are model parameters.

Minute-Level Consumer Zapping

An important feature of our data is that we observe consumers' TV viewing behavior at each minute t in a discrete manner rather than at each advertisement j. This means that if we observe a consumer viewing an advertisement at $t-1$ but not at t, he or she must have zapped during one of the advertisements between minute $t-1$ and t. Therefore, our modeling and estimation strategy aim to model the consumer's viewing decision at each advertisement level, as in Equation (2), aggregate these decisions across the time window of one minute, and match them to the actual minute-level observations in the data.

Next, we introduce the minute-level consumer zapping model under the following assumption. First, once a consumer zaps any ad between minute $t-$ 1and t, he or she will remain in the "zapped state" and will not return to consume any of the remaining ads until t. A similar assumption was made in Wilbur, Xu, and Kempe (2013). Second, by controlling for some advertisement characteristics, we model a consumer's decision to zap an advertisement as independent of other consumers' decisions. Third, consumers are fully informed about the TV programs—that is, consumers know the schedules of all the programs and advertising breaks on other channels.

Let Z_{itj} be a binary variable that takes the value of unity if consumer i zaps the j^{th} advertisement placed between minute $t-1$ and t, and zero otherwise. In addition, let another binary variable Z_{it} be unity if consumer i zaps between commercial break minute $t-1$ and t, and zero otherwise. Critically note that if consumer i zaps at the j^{th} ad $(1\le j\le J_t)$, where J_t is the number of ads between $t-1$ and t, it must be true that consumer i did not zap in any of the previous ads k, $1\le k\le j$, between $t-1$ and t. Therefore, the probability of observing consumer i zapping at t is expressed as follows:

$$\begin{aligned}\Pr\ (Z_{it}=1|\boldsymbol{X},\ \boldsymbol{\Theta}) &= 1-\Pr\ (Z_{it}=0|\boldsymbol{X},\ \boldsymbol{\Theta})\\ &= 1-\prod_{j=1}^{J_t}\Pr\ \left(Z_{itj}=0|\boldsymbol{X},\ \boldsymbol{\Theta}\right).\end{aligned} \tag{3}$$

Note that $\Pr\left(Z_{itj}=1|\boldsymbol{X},\ \boldsymbol{\Theta}\right)$ is the probability that consumer i zaps at the j^{th} ad, and the composite term $\prod_{j=1}^{J_t} Pr\left(Z_{itj}=0|\boldsymbol{X},\ \boldsymbol{\Theta}\right)$ is the probability that consumer i did not zap during any ad between minute $t-1$ and t. In our empirical application, we model the zapping behavior of consumers who are watching the advertising channel at the beginning of minute t. Therefore, we set $Z_{it0}=0$.

Estimation

To capture unobserved viewer heterogeneity, we use a latent class approach in the estimation. We divide viewers into latent discrete segments based on their sensitivities to all explanatory variables. Assume C different segments and let r_c be the probability that each viewer belongs to segment c. Further, $r=(r_1,\ \ldots,\ r_C)$ and $\sum_c r_c=1$. Given that viewer i belongs to segment c, the probability that he or she will zap the j^{th} ad in minute t is

$$P_{itj}\ (\Theta_c)=\Pr\ \left(Z_{itj}=1|X,\ \Theta_c\right)=\frac{\exp(X'\Theta_c)}{1+\exp(X'\Theta_c)}. \tag{4}$$

Subscripts of i, t, and j of X and Θ_c are omitted for notational simplicity wherever possible.

The likelihood of observing viewer i zapping at t is

$$\begin{aligned}L_{it}\ (\Theta_c|X,Z_{it}) &= \Pr\ (Z_{it}=1|X,\ \Theta_c)^{Z_{it}}\\ &\quad(1-\Pr\ (Z_{it}=1|X,\ \Theta_c))^{1-Z_{it}},\end{aligned} \tag{5}$$

Table 2. Model selection.

Model	Number of Parameters	−LL	BIC
1-segment	110	294,690	587,710
2-segment	221	276,650	556,660
3-segment	332	272,710	550,450
4-segment	443	270,430	547,580

Note. 3-segment is the chosen model.

where *PrZit* is found in Equation (3). Then, conditional on the viewer's membership in segment c, the likelihood of observing the zapping history of viewer i, $\{Z_{it}\}$, is the product of $L_{it}(\Theta_c)$ over t:

$$L_i\ (\Theta_c|X, \{Z_{it}\}) = \prod\nolimits_{t \in T_i} L_{it}\ (\Theta_c|X, Z_{it}), \tag{6}$$

where T_i is the collection of all commercial break minutes in which we model viewer i's zapping decisions. Then the posterior probability for viewer i is

$$h\ (\Theta_c|Z_i,\ r) = \frac{r_c L_i(\Theta_c|X, Z_i)}{\sum_c r_c L_i(\Theta_c|X, Z_i)}, \tag{7}$$

where $Z_i = \{Z_{it}\}_{t\ =\ 1, \ldots, T_i}$.

The parameters to be estimated in this latent class model are $\Theta = \{\Theta_c\}$ for all C segments and $\{r_c\}$. For a given C, the log-likelihood over all viewers is as follows:

$$\begin{aligned} LL\ (\Theta, r|X, Z_i) &= \sum\nolimits_i \log\left(\sum\nolimits_c r_c L_i\ (\Theta_c|X, Z_i)\right) \\ &= \sum\nolimits_i \log\ \left(\sum\nolimits_c r_c \prod\nolimits_{t \in T_i} L_{it}\ (\Theta_c|X, Z_{it})\right) \end{aligned} \tag{8}$$

This nonquadratic function is difficult to directly maximize when the number of parameters to be estimated is large (Train 2009). Therefore, we use an EM approach and maximize the following function instead (Train 2009):

$$\begin{aligned} e\ \ (\Theta, r) &= \sum\nolimits_i \sum\nolimits_c h\ (\Theta_c|Z_i, r)\ \log(r_c L_i(\Theta_c)\,) \\ &= \sum\nolimits_i \sum\nolimits_c h\ (\Theta_c|Z_i, r)\ \log(r_c) \\ &\quad + \sum\nolimits_i \sum\nolimits_c \sum\nolimits_{t \in T_i} h\ (\Theta_c|Z_i, r)\ \log(L_{it}(\Theta_c)) \end{aligned} \tag{9}$$

In the equalization step of EM, given initial values of $\{\tilde{\Theta}_c\}$ and $\{\tilde{r}_c\}$, we compute the values of $h\ \left(\tilde{\Theta}_c|Z_i,\ \tilde{r}\right)$ and $L_{it}\ \left(\tilde{\Theta}_c\right)$. In the maximization step, given $h\ \left(\tilde{\Theta}_c|Z_i, \tilde{r}\right)$ and $L_{it}\ \left(\tilde{\Theta}_c\right)$, we search for $\{\Theta_c\}$ and $\{r_c\}$ that maximize $e\ (\Theta, r)$. We repeat these two steps until we reach a convergence. Because in Equation (9) $\{r_c\}$ only enters the first term while $\{\Theta_c\}$ only enters the second term, we can separately maximize and update r_c and Θ_c for each segment c. This largely reduces the computational burden. We estimate the model with different values of C and choose the best model for our simulation.

Empirical Analysis

Model Selection and Validation

For model estimation and validation, we divide our sample data into two parts. We use 3.9 million observations, or 80% of the data, for estimation and keep the rest as a holdout sample. For our model selection, we estimate the model with different numbers of segments ($C = 1$, 2, 3, 4), as in Table 2. Although the Bayesian information criterion (BIC) keeps improving with more segments, its improvement becomes marginal, with 0.5% improvement from $C = 3$ to $C = 4$. In addition, the model fit and predictions in terms of hit rates are similar between three- and four-segment models. Therefore, for model parsimony, we chose a three-segment model and use the corresponding estimates for our simulation studies.

For model validation, we compare the individual-level zapping predictions from our model against the actual observations. To that end, we first compute viewer i's zapping probabilities for all advertisements between $t-1$ and t and use this probability set as the basis for zapping predictions for i. In detail, given i's zapping probability set for different ads between $t-1$ and t, once viewer i's advertising-level zapping probability during a one-minute window exceeds a cutoff value, we denote that this viewer has zapped. If not, we assume that the viewer stays on the channel. For this exercise, we need to choose the cutoff value for the binary state of viewers. Zapping is sparse in the full sample data, as only about 4.9% of all viewers zap conditional on nonzapping in the prior minute. Using a conventional cutoff value of 0.5 leads to a poor prediction of the zapping hit rate. Therefore, we test different values for the cutoff and conclude that the value of 0.13 leads to balance in the confusion matrix. The chosen cutoff value maximizes the sum of false positives for minute-level zapping and viewing. A similar approach to the choice of a cutoff value is applied in the credit-rating research of Engelmann and Rauhmeier (2011), in which default is a sparse event. Using the proposed cutoff value, we can correctly predict viewer zapping and viewing with 76.18% and 73.02% hit rates (i.e., true positive rates), respectively, while achieving a combined hit rate of 73.51%. Based on this set of experiments, we use the cutoff value of 0.13 in our simulation studies.

Table 3. A subset of key parameter estimates for the three-segment model.

Variables	Segment 1 Estimate (*t* Value)	Segment 2 Estimate (*t* value)	Segment 3 Estimate (*t* Value)
Intercept	0.366 (4.04)	1.931 (23.66)	2.809 (27.18)
Environmental factors			
Channel P (vs. channel Q)	0.086 (1.81)	0.261 (6.22)	0.499 (9.6)
Between-program break	−0.781 (−17.48)	−1.148 (−28.64)	−1.277 (−23.29)
Relative pod	−0.128 (−3.01)	−0.068 (−1.49)	0.159 (2.38)
Lag (TVR) of subsequent program segment	0.015(10.29)	0.014 (10.81)	0.02 (11.62)
TVR of other channel	−0.013 (−6.68)	−0.013 (−7.42)	−0.001 (−0.48)
Simultaneous viewers	−0.036 (−5.79)	−0.21 (−37.89)	−0.259 (−44.09)
Advertisement characteristics			
Ad duration	−0.004 (−6.21)	−0.002 (−3.37)	−0.003 (−5.62)
Price information	0.061 (1.84)	0.068 (2.16)	0.038 (0.98)
Product information	−0.047(−2.71)	0.001 (0.09)	0.04 (1.95)
Endorser	−0.024 (−1.21)	−0.022 (−1.15)	0.039 (1.49)
Narrative	−0.145 (−7.73)	−0.125 (−7.11)	−0.114 (−5.02)
Comparative	−0.037(−1)	−0.078 (−2.23)	−0.081 (−1.81)
Cumulative ad exposure	0.629 (40.05)	0.509 (35.99)	0.486 (27.72)
(Cumulative ad exposure)^{2}[a]	−0.06 (−36.28)	−0.048 (−31.64)	−0.043 (−23.49)
Viewer involvement level with associated programs			
Immediate involvement level	1.254 (34.13)	0.979 (28.96)	0.979 (21.19)
Log of cumulative involvement level	0.197 (7.24)	0.471 (17.5)	0.436 (14.25)
Segment size	0.17	0.40	0.43

Note. Numbers in parentheses are *t* values for the estimated coefficients.

[a]Correlation coefficients between variables in this table are relatively small except for the following four coefficients that have values larger than 0.5. They are the correlation coefficients of relative pod and between-program break ($r = 0.8$), channel P (vs. channel Q) and lag (TVR) of subsequent program segment ($r = 0.74$), channel P (vs. channel Q) and TVR of other channel ($r = -0.92$), and cumulative ad exposure and (cumulative ad exposure)^2 ($r = -0.78$). Our model is not in a standard linear or generalized linear regression form such that a standard way of detecting multicollinearity is available. We still calculate VIF of all 16 independent variables in Table 3 and find all values of VIF are less than 10. Hence, we believe that there is no serious multicollinearity problem in our model.

Results and Inferences

Although our primary focus in this research is various simulation studies to quantify the externality's impact on the network's revenue, we briefly discuss some important findings from our estimated model. Table 3 provides the estimation results of a subset of key variables.[2] First, we discuss viewer heterogeneity. Of the three segments, segment 1 is the smallest group (0.17) but is the most zap prone, whereas segment 3 is the largest (0.43) group but also the least zap prone.[3] Given that segment 1 is the most zap prone, we discuss several parameter estimates in this segment. Note that a positive coefficient induces a higher utility of watching commercials and thus leads to lower probability of zap. In terms of environmental variables, ads that air during earlier prime time (−0.332 for 9 pm to 10 pm) rather than later prime time (−0.746 for 11 pm to 12 am) or are aired in breaks located in earlier pods (−0.128) are less likely to be zapped. Across slots within a break, consumer zaps are more likely during the first two slots. In addition, viewers zap less for advertisements embedded in news/current affairs/sports genres than other genres. Content attractiveness on other channels also positively affects viewers' zapping propensities during commercial breaks. In contrast, viewer zapping propensity drops significantly if competing channels are also in a commercial break.

For ad characteristics, we find that ad duration (−0.004), whether the ad includes product information (−0.047), or whether the ad is conveyed in a narrative manner (−0.145) are positively related to consumer zapping probability. In terms of product categories, viewers are less likely to zap ads for real estate and wine and more likely to zap ads for household products. As expected, viewers' zapping propensity is influenced by prior exposure to the same ad. The positive coefficient value (0.629) for cumulative ad exposure and the negative coefficient value (−0.06) for its square term indicate that a viewer's viewing probability initially increases with exposure but decreases with additional exposure. This pattern is consistent with the inverted U-shaped relationship between zap probability and number of previous exposures in Siddarth and Chattopadhyay (1998), as well as the wear-in and wear-out effects of Pechmann and Stewart (1988). In line with the findings of previous research, we report that high levels of immediate (1.254) and cumulative (0.197) involvement with associated programs lead to lower zapping propensity. Using the estimated model and actual advertising cost data, we conduct various simulation studies in the next section.

Simulation Studies

Overview

In the set of simulation studies we aim to quantify the impact on the TV network's revenue of the zapping-induced externality across ads within a commercial break. First, we examine the externality generated by different ad sequences by estimating the possible viewer size and corresponding monetary value for each ad sequence in the commercial break. As we consider the commercial zapping behavior only for viewers who have watched the preceding program when estimating the model, the predicted viewer size for each ad is adjusted by the actual number of non-program viewers tuning in at the minute when the ad is broadcast. We then calculate the difference between the best (worst) ad sequence and the current ad sequence and aggregate these differences at the network level. In the next simulation, we vary the overall viewing probabilities of ads in different slot positions to examine the relationship between slot position and impact size of the externality. In both simulations, we are able to simulate the viewer size for an ad if it were assigned to another slot position within the same commercial break. To render the results comparable, we use the estimated rather than actual audience size and corresponding monetary value generated by the current ad sequence as the baseline condition.

Audience Sizes and Monetary Values Generated by Different Ad Sequences

The degree of zapping-induced externality varies across ad sequences with different ordering. A higher level of externality is present in an ad sequence if ads with lower audience retention rates are placed toward the start of the sequence, and vice versa. We examine the difference in audience sizes and corresponding monetary values generated by different ad sequences to quantify the impact of this externality. Given the same set of ad creatives in the same break, higher break-level revenue generated by an ad sequence suggests a lower level of externality across this ad sequence. Considering that there are $n! = n \times (n-1) \times \cdots \times 2 \times 1$ possible ad sequences in a break with n slots, it is almost computationally impossible to investigate the full set of ad sequences, because the total number of possibilities dramatically increases with the number of slots. For instance, the number of possible ad sequences is 40,320 for a break with eight slots (the average number in our sample), and this number increases to more than 1.3 trillion for a break with 15 slots (the maximum number in our sample). Therefore, we use the alternative of examining the highest and lowest audience size and monetary value that can possibly be generated by the best and worst ad sequences. Such an approach is feasible because our model allows us to predict advertisement-level consumer zapping probability. In the best (worst) ad sequences, the negative impact of the zapping-induced externality is minimized (maximized). Specifically, we calculate the retention rate for ads in each commercial break and reorder them according to those rates. We consider the ad sequence in descending (ascending) order of retention rates to be the best (worst) ad sequence that minimizes (maximizes) the level of externality.

Next, we illustrate how we calculate the retention rate of each ad. In addition to the ad's content, an ad's capability to retain viewers depends on the broadcasting environment (such as the corresponding program and broadcasting time), viewer characteristics (such as viewers' involvement in the corresponding program and viewers' previous exposure to the same ad), and the interactions of ad content with the broadcasting environment and viewer characteristics. Consequently, the retention rate for the same ad in different commercial breaks would vary. As the goal of this simulation is to study the ad sequence within the commercial break, we calculate the retention rate for each ad in each break so that general broadcasting environment and viewer characteristics remain the same even after the ads are reordered.

For each ad A in break H, based on the estimated coefficients, we calculate the probability of each individual viewer watching ad A (unconditional on the viewing decision of the previous ad) in the current ad sequence in the data. We then average the viewing probabilities across all viewers in the break to get ad A's average retention rate in break H. To eliminate the possible impact of slot position on ads' capability to retain viewers, we set the slot position to be the first slot for all ads when calculating the retention rate. Figure 3 shows the distribution of retention rates across ads and breaks. Of the 4,893 combinations of ad and break, the estimated retention rate ranges from 0.709 to 0.986, with a mean (*SD*) of 0.923 (0.046).

We reorder ads within commercial breaks using the retention rates calculated and estimate the viewer size and monetary value of the break after the reordering. The following example illustrates the process. The example break was broadcast between 11 pm and 12 am on June 24, 2005. It contained eight slots and

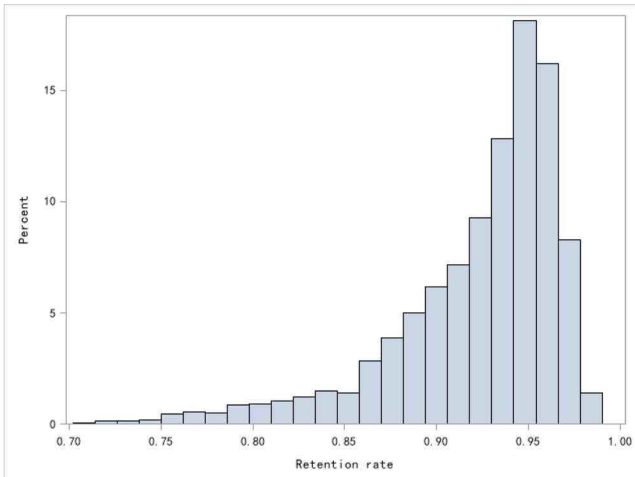


Figure 3. Distribution of retention rate across ads and breaks.

Table 4. Viewer size and monetary value in the current, best, and worst conditions for an example break.

				Current		Best				Worst			
Advertiser	Product Category	Retention Rate	Total Spend (HKD)	j	AS	j	AS	△AS	△M	j	AS	△AS	△M
Darlie	Toothpaste	0.924	108,300	1	144	3	151	7	5,265	6	119	−25	−18,802
Quaker	Oatmeal	0.947	54,150	2	134	2	154	20	8,082	7	115	−19	−7,678
Vita	Soymilk	0.961	41,840	3	132	1	160	28	8,875	8	111	−21	−6,656
China Travel	Caribbean coast	0.920	378,840	4	136	5	148	12	33,427	4	122	−14	−38,998
Magnum	Ice cream	0.920	62,280	5	136	4	152	16	7,327	5	121	−15	−6,869
Taoti	Tea	0.915	236,100	6	130	6	145	15	27,242	3	123	−7	−12,713
UA	Movie promotion	0.902	108,300	7	130	7	146	16	13,329	2	126	−4	−3,332
Amoy	Sauce	0.898	143,220	8	124	8	140	16	18,480	1	133	9	10,395
Sum			1,133,030		1,066		1,196	130	122,027		970	−96	−84,654
%								12.2	10.8			−9.0	−7.47

Note. AS = audience size; j = slot; M = monetary value; △ = difference relative to the value in the current condition.

lasted for 230 seconds. The ads were aired in the following order: Darlie toothpaste, Quaker oatmeal, Vita soymilk, China Travel Caribbean coast, Magnum ice cream, Taoti tea, UA movie promotion, and Amoy sauce. The fourth column in Table 4 shows the total amount of money (the product of per-second price and ad length) that each advertiser spent for broadcasting their ad in this commercial break. In total, advertisers paid around HKD 1 million.

Based on the estimated coefficients, we calculate the number of viewers that each ad can be exposed to in the current ad sequence in the data. Columns 5 and 6 of Table 4 report the current slot position and audience size for each ad. According to the calculated retention rates in the third column, we reorder the ads in descending order of retention rates in the best-ad-sequence condition. The new slot position and audience size for each ad are reported in Columns 7 and 8. Column 9 is the difference between the audience size in the best and current baseline sequence condition. We convert the audience size difference into monetary value as follows: For each ad in a given ad sequence, we divide the actual price the advertiser paid by the estimated audience size to get the willingness to pay per viewer for the advertiser. Multiplying the willingness to pay per viewer for the given advertiser by the difference in audience size between the best and baseline conditions gives us the monetary value. The result is reported in Column 10.

Column 11 reports the slot position in the worst-sequence condition. The new audience size for each ad is reported in Column 12. The results for the difference in audience size and monetary value between the worst case and the baseline level are reported in Columns 13 and 14. Summing the numbers across all ads in the break gives us the magnitude of the impact of the externality at each commercial-break level. In the best ad sequence, the commercial break attracts 130 (12.2%) more viewers or HKD 122,027 (10.8%) more revenue; in the worst ad sequence, the break loses 96 viewers (9%) and HKD 84,654 (7.47%).

We repeat the same exercise for all 627 commercial breaks in our holdout sample. Figure 4 depicts the audience size generated by the current, best, and

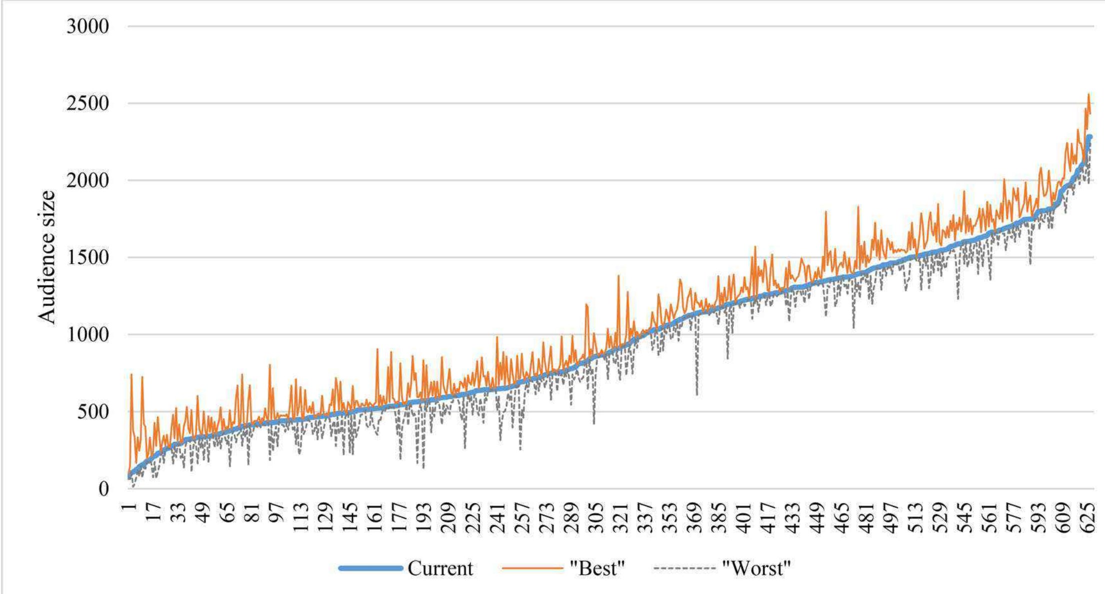


Figure 4. Audience sizes generated by the current, best, and worst ad sequences.

worst ad sequences. The horizontal axis refers to commercial breaks. The breaks are ordered by the current audience size in ascending order from left to right. For 89% of breaks, the current sequence is neither the best nor the worst. Compared with the break in the current ad sequence, a break in the best condition can attract a maximum of five times more viewers, while a break in the worst condition can retain a minimum of 12% of current viewers. Summing for all breaks in our holdout sample, we find that the best (worst) condition generates 9.45% more (6.45% less) viewers than the current condition. We regress the viewer size generated by the best (worst) ad sequences on the number of slots in the break and find the coefficient to be 0.023 (−0.012), with t value 4.11 (−5.72). The significant coefficient indicates that the potential change as a result of reordering is larger for breaks with more slots.

In addition, we find that the audience size difference generated from the best (worst) condition converts to about HKD 128 (−38) million across all ads, which is equal to 19.38% (−5.76%) of the current advertising revenue in our holdout sample. This suggests the extent that the revenue of the focal TV network might increase if the externality effect were being considered in ordering and/or pricing of ads within the same commercial break. This result also indicates the amount of "make-good" advertising cost (Danaher, Dagger, and Smith 2011) the TV network can potentially save if it fails to achieve the guaranteed ratings committed to advertisers. Given the high amount of advertising spending in the global market (e.g., USD 176.3 billion), our results illustrate the significant economic implications of the audience externality in the TV advertising industry.

An interesting finding from this simulation study is that the percentage change in the monetary value is larger than the change in audience size when comparing the best sequence condition with the baseline condition. This suggests that advertisers with higher willingness to pay benefit more from better ad sequences. One managerial implication would be the value of selling commercial airtime at a higher average price when externality is minimized, because advertisers with higher willingness to pay would indeed pay more for the increase in audience size.

Relative Importance of Different Slot Positions

The previous simulation study reveals the economic implications of an audience externality aggregated at the level of TV commercial break. However, it remains unknown whether and how different slot positions in the commercial break contribute differently to the externality. In this section, we examine the influence of different slot positions in contributing to the externality by comparing the differences in audience size and monetary gain (loss) when the average retention rates of ads broadcast in different slot positions are increased (decreased).

Considering an ad broadcast in slot k in a commercial break and holding everything else equal, we increase (decrease) all viewers' probabilities of watching the ad by the same percentage simultaneously as a way to increase (decrease) its audience retention rate. The viewing probability is set to be 1 if it is larger than 1 after being

Table 5. Change in audience size when the viewing probability of an ad in slot X is increased/decreased.

	Increase				Decrease			
Slot	0.1% *M (SD)*	0.5% *M (SD)*	1.0% *M (SD)*	5.0% *M (SD)*	0.1% *M (SD)*	0.5% *M (SD)*	1.0% *M (SD)*	5.0% *M (SD)*
1	0.30% (0.57%)	1.47% (2.10%)	2.90% (4.10%)	12.61% (19.71%)	−0.29% (0.45%)	−1.51% (2.05%)	−3.13% (4.01%)	−18.68% (17.46%)
2	0.25% (0.40%)	1.27% (1.79%)	2.52% (3.58%)	7.33% (12.53%)	−0.25% (0.38%)	−1.32% (1.73%)	−2.72% (3.40%)	−16.10% (14.64%)
3	0.21% (0.35%)	1.06% (1.44%)	2.00% (2.80%)	3.16% (4.83%)	−0.21% (0.34%)	−1.11% (1.44%)	−2.28% (2.84%)	−13.45% (12.44%)
4	0.18% (0.32%)	0.90% (1.25%)	1.68% (2.31%)	2.53% (3.76%)	−0.18% (0.31%)	−0.95% (1.24%)	−1.93% (2.41%)	−11.33% (10.80%)
5	0.16% (0.28%)	0.76% (1.07%)	1.37% (1.90%)	1.81% (2.58%)	−0.15% (0.27%)	−0.80% (1.05%)	−1.62% (2.04%)	−9.47% (9.31%)
6	0.13% (0.22%)	0.62% (0.83%)	1.01% (1.36%)	1.13% (1.57%)	−0.13% (0.23%)	−0.66% (0.89%)	−1.35% (1.75%)	−7.85% (7.90%)
7	0.11% (0.18%)	0.49% (0.69%)	0.80% (1.13%)	0.92% (1.31%)	−0.10% (0.20%)	−0.54% (0.77%)	−1.10% (1.50%)	−6.33% (6.56%)
8	0.08% (0.14%)	0.40% (0.59%)	0.64% (0.91%)	0.72% (1.08%)	−0.09% (0.17%)	−0.47% (0.69%)	−0.94% (1.31%)	−5.10% (5.46%)

increased by a certain percentage. We estimate the resulting audience size change for ads in each slot and sum the change for the commercial break. The percentage change is obtained by dividing the absolute change by the current audience size. For all commercial breaks in our holdout sample, we compute the mean and standard deviation of the percentage change in audience size and report the results in Table 5. For each slot k, we increase (decrease) the retention ability of the ad embedded by 0.1%, 0.5%, 1%, and 5%, respectively, to examine the corresponding audience size changes. Table 5 reports the results when k is less than or equal to 8––the average number of slots in a break in our sample. The results are consistent with the common belief that an increase in the retention rate for slots toward the beginning of the sequence has a larger impact on audience size increase than for slots later in the sequence. We also find that the larger the change in the magnitude of the retention rates for embedded ads, the bigger the difference in audience size induced by slot positions. For example, increasing (decreasing) the ad's retention ability by 0.1% leads to a 0.3% increase (0.29% decrease) in audience size if the ad is broadcast in the first slot, and a 0.08% increase (0.09% decrease) in audience size if the ad is broadcast in the eighth slot. The resulting difference between the audience size change for the first and eighth slots is 0.22% increase (0.2% decrease). However, this difference increases significantly when the percentage of increase (decrease) in the ad's retention ability rises to 5%, which leads to a 12.61% increase (18.68% decrease) in audience size for an ad broadcast in the first slot, and a 0.72% increase (5.1% decrease) for an ad broadcast in the eighth slot. The resulting difference between the audience sizes induced by the two slot positions is as high as 11.89% increase (13.58% decrease).

Following the same approach as before, we convert the audience size in Table 5 to monetary value, as reported in Table 6. We find that the percentage change in monetary value is significantly larger than the percentage change in audience size when the retention ability of ads is increased, which is consistent with our finding from the previous simulation study. This finding suggests that advertisers with higher willingness to pay benefit more from better ad sequences, as their valuation for each viewer is higher compared to those with lower willingness to pay.

This audience externality and its impact on slot pricing and sequencing has drawn attention from researchers and practitioners. Our simulation studies quantify the magnitude of the economic implications of this externality at the aggregate level. We also demonstrate the roles that different slot positions play in the presence of the externality. Our results suggest the importance of considering not only audience retention rates but also the slot position and the interplay of the two in pricing and sequencing ads in the presence of this externality.

General Discussion

Theoretical and Methodological Implications

This article aims to examine the economic implications of zapping-induced externality on the TV network's revenue through understanding viewers' zapping decisions. Although a wide range of prior research has investigated factors that affect TV viewers' zapping behavior, findings of these research are fragmented, as each research approach utilizes only a subset of variables, mainly due to data limitations. Using multisource data with rich information on television viewing, advertising pricing, and ad content, we

Table 6. Change in monetary value when the viewing probability of an ad in slot X is increased/decreased.

	Increase				Decrease			
Slot	0.1% *M (SD)*	0.5% *M (SD)*	1.0% *M (SD)*	5.0% *M (SD)*	0.1% *M (SD)*	0.5% *M (SD)*	1.0% *M (SD)*	5.0% *M (SD)*
1	0.32% (0.65%)	1.71% (3.19%)	3.54% (7.36%)	17.00% (46.98%)	−0.31% (0.51%)	−1.64% (2.43%)	−3.35% (4.57%)	−19.02% (17.93%)
2	0.30% (0.64%)	1.58% (3.10%)	3.28% (7.23%)	9.45% (23.21%)	−0.29% (0.49%)	−1.53% (2.33%)	−3.10% (4.38%)	−17.44% (16.96%)
3	0.26% (0.61%)	1.38% (2.81%)	2.74% (6.26%)	4.30% (10.15%)	−0.25% (0.47%)	−1.33% (2.12%)	−2.68% (3.92%)	−14.94% (15.17%)
4	0.24% (0.60%)	1.21% (2.56%)	2.38% (5.27%)	3.51% (7.48%)	−0.22% (0.44%)	−1.17% (1.93%)	−2.34% (3.53%)	−12.93% (13.83%)
5	0.21% (0.56%)	1.05% (2.06%)	1.95% (3.93%)	2.62% (5.78%)	−0.19% (0.40%)	−1.02% (1.72%)	−2.01% (3.05%)	−10.99% (12.12%)
6	0.19% (0.47%)	0.91% (1.95%)	1.53% (3.28%)	1.72% (3.69%)	−0.16% (0.36%)	−0.87% (1.45%)	−1.71% (2.59%)	−9.23% (10.45%)
7	0.16% (0.40%)	0.71% (1.43%)	1.28% (3.13%)	1.54% (4.04%)	−0.14% (0.34%)	−0.70% (1.29%)	−1.41% (2.28%)	−7.63% (9.36%)
8	0.10% (0.21%)	0.60% (1.37%)	1.03% (2.49%)	1.21% (3.18%)	−0.12% (0.30%)	−0.62% (1.14%)	−1.21% (1.97%)	−6.18% (7.84%)

propose and estimate a viewer-zapping model that integrates and consolidates past empirical findings in one single model. This allows us to have a comprehensive understanding of viewers' ad viewing behavior and contribute to the previous work on TV advertising by providing validation to previous findings. Consistent with prior literature, variables related to ad content, environmental factors and viewer heterogeneity are found to have important roles in affecting viewers' zapping decisions. Furthermore, our research also examines factors that are not previously explored. For instance, we test the impact of the congruity between advertising and the associated TV program on viewers' zapping decisions by including the interaction terms between product category of the advertisement and the preceding program genre in our model. Most of the interaction effects are significant, suggesting the importance of congruity between product category of the advertisement and the preceding program genre in affecting viewers' zapping behavior. We also test the impact of viewers' immediate and cumulative involvement with TV programs on their zapping decisions. Results show that both types of involvement positively affect viewers' zapping propensity, with the impact of immediate involvement having a larger magnitude.

Estimation of the viewer zapping model allows us to conduct simulations to explore the economic implications of zapping in the presence of an externality that affects ads sequentially broadcast within the same commercial break. Externality is a common phenomenon that affects advertising effectiveness and therefore directly relates to the ad pricing and sequencing decision of the advertising platform. However, there is a large gap between the significance of the externality problem in advertising and the amount of empirical research on this topic. As one of the few earliest studies to explore the economic implications of externality in TV advertising, our research fills in the gap by quantifying the inefficiencies in the TV advertising market that derive from consumer zapping behavior. Our simulation results suggest that slot positions interact differently with ads of different audience retention rates in generating externality, and the incremental revenue could be 19.38% of the network's current revenue if the externality is minimized. While quotas and tax/subsidy are considered to be important methods to reduce negative externality in the economic literature (Mas-Colell, Whinston, and Green 1995), our study suggests that ad sequencing can be a strategic decision for the advertising platform to reduce negative audience externality.

Zapping-induced externality is a potential problem in any advertising platform as long as ads appear in sequence and are skippable by the audience. For example, a sequence of skippable ads is often offered within a commercial time slot for targeted TV advertising (Deng and Mela 2018) and online advertising (Kar, Swaminathan, and Albuquerque 2015), leading to zapping-induced externality and loss of efficiency. Although the focus of the current article is to quantify the economic impact of audience externality on TV advertising, the method developed in this article can also be adapted to other advertising markets with audience externality.

Managerial Implications

As the current industry still lacks the technique of measuring audience externality, the common practice in TV advertising is such that ad price and location of an ad within a commercial break are not directly linked to the audience retention ability of the ad. Our research demonstrates the value of this critical aspect of the ad to the TV network's revenue and offers insights on sequencing and pricing of ads. In particular, the TV network could penalize ads with lower audience retention rates, either by assigning them to less favorable locations within a commercial break or by raising their prices. Our first simulation study offers insights for the sequencing decision by showing the revenue gain of the TV network when arranging ads in descending order of their (predicted) audience retention rates (i.e., in the "best condition"). For the pricing decision, the TV network could adopt an approach similar to that demonstrated in our first simulation study to predict audience retention rates of ads and charge advertisers accordingly. The same logic for pricing and sequencing applies to other advertising platforms as well.

This study is conducted based on 2005 TV advertising data from Hong Kong, during which time only two main channels were available on the market, with one channel clearly dominating the other. The zapping-induced externality problem is particularly serious in this highly concentrated market where advertisers have limited outlets to choose from, especially for advertisers with high-audience-rate ads and/or high willingness to pay. There have been entries and exits of TV networks in the Hong Kong market since 2005, decreasing its concentration as the number of main competing TV channels grows to three and new advertising platforms (such as Internet and mobile devices) emerge. Meanwhile, the traditional TV remains the most popular advertising platform in Hong Kong.[4] When the advertising market is less concentrated, advertisers may easily switch to other platforms with less audience externality or lower prices. In such a case, the impact of externality on the TV network's revenue could be even more severe due to advertiser loss. Hence, we believe the importance of the research question and findings of this article are highly relevant in today's market for TV networks that aim to increase efficiency in pricing and sequencing of ads, as well as their attractiveness as an ad outlet.

Limitations and Future Research

One limitation of our data is that the consumer TV viewing behavior is observed at the minute level rather than the ad level, rendering zapping behavior within a minute undetectable. Although we developed a model to match minute-level observations to ad-level predictions to address this data problem, using ad-level observations would definitely enhance efficiency. Also, we find that ad creative tactics, such as whether the ad is narrative or comparative, are linked to consumers' zapping decision. It would be valuable to test causal impacts of such ad creative variables on consumer zapping and ad effectiveness in future research.

Our findings also suggest that ads in earlier pods are less likely to be zapped. However, the current research focuses only on ad sequence within a commercial break. Future research on ad placement across commercial breaks and its economic implications for the TV network and advertisers would be interesting and valuable.

Notes

1. https://www.edgepicture.com/audience-retention-rate-vs-video-length/
2. Due to the space limitation, full estimation results are available upon request.
3. We also try to specify prior individual segment membership as a function of demographic variables of gender, sex, and occupation (as did Gupta and Chintagunta 1994), but we find that these are not statistically significant. This finding is consistent with that of Siddarth and Chattopadhyay (1998).
4. https://www.statista.com/statistics/1124908/hong-kong-share-of-ad-spending-by-medium/

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