The Value of Sampling: The Case of TV Commercial Breaks

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Abstract: The Value of Sampling

This is a first draft. Comments are welcome.

This paper investigates consumer welfare implication of commercial breaks during television programmings. The conventional wisdom dictates that consumers prefer watching television without the disruption of commercial breaks. However, we argue that commercial breaks may improve the welfare of consumers under certain conditions. In particular, when there is uncertainty in television programmings such that a consumer is unclear about the exact utility levels of different channels, she has to engage in costly search to resolve the uncertainty before choosing a channel to watch. The commercial breaks lower the opportunity cost of search, allowing the consumer to sample alternative channels without (further) interrupting the viewing experience on her current channel. Starting January 1, 2012, Chinese government banned all in-show commercial breaks for episode-based TV series with the intention of improving the TV viewing experience of consumers. Using data from this natural experiment period in Chinese TV market, we estimate a sequential search model to evaluate our conjecture. Especially, this new policy of banning commercial breaks created exogenous variations in the data that allow us to separately identify heterogenous consumer preference and search cost. Based on the analyses, we have found evidence that the intended improvement in TV viewing experience was limited. Many consumers were worse off due to the ban on commercial breaks because they could no longer sample alternative channels that were more preferable than their current choices.
1 Introduction

TV is still the dominant media channel for advertising. As of 2013, TV commercials account for 40% of global advertising spendings and will remain as one of the most significant advertising channels in the foreseeable future.¹ The conventional wisdom is that viewers prefer to watch TV programs without disruptions. The disruptions caused by TV commercials are commonly considered to diminish the welfare of consumers, resulting in less satisfactory viewing experience. Indeed, in the past decade, we witnessed considerable investment and development on ad-avoidance technology such as DVR devices that allows viewers to skip commercials.

Our paper, on the other hand, proposes that the presence of TV commercial breaks does not necessarily lower the welfare of viewers when they are uncertain about which shows are the most preferable. Under certain circumstance, it may actually enhance consumer viewing experience. TV programmings change over time. Correspondingly, the most preferable channel for a viewer varies from time to time. However, at any given point of time, the viewer has uncertainty pertaining to the programmings of alternative channels other than the one she is watching. To determine whether any alternative channels are superior to the viewer’s current one, it requires that the viewer sample alternative channels so as to resolve the uncertainty. Such samplings are costly, which can be attributed to the time and cognitive efforts spent during the samplings. Furthermore, it disrupts one’s viewing experience at the current channel if it is not already on a commercial break. Accordingly, people may refrain themselves from sampling during regular shows. In contrast, during a commercial break of the current channel, the sampling does not (further) disrupt one’s regular show viewing experience. Thus the commercial break naturally becomes an opportunity for the viewer to sample alternatives. Correspondingly, were the commercial breaks removed from all TV programmings, the viewer would be less likely to search alternative options and become locked in at her initial channel.

The net effect of commercial breaks on the welfare of viewers is ambiguous. The effect of commercial breaks may depend on the consumer’s (1) level of search cost for sampling alternative channels, (2) level of dislikeness towards commercial breaks, and (3) the programmings across channels. On the other hand, the answer to the question about the welfare implications of commercial breaks has important ramifications for TV networks, advertisers as well as policy makers. From the perspective of networks and advertisers, the welfare of viewers will ultimately affect the equilibrium amount and clearing price of commercials. From the perspective of policy makers, this will provide guidelines on the regulation of TV commercials and R&D on ad-avoidance technology.

By investigating consumer TV viewing behavior, we intend to investigate the welfare effect of commercials on consumers. Using detailed rating, program scheduling, and individual channel switching data from Chinese TV market, we calibrate an empirical model under the framework of classical economic search model, taking into account the effect of commercial breaks on viewing experience. Our data cover the period from December 11, 2011 to January 19, 2012. One unique feature of our data is that on January 1, 2012, Chinese government dramatically changed its regulation on the timing of commercial breaks for all episode-based TV series. Before January 1, 2012, TV channels could broadcast commercials between two shows (“between-show” commercials henceforth) or during a show (“in-show” commercials henceforth). Starting on January 1, 2012, however, the authorities banned all in-show commercial breaks for episode-based TV series nationwide with the intention of improving consumers’ viewing experience. This dramatic regulation change were announced on November 25, 2011, leaving TV networks and advertisers little time for strategic reactions of adjusting TV programmings.\(^2\) TV networks simply chose to move the in-show commercials into between-show slots and partially refund advertisers for their advance payments. Consequently, this exogenous regulation change creates a natural experiment that allows us to observe TV viewing behavior under both situations with and without in-show commercials.

More importantly, this new regulation generated exogenous data variations that underpin our empirical identification strategy.

Using our model, we are able to show that, for Chinese TV market, the effects of commercials vary across channels, depending on the then-current rating of a channel. Intuitively, suppose that a viewer is watching a channel that is broadcasting a low quality show. During commercial breaks, the viewer is more likely to sample alternative channels with higher ratings because the marginal gain of the search is high. Were the commercials removed altogether, the viewer would lose the opportunities of sampling and become stuck with the low quality channel. In contrast, if the viewer starts with a high rating channel, the marginal gain for sampling alternative channels is low even during commercial breaks. Hence the viewer is less likely to sample the alternatives anyway. Consequently, the removal of commercials has less impact on such a viewer’s viewing experience.

The contributions of this paper are threefold. First, we advance the empirical literature on consumer TV viewing behavior. We relax the assumption that viewers have full information about alternative channels. Since the seminal work by Lehmann (1971), there has been a growing body of studies exploring consumer TV show choices and switching decisions, such as Rust and Alpert (1984), Shachar and Emerson (2000), Goettler and Shachar (2001), Wilbur (2008), Yang et al. (2010). One common assumption in the literature is that viewers have little uncertainty about alternative options. A few exceptions are Moshkin and Shachar (2002), Byzalov and Shachar (2004) and Deng (2014). These papers assume that viewers have uncertainty about shows before watching. In particular, the first two papers explore the information role of TV commercials. They show that promotional ads for upcoming shows by the networks (“tune-in”) reduce the uncertainty and increase the likelihood of better matchings between viewers and shows. In our model, we explicitly consider viewers’ channel choices under the framework of a classical sequential search model. The consumer has to sample to know an alternative channel’s programming. The observed TV ratings are the outcome of a unified framework of viewers optimal search and utility maximization.
Second, we empirically measure the welfare effect of commercial breaks on viewers. While the conventional wisdom dictates that people have ad-aversion and dislike the disruptions caused by commercial breaks, some studies provide different perspectives. Advertisements can provide product information and enhance brand equity (e.g., Nelson (1970), Nelson (1974), Ackerberg (2001), Moshkin and Shachar (2002), Ackerberg (2003), Byzalov and Shachar (2004), Goeree (2008)). Advertisements may also work as a complement to the actual product consumption. As a result, the consumptions of ads and the product enhance the utilities of one another (e.g., Becker and Murphy, 1993; Tuchman et al., 2014). In consumer behavior literature, it has also been shown that commercials may provide viewers a break from the satiation of watching the show and hence enhance the overall viewing experience (e.g., Nelson et al., 2009). In our study, we explore another dimension of the benefit of commercial breaks. Commercial breaks provide a natural opportunity for viewers to explore alternative channels, resolve uncertainty, and hence potentially result in better matchings between shows and viewers. As a result, we are able to obtain managerial insights for policy makers, TV networks, and advertisers. Especially, we show that the removal of commercial breaks may not be universally beneficial for viewers.

Third, for classical empirical search models, because consumer preference and search cost are often confounded in field data, the identification of empirical search model is often problematic (e.g., Sorensen, 2000). The growing empirical literature on search models has paid considerable attention to addressing this identification concern (e.g, Hortacsu and Syverson (2004); Hong and Shum (2006); De los Santos et al. (2012); Honka (2012); Koulayev (2013); Chen and Yao (2014); Pinar and Seiler (2014)). In our data, as an exogenous shock, the regulation changed the distribution of preference independent of search cost, providing us with a convincing identification approach.

The paper is organized as the follows. We first discuss the data that underpin our study and provide some model-free evidence about viewer search activities. In Section 3, we detail the sequential search model that we use to describe viewing behavior. We discuss
the estimation strategy and identification in Section 4. Next, we present the results and counterfactual simulations to explore managerial implications. We conclude with a discussion of main findings and suggestions for future research.

2 Data

The data are provided by a leading media research company. For the reason of confidentiality, we cannot disclose the company’s identity. The company operates the world largest TV audience panel of TV viewers of China mainland and Hong Kong. Using diaries and set-top meters, the company is able to collect and construct TV ratings data that represent the viewing activities of about 370 million households in China mainland and 2.4 million households in Hong Kong.

On January 1, 2012, Chinese government banned all in-show commercials for episode-based TV series. We have access to 16 days of prime time data of Beijing TV market for this period of the regulation change. The 16 days are from Monday to Thursday during the weeks of December 11 and December 18 of 2011, and January 8 and January 15 of 2012. In the data, we observe the following components that are crucial for the understanding of consumer viewing behavior:

- The rating data of top 29 channels of 15-minute intervals during prime time from 7:30PM to 10PM. Following the industry standard, the rating of a channel for a given time period is defined as the percentage of viewers who have tuned to that channel during that period among the total number of viewers who own TV sets. In other words, the rating data reflect the market shares of the channels during each 15-minute interval, including the share of people who do not watch TV during that interval.

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3 Throughout the paper, we use viewer and household interchangeably.  
4 The choice of 15-minute intervals is related to Chinese government’s rule that a show must have at least 15-minute consecutive showing time before starting a commercial break, unless the show concludes before 15 minutes.
• Individual-level set-top box TV viewing data of 1022 viewers. These viewers are a representative random sample from the viewers used for calculating the channel ratings. For each viewer, we observe which channel she was watching (including not watching TV) on a second-by-second level from 7:30PM to 10PM.

• The programming data of each one of the 29 channels. We observe which programs were being broadcasted during each 15-minute interval, including episode-based TV series, sport events, reality shows, news, movies, etc. We also observe the percentages of in-show and between-show commercials during each interval.

2.1 TV Market Before and After the Ban

The ban on in-show commercials had profound effect on consumer viewing behavior and hence TV ratings.

First, the regulation inevitably affected the percentages of commercials. Table 1 documents the changes. In the table, while the large standard deviations of the statistics prevent us from reaching statistically meaningful conclusions, we may still observe some patterns from the table. The percentages of commercials dropped after the ban. Because between-show commercials increased across channels, the decrease in commercials was mainly caused by the decrease of in-show commercials. Especially for channels whose average ratings were in the middle range (Channel 11 to Channel 20), in-show commercials dropped more than 40%.

Table 2 shows the ratings before and after the regulation change. The rating after the commercial ban was not significantly improved. In fact, the average rating dropped slightly after the ban. However, an interesting pattern from Table 2 is that the rating of high rating channels (channel 1 to channel 10) dropped after the ban. In comparison, channels in the middle range (channel 11 to channel 20) had a slight increase in their ratings after January 1, 2012. There may be alternative factors contributing to this observed pattern. Also, with the large standard deviations, we cannot obtain any conclusive insights. However, one potential
Table 1: Descriptive Statistics: Average Commercial Percentages during 15-minute Intervals

<table>
<thead>
<tr>
<th>Channels Rating Rankings</th>
<th>Before the Ban</th>
<th>After the Ban</th>
</tr>
</thead>
<tbody>
<tr>
<td>In-show: Average (Std. Dev.)</td>
<td>Channel 1 to Channel 10</td>
<td>6.71 (11.44)</td>
</tr>
<tr>
<td></td>
<td>Channel 11 to Channel 20</td>
<td>8.43 (10.65)</td>
</tr>
<tr>
<td></td>
<td>Channel 21 to Channel 29</td>
<td>8.10 (10.42)</td>
</tr>
<tr>
<td>Between-show: Average (Std. Dev.)</td>
<td>Channel 1 to Channel 10</td>
<td>9.70 (16.78)</td>
</tr>
<tr>
<td></td>
<td>Channel 11 to Channel 20</td>
<td>12.18 (20.50)</td>
</tr>
<tr>
<td></td>
<td>Channel 21 to Channel 29</td>
<td>9.37 (17.03)</td>
</tr>
<tr>
<td>In-show Commercials</td>
<td></td>
<td>7.74</td>
</tr>
<tr>
<td>Between-show Commercials</td>
<td></td>
<td>10.42</td>
</tr>
<tr>
<td>Average of All Commercials</td>
<td></td>
<td>9.08</td>
</tr>
</tbody>
</table>

explanation is that this is consistent with the consumer search conjecture we proposed above. For medium rating channels (channel 11 to channel 20), they might still attract reasonable amount of viewers. Before the ban, people would be more likely to switch to higher ranked channels (channel 1 to channel 10). After the ban, however, people would be more likely to stay with their original channels. This would result in the increase in ratings for medium ranking channels and the decrease in ratings for high ranking channels.

Table 2: Descriptive Statistics: Average Ratings during 15-minute Intervals

<table>
<thead>
<tr>
<th></th>
<th>Before the Ban (S.D.)</th>
<th>After the Ban (S.D.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall</td>
<td>0.83 (1.53)</td>
<td>0.77 (1.05)</td>
</tr>
<tr>
<td>By Show Types</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TV Series</td>
<td>0.98 (2.11)</td>
<td>1.10 (1.55)</td>
</tr>
<tr>
<td>Others Shows</td>
<td>0.80 (1.37)</td>
<td>0.71 (0.86)</td>
</tr>
<tr>
<td>By Channel Rating Ranking</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Channel 1 to Channel 10</td>
<td>1.62 (2.34)</td>
<td>1.39 (1.51)</td>
</tr>
<tr>
<td>Channel 11 to Channel 20</td>
<td>0.55 (0.47)</td>
<td>0.63 (0.48)</td>
</tr>
<tr>
<td>Channel 21 to Channel 29</td>
<td>0.28 (0.28)</td>
<td>0.29 (0.26)</td>
</tr>
</tbody>
</table>

Viewers’ searching behavior also changed after the regulation. In the individual-level data, we observe a viewer’s second-by-second viewing activities. We first define “searching a channel” as that a viewer stays at a given channel for at least 30 seconds so as to explore the
programming at that channel.\textsuperscript{5} We also define “channel chosen” during an interval as the
channel that (1) is watched for more than 30 seconds, and (2) is watched the longest.\textsuperscript{6} We
calibrate the average number of channel searches during a 15-minute interval across viewers.
Table 3 shows the number of searches before and after the regulation. We find the average
of searches decreased after the ban of in-show commercials. The ban had a bigger impact for
those intervals with episode-based TV shows, which is not surprising because the regulation
only applied to such shows. Furthermore, the regulation also has a greater impact on those
channels with low and median ratings. While there may be alternative explanations and
the effects are statistically insignificant, the average effects are again consistent with our
conjecture, i.e., people on low rating channels were stuck with low quality programmings.
Next, we provide some additional evidence for consumer search.

Table 3: Descriptive Statistics: Search Activities during 15-minute Intervals

<table>
<thead>
<tr>
<th></th>
<th>Before the Ban (S.D.)</th>
<th>After the Ban (S.D.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Number of Searches</td>
<td>3.33 (1.64)</td>
<td>2.66 (1.65)</td>
</tr>
<tr>
<td>Average Number of Searches By Show Types</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TV Series</td>
<td>2.98 (1.11)</td>
<td>2.08 (1.32)</td>
</tr>
<tr>
<td>Others Shows</td>
<td>3.56 (1.88)</td>
<td>3.62 (1.22)</td>
</tr>
<tr>
<td>Average Number of Searches By Rating Ranking</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Channel 1 to Channel 10</td>
<td>2.51 (1.98)</td>
<td>2.32 (1.62)</td>
</tr>
<tr>
<td>Channel 11 to Channel 20</td>
<td>3.47 (1.47)</td>
<td>2.87 (1.82)</td>
</tr>
<tr>
<td>Channel 21 to Channel 29</td>
<td>3.69 (2.19)</td>
<td>3.05 (1.11)</td>
</tr>
</tbody>
</table>

\textsuperscript{5}We also considered alternative intervals for the definition, including 15 seconds, 20 seconds, and 1 minute. The insights stay unchanged.

\textsuperscript{6}Under this definition, the channel watched the longest may not be the one watched the last during a 15-minute interval. In such cases, we choose to drop those channels after the “watched/chosen” channel. Conceptually, this implies that the viewer makes another round of search process during this interval after she has finished one search process and decided on a channel. We only consider the first round of search process in the model and estimation.
2.2 Evidence of Consumer Search

In this section we further consider evidence from data to show that (1) viewers search for alternative channels during commercial breaks, and (2) among the searched channels, they choose the options with the highest utility levels.

2.2.1 Evidence from Aggregate Rating Data

The first evidence is predicated upon the notion that when there is a commercial break on a channel, the viewer switches to alternative channels. After the commercial break, the viewer should switch back to the original channel if the original channel had the highest utility level before the commercial break. On the other hand, if the viewer does not go back to the original channel, it implies that some alternative channel has a higher utility level. However, if the viewer has full knowledge about the higher utility of the alternative channel, as a rational agent, she should have watched that channel even before the commercial break. Empirically, if we observe post-commercial ratings of a channel are on average lower than its pre-commercial levels, it is consistent with our viewer searching conjecture. Accordingly, we consider a linear regression of ratings on commercial percentages and lagged commercial percentages, after controlling other factors. Table 4 presents the results (only showing coefficients regarding commercials). We can see that the lagged commercial percentage has a significant negative effect on ratings, which is consistent with our conjecture.

<table>
<thead>
<tr>
<th></th>
<th>Estimates (S.E.)</th>
<th>Estimates (S.E.)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Without Lagged Commercials</td>
<td>With Lagged Commercials</td>
</tr>
<tr>
<td>Constant</td>
<td>3.32(0.14)</td>
<td>3.60(0.16)</td>
</tr>
<tr>
<td>Commercial Percentage</td>
<td>-0.03(0.005)</td>
<td>-0.03(0.005)</td>
</tr>
<tr>
<td>Lagged Commercial Percentage</td>
<td>-</td>
<td>-0.02(0.005)</td>
</tr>
<tr>
<td>Number of Obs.</td>
<td>4640</td>
<td>4640</td>
</tr>
<tr>
<td>Adjusted-$R^2$</td>
<td>30.88</td>
<td>39.15</td>
</tr>
</tbody>
</table>
An alternative explanation for the observed data pattern, however, is viewer inertia. After the commercial break ends at the original channel, viewers who do not return might be lazy or forget to switch back. As a robustness check, we divide the channels into two groups: The ones with lagged ratings higher than the then-current median ratings and those with lagged ratings lower than the median. We then re-estimate the linear regression model above. Intuitively, if inertia is the reason for ratings not returning to the pre-commercial levels, the coefficients of the lagged commercial percentage should be similar across the two groups of channels. In comparison, if viewer search is the main reason, we should see the coefficient of the higher rating channels has a smaller (absolute) value than the lower rating channels. This is because viewers who are watching lower rating channels will be more likely to search, find better channels, and not switch back to the originals. Table 5 presents the results. Being consistent with the explanation of viewer search, lagged commercial percentage has a greater impact for low-rating channels. In fact, the effect of lagged commercial percentage has become insignificant for high-rating channels.

Table 5: Searching vs. Inertia

<table>
<thead>
<tr>
<th></th>
<th>Estimates (S.E.)</th>
<th>Estimates (S.E.)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Higher Rating Channels</td>
<td>Lower Rating Channels</td>
</tr>
<tr>
<td>Constant</td>
<td>4.70(0.22)</td>
<td>1.03(0.03)</td>
</tr>
<tr>
<td>Commercial Percentage</td>
<td>-0.04(0.007)</td>
<td>-0.02(0.008)</td>
</tr>
<tr>
<td>Lagged Commercial Percentage</td>
<td>-0.001(0.007)</td>
<td>-0.01(0.003)</td>
</tr>
<tr>
<td>Number of Obs.</td>
<td>2320</td>
<td>2320</td>
</tr>
<tr>
<td>Adjusted-$R^2$</td>
<td>38.41</td>
<td>42.19</td>
</tr>
</tbody>
</table>

2.2.2 Evidence from Disaggregate Rating Data

We have access to 1022 viewers’ TV viewing data up to second-by-second level. We consider some model free evidence for viewers’ searching activities using these individual-level data.

We track each viewer’s activities for 8 minutes after her channel starts to show an in-show commercial. During the 8 minutes, for each individual viewer, her original channel is indexed as “1”. The second channel that she stays for more than 30-second is indexed as “2”;
the third channel is indexed as “3”, and so on. We plot each viewer’s channel switching or staying on the 30-second intervals during the 8 minutes. Figure 1 demonstrate viewers’ search activities. To clearly show the switching patterns, we apply a non-parametric local regression at individual level and then add the local smoothing line to each individual. The median length of in-show commercial break is 2 minutes. If the viewer has the most preferable show before the commercial break, after the commercial break ends in about 2 minutes, we should see that the “rational” viewer returns to her original channel, “1”. However, from the Figure we can see that many viewers do not return to channel “1” during the 8-minute interval and instead stay at one of the alternatives that they have searched.

To further elaborate upon these insights arising from Figure 1, we consider how search activities differ depending on the ratings of the original channels. Using the then-current median ratings across channels as the cut-off levels, we further divide the viewers into two groups, (1) those whose original channels having ratings higher than median ratings, and (2) those whose original channels having ratings lower than median ratings. Figure 2 shows the comparison between the two groups. When the ratings of the original channels are high, viewers on average search less. Many stay at or return to the original channels. In contrast, when the original channels have lower ratings, viewers search more intensively. Overall, we conclude that there exists some model free evidence of search behavior in the data.

Figure 1: Consumers Search Activities: Overall
3 Model

3.1 Utility

During period $t$, there are $J + 1$ alternative options available to consumer $i$, watching one of the $J$ TV channels ($j = 1, 2, ..., J$) or choosing the outside option, not watching TV ($j = 0$).

Suppose the consumer is watching channel $j$ ($j = 1, 2, ..., J$) at the beginning of period $t$. The utility of the viewer for continuing watching channel $j$ during period $t$ is

$$ u_{ijt} = y_{ijt} \epsilon_{ij} + \beta_{InShowAd} InShowAd_{ijt} + \beta_{BtwShowAd} BtwShowAd_{ijt} + \beta_{SameShow} SameShow_{ijt} $$

(1)
where $\gamma_{jt}$ is a vector of dummy terms, including fixed effects of shows, channels, and weekdays. $\iota_i$ is the vector of the coefficients for $\gamma_{jt}$. $\varepsilon_{ijt}$ is some idiosyncratic preference shock. $InShowAd_{jt}$ and $BtwShowAd_{jt}$ are in-show commercial percentage and between-show commercial percentage for the duration of period $t$. Commercials affect one’s viewing experience and $\beta^InShowAd_i$ and $\beta^BtwShowAd_i$ accounts for such effects for in-show commercials and between-show commercials, respectively. Further, people often demonstrate strong state-dependency in TV viewing behavior (Byzalov and Shachar (2004)), especially if the programming is the continuity of the same show. We define $SameShow_{jt}$ as a dummy variable, taking the value of 1 if channel $j$ is broadcasting the same show as previous period and during period $t$. Accordingly, the coefficient $\beta^SameShow_{ij}$ captures consumers’ preference for continuing watching the same show, if any.

For channel $k$ that the viewer is not currently watching, the utility of watching is specified as

$$u_{ikt} = \gamma_{kt}t_i + \varepsilon_{ikt}$$

$$+ \beta^InShowAd_i InShowAd_{kt}$$

$$+ \beta^BtwShowAd_i BtwShowAd_{kt}$$

$$+ \beta^SameShow_{ik} SameShow_{kt}$$

The covariates are defined similarly to those of the current channel (Equation 1). However, for these alternative channels, the interpretation of coefficients $\beta^SameShow_{ik}$ is different from $\beta^SameShow_{ij}$ in Equation 1. $\beta^SameShow_{ik}$ is measuring the “missing-the-start-of-the-show” effect, i.e., the consumer may enjoy a show in its entirety rather than missing the beginning of the show.
For identification purpose, we normalize the mean utility level of the outside option, not watching TV, to the average 15-minute wage of Beijing in 2012, which is 8RMB.

\[ u_{i0t} = 8 + \varepsilon_{i0t} \]

The preference shocks \( \{\varepsilon_{ijt}\}_{j>0} \) and \( \varepsilon_{i0t} \) are assumed to be i.i.d, following standard normal distribution.

### 3.2 Uncertainty and Search Cost

Suppose that the consumer starts period \( t \) with channel \( j \). We assume that the viewer knows the exact utility level of option \( j \). This implies that the consumer knows the levels of covariates of channel \( j \) during period \( t \) as well as the preference shock \( \varepsilon_{ijt} \). We also assume that the viewer always knows the level of the outside option \( \varepsilon_{i0t} \), independent whether she chose the outside option in the previous period \( t - 1 \).

For other options, however, the viewer is uncertain about their utility levels. The viewer knows her sensitivity for each component in TV programming (i.e., the coefficients in her utility function). The uncertainty is a result of the uncertainty about the preference shocks \( \{\varepsilon_{i,t}\} \) and the programmings. Before exploring a channel, the consumer only knows the distributions of the shock and the programming. However, the consumer has to engage in costly search by sampling a channel so as to know the exact levels of those components and hence her utility level for that channel.

There is a search cost \( Cost_i \) for each channel searched, which can be interpreted as the cognitive cost incurred due to time and efforts spent on evaluating the channel.

### 3.3 Consumer Decisions

The decisions that a consumer needs to make at the beginning of period \( t \) include: (1) whether and how to search alternative channels; (2) given the channels searched and the
outside option, which option to choose during period \( t \). The optimal rule for the second decision is straightforward – the consumer should choose the option that has the highest utility. We focus our discussion on the first decision.

Denote the consumer’s belief about the utility distribution of an unsearched option \( k \) as \( F(u_{ikt}) \), which depends on the distributions of the preference shocks and the programmings. Let \( u_{i}^{*} \) be the highest utility among the then-current already searched options. The expected marginal gain for searching option \( k \) is (Weitzman, 1979):

\[
\int_{u_{i}^{*}}^{\infty} (u_{ikt} - u_{i}^{*})dF(u_{ikt})
\]

The optimal decision rule of the consumer is to continue searching as long as the search cost is lower than the marginal gain, i.e.,

\[
\int_{u_{i}^{*}}^{\infty} (u_{ikt} - u_{i}^{*})dF(u_{ikt}) - Cost_{i} \geq 0
\]  

Furthermore, if there are multiple candidate channels that have positive net expected return, the consumer should search the one with the highest level.

### 3.4 Heterogeneity

Denote the model parameters to be estimated as vector

\[
\Theta_{i} = [\nu_{t}, \beta_{i}^{InShowAd}, \beta_{i}^{BtwShowAd}, \beta_{ij}^{SameShow}, \beta_{ik}^{SameShow}, Cost_{i}]'.
\]

Further define

\[
\Theta_{i} = \Theta + \Sigma_{i}\sigma,
\]

\[
\Theta = [\nu', \beta^{InShowAd}, \beta^{BtwShowAd}, \beta_{j}^{SameShow}, \beta_{k}^{SameShow}, Cost]'
\]
where $\Theta$ is the vector of the means of parameters; $\Sigma_i$ is a $m \times m$ diagonal matrix that captures unobserved heterogeneity ($m$ is the dimension of $\Omega$). The diagonal elements of $\Sigma_i$ follow independent standard normal distributions. $\sigma$ is a $m$-vector that measures the relative magnitude of unobserved heterogeneity. Together, $\Sigma_i \sigma$ account for the heterogeneity distribution across viewers in the market. The model coefficients to be estimated are

$$\Omega = [\Theta', \sigma']'$$

(6)

4 Estimation and Identification

4.1 Estimation

To start the estimation, for unsearched channels, we assume that the consumer knows the distribution of the preference shocks ($\varepsilon_{i,t}$) and the distribution of the components of TV program samplings. This assumption is consistent with Chinese TV market where (1) program schedules are fairly stable and well-publicized in advance, (2) the frequency, duration, and scheduling of commercials are stable and strictly regulated by the government.

The estimation is implemented with the following two criteria:

1. At the aggregate level, we need to minimize the difference between observed ratings and simulated ratings based on the search model detailed above.

2. At the disaggregate level, we need to minimize the difference between observed activities and simulated activities of channel switching and search based on the search model detailed above.

To be specific, we simulate the channel ratings of period $t$ as the following:

1. Draw $R = 3000$ individual pseudo-viewers and allocate them to the channels and outside option according to the ratings at the beginning of each period observed in the data (i.e., market shares of channels at the beginning of a given period).
2. For a given individual, draw the heterogeneity components $\Sigma_i$ from independent standard normal distributions.

3. Determine the individual’s initial utility level at the beginning of period $t$.

   (a) If the individual had the outside option in the previous period, draw $\varepsilon_{i0t}$ from standard normal distribution and use it as her then-current maximum utility $u^*$. 

   (b) If the individual was watching TV channel $j$ in the previous period, calculate the mean utility level using channel $j$’s attributes level in period $t$, her heterogeneity draws $\Sigma_i$ and a set of parameters $\Omega$. Further draw the preference shock $\varepsilon_{ijt}$ from standard normal distribution. The greater utility level between $u_{ijt}$ and $\varepsilon_{i0t}$ is the consumer’s then-current $u^*$.

4. Evaluate the net expected marginal gains of unsearched options, using Equation 3. In particular, because we assume that viewers only know the distributions of the programmings of alternative channels, the levels of the components are drawn from the observed empirical distributions.

5. If the maximum of the net expected marginal gain is positive, the consumer searches that option. Draw the preference shock for the just-searched option from standard normal distribution, evaluate the overall utility, and update $u^*$.

6. Repeat Step 4 and Step 5 until Equation 3 is no longer satisfied. Among the searched options, the option with the maximum utility $u^*$ is the final choice of period $t$.

7. Repeat Step 2 – Step 6 for every individual to determine their choices of period $t$.

From these seven steps, we are able to obtain:

1. The simulated ratings of channels in period $t$, which are the aggregated shares of the channels chosen across the $R = 3000$ individuals.
2. The simulated channel switching activities, namely for consumers who are watching channel \( j \) at the beginning of period \( t \), what is percentage of them choose to switch in period \( t \)?

3. The simulated average number of searches among consumers who are watching channel \( j \) at the beginning of period \( t \).

We use a minimum distance estimator to estimate the parameters. Define vectors \( G_r \), \( G_s \), and \( G_n \) as:

\[
G_r = [r_{jt} - \hat{r}_{jt} (\Omega)]_{\forall j, t} \\
G_s = [s_{jt} - \hat{s}_{jt} (\Omega)]_{\forall j, t} \\
G_n = [n_{jt} - \hat{n}_{jt} (\Omega)]_{\forall j, t}
\]

\[
G(\Omega) = \begin{bmatrix} G_r \\ G_s \\ G_n \end{bmatrix}
\]  

where \( \Omega \) are parameters defined in Equation 6. \( r_{jt} \) and \( \hat{r}_{jt} \) are the observed and simulated ratings of channel \( j \) in period \( t \), respectively. \( s_{jt} \) and \( \hat{s}_{jt} \) are the observed and simulated switching percentages of viewers who are watching channel \( j \) at the beginning of period \( t \), respectively. \( n_{jt} \) and \( \hat{n}_{jt} \) are the observed and simulated average numbers of searches for consumers who are watching \( j \) at the beginning of period \( t \). The estimator is constructed so as to minimize the distance between the observed and simulated measures of interest.

\[
\Omega^* = \arg \min_{\Omega} G'WG
\]

where \( W \) is the sample weighting matrix.\(^7\)

\(^7\)We use two iterations of the estimator to obtain the weighting matrix \( W \). We first start with an identity matrix and use Equation 9 to obtain the “first-iteration” estimates \( \hat{\Omega} \). With these estimates \( \hat{\Omega} \), we are able to calculate the estimated variance matrix of \( G(\hat{\Omega}) \) in Equation 8. The inverse of this variance matrix is then used in the second iteration as the weighting matrix to re-estimate the coefficients.
4.2 Identification

We now discuss the identification of the search model. We are particularly interested in what assumptions and data features are crucial for the identification of model parameters.

For the ease of exposition, we first define “reservation utility” $z_{ikt}$ as the cutoff utility level for searching channel $k$. That is, if the highest utility level among the already-searched options is $z_{ikt}$, the consumer is indifferent between searching $k$ or not, i.e.,

$$Cost_i = \int_{z_{ikt}}^{\infty} (u_{ikt} - z_{ikt})dF(u_{ikt})$$

Following classical search literature (e.g., Weitzman (1979)), it can be shown that the optimal search strategy (see Section 3.3) can be equivalently expressed using the reservation utility:

1. The consumer continues the search if there is any unsearched option having a reservation utility greater than the then-current maximum $u^*_i$,

2. If the search continues, the consumer should search the option with the highest reservation utility.

4.2.1 The Separation of Utility and Search Cost

Empirical search models face the challenge of identification because it is difficult to separate preference and search cost using field data (e.g., Sorensen, 2000). To give a heuristic example, suppose we observe that the consumer did not search in the data. Even with the normalized outside option and a known distribution for the preference shocks, it is unclear whether this is because the consumer has a high search cost or a low expectation about the alternatives. Formally, it is possible to vary both search cost $Cost_i$ and preference $u_{ikt}$ such that the implicit function in Equation 10 remains held. As a result, the observed ratings and switching patterns alone are not sufficient to separate preference from search cost.

To separate utility and search cost, we need exogenous variations in the data that affect either utility or search cost but not both. One example of such exogenous variations is
instrument or exclusion restriction variables. For example, it is reasonable to expect time-constrained consumers incur a higher search cost. Accordingly, Pinar and Seiler (2014) study consumers’ price search activities during grocery shopping trips. The authors use consumers’ walking speeds to instrument their search costs because more time-constrained consumers tend to walk faster on average. Similarly, in Chen and Yao (2014), when studying consumers hotel search and booking behavior, the authors use days-till-checkin-date as an exclusion variable to measure one’s time constraint.

In our current setting, however, we do not have such exclusion restrictions in the data. Fortunately, the government’s regulation on commercial breaks inevitably affects the programings and hence the utility of each channel. On the other hand, such a policy has little effect on consumers’ search cost, which is attributed to the time and efforts spent on evaluating a channel. Consequently, the policy change acts as an exogenous shock that helps to separate utility from search cost, making the identification feasible. In particular, consider the following two implicit functions based on Equation 10, with $F_{before}$ and $F_{after}$ standing for the utility distributions before and after the ban on commercial breaks, respectively.

\[
\begin{align*}
\text{Cost}_{i} &= \int_{z_{jt}}^{\infty} (u_{ijt} - z_{ijt})dF_{before}(u_{ijt}) \\
\text{Cost}_{i} &= \int_{z_{jt}}^{\infty} (u_{ijt} - z_{ijt})dF_{after}(u_{ijt}),
\end{align*}
\]

These two equations determine the search activities and ultimately the ratings of channels. Note that search cost $\text{Cost}_{i}$ stays stable before and after the commercial ban while $F_{before}$ and $F_{after}$ differ from each other. Accordingly, the observed changes before and after the commercial ban in (1) channel ratings, (2) switch patterns, and (3) the numbers of searches will be attributed to the programming changes and hence the utility changes.

In our data, we observe ratings, switch patterns, and numbers of searches across channels and time, and more importantly, before and after the policy change. We have also made the standard assumptions as in classical discrete choice models, including: (1) the preference
shocks follow a known distribution (standard normal distribution) (2) the heterogeneity in preference follow a normal distribution. Accordingly, conditional on search cost and preference can be separated as discussed above, if we considered search cost $Cost_i$ as if it is an additional component in one’s utility function, the mean and heterogeneity of the coefficients would be identified, in a similar fashion to classical discrete choice models with both aggregate and micro data (e.g., Berry et al., 2004).

5 Results

In this section we report the results of our model estimation along with a number of managerial implications.

5.1 Parameter Estimates

Table 6 reports the parameter estimates. Because we normalize the outside option of not watching TV to the average wage level of Beijing (8 RMB), we may consider 1 RMB as the numeraire and interpret the coefficients on a monetary scale. Considering the utility estimates first. We divide the 29 channels into two groups depending on whether a channel’s median rating over time is above or below the median rating of all channels across time. Both low rating channels and high rating channels have their baseline utility levels slightly higher than average wage (9.45 and 12.71, respectively). However, the difference is statistically insignificant. Commercial breaks reduce consumer utility levels. Especially, in-show commercials cause a higher drop in utility than between-show commercials. On the other hand, if the current channel continues the same show, it increases the utility level by 4.41. If the viewer misses the beginning of a show, it decreases her utility level by 1.34. These coefficients together imply that viewers prefer to watch a show without disruption and in its entirety.
In terms of search cost, the average is at a relatively low level (1.71). To put it in perspective, one minute of in-show and between-show commercials decrease one’s utility level by 2.53 and 1.56, respectively. For an average viewer, suppose that the current channel continues the same show and the viewer also misses the beginning of a show on an alternative channel. Other things equal, the low search cost implies that she may start searching the alternative if she expects it has 2.9 minute less in-show commercials or 4.8 minutes less between-show commercials than her current channel ($\frac{4.41 + 1.34 + 1.71}{2.53} = 2.9$ and $\frac{4.41 + 1.34 + 1.71}{1.56} = 4.8$).

Table 6: Estimates

<table>
<thead>
<tr>
<th>Utility</th>
<th>Estimates</th>
<th>95% CI</th>
<th>Heterogeneity</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low Rating Channels</td>
<td>9.45</td>
<td>(0.41, 16.56)</td>
<td>1.96</td>
<td>(0.44, 3.57)</td>
</tr>
<tr>
<td>High Rating Channels</td>
<td>12.71</td>
<td>(6.12, 17.68)</td>
<td>4.43</td>
<td>(4.32, 4.47)</td>
</tr>
<tr>
<td>In-show Commercial (minute)</td>
<td>-2.53</td>
<td>(-3.77, -0.84)</td>
<td>0.63</td>
<td>(0.10, 2.10)</td>
</tr>
<tr>
<td>Between-show Commercial (minute)</td>
<td>-1.56</td>
<td>(-4.29, -0.97)</td>
<td>1.35</td>
<td>(0.39, 2.34)</td>
</tr>
<tr>
<td>Current Channel Same Show</td>
<td>4.41</td>
<td>(3.80, 7.90)</td>
<td>1.22</td>
<td>(0.35, 1.99)</td>
</tr>
<tr>
<td>Alternative Channel Same Show</td>
<td>-1.34</td>
<td>(-3.43, -0.23)</td>
<td>1.49</td>
<td>(0.35, 3.24)</td>
</tr>
<tr>
<td>Episode-based TV Series</td>
<td>6.70</td>
<td>(0.76, 10.77)</td>
<td>2.84</td>
<td>(0.53, 3.97)</td>
</tr>
<tr>
<td>Sports Events</td>
<td>5.66</td>
<td>(2.55, 9.78)</td>
<td>2.17</td>
<td>(0.66, 3.41)</td>
</tr>
<tr>
<td>Medical and Health</td>
<td>2.52</td>
<td>(0.91, 5.84)</td>
<td>5.21</td>
<td>(3.66, 7.33)</td>
</tr>
<tr>
<td>News</td>
<td>-4.71</td>
<td>(-9.81, -1.76)</td>
<td>3.39</td>
<td>(0.52, 4.41)</td>
</tr>
<tr>
<td>Other Types of Shows</td>
<td>-0.96</td>
<td>(-1.23, 0.08)</td>
<td>3.18</td>
<td>(2.22, 5.25)</td>
</tr>
<tr>
<td>Monday</td>
<td>7.52</td>
<td>(-4.13, 10.90)</td>
<td>2.74</td>
<td>(0.59, 4.44)</td>
</tr>
<tr>
<td>Tuesday</td>
<td>2.88</td>
<td>(-5.72, 4.93)</td>
<td>1.76</td>
<td>(0.48, 3.02)</td>
</tr>
<tr>
<td>Wednesday</td>
<td>5.50</td>
<td>(-0.20, 8.68)</td>
<td>2.41</td>
<td>(0.66, 4.41)</td>
</tr>
<tr>
<td>Search Cost</td>
<td>1.71</td>
<td>(0.01, 5.15)</td>
<td>4.43</td>
<td>(4.32, 4.47)</td>
</tr>
</tbody>
</table>

*Note: TV show fixed effects are not displayed.

5.2 Model Fit

We conduct several tests to examine the fit of the model.

First, we consider the model’s ability for predicting channel ratings. We have 16 days of ratings data. There are 10 fifteen-minute intervals per day for 29 channels and the outside
option. In total we have 4800 observations (30 × 11 × 16). Out of these observations, we randomly reserve one interval per day as a hold-out sample, which contains 480 observations. Using the remaining 4320 observations, we re-estimate the model. For the hold-out sample, we then calculate the out-of-sample Mean Absolute Percentage Error (MAPE) of channel rating predictions. The MAPE has a value of 0.15. In comparison, we also estimated a classical discrete-choice demand model with aggregate market share data in the spirit of Berry (1994). In the discrete-choice demand model, we control the same set of covariates as in the search model. The MAPE deteriorates to the level of 0.21.

Next, we measure the model’s ability of predicting channel switching patterns. We use the same hold-out sample as above. For each group of “dummy” viewers who were watching channel \( j \) \( (j = 0, 1, \ldots, 29) \) in the previous period, we predict the percentages of viewers who will switch to alternative options. The out-of-sample MAPE is 0.19. We further consider a discrete-choice model (logit) where each “dummy” viewer has full-information of alternative channels and control the same set of covariates as in the search model. We then use the model to predict the percentages of switching in the holdout sample. We find that the MAPE of this discrete-choice model is 0.27.

Finally, we consider the prediction of average numbers of searches conditional on viewers’ lagged channels. Using the same holdout sample, the MAPE on the predicted numbers of searches is 0.17. Since full-information discrete-choice model by definition assume that the consumers consider all available products, there is no meaningful prediction on the numbers of searches.

Overall our model has a decent fit and more accurate than discrete-choice models that assume viewers have full information of alternative channels.
6 Policy Implications

6.1 Welfare Implications

Using the estimates from the model, we investigate the welfare effect of the commercial break regulation. To measure the welfare effect, we first use the two-week data of 2012 when the regulation came into place. From these data, we observe the programmings and the ratings of channels. Based on these information, we simulate the search activities and final channel choices of $R = 3000$ viewers. The net welfare level of a viewer is the utility level of her final channel choice minus the search costs incurred during her sampling process. The average welfare level of all viewers is measured by averaging the individual welfare levels across the viewers. Next, from the two-week data of 2011 when the regulation was not carried out, we use the same method to measure the average welfare level. The comparison between the two welfare measures shows that the average level increases by merely 0.2% after the ban of in-show commercials. Furthermore, there is a large variance of the welfare levels such that the improvement in welfare is statistically insignificant. The 95% confidence interval of the welfare improvement is (-6.6%, 5.4%).

To further explore the changes in welfare levels, for each period, we divide the viewers into two groups, those who start the period with high-rating channels and those start with low-rating channels. We then do the same welfare calculation as above. We find that for the low rating group, the viewers’ average welfare drops by 1.4% with a 95% confidence interval of (-7.3%, -0.7%). We further compute the mean utility level of the final choices before and after the in-show commercial regulation, we find that the mean utility level drops by 2.2%. At the same time, the average number of searches decreases from 3.53 to 3.03. In other words, although the viewers incur less search costs, the reduction in search costs is not sufficient to compensate the lower utility levels of their final channel choices, which ultimately leads to the decrease of the net welfare levels.
In comparison, for the high rating group, the viewers’ average welfare increases by 1.0% with a 95% confidence interval of (-0.004%, 6.0%). The average utility level of their final channel choices increases by 0.8%. And because the programmings of shows are relatively stable before and after the regulation, the utility change mainly comes from lowering the level of in-show commercials. The average number of searches decreases slightly from 2.77 to 2.72. To some extent, the improvement in the average welfare can be attributed more to the increase in the utility level than to the decrease in the search costs.

In conclusion, the welfare improvement of the commercial regulation is rather limited. In particular, it hurts those viewers who were on lower rating channels because they searched less for alternative channels with potentially higher utility levels.

6.2 Alternative Commercial Regulation

In light of the limited improvement of the current commercial regulation, we consider an alternative to the current policy. Based on our insight above, the in-show commercial ban benefits the viewers who were on high-rating channels. The limited improvement mainly comes from the reduction of in-show commercials. Also, because these viewers search less at the first place, it is unlikely that the search costs have a considerable impact. On the other hand, the removal of in-show commercials hurts viewers who are on low rating channels. One possible alternative to the current regulation is to allow the in-show commercials to be broadcasted but with shorter durations. In this scenario, the viewing experience may be improved because it still gives viewers at low rating channels a natural opportunity to search alternative channels.

We pull the commercial distribution from the two-week data of 2011 and cut the in-show commercials by 50%, in contrast to the “0%” level of the regulation. We then simulate viewers’ search activities and their final choices of channels. Compared to the 2011 level of commercials, for viewers who start with high rating channels, we find their average welfare increases by 0.6%, lower than “0%” in-show commercials case but the difference is statistically
indistinguishable. The utility levels of their final channel choices increase by 0.7% and their searches keep at the same level (2.77 vs. 2.76). For viewers who start with low rating channels, the average welfare level improves by 1.9%. The mean utility level of their final channel choices improves by 2.1%. The average number of searches stay roughly the same, 3.53 vs. 3.55. So the main reasons of the improvement are (1) the overall decrease of commercials in programings, and (2) the viewers still have the opportunities to explore alternative channels during commercial breaks.

The total welfare improvement is 1.2% with a 95% confidence interval of (0.4%, 2.5%). Accordingly, this alternative commercial regulation results in a significant welfare improvement across viewers without jeopardizing viewers who start with low rating programings.

7 Conclusions

TBD.
References


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