TV Channel Search and Welfare Implications of Commercial Breaks

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Abstract: TV Channel Search and Welfare Implications of Commercial Breaks

This paper investigates the implication of time lapses that interrupt product consumption. The preeminent examples of such time lapses are commercial breaks during television or radio programming. In the case of TV commercial breaks, for example, conventional wisdom dictates that consumers prefer watching TV shows without the disruption of commercial breaks. However, we argue that breaks may facilitate consumers searching for alternatives. In particular, when there is so much uncertainty that the consumer is unclear about the exact utility levels of different products, she has to engage in a costly search to resolve the uncertainty before choosing a product. In the context of TV programming, breaks lower the opportunity cost of search, allowing the consumer to sample alternative channels without further interrupting the viewing experience on her current channel. Using data from the Chinese TV market, we estimate a sequential search model to evaluate our conjecture. The data contain a quasi natural experiment: the Chinese government banned all in-show commercial breaks for episodic TV series on January 1, 2012. The data patterns support that viewers search alternatives during commercial breaks. More importantly, this new policy on commercial breaks created exogenous variations in the data that allow us to separately identify heterogeneous consumer preference and search cost. Based on the model estimates, we investigate how the timing of breaks affects TV channels' viewership, which offers managerial insights about how firms should strategically adjust the timing of breaks.
Keywords: Advertising, Television, Consumer Search, Demand Estimation

1 Introduction

TV is still the dominant media for advertising. As of 2013, TV commercials account for 40% of global advertising spendings and will remain one of the most significant advertising channels in the foreseeable future.[1] This paper investigates how TV viewers make channel switching decisions when they face uncertainty about organic programming of regular shows and commercials on alternative channels. Furthermore, we explore strategic decisions of TV channels on the timing of commercial breaks in response to viewers switching activity.

TV programming changes over time. As a result, the most preferable channel for a viewer varies as time goes by. However, at any given point in time, the viewer has uncertainty about the programming of alternative channels other than the one she is watching. To determine whether any alternative channels are superior to the current one, the viewer must search the alternatives to resolve the uncertainty. Such searches are costly due to the time and cognitive effort spent during the search. Furthermore, it disrupts one's viewing experience at the current channel. Accordingly, viewers may refrain from searching during the organic programming of regular shows. In contrast, conventional wisdom holds that viewers dislike commercials (e.g., Ellioit, 2004). And during a commercial break, the search does not further disrupt one's regular show-viewing experience. Thus the commercial break may be a natural opportunity for the viewer to search and switch to alternatives. Correspondingly, the timing of commercial breaks becomes a crucial strategic decision for TV channels because viewers channel switching activity bears crucial implications for advertising revenues.

To investigate consumer TV-viewing behavior when they face uncertainty, we calibrate an empirical model under the framework of the classical economic search model. We use detailed rating, program-scheduling, and individual channel-switching data from the Chinese TV market, 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 an exogenous policy shock that dramatically changed the distribution of

[1]"Taking the Pulse of China's Ad Spending," McKinsey Quarterly, June 2013.

commercial breaks in TV channels' programming. On January 1, 2012, the Chinese government abruptly changed its regulation of commercial breaks for all episodic TV series. Before January 1, 2012, TV channels could broadcast commercials (1) between two different shows, (2) between two episodes of the same show (both cases are labeled as "between-show" henceforth), (3) during a show or an episode (both cases are labeled as "in-show" henceforth). Starting on January 1, 2012, however, the authorities banned all in-show commercial breaks for episodic TV series nationwide with the intention of improving consumers' viewing experience. This dramatic regulatory change was announced on November 25, 2011, less than 40 days before it became effective.[2] This abrupt announcement left TV networks little time to strategically adjust their programming in response to this new rule, especially when commercial slots in China were normally sold several months in advance of the broadcasting. TV networks had to fully refund advertisers for their in-show commercial slot purchases or move some in-show commercials into between-show slots in conjunction with partial refund. Consequently, for the period of our observation window, this regulatory change created a quasi natural experiment that exogenously changed the distribution of commercial breaks in programming (both amounts and types) and allows us to observe TV viewing behavior under both before and after the change. More importantly, the exogenous data variations underpin our empirical identification strategy as we will discuss in Section 4.2.

Using our model, we are able to show that, for the Chinese TV market, the effects of commercials vary across channels. Suppose that a viewer is watching a channel that turns out to be of low utility to her. During commercial breaks, the viewer is more likely to search alternative channels with higher (expected) utility levels because the marginal gain of the search is high. When the commercials are removed altogether, the viewer will refrain from searching during the organic programming because the search leads to disruption of watching the current show. As a result, the viewer would become more likely to stuck with the current

[2] Regulation 66, the State Agency of Radio, Film and Television of the People's Republic of China, November 25, 2011 (in Chinese): http://www.gov.cn/flfg/2011-11/28/content_2005138.htm.

channel.[3] In contrast, if the viewer is watching a preferable channel, the marginal gain of searching alternative channels is low even during commercial breaks. Hence the viewer is less likely to search the alternatives anyway. Consequently, the removal of commercials has less impact on the viewing experience of such a viewer.

Based on such insights, we explore the implications of the timing of commercial breaks across TV channels. A TV channel may have the incentive to either coordinate (synchronize) its commercial breaks with other channels, or differentiate the timing from competing channels, depending on how viewers make their decisions. In our empirical application, we find that low-rated channels should try to synchronize their breaks with high-rated ones. Doing so lowers the expected return of searching alternatives during breaks, because other channels will also air commercials at the same time. Hence it will help to discourage viewers from switching channels during breaks. In contrast, a high-rated channel should try to differentiate the timing of its breaks from competing channels, especially those with lower ratings. With the differentiation, the high-rated channel may poach viewers from competing channels that are on commercial breaks, because it is not broadcasting commercials at the same time. Meanwhile, it loses less viewers to competitors during its own breaks.

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 programming. Especially, we propose that viewers' switching decision inherently depend on their uncertainty about organic programming and commercials of alternative channels. The seminal work of Lehmann (1971) has led to 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), and 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

[3] Under full information where the viewer knows all programming details of alternative channels, there would be no need to search and hence no search cost. The optimal choice for the viewer is to switch to the most preferred channel of that moment.

(2004), and Deng (2014). These papers assume that viewers have uncertainty about shows before watching. In particular, the first two papers explore the informational 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 must search to know exactly an alternative channel's programming. The observed TV ratings and channel-switching activities are the outcome of a unified framework of viewers' optimal search and utility maximization.

Second, the identification of empirical search models is often problematic, because consumer preference and search cost are confounded in field data (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, 2015; Pinna and Seiler, 2015). 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.

Third, with the second contribution of identifying the search model, we are able to advance the research on the timing decisions of breaks that interrupt product consumption. The timing of commercial breaks is an important strategic decision of TV channels and radio stations (e.g., Sweeting 2006, 2009; Wilbur et al., 2013). While our empirical context is the TV industry, our research also sheds light onto other scenarios where breaks have lower utility levels than the consumption utility of the focal product. For example, consumers may experience such breaks in the context of sequel introduction of video games (or mobile games) after they finish playing the early version but have to wait for the new version to be launched. On one hand, by synchronizing with competing firms on the breaks, a firm can prevent its own consumers from leaving during its breaks. On the other hand, by differentiating the timing, the firm can potentially poach consumers from competitors while they are on breaks. The trade-off depends on the characteristics of consumers in a specific market. With our empirical model, we are able to characterize consumer TV-viewing activities and hence offer managerial prescriptions for TV channels pertaining to their timing of commercial breaks.

The paper is organized as follows. We first discuss the data that underpin our study and provide some model-free evidence about viewer search activity. 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 explore policy implications in Sections 5 and 6. We conclude with a discussion of main findings in Section 7.

2 Data

The data are provided by a leading media research company, whose identity we cannot disclose for reasons of confidentiality. The company compiles data on the world's largest TV-viewing audience in mainland China and Hong Kong.[4] 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.

One unique feature of the data is that they cover the period of a quasi natural experiment. On January 1, 2012, the Chinese government banned all in-show commercials for episodic TV series. This swift policy change left the networks with little time to strategically change their programming in the short run. This is because, according to Chinese government regulation, any programming change by TV networks needs a prolonged review process by the government agency, which takes more than 50 days just for the initial round. Any appeal for an initial denial takes another 30 days.[5] Because of this long review process, and because neither TV networks nor advertisers were aware of the new policy in advance,

[4]Throughout the paper, we use "viewer" and "household" interchangeably. We do not explicitly consider group decisions within a household as discussed in Yang et al. (2010).

[5]Regulation 63, the State Agency of Radio, Film and Television of the People's Republic of China, May 14, 2010 (in Chinese): http://www.gov.cn/flfg/2010-05/20/content_1609751.htm

commercial slots had been sold several months before the regulatory change announcement.[6] Based on our discussion with multiple networks and advertisers, networks had to fully refund advertisers for their in-show slot purchases or move the commercials to between-show slots and issue partial refund. The distribution of commercials was changed by the plausible exogenous shock of the new policy, both in amounts and types. Consequently, we observe TV viewing behavior under different distributions of commercials. Meanwhile, at least for a short time window, there is minimal changes in TV organic programming of regular content due to the same long administrative review process of programming.

We focus on a short period of prime-time data from the Beijing TV market, 8 days before and 8 days after the policy change. Specifically, the data are from Monday to Thursday during the weeks of December 11 and December 18, 2011, and January 8 and January 15, 2012. In the data, we observe the following components that are crucial for our analyses of consumer-viewing behavior:

- Rating data from the top 29 channels of 1-minute intervals during prime time, from 7:30PM to 10PM. These 29 channels account for 80% Beijing TV market share. 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 out of all viewers who own TV sets. In other words, the rating data reflect the market shares of the channels during each 1-minute interval, including the share of people who do not watch TV.

[6] Another piece of evidence that networks and advertisers were unaware of the regulatory change beforehand comes from online keyword search volume. In Figure 4 in the Appendix, we depict the online search volume of the keyword "TV show commercials" (in Chinese) using "Google Trends Index" from January 1, 2011 to December 31, 2012. In November 2011, upon the announcement of the new policy, the search index reached its highest level (Google always normalizes the highest search volume to 100). However, before the announcement the index was consistently at a much lower level for months. Note that the index does not directly measure the knowledge networks and advertisers had about the new policy. However, if the networks and advertisers had any knowledge in advance, we would expect at least some information leakage would have led to increases in the online search of relevant keywords. Accordingly, the consistently low search volume before November 2011 supports the notion that networks and advertisers were unlikely to be aware of the policy change in advance. Baidu Search Index, a similar search index by the search engine Baidu, shows a similar pattern as Figure 4.

- Individual-level, set-top box TV-viewing data of 1,022 viewers. These viewers are a representative, random sample from the panel 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 from each channel. We observe which show was being broadcasted at a given channel during each 1-minute interval, including episodic TV series, sport events, reality shows, news, movies, etc. We also observe whether an interval is used for for in-show or between-show commercials.[7]

2.1 TV Market Before and After the Ban

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

First, the regulation inevitably affected the amount and types (in-show vs. between-show) of commercials during the total broadcasting time. Table 1 documents the changes. For each channel, we calculate the percentage of commercial break minutes during a given hour (i.e., 60 minutes). We report the distribution of the in-show and between-show commercial percentages across channels, episodic vs. non-episodic shows, and before vs. after the commercial ban.[8] While the large standard deviations of the statistics prevent us from reaching statistically meaningful conclusions, we may still observe some patterns. The percentages of in-show commercials dropped after the ban. Especially, in-show commercials for TV series dropped to 0 due to the ban. Between-show commercials increased slightly. This is consistent with our discussion with channel managers and advertisers, where some in-show commercials sold were shifted to between-show slots. We further evaluate the variation of the amount of commercials across channels within the same hour. The purpose of this calculation

[7] In the data, a minute is defined as a commercial break if it contains at least 30 seconds of commercials.

[8] In the Appendix, we also report the same set of statistics after further dividing channels into 3 tiers based on their October/November 2011 median ratings, i.e., high-rated, media-rated, and low-rated channels. The distributions across ratings tiers are similar to each other and to Table 1.

is to see whether different channels had considerable difference in commercial amounts. More precisely, for each types of commercials before and after the ban (episodic in-show/between-show, non-episodic in-show/between-show), we regress the amount of commercials on the day-hour fixed effects. We then compute the standard deviations of the residuals of these regressions. The standard deviations of the residuals are reported in Column (3) in Table 1, which can be viewed as the magnitude of variation of commercials across channels within the same hour. In comparison to the overall variation across both channels and hours reported in Column (2), we can see that the across-channel variation was much smaller, on average less than 1/3 magnitude of the overall variation. It implies that commercial amounts varied less across channels and most of the fluctuation came from the across-time variation.

Table 1: Descriptive Statistics: Percentages of Commercial Time among Total Broadcasting Time Across Channels and Hours

Commercial Percentage	Commercial Ban	Mean (1)	S.D. (2)	S.D. across Channels (3)	5th Perc. (4)	95th Perc. (5)	Max. (6)	Avg. Frequency (7)
TV Series In-show	Before the Ban	1.41	2.15	0.98	0	5.67	10.67	1
	After the Ban	0	0	0	0	0	0	0
TV Series Btw-show	Before the Ban	4.26	7.79	2.12	0	16.67	21.67	2
	After the Ban	4.95	8.24	2.27	0	23.33	35.00	2
Non-TV Series In-show	Before the Ban	4.25	5.97	1.61	0	18.33	23.33	2
	After the Ban	3.01	4.58	1.30	0	13.33	28.33	2
Non-TV Series Btw-show	Before the Ban	3.41	5.36	1.31	0	13.33	26.67	2
	After the Ban	3.03	4.56	1.15	0	11.67	21.67	2

Table 2 further shows the organic programming (non-commercial) ratings of 1-minute intervals before and after the regulatory change. After the commercial ban, the ratings were not significantly improved. In fact, the average rating across channels and intervals dropped slightly after the ban (first row of the Table, 0.77 vs. 0.65). TV series' ratings on average increased while non-TV series dropped, potentially due to the change in commercial amounts across the two types of shows.

One question of interest is whether ratings within a channel was relatively stable over time (i.e., some channels consistently had high ratings while others consistently had low ratings). To answer this question, we first compute the standard deviations of 1-minute ratings across both channels and intervals, before and after the commercial ban. The results are reported in the parentheses of the first row of Table 2. We then compute across-time rating variation within a channel. More specifically, we calculate the standard deviations of residuals from regressions of ratings onto channel fixed effects, before and after the ban. With channel fixed effects controlled, these standard deviations provide us with the assessment of the average rating fluctuation over time within each channel. The results are reported in the second row of Table 2. From the results, we can see that before the ban the majority of rating variation came from the difference across channels. Before the ban, the overall standard deviation was quite high, reaching the level of 1.48. The across-time variation within a given channel was only about 1/4 of that level (0.39/1.48=0.26). After the ban, the overall rating variation became smaller (0.87). The across-time variation (0.37) still accounted for less than half of the variation. In other words, the ratings of each channel was relatively stable over time compared to the variation across channels. Hence, we next consider the ratings within each rating tier of channels. We first collect the median rating of each channel during October and November 2011 (i.e., before the data window we use for estimation). We rank the channels from 1 to 29 based on the median ratings and then categorize them into three tiers: high-rated, median-rated, and low-rated channels (indexed as Channel 1 to Channel 10, Channel 11 to Channel 20, and Channel 21 to Channel 29). As shown in Table 2, there was a drop in the ratings of high-rated channels (channel 1 to channel 10) after the ban. In comparison, low-rated channels (channel 21 to channel 29) witnessed an 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 conclusive insights without a formal model. However, one potential explanation is that this pattern is consistent with the consumer search conjecture we proposed above. Low-rated channels might still attract a reasonable amount of viewers because sometimes they still broadcasted high-quality shows. Before the ban, however, people would be more likely to switch to higher-ranked channels during commercial breaks, especially if the utility of watching low-rated channels dropped at the time. After the ban, however, people would be more likely to stay with their original channels. This would result in the average ratings increase for low-ranking channels and the decrease for high-ranking channels.

Table 2: Descriptive Statistics: Ratings of Organic Programming of 1-minute Intervals

	Average Before the Ban (S.D.)	Average After the Ban (S.D.)
1-minute Ratings across Channels and Intervals	0.77 (1.48)	0.65 (0.87)
1-minute Ratings S.D. across Intervals (Within Channel Across-Time Variation)	0.39	0.37
By Show Types across Channels and Intervals		
TV Series 1-minute Ratings	1.06 (2.28)	1.24 (1.19)
Others Shows 1-minute Ratings	0.53 (0.50)	0.46 (0.54)
By Channel Rating Ranking across Channels and Intervals		
Channel 1 to 10 1-minute Ratings	1.48 (2.25)	1.03 (1.22)
Channel 11 to 20 1-minute Ratings	0.45 (0.42)	0.45 (0.36)
Channel 21 to 29 1-minute Ratings	0.28 (0.29)	0.41 (0.26)

Viewers' searching behavior also changed after the regulation. In the individual-level data, we observe a viewer's second-by-second activities. We first define "searching a channel" as staying at a given channel for at least 5 seconds so as to explore the programming at that channel.[9] We also define "channel chosen" during an interval as the channel that is (1) watched for more than 30 seconds, or (2) watched the longest.[10] We calibrate the average number of channels searched during a 1-minute interval across viewers and intervals. Table

[9] We also considered alternative intervals for the definition, including 3, 7, and 10 seconds. The insights stay unchanged.

[10] Under this definition, the channel watched the longest may not be the one watched last during an interval. In such cases, we choose to drop those channels after the "watched/chosen" channel. Conceptually, this implies that the viewer engages in a new search process during this interval after she has finished one search process and decided on a channel. We consider only the first round of the search process in the model and estimation.

3 shows the number of searches before and after the regulatory change. We find that the average number of searches across viewers and intervals decreased after the ban. The ban had a bigger impact for those intervals with episodic TV shows, which is not surprising because the regulation only applies to such shows. While there may be alternative explanations for the decrease in the number of searches and the effects are statistically insignificant, the average effects are again consistent with our conjecture, i.e., with less in-show commercial breaks for TV shows, viewers on average search less and hence are more likely stay with their original channels. Next, we provide some additional evidence for consumer search.

Table 3: Descriptive Statistics: Search Activities during 1-minute Intervals

	Average Before the Ban (S.D.)	Average After the Ban (S.D.)
Number of Searches in 1-minute across Viewers and Intervals	3.53 (1.94)	2.70 (1.41)
By Show Types		
Viewers who were watching TV Series	2.89 (1.94)	1.98 (0.90)
Viewers who were watching Others Shows	4.33 (2.46)	4.30 (2.23)
By Rating Ranking		
Viewers who were watching Channel 1 to 10	3.12 (1.99)	2.35 (2.03)
Viewers who were watching Channel 11 to 20	3.59 (2.32)	3.51 (2.21)
Viewers who were watching Channel 21 to 29	3.84 (2.13)	3.01 (1.97)

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 searched channels they choose the options with the highest utility levels.

2.2.1 Evidence from Aggregate Rating Data

The first piece of evidence is predicated upon the notion that the viewer switches to alternative channels when there is a commercial break on a channel. After the commercial break, the viewer should switch back to the original channel if it had the highest utility level before the break. If the viewer does not return to the original channel, we can infer 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 that post-commercial ratings of channels are on average lower than their pre-commercial levels, it is consistent with our conjecture about viewers' uncertainty of alternatives and searching and switching to better alternatives. Accordingly, we consider a linear regression of 1-minute ratings (in logarithm) on commercial dummy and lagged commercial dummy, after controlling for channel, hour, weekday, week, and show genre fixed effects. Column (1) and (2) in Table 4 present the results (showing only coefficients regarding commercials). We can see that commercial has a significant impact on ratings. More importantly, the lagged commercial also has a significant negative effect on ratings, which is consistent with our conjecture.

Table 4: Effect of Commercials and Lagged Commercials on Log Ratings

Dependent Variable: Log Rating	(1) Estimates (S.E.) Without Lagged Commercials	(2) Estimates (S.E.) With Lagged Commercials	(3) Estimates (S.E.) With Pre-commercial and Lagged Rating Inter.
Constant	**0.610 (0.048)**	**0.612 (0.048)**	**0.615 (0.048)**
Commercial Dummy	**-0.201 (0.046)**	**-0.103 (0.043)**	**-0.106 (0.047)**
Lagged Commercial Dummy	–	**-0.130 (0.013)**	-0.042 (0.034)
Lagged Commercial Dummy Inter. w/ Pre-commercial Rating	–	–	**-0.151 (0.042)**
Channel FEs	Yes	Yes	Yes
Hour FEs	Yes	Yes	Yes
Weekday FEs	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes
Show Genre FEs	Yes	Yes	Yes
Number of Obs.	69,600	69,136	68,672
Adjusted-R^2	0.68	0.69	0.69

An alternative explanation for the pattern above, 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 create a dummy of *pre-commercial* lagged rating. For a given channel during a given period, the dummy takes the value of 1 if the channel's pre-commercial rating is lower than the then-current median rating across all channels. We then re-estimate the linear regression model above but further interact the lagged rating dummy with the pre-commercial rating dummy. Intuitively, if inertia is the reason that ratings do not return to the pre-commercial levels, the coefficients of the interaction term between pre-commercial rating and lagged commercial should be similar across high-rated channels and low-rated ones. In comparison, if viewer search is the main reason, the channels with a lower pre-commercial rating should suffer a greater reduction in their rating after the commercial ends. This is because viewers who were watching channels with lower pre-commercial ratings will be more likely to search, find better channels, and not switch back to the originals. Column (3) in Table 4 presents the results. Consistent with the explanation of viewer search, the interaction term has a significant coefficient, implying greater impact on channels with low pre-commercial ratings. In fact, the effect of lagged commercial dummy has become insignificant, i.e., though people might still switch away during commercials, they switch back after the commercial ends if the channel had a high rating before the commercial break.

2.2.2 Evidence from Disaggregate Rating Data

We have access to 1,022 viewers TV watching data up to second-by-second level. We consider some model-free evidence in addition to those discussed above for viewers' searching activities using these individual-level data.

By government regulation, the in-show commercials of episodic TV shows during prime time can be no longer than 1 minute.[11] Accordingly, for TV shows before the ban, at each in-show commercial break, we track every viewer's channel switching activity for 5 seconds before, 1 minute during, and 30 seconds after the commercial break, in total 95 seconds. We divide the 95 seconds into 19 5-second intervals. The 1st 5-second starts right before the

[11] The National Bureau of Radio, Movie, and Television Regulation 61, http://www.sarft.gov.cn/art/2009/9/10/art_1583_26310.html (in Chinese).

in-show commercial break. The commercial break starts on the 2nd 5-second slot and ends at the 13th. We index the initial channel watched by each individual before the commercial break as "1", the 2nd channel watched for at least 5 seconds as "2", the 3rd channel as "3", and so on. By construction, at the first interval all individuals are on channel "1", i.e., their initial channels. Depending on a viewer initial channel's rating ranking at the time of the first interval (i.e., pre-commercial rating), we divide individuals into three groups, low-ranked, median-ranked, and high-ranked initial channels.[12]

In the 2nd interval, when the commercial starts, some viewers start to switch to other channels (channel "2"). People continue switching channels in the following intervals. We plot each viewer's activities in Figure 1, where the three subfigures correspond to low, median, and high-ranked initial channels. The horizontal axis stands for time intervals and the vertical axis represents searched channel indices. Correspondingly, each dot in the graph is the combination of a 5-second time slot and a channel index. To understand the figure, imagine that a viewer stays at the same channel throughout the 95 seconds. In this case, we should see her appearing on channel "1" for all time intervals. If the viewer starts on her initial channel and then switches to a second channel and stays there, we should see her appearing on channel "1" in interval 1 and then on "2" for the remaining time slots. Because there may be many viewers on each slot in the graph, to avoid over-plotting and clearly show the patterns in the data, we allow the points to jitter. Accordingly, if there are more individuals at a given spot in the graph, that spot will show a higher density of dots. To make the densities even more transparent, for each group (low, median, high-ranked initial channels), we also depict the percentage of individuals on each channel at a given time interval. For example, in the 2nd interval of the first subfigure, Channel "1" and "2" have percentage "54.8" and "45.2", respectively. It means that when the commercial starts on the

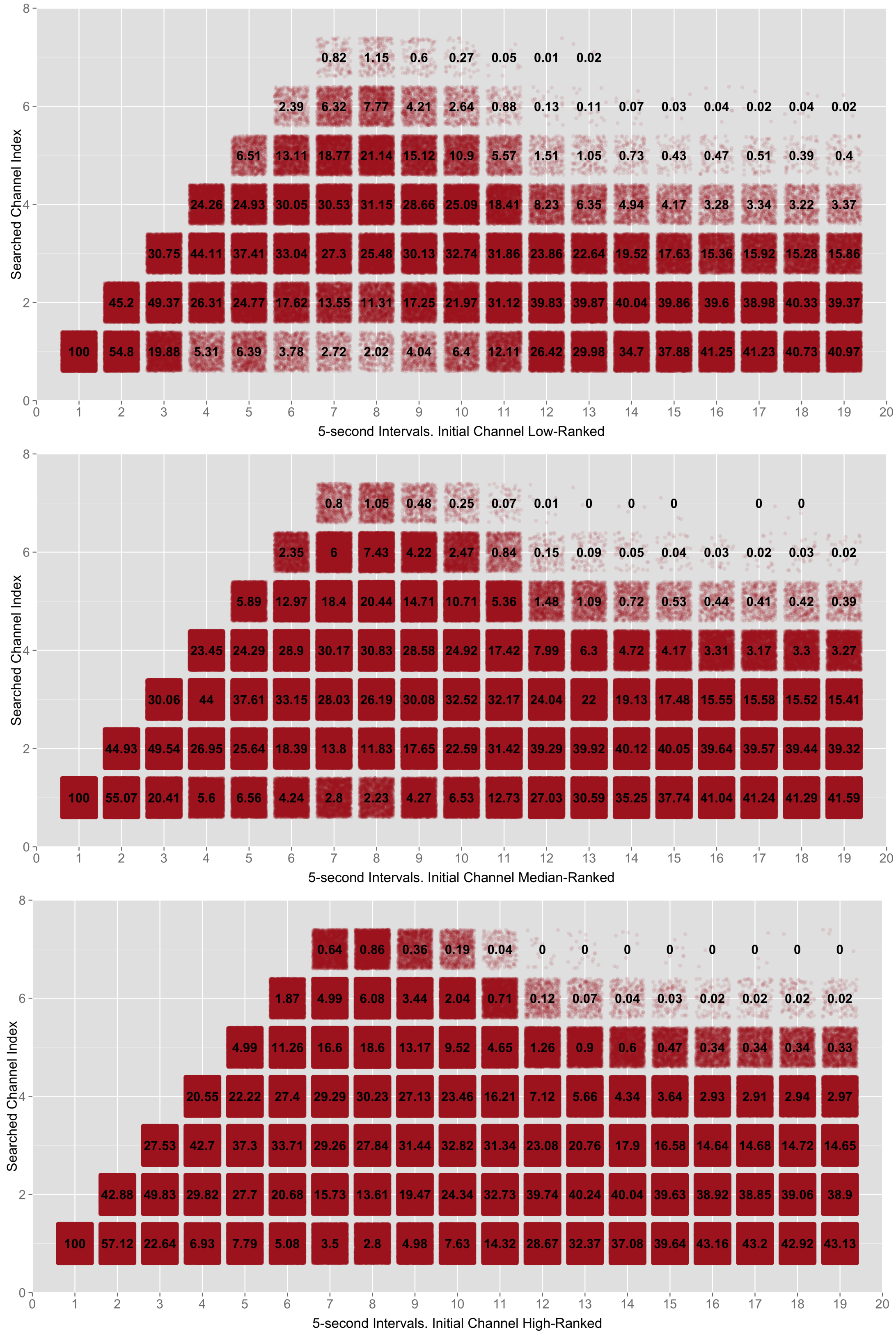
[12]In the Appendix, we further show a set of 29 figures where each represents a group of viewers whose initial channels are ranked at 1 to 29, respectively. The insights of the 29 figures are similar to the three subfigures depicted here.

2nd interval, 54.8% individuals stay at their initial channels and 45.2% switch to their second channels.

From these figures, we can see that when the commercial breaks start at the second interval, some stay at Channel "1" while many switch to Channel "2," i.e., some alternative to their originals. At the third 5-second interval, even fewer people stay at their original channels and some start to explore their third channels ("3"), and so on. The length of an in-show commercial break is 1 minute per the regulation. "Rational" viewers who had their most preferable shows before the commercial break should return to their original channels "1" when the commercial breaks end after about 1 minute (the 13th 5-second interval). However, as demonstrated by the dense plots and high percentages on Channel "2" and Channel "3" across all three subfigures, the majority of viewers do not return to channel "1" and instead stay at one of the alternatives they have searched during the commercial breaks.[13] The pattern in the figure is again consistent with the findings in the previous analyses. It implies that people take the opportunity of commercial breaks to exploring alternatives and the exploration may lead to more preferable options than their previous choices. Consequently, we see many people do not return to their original channel "1" but instead stay at some alternative channels. In conclusion, we find the data patterns discussed in this section are consistent with the model of consumer searching for better alternatives under uncertainty.

[13]The high-ranked initial channel group has a slightly higher percentage of viewers switching back to their initial channels. In contrast, the low-ranked initial channel group has a lower percentage switching back and more people staying at new channels.

Figure 1: Consumers Switching Activities for Episodic TV Shows Before the Commercial Ban



3 Model

3.1 Utility

During period t (defined as a minute), 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 ($j = 0$).

The utility of viewer i for watching channel j during period t is

$$\begin{aligned} u_{ijt} &= \gamma'_{jt}\iota_i + \nu_{jt} \\ &\quad + \beta_i^{InShowAd} InShowAd_{jt} \\ &\quad + \beta_i^{BtwShowAd} BtwShowAd_{jt} \\ &\quad + [\beta_i^{Continue} I_{ijt} + \beta_i^{NoStart}(1 - I_{ijt})] SameShow_{jt} \\ &\quad + \varepsilon_{ijt}, \end{aligned} \tag{1}$$

where γ_{jt} is a vector of dummy terms, including fixed effects of show genre, hour, weekday, and week.[14] ι_i is the vector of the coefficients for γ_{jt}. $\nu_{jt} \sim N(\nu_j, \sigma_\nu^2)$ is a channel-time specific intercept term, which follows a normal distribution, with the mean as ν_j and standard deviation as σ_ν. ν_{jt} can be viewed as the channel's "quality" at minute t that is common across individual viewers. Essentially, the mean ν_j can bee seen as a channel fixed effect term that measures the average "quality" level of the channel, which is common across viewers and time.[15] Each period, the realized "quality" may deviate from the mean ν_j and σ_ν captures the average magnitude of the deviation. Note that these intercept terms (ν_{jt}) are measured against the baseline of "Not Watching TV." $InShowAd_{jt}$ is the in-show commercial

[14] Because the policy change can only be considered a quasi natural experiment, we cannot exhaustively rule out other factors that happened at the same time and also affected viewing behavior. Accordingly, controlling the time-specific fixed effects (week) is crucial to mitigate such a concern. We also run the same model but further control day fixed effects and the results are similar. The identification assumption here is that the other factors affecting viewing behavior have the same effect across channels. Hence they may be captured by the time-specific fixed effects.

[15] Ideally we should also have show fixed effects. With the large amount of shows, however, estimating the show fixed effects is computationally infeasible.

dummy for period t, which takes the value of 1 if minute t is an in-show commercial break. Similarly, $BtwShowAd_{jt}$ is the dummy for between-show commercials. Commercials affect one's viewing experience and $\beta_i^{InShowAd}$ and $\beta_i^{BtwShowAd}$ accounts for such effects. 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 hence define $SameShow_{jt}$ as a dummy variable, taking the value of 1 if channel j is broadcasting the same show during period t as the previous period. And if period t is a commercial break, $SameShow_{jt}$ takes the value of 1 if the channel continues the same show when the break ends. We further introduce an indicator I_{ijt}, which takes the value of 1 if the viewer was watching channel j in the previous period or before the commercial break if the then-current period is commercial. Accordingly, under such a specification the coefficient $\beta_i^{Continue}$ captures consumers' preference for continuing to watch the same show, if any. In comparison, if the consumer did not watch channel j in period $t-1$, $\beta_i^{NoStart}$ measures the "missing-the-start-of-the-show" effect, i.e., the consumer may dislike starting from the middle of the show. ε_{ijt} is some idiosyncratic preference shocks which follows standard normal distribution.

There is also the outside option of not watching TV. For identification purpose, we normalize the mean utility level of the outside option to 0 and $\varepsilon_{i0t} \sim N(0,1)$:

$$u_{i0t} = \varepsilon_{i0t}. \tag{2}$$

3.2 Uncertainty and Search Cost

Let the preference shocks $\{\varepsilon_{i\cdot t}\}$ be i.i.d., following standard normal distribution. We assume that the viewer always knows ε_{i0t} of the outside option, no matter whether she chose the outside option in the previous period. Furthermore, if the consumer starts period t with Channel j, it is reasonable to assume that the viewer knows the exact level of ε_{ijt}, ν_{jt}, and all programming attributes of Channel j, including $InShowAd_{jt}$, $BtwShowAd_{jt}$, $SameShow_{jt}$, and the fixed effects of genre, hour, weekday, and week.

For channel $k \neq j$ that the viewer is not watching at the beginning of period t, we assume that the viewer knows the genre, hour, weekday, and week fixed effects.[16] However, before search, the viewer is uncertain about ε_{ikt}, ν_{kt}, and other attributes of the programming, including $InShowAd_{kt}$, $BtwShowAd_{kt}$, and $SameShow_{kt}$. Before exploring Channel k, the consumer only knows the distributions of these components. Especially, we assume that the consumer knows $\varepsilon_{ikt} \sim N(0,1)$, $\nu_{kt} \sim N(\nu_k, \sigma_\nu^2)$, and the joint distribution of programming attributes of $InShowAd_{kt}$, $BtwShowAd_{kt}$, and $SameShow_{kt}$. We use the observed tier-minute-specific (high, media, and low-rated channels) empirical distribution of the attributes as the joint distribution known to the viewer.[17] Because of the restrictive regulation on the amount of commercials and the prolonged review process for any schedule changes, the distribution is quite stable over time. Hence such an assumption is reasonable.[18]

After searching the channel in period t, the viewer becomes to know the exact levels of ε_{ikt}, ν_{kt}, and the programming attributes of $InShowAd_{kt}$, $BtwShowAd_{kt}$, and $SameShow_{kt}$ for the duration of period t.

To search a channel during a given period, however, is costly. 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.

[16] One implicit assumption here is that the viewer knows the show genre of Channel k at period t. We examine the schedules of the 29 channels. The genres of each hour during the prime time are quite stable over time. Also, the schedule of shows is publicized well in advance and any schedule changes takes more than 50 days for review by the government agency. Hence we consider this assumption is tenable.

[17] More precisely, for a given tier (high, median, low-rated tier based on October/November 2011's median ratings), we pool channels of the same tier. Then for a given minute (e.g., 8:00PM-8:01PM) before or after the ban, we compute the proportion of that minute to be an in-show commercial break, a between-show commercial break, and have the same show, out of all observations across channels and days. Ideally, we should evaluate the distributions as channel-specific. However, because we only have a short time window, the observations for one channel are too sparse to construct the distribution. This is a limitation of the data and, with a larger dataset, one should use the empirical distributions at a more granular level.

[18] In a context where the consumer does not know the attributes distribution, this model cannot be applied and we call for further research on the topic of consumer search and learning the distribution during the search.

3.3 Viewer Decisions

The decisions of a viewer include (1) whether and how to search alternative channels, and (2) after the search stops, 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 preference shocks $\{\varepsilon_{i\cdot t}\}$, $\{\nu_{\cdot t}\}$, and the programming attributes. As we assume that the viewer knows the distributions of $\{\varepsilon_{i\cdot t}\}$, $\{\nu_{\cdot t}\}$, and the programming attributes of $InShowAd_{kt}$, $BtwShowAd_{kt}$, and $SameShow_{kt}$ (see Section 3.2), the $F(u_{ikt})$ is known to the viewer.

Let u_i^* be the highest utility among the then-current options that have already been searched. 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 viewer is to continue searching as long as the expected marginal gain is greater than the search cost, i.e.,

$$\int_{u_i^*}^{\infty}(u_{ikt}-u_i^*)dF(u_{ikt})-Cost_i\geq 0. \tag{3}$$

Furthermore, if multiple candidate channels have positive net returns, the consumer should search the one with the highest level.

3.4 Heterogeneity

Denote the model parameters as Θ_i', $\{\nu_j\}_{\forall j}$, and σ_ν, where

$$\Theta_i = [\iota_i', \beta_i^{InShowAd}, \beta_i^{BtwShowAd}, \beta_i^{Continue}, \beta_i^{NoStart}, Cost_i]'.$$

In other words, viewers have common $\{\nu_j\}_{\forall j}$ and σ_ν but Θ_i vary across individuals.

Further define

$$\begin{aligned} \Theta_i &= \Theta + \Sigma_i \sigma, && (4) \\ \Theta &= [\iota', \beta^{InShowAd}, \beta^{BtwShowAd}, \beta^{Continue}, \beta^{NoStart}, Cost]' && (5) \end{aligned}$$

where Θ is the vector of the mean preference parameters of Θ_i; Σ_i is an $m \times m$ diagonal matrix that captures unobserved heterogeneity (m is the dimension of Θ). The diagonal elements of Σ_i follow independent standard normal distributions. σ is an m-vector that measures the relative magnitude of unobserved heterogeneity. Together, $\Sigma_i \sigma$ accounts for the heterogeneity distribution across viewers in the market. The model coefficients to be estimated are

$$\Omega = [\Theta', \sigma', \{\nu_j\}_{\forall j}, \sigma_\nu]'. \quad (6)$$

4 Estimation and Identification

4.1 Estimation

To re-iterate, for unsearched channels, we assume that the consumer knows the fixed effects, the distribution of $(\varepsilon_{i \cdot t})$, $\{\nu_\cdot\}$, σ_ν, and the distribution of TV programming ($InShowAd_{kt}$, $BtwShowAd_{kt}$, and $SameShow_{kt}$). This assumption is consistent with the Chinese TV market where (1) program schedules are fairly stable and well-publicized in advance, and (2) the frequency, duration, and scheduling of commercials are stable and strictly regulated by the government.

The estimation is implemented subjecting to the following two criteria:

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

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

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

1. Draw $R = 3,000$ 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 Σ_i from independent standard normal distributions.

3. For a given channel, draw the channel intercept shock ν_{jt} from $N(\nu_j, \sigma_\nu^2)$.

4. Determine the individual's utility level of the initial option at the beginning of period t.

   (a) If the individual had the outside option in the previous period, draw ε_{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 ν_{jt}, attributes level in period t, her heterogeneity draws Σ_i, and a set of parameters $[\Theta', \sigma']'$. Further draw the preference shock ε_{ijt} from standard normal distribution. The greater level between u_{ijt} and ε_{i0t} is the consumer's then-current u^*.

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

6. 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^*.

7. 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.

8. Repeat Step 3-7 100 times to integrate out the uncertainty of ν_{jt} and programming attributes.

9. Iterate through all pseudo-viewers to determine their choices of period t.

From these steps, we are able to obtain:

1. At the aggregate level, the simulated ratings of option j ($j = 0, 1, 2, ..., J$) in period t, i.e., the aggregated shares of the options chosen by the $R = 3,000$ individuals.

2. At the disaggregate level, among those whose initial choice is j ($j = 0, 1, 2, ..., J$) at the beginning of period t, the percentage of viewers who choose to switch during period t.

3. At the disaggregate level, the simulated average number of searches among those viewers who have the same initial choice j ($j = 0, 1, 2, ..., J$) 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:

$$G_r = [r_{jt} - \hat{r}_{jt}(\Omega)]_{\forall j,t} \tag{7}$$

$$
\begin{aligned}
G_s &= [s_{jt} - \hat{s}_{jt}(\Omega)]_{\forall j,t} \\
G_n &= [n_{jt} - \hat{n}_{jt}(\Omega)]_{\forall j,t} \\
G(\Omega) &= \begin{bmatrix} G_r \\ G_s \\ G_n \end{bmatrix}
\end{aligned} \tag{8}
$$

where Ω are parameters defined in Equation 6. r_{jt} and $\widehat{r}_{jt}$ are the observed and simulated ratings of channel j in period t, respectively. s_{jt} and $\widehat{s}_{jt}$ are the observed and simulated switching percentages of viewers whose initial choice is j at the beginning of period t, respectively. n_{jt} and $\widehat{n}_{jt}$ are the observed and simulated average numbers of searches for consumers whose initial choice is j at the beginning of period t. We construct the estimator so as to minimize the distance between the observed and simulated measures of interest:

$$
\Omega^* = \arg\min_{\Omega} G'WG \tag{9}
$$

where W is the sample weighting matrix.[19] The 95% confidence intervals of parameters are obtained using bootstrapping.

4.2 Identification: 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 normalization of the outside option and a known distribution for the preference shocks, it is unclear whether the "not searching" stems from the consumer's high search cost or a low expectation about the alternatives. Formally, it is possible to vary both search cost $Cost_i$

[19] We use two iterations of the estimator to obtain the weighting matrix W. We first start with an identity matrix as the weighting matrix and use Equation 9 to obtain the "first-iteration" estimates $\widehat{\Omega}$. With these estimates $\widehat{\Omega}$, we are able to calculate the estimated variance matrix of $G(\widehat{\Omega})$ 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.

and preference u_{ikt} such that the inequality in Equation 3 remains held, rendering the model being unidentified. As a result, the observed ratings (from aggregate data) and switching patterns (from disaggregate data) alone are not sufficient to identify preference and search cost.

We next discuss the identification of the search model in our setting. 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 maximum already-searched 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 towards searching k or not, i.e.,

$$Cost_i = \int_{z_{ikt}}^{\infty} (u_{ikt} - z_{ikt}) dF(u_{ikt}). \tag{10}$$

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

(1) The consumer continues the search if any unsearched option has a reservation utility greater than the then-current maximum u_i^*, and

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

To separate utility and search cost, we need exogenous variations in the data that affect either utility (right-hand-side of Equation 10) or search cost (left-hand-side of Equation 10), *but not both*. One example of such exogenous variations are instrument or exclusion restriction variables. For example, it is reasonable to expect time-constrained consumers to incur a higher search cost. Accordingly, when Pinna and Seiler (2015) 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 (2015), in the context of consumers' hotel searches and booking, the authors use days-till-check-in-date as an exclusion variable to measure one's time constraint. In both cases, the exclusion restriction affects one's search cost, but not the preference.

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 utility level of each channel as in-show commercials are suddenly and exogenously removed. In comparison, 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 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, respectively:

$$Cost_i = \int_{z_{jt}}^{\infty} (u_{ijt} - z_{ijt}) dF_{before}(u_{ijt}) \tag{11}$$

$$Cost_i = \int_{z_{jt}}^{\infty} (u_{ijt} - z_{ijt}) dF_{after}(u_{ijt}). \tag{12}$$

These two equations determine the search activities and consequently the ratings of channels before and after the ban. Note that search cost $Cost_i$ (left hand side of the equation) stays stable, while F_{before} and F_{after} differ from each other. Accordingly, the observed changes before and after the commercial ban in channel ratings, switch patterns, and the numbers of searches will be attributed to the utility changes.[20]

In our data, we observe ratings, switch patterns, and numbers of searches across channels and time, and the most importantly, before and after the policy change. We have also made the standard assumptions as in classical discrete choice models, including (1) the outside option, not watching TV, is normalized to have zero mean utility, (2) preference shocks follow a known distribution (standard normal distribution), (3) the heterogeneity in preference follows a normal distribution, (4) viewers know the distribution of programming.

[20]We do not study habit formation in TV watching behavior, which is an important aspect and deserve more attention from future research.

Accordingly, because search cost and preference can be separated as discussed above, if we consider search cost $Cost_i$ as if it is an additional component in one's utility function, the mean and heterogeneity of the coefficients will be identified, in a fashion similar 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 the estimation along with some model fit analyses.

5.1 Parameter Estimates

Table 5 reports the parameter estimates. Commercial breaks severely reduce consumer utility levels. In particular, the average magnitude of the disutility of one minute of in-show commercial (-4.56) is greater than the utility of watching 1 minute of episodic show (4.36), the show genre with the highest utility level. Between-show commercials cause a slightly higher drop in utility than in-show commercials, though the difference is insignificant. If the current channel continues airing the same show, it increases the utility level significantly by 3.32. If the viewer misses the beginning of a show, it decreases her utility level by 2.11. 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 (1.12). To put it in perspective, one minute of in-show and between-show commercials decreases one's utility level by 4.56 and 5.30, respectively. For an average viewer, suppose that (1) the current channel starts a commercial break (in-show or between-show), (2) the current channel continues airing the same show after the break, and (3) the viewer does not expect to miss the beginning of a show of the same genre on an alternative channel. Other things equal, the low search cost implies that she may start searching the alternative if she expects it is not on a commercial break (i.e., $3.32 + 1.12 < 4.56$ and $3.32 + 1.12 < 5.30$).

Table 5: Estimates*

	Estimates	95% CI	Heterogeneity	95% CI
Utility				
In-show Commercial (minute)	**-4.56**	(-5.19, -3.55)	**0.99**	(0.17, 1.99)
Between-show Commercial (minute)	**-5.30**	(-5.99, -4.14)	**0.97**	(0.14, 1.88)
Current Channel Same Show	**3.32**	(2.25, 4.79)	**1.04**	(0.24, 1.93)
Alternative Channel Same Show	**-2.11**	(-3.19, -0.16)	**1.37**	(0.49, 3.16)
Episodic TV Series	**4.36**	(1.03, 7.04)	**2.97**	(0.79, 3.99)
Sports Events	**3.19**	(2.10, 5.66)	**2.22**	(0.51, 4.14)
Medical and Health	**1.97**	(0.96, 4.85)	**4.97**	(2.71, 7.31)
News	**-1.82**	(-4.17, -0.91)	**3.24**	(1.08, 5.17)
Other Types of Shows	-0.51	(-1.23, 0.10)	**4.11**	(2.59, 5.15)
Channel-Time "Quality" (ν_{jt})				
Channel FEs, Mean (ν_j)	Yes		–	
Standard Deviation (σ_ν)	1.19	(0.61, 2.16)	–	
Weekday FEs	Yes		Yes	
Week FEs	Yes		Yes	
Hour FEs	Yes		Yes	
Search Cost	**1.12**	(0.17, 2.09)	**3.62**	(2.47, 5.00)

*Note: Bold fonts indicate that the estimate is 95% significant.

5.2 Model Fit

Next, we discuss several tests to examine the fit of the model.

First, we consider the model's ability to predict channel ratings. We have 16 days of ratings data. There are 150 1-minute intervals per day for 29 channels and the outside option. In total we have 72,000 observations of ratings ($30 \times 150 \times 16$). Out of these observations, we randomly reserve 15 intervals per day as a hold-out sample, which contains 7200 observations. Using the remaining 64,800 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 0.12. In comparison, we also estimated a classical discrete-choice demand (logit) 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 0.19.

Next, we measure the model's ability to predict channel-switching patterns. At the disaggregate level, for each group of viewers who were watching channel j ($j = 0, 1, ..., 29$) in the previous period, we predict the percentages of viewers who will switch to alternative options. The out-of-sample MAPE is 0.20. We further consider a discrete-choice model (logit) where each viewer has full information about alternative channels. We estimate the logit model and control for the same set of covariates as in the search model. We then use the model to predict the percentages of switching viewers in the disaggregate sample. We find that the out-of-sample MAPE of this discrete-choice model is 0.34, much worse than the search model.

Finally, we consider the prediction of average numbers of searches conditional on viewers' previous channels. Using the disaggregate data, the out-of-sample MAPE on the predicted numbers of searches is 0.19. Since the full-information, discrete-choice model by definition assumes 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 is more accurate than discrete-choice models, which assume viewers have full information of alternative channels.

6 Policy Implications – The Timing of Commercial Breaks

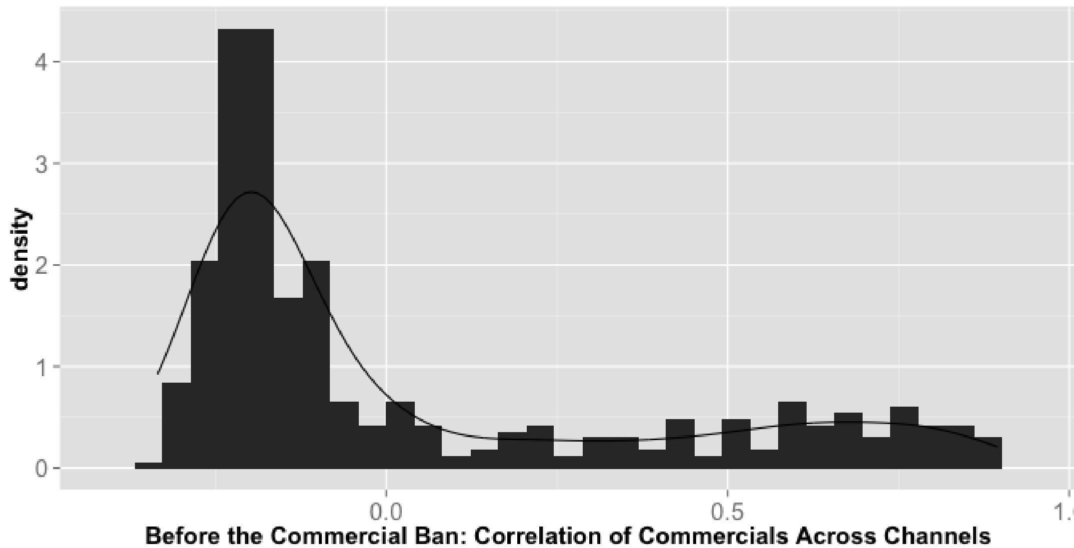
The timing of commercial breaks is always an important strategic decision of TV channels. The channels may choose either to synchronize or differentiate the timing of their commercial breaks. Sweeting (2006, 2009) uses commercial breaks data from radio stations to investigate the timing decisions. The author shows that the equilibrium may depend on the characteristics of a specific market, especially how viewers switch channels during commercial breaks. As documented by our analyses and extant literature (e.g., Wilbur et al., 2013), many viewers do not return to their original channels after the commercial breaks end, causing the original channels to lose viewerships and damaging advertising revenue potentials of channels. Intuitively, if all channels have commercials at the same time, viewers have less incentives to switch channels during the breaks, because they will also find commercials on alternative channels. However, such a coordination is delicate. A channel may have an incentive to deviate from the coordinated timing, because it may gain more viewers by not broadcasting commercials when all its competitors are airing commercials at the same time.

Pertaining to the observed timing of commercial breaks in our data, TV channels had little coordination, even though there is no explicit regulation against such a practice across channels.[21] To illustrate this, we focus on in-show commercials before the regulation change.[22] We introduce a time-channel specific dummy variable, which reflects whether a channel was broadcasting in-show commercials during a 1-minute interval. The dummy variable takes the value of 1 if a given channel was showing in-show commercials during a specific interval, and 0 otherwise. For every pair of channels, we then calculate the correlation of the dummy variables across time. If the channels had the same timing for commercial breaks (i.e., starting commercials during the same minute), the correlation coefficients of the dummy variables should be closed to 1. Figure 2 depicts the histograms of these correlation coefficients. The majority of the correlation coefficients are very distant from 1. The mean levels of the correlations is only 0.04 and statistically insignificant; and the median is in fact negative.

[21]See the Chinese State Council Decree No. 228, "Regulations on Broadcasting and Television Administration (in Chinese)", which serves as the guideline of all regulations pertaining to broadcasting and television. In the document, there is no clear indication against coordination of commercial breaks (http://www.pkulaw.cn/fulltext_form.aspx?Gid=18601).

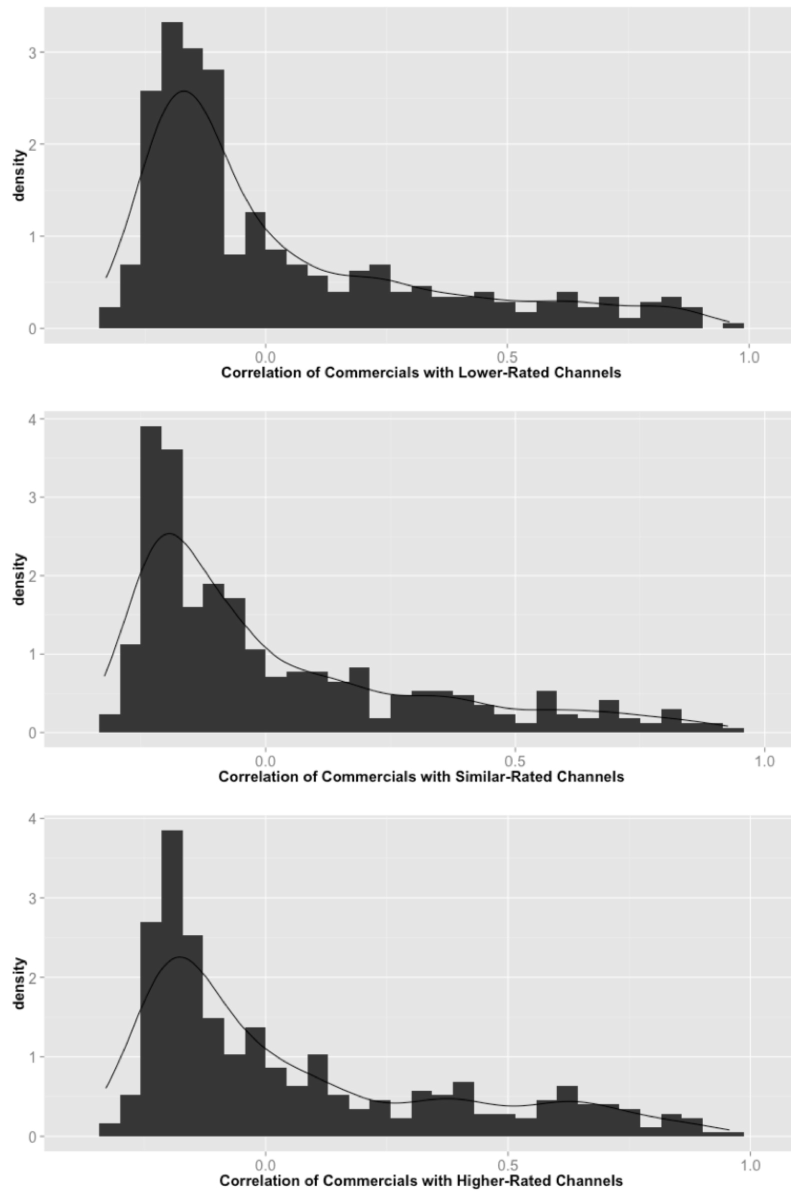
[22]After the regulation change, episodic programs no longer had in-show commercial breaks. Also, the results of the analyses are similar for in-show commercials of non-episodic programs after the regulation change. For between-show commercials, the coordination is inherently difficult because the shows often end at different time slots.

Figure 2: Coordination of Commercial Breaks



It is possible that at a given time, a channel's decision on coordination depends on how its rating compares to its competitors'. To check into this possibility, for each in-show commercial break of a given channel, we record its rating and its competing 28 channels' ratings before the focal commercial break. Based on the ratings, we divide the competitors into three break-specific groups: (1) Similar-rated: A channel whose rating is within ± 0.07 of the focal channel's (i.e., $\pm 5\%$ S.D. of ratings before the ban); (2) Higher-rated: A channel whose rating is at least 0.07 higher than the focal channel's; and (3) Lower-rated: A channel whose rating is at least 0.07 lower than the focal channel's. Note that the grouping is not fixed over time because of the variation of ratings across breaks. Next, for the focal channel and each of its competitors in a given tier, we repeat the same correlation calculation for the dummy variables across time. Figure 3 shows three histograms of the correlation coefficients by pooling all channels within the same tier. The three histograms correspond to a focal channel's timing correlation with competing channels which have lower, similar, or higher ratings, respectively. As we can see, the patterns are essentially the same as Figure 2 above, which shows little coordination in timing across groups. In the Appendix, we further show another set of histograms focusing on adjacent minutes instead of the same minute (i.e., one minute before or after the focal channel's commercial break). The insights remain the same. In conclusion, we find little evidence that channels were coordinating their commercial breaks at the time of our data window.

Figure 3: Coordination of Commercial Breaks Across Different Rating Groups



Having established that channels had little coordination in their commercial timing, we are interested in how a full coordination of timing may affect viewers' behavior and ratings across channels. We hereby consider the following policy simulation on in-show commercial timing coordination. Based on observed rating data before the ban, we define a daily top channel as the one with the highest average rating during that given day. When the remaining non-top channels of that day had their shows overlapped with the shows of the top channel,[23] we adjust the timing of their in-show breaks such that their commercials are all synchronized with the top channel's. More precisely, in the data:

1. During the overlapped portion, both the top channel and a non-top channel have breaks and the number of breaks are the same, we align the non-top channel's breaks such that they start at the same time as the top channel's breaks.

2. During the overlapped portion, both channels have breaks but the numbers of breaks are different. In this case, we first combine or divide the non-top channel's breaks so that (1) its breaks all have the same length, and (2) the number of breaks becomes the same as the top channel.[24] Next, we align these new breaks of the non-top channel such that they start at the same time as the top channel.

3. During the overlapped portion, the non-top channel have breaks but the top channel has none. In this case, we relocate the non-top channel's breaks randomly to its non-overlapped portion of programming as in-show breaks.

4. During the overlapped portion, the non-top channel has no breaks but the top channel has breaks. In this case, we add new in-show breaks and align its start as the top channel's break.

Next, based on our model and estimates, we simulate two sets of ratings of all channels for the duration of the top channel's regular shows, including the ratings of the commercial breaks. The first set of ratings is simulated based on the observed commercial timing without the adjustment mentioned above. The second set is based on the timing after the adjustments

[23]Note that it is nearly impossible for the channels have no overlapped shows at all in their programming. We have no such observations in our data.

[24]This implies that the length of each break may change from its original level observed in the data.

above. Note that as a consequence of those adjustments, for the second set of simulated ratings, all channels have *the same* in-show commercial starting time and frequency. And we assume that viewers know the updated distributions of in-show commercials.

Comparing the two sets of ratings, we found that, with synchronized commercial timing, the average ratings of high-rated channels drop, while low-rated channels have a boost in their average ratings. To be specific, we again use the October/November 2011 median rating of each channel to divide them into high-rated (10 channels), median-rated (10), and low-rated (9) groups.[25] We then compare the average ratings between the two simulations (i.e., non-synchronized timing vs. synchronized timing). When the break timing is changed from differentiated to synchronized, the average rating of high-rated channels across channels and intervals drops from 1.46 to 1.42, a 2.7% decrease. For the average rating of each high-rated channel across time, all have lower values in the synchronized condition and 7 channels' drop significantly at the 95% confidence level. For low-rated channels, in contrast, the average across channels and time increases by 6.4%, from 0.29 to 0.31. For the average ratings across time, all 9 channels become higher, and for 8 out of 9 the changes are 95% significant. For the median-rated channels, the changes are mix. 4 out of the 10 channels have an increase in their average ratings but none is significant. The remaining 6 have lower ratings and one of them drop significantly at the 95% level. Overall, the change in average rating of median-rated across channels and time becomes slightly lower (-0.008) but statistically insignificant. The average number of searches across viewers from all groups drops from 3.50 to 2.58, though not statistically significant.

To understand the results from this simulation, note that viewers are more likely to search other channels during the commercial breaks, as shown in the discussion of data patterns in Section 2 (and the simulation). Intuitively, for viewers of low-rated channels, in comparison to viewers of high-rated channels, such searches have a higher likelihood

[25]We also consider an alternative grouping approach. Instead of using October/November 2011 median rating of each channel, we use the average rating of each channel of the focal day to group channels into three tiers. The insights remain the same.

to find alternatives with high utility levels. So compared to high-rated channel viewers, the viewers of low-rated channels are less likely to choose their original channels after the search. But when the commercial breaks are coordinated, viewers are less likely to search overall, because the alternatives are showing commercials as the same time. As a result, coordination enhances the average rating of low-rated channels. At the same time, the low likelihood of search implies that high-rated channels now have fewer viewers who would have switched from low-rated channels, in comparison to the situation where the commercial timing is differentiated. Accordingly, the average rating of high-rated channels deteriorates due to the coordination. Finally, for the median-rated channels, their ratings face both the upward and downward forces when the timing is coordinated and the net result is uncertain. From a managerial perspective, this simulation implies that low-rated channels should try to synchronize their commercial breaks with high-rated channels, and high-rated channels should try to differentiate their breaks from competing channels.

7 Conclusions

It is crucial for TV channels to understand how commercial breaks affect their viewership and how they can strategically manage the timing of breaks. Our paper proposes a sequential search model and uses it to measure consumers' choices of TV channels. The model provides a more realistic characterization of TV-viewing behavior. We advance the TV-viewing choice literature by allowing uncertainty in consumers' knowledge about upcoming programming. In our model, a consumer needs to search alternative channels to resolve the uncertainty in programming. The search is costly and commercial breaks affect the expected net return of the search. We show how commercial breaks affect the trade-off between search cost and expected returns, and ultimately influence how viewers behave.

We apply the model to a unique dataset of the Chinese TV market. In our data, the market experienced an exogenous policy change where the government banned all in-show commercial breaks for episodic programs. The identification of classical empirical search models is difficult because consumer preference and search cost are often confounded in field data. The regulation change in our data functions as an exogenous shock that affects the preference distribution independent of search cost, which makes identification feasible. Based on the model estimates, we also present managerial insights for TV channels regarding the timing of breaks. Low-rated channels will benefit from synchronizing their breaks with high-rated competitors so as to prevent their own viewers from searching and leaving after the search during commercial breaks. High-rated channels should try to differentiate their breaks from competitors. When a high-rated channel differentiates its timing from competitors, it can capture churning viewers from competing channels during their breaks. Meanwhile, when the high-rated channel has commercial breaks itself, its viewers are on average less likely to search because of lower expected net return of the search. Breaks between consumptions appear in other contexts, e.g., commercial breaks in radio shows, time lapses for sequels of games, etc. Accordingly, the results of strategic timing decisions of TV commercials may be applied more broadly.

TV remains the preferred advertising medium for many firms. However, with the television industry faces increasingly intense competition from new media channels and the advance of technology that enables consumers to skip commercials, it is imperative that the TV industry, advertisers, and policy makers obtain better insights about how viewers respond to commercial breaks and hence strategically determine the timing of breaks. We hope that our study can enrich our understanding of viewer behavior and encourage future studies in this area.

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Appendix

Table 6: Descriptive Statistics: Percentages of Commercial Time among Total Broadcasting Time Across Channels and Hours

In-Show Commercial Percentage	Channels Rating Rankings	Mean	S.D.	5th Perc.	95th Perc.	Max.
Before the Ban: TV Series	Channel 1 to Channel 10	1.31	2.67	0	6.67	16.67
	Channel 11 to Channel 20	1.34	2.09	0	6.67	11.67
	Channel 21 to Channel 29	1.60	4.37	0	8.33	20.00
After the Ban: TV Series	Channel 1 to Channel 10	0	0	0	0	0
	Channel 11 to Channel 20	0	0	0	0	0
	Channel 21 to Channel 29	0	0	0	0	0
Before the Ban: Non-TV Series	Channel 1 to Channel 10	3.59	5.11	0	16.67	18.33
	Channel 11 to Channel 20	4.34	6.13	0	18.33	21.67
	Channel 21 to Channel 29	4.86	6.58	0	18.33	23.33
After the Ban: Non-TV Series	Channel 1 to Channel 10	2.81	4.08	0	11.67	16.67
	Channel 11 to Channel 20	2.43	3.67	0	10.00	15.00
	Channel 21 to Channel 29	4.13	5.74	0	15.00	28.33
Between-Show Commercial Percentage	**Channels Rating Rankings**	**Mean**	**S.D.**	**5th Perc.**	**95th Perc.**	**Max.**
Before the Ban: TV Series	Channel 1 to Channel 10	4.32	7.65	0	16.67	23.33
	Channel 11 to Channel 20	6.67	9.38	0	21.67	36.67
	Channel 21 to Channel 29	1.51	4.41	0	13.33	18.33
After the Ban: TV Series	Channel 1 to Channel 10	5.03	8.48	0	21.67	25.00
	Channel 11 to Channel 20	6.81	9.14	0	23.33	35.00
	Channel 21 to Channel 29	2.38	5.92	0	20.00	25.00
Before the Ban: Non-TV Series	Channel 1 to Channel 10	2.51	4.91	0	11.67	26.67
	Channel 11 to Channel 20	4.34	6.13	0	18.33	21.67
	Channel 21 to Channel 29	4.49	5.18	0	13.33	18.33
After the Ban: Non-TV Series	Channel 1 to Channel 10	2.16	4.26	0	11.67	21.67
	Channel 11 to Channel 20	2.97	4.69	0	11.67	20.00
	Channel 21 to Channel 29	4.06	4.54	0	13.33	21.67

Figure 4: Google Trends Index of "TV Show Commercials"

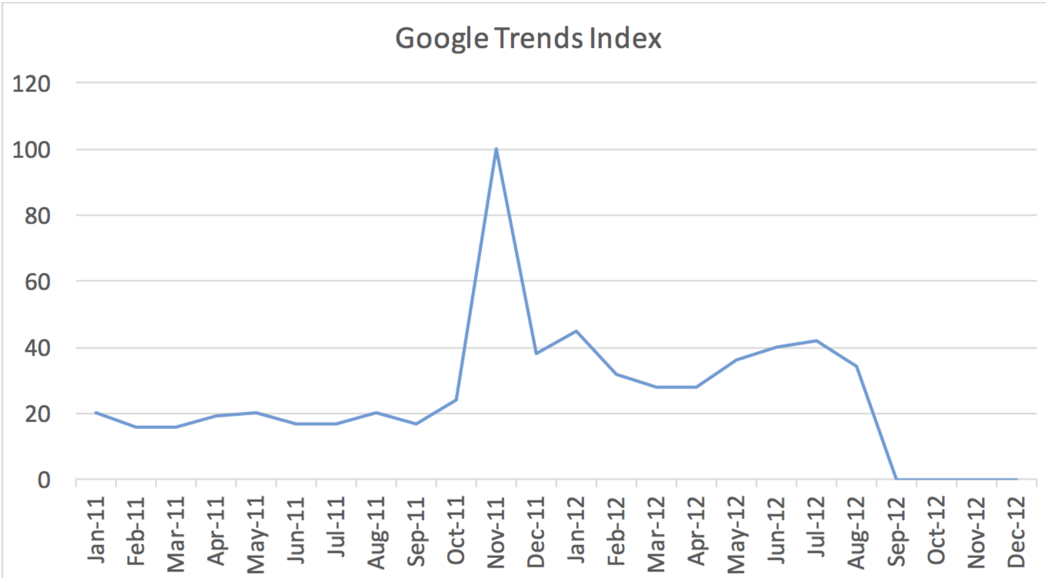


Figure 5: Consumers Switching Activities: Initial Channel Ranked 1-10

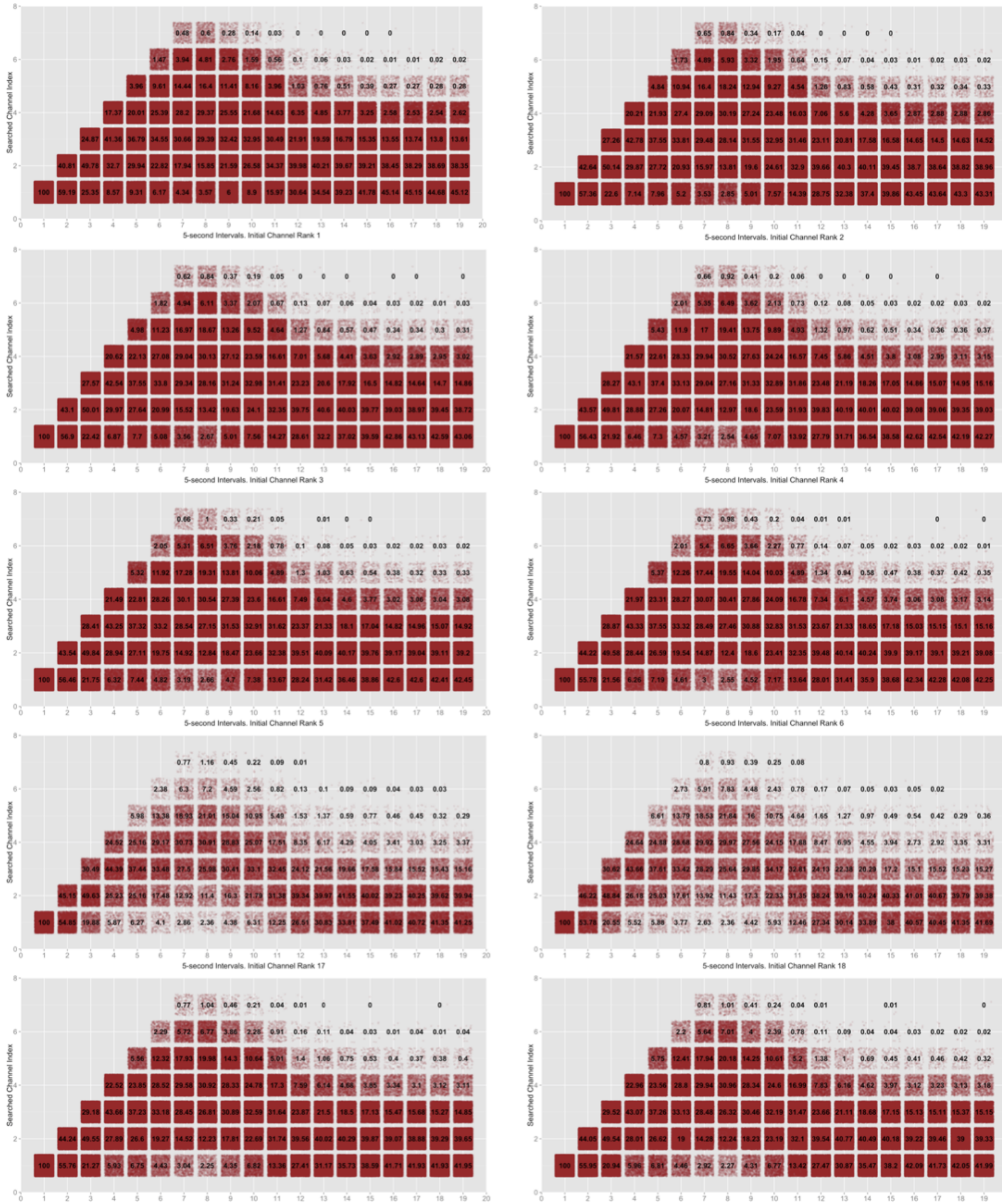


Figure 6: Consumers Switching Activities: Initial Channel Ranked 11-20

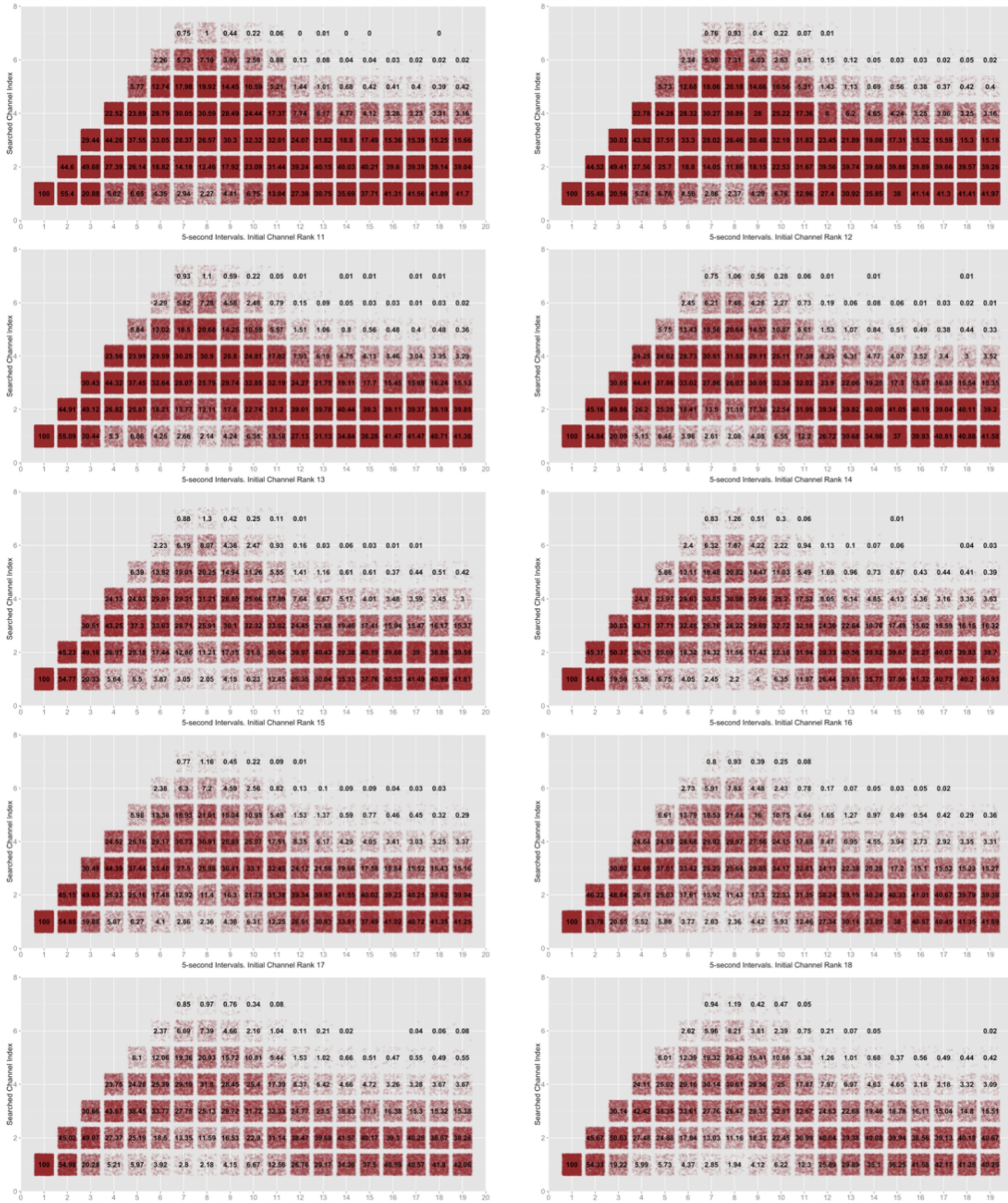


Figure 7: Consumers Switching Activities: Initial Channel Ranked 21-29

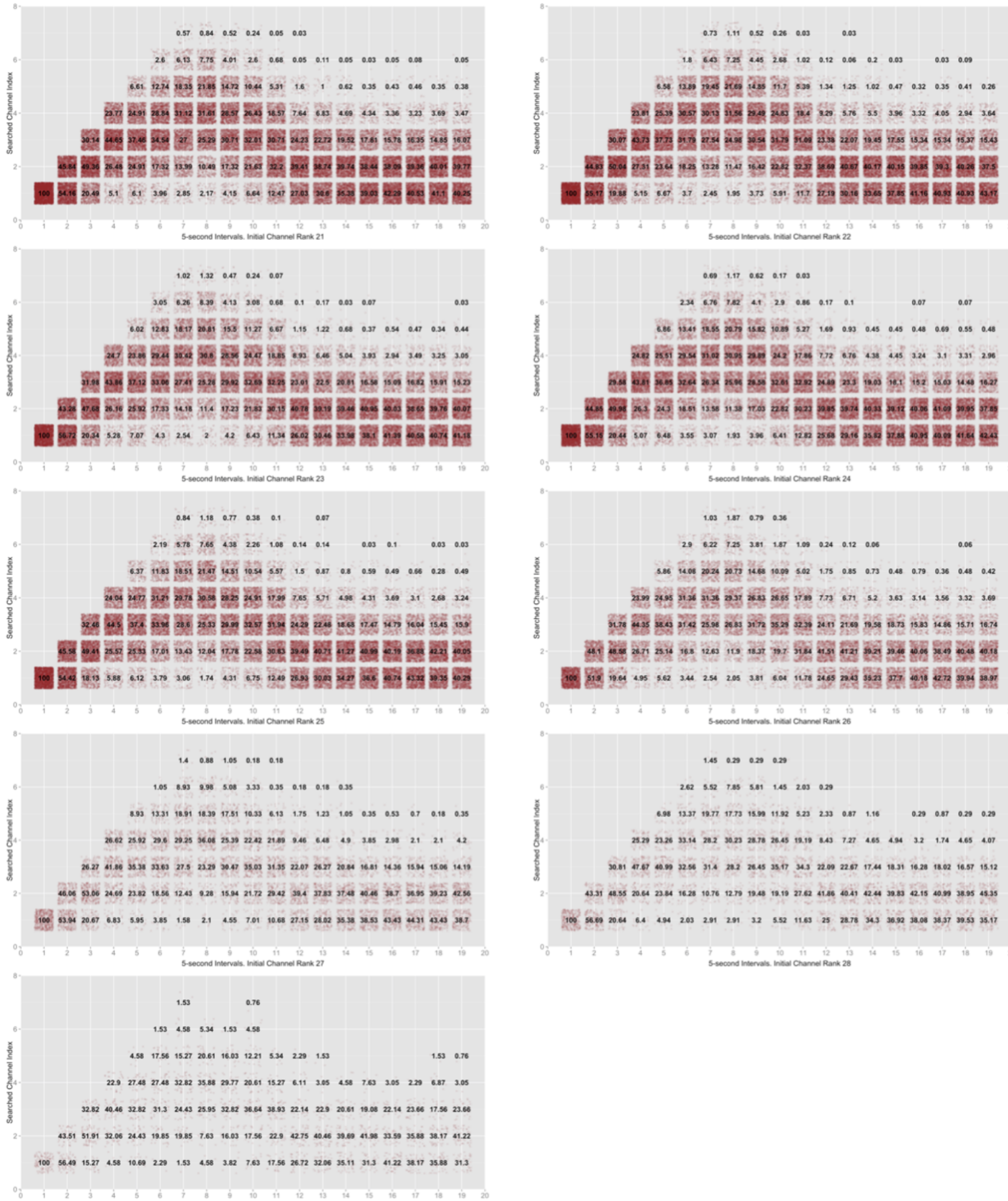
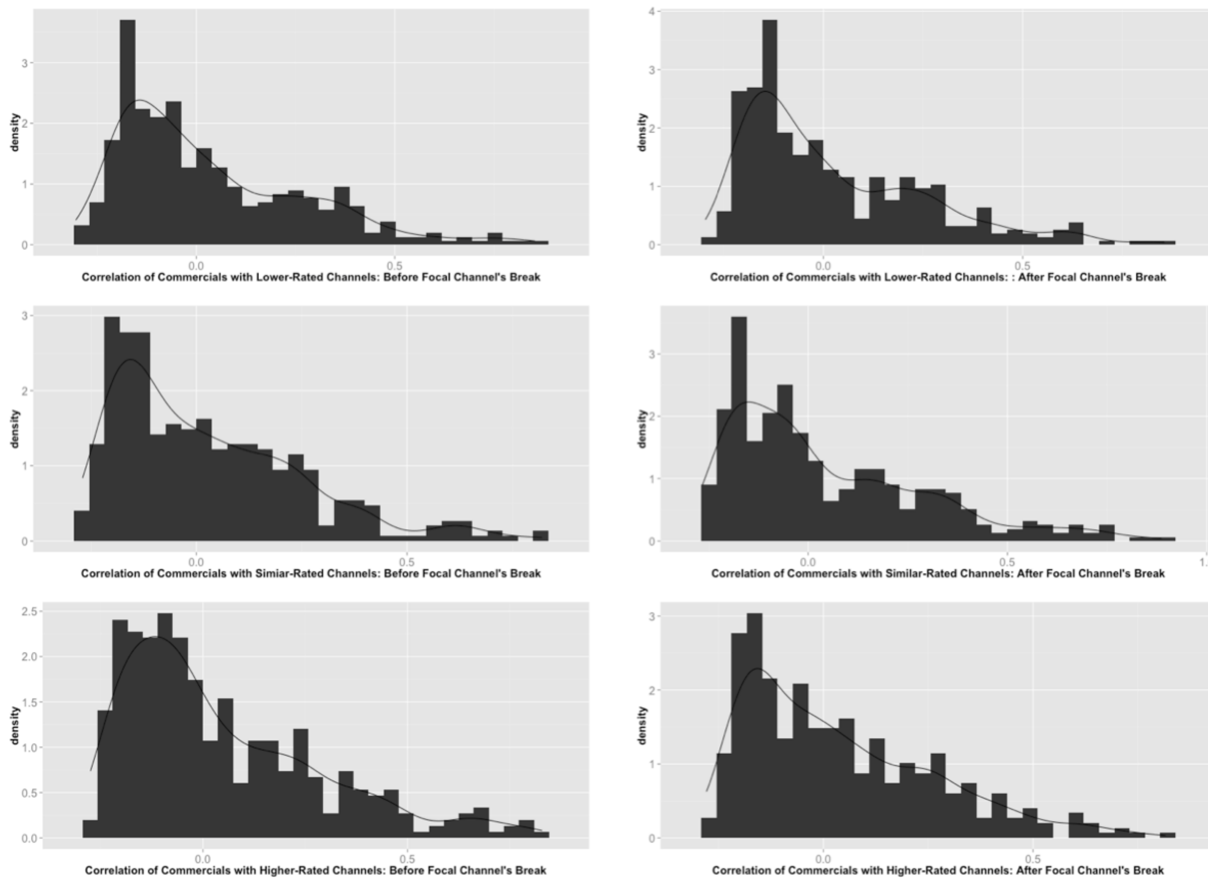


Figure 8: Coordination of Breaks Across Different Rating Groups: Before/After the Focal Break



In this Figure, we use a similar approach as in Section 6 to create correlation coefficients of commercial timing. However, instead focusing on the commercial breaks on the same minute across channels, we focus on one minute before or after the focal channel starts its commercial break.