# What is Affecting Total Loss Percentage of Television Audience: An empirical study on series *Blindspot* *

Wanlin Ji†

June 2017

**Abstract**

For half a century, television has been a dominant and pervasive mass media, driving many technological advances. Total loss percentage measures percentage of individuals who stopped watching the broadcast in that minute from the total number of viewers in that minute. It is an important dynamic indicator of audience loss in broadcasting and television industry. Based on the minute-by-minute rating data from acclaimed television series *Blindspot*, ranging from September 2015 to May 2016, this study built a Two-Stage Least Squares (2SLS) Model to analyze what factors is influencing the total loss percentage of audience. Using time as instrumental variable, the results showed that commercial has a significant influence on the total loss percentage, and the time affects the total loss percentage through the channel of rating. The findings suggest insights for broadcasters and producers both in terms of managing advertisements.

*keywords:* Rating, advertising, audience loss.

*JEL classification:* C36, D12, M37

*I thank Richard W. Evans, Benjamin Soltoff and Ging Cee Ng for their instructions and suggestions, as well as participants on computational poster presentation for their helpful comments.

†University of Chicago, Master of Arts Program in Computational Social Sciences, (562) 298-0258, wji@uchicago.edu.

# Contents

# 1 Introduction

Despite the ever expanding forms of digital entertainment and the emergence of consumer recording cookies allowing viewers to time shift their TV viewing habits, there are still certain TV shows and events that create an audience desire to be part of a mass shared experience. Such attention, no matter from television or internet, is the valuable asset to content providers, and has been widely used to advertise and affect consumer beliefs. The rating has been widely studied to guide the advertising investment strategy, but few research is on audience loss, which causes negative externality of advertisement price.

In this paper, we use minute-by-minute rating data from the acclaimed television series *Blindspot*, to study what and how do other major factors affect the total loss percentage, including commercials, ratings and time. *Blindspot* is an American crime drama television series aired from September 2015 to May 2016. By measuring and modeling what is affecting the audience loss per minute, we are curious about the influencing about influencing mechanism, and possible distinct channels it involves.

Total loss percentage we study offers more precision for advertisers to guide their investment more precisely. The availability of minute-by-minute rating data for television provides even more information to the old 5 minutes or 15 minutes rating. By building a Two-Stage Least Squares (2SLS) Model, we specify that commercials has a strong influence in audience loss directly, and the instrumental variable time has an influence on the loss percentage through the channel of rating.

This study controls lots of other factors, for example, the effect of scheduling, which is a major factor that affects rating, and potentially audience loss. The heterogeneity is also not important here as we focus on one television series aired on one network. The narrative is not under control because it varies as broadcasting goes on.

Research on television advertising, potentially based on less frequent data, has been focused on the influencing mechanism of audience attention/involvement, or the program demand. Through this stage most methods are based on the quantitative rating data provided by panel measurement methods. Tainsky (2010) estimates demand for National Football League games using television broadcast ratings. They adapted a linear mixed model to demonstrate that many of the factors contained in rating, like the team quality or tenure in the market, are influencing attendance hold true with respect to television demand.

Besides that, the media factors of audience involvement, which turn a creative message into an effective sales message, include not only quantitative factors but also qualitative ones. Lynch and Stipp (1999) examined the research on qualitative factors like program lilting, lack of distractions as well as the scheduling of time (mostly related to the arrangement and content design). They studied how to incorporate them into the optimization process, concluded that the data point to significant differences in qualitative audience factors and they impact advertising effects significantly.

On the other hand, the digital age allows more information to help measure the audience. Harrington et al. (2012) argued that online social network sites like twitter can act as a complementary information channel to the television and traditional media. Lochrie and Coulton (2012) investigated the emerging role of mobile phones as the facilitator of second screen for TV, by analyzing tweets related to a highly popular UK TV show X Factor and comparing tweets from this show with other shows from a different format. It highlights the rich information that can help to reveal audience viewing habits.

This paper contributes mostly to the area of analyzing frequent audience loss and help to connect it better to advertising investment. Becker et al. (2015) discusses the audience migration between Brazilian television and digital media like Internet. The television audience loss is influenced by the rising of Internet access in the long run. In the short run, Van Meurs (1998) looked into the switching behaviors during the commercial breaks and built a multivariate model to determine which factors bring about this kind of channel switching. They found that characteristics of the break itself, the commercials in it, the audience, and the programs before and after the break could have influence on leaving during commercial breaks. Sometimes, audience loss may not be reflected in the advertisement price, resulting in an audience externality.

Wilbur et al. (2013) proposes the Audience Value Maximization Algorithm (AVMA), which considers many possible advertisement orderings within a dynamic programming framework with a strategy-proof pricing mechanism. This study goes beyond the existing literature by applying frequent audience rating data and analyze the influencing mechanism in the short run. The findings is significant in evaluating audience value and guide advertising investments. Besides, the methods applied to analyze the loss percentage remains equally valid for both online advertising as well as television advertising.

The paper proceeds as follows: Section 2 describes the *Blindspot* rating data used in the study in detail and explores the relations between major variables; Section 3 explains the hypothesis and empirical model used in this paper to analyze the total loss percentage; Section 4 presents the result of our empirical analysis, as well as discuss alternative theoretical explanations; Section 5 concludes the thoughts.

# 2 Data

Our research is based on the case of acclaimed series *Blindspot*. *Blindspot* is an American crime drama television series created by Martin Gero, starring Sullivan Stapleton and Jaimie Alexander. The series is aired from September 21st, 2015 to May 23rd, 2016. A back nine order was given on October 9, 2015, bringing the first season to a total of 22 episodes, plus an additional episode bringing the order to 23 episodes. *Blindspot* focused on a beautiful woman named Jane Doe left in Times Square inside of a duffel bag with no memory and her body completely covered in tattoos. The main character Kurt Weller, and his FBI Team are to investigate the circumstances around Jane and solve the puzzles hidden in her intricate tattoos.

## 2.1 Nielsen Minute-by-minute Television Rating Dataset

Our primary data source for *Blindspot* is Nielsen Minute-by-minute Television Rating Dataset. Nielsen Rating Data provides a detailed and minute-by-minute measurement of ratings and total loss percentage of audience for every one of 23 episodes of

*Blindspot*" through all available television networks, DKN in this case. Nielsen sets up previously electronic and proprietary metering equipments to carry out their audience measurement throughout the country. Nielsen also cooperates with television network providers to collect audience behavior data and capture information about whats being viewed and when. The minute-by-minute precision of data extends our ability for analyzing each episode dynamically to see if there were significant points in a given episode that resulted in losing large chunks of the audience.

Abundant literature has been using Nielsen Minute-by-minute Television Rating Dataset for a long time. Alavy et al. (2010) used the minute-by-minute data of football games and found that although uncertainty matters, it is the progression of the match which drives viewership and as a draw looks increasingly likely, viewers are likely to switch channels. The use of this data source is not restricted by the topic of television advertising, but expands into measuring the audience attention for broader topics, like social belief or neural signals. Kanazawa and Funk (2001) used the data for locally televised NBA basketball games and found strong evidence that viewership increases when there is greater participation by white players. Dmochowski et al. (2014) combined minute-by-minute rating with real-time neural data, and found ratings of the larger audience are predicted with greater accuracy than those of the individuals from whom the neural data is obtained.

The Nielsen Nielsen Minute-by-minute Network Ratings Dataset has some limitations for analysis. Generally speaking, the quality of the content has a strong influence on the audience behavior, and this information is highly abstract for the rating and audience loss. Panel measurement does not quantify the narratives. This could cause the endogeneity problem between ratings and error term, because of the omitted variable about narrative quality. We would discuss how to overcome endogeneity further in our model section.

## 2.2 Variables

There are nine variables in the "*Blindspot*" minute-by-minute ratings data. According to the Time variable, all the factors are measured by minute. Variables include:

- X: Index order for data point in each minute among all 23 episodes

- Network: The name of the network the show (also known as a telecast) aired on

- Date: The airing date of a particular telecast

- Time: The local time indicating the particular minute for the show

- Program: The name of the telecast

- Length: The duration length of the telecast

- Rating: the rating of the show, i.e. share of people/households watching the show relative to the total people/households with a TV

- Minute in Commercial: Dummy variable for whether there is a commercial during that given minute or not (1 = minutes with commercials)

- Total Loss Percentage: Percentage of individuals who stopped watching the broadcast in that minute from the total number of viewers in that minute

Through the inspection, it can be shown that the Length, Network, Program are almost the same for all the cases in dataset. Our focus would be on the main four variables available to us: Total Loss Percentage, X, Rating, Minute In Commercial, with the Total Loss Percentage as the dependent variable.

## 2.3 Exploratory analysis

After inspection, there is no missing value in the dataset, thus no need for data imputation. Next we want to carry out exploratory analysis on our data at hand. This is helpful to better understand the data and to test the hypotheses based on data experience. However, sometimes there are counter-intuitive findings so it is important to have an unbiased understanding of the data before proceeding with more advanced analysis. Firstly, the five number summary for key variables can be found in the table below.

To identify the influence of rating and commercial factors on total loss percentage, we are concerned with the pattern of loss in long term. Appendix A-1 figure shows the overall tendency of total loss percentage during the year when *Blindspot* was on air. Although we can tell the loss percentage shows fluctuations around the same

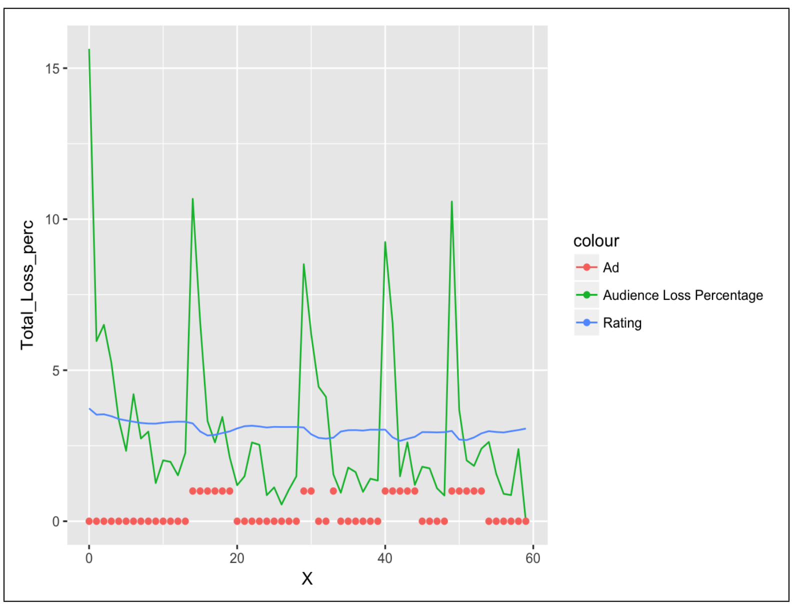
**Table 1: Descriptive statistics for key variables**

| Variables | Min | 1st Quartile | Median | 3rd Quartile | Max |
|---|---|---|---|---|---|
| X | 0 | 521.8 | 1043.5 | 1565.2 | 2087.0 |
| Rating | 0.955 | 1.372 | 1.552 | 1.964 | 3.831 |
| Minute In Commercial | 0 | 0 | 0 | 1 | 1 |
| Loss Percentage | 0 | 1.776 | 2.548 | 3.824 | 29.634 |

* Calculated under R. All codes disclosed on the Github.

level, it is apparent that data points are highly condensed in the long run. Then we zoom into the first episode of *Blindspot* to observe its short-run relationships between major variables.

**Figure 1: Variable tendency in the first episode**




By comparing the three major variables, commercial, rating and total loss percentage, we found that the scope can really mislead us. The ratings are not so violent as we saw previously. Until now, we have got some solid knowledge of our data at hand.

Through above graphs, we find that the total loss percentage has high correlation with the ratings. The ratings show similar patterns of fluctuations in the short term, reflecting the endogeneity problem. Since the total loss percentage and rating are influencing each other in our dataset and the total loss percentage is our dependent variable, an instrumental variable that is correlated with rating but not with the total loss percentage can clarify the causal relationship between these two.

# 3 Model

We can regress total loss percentage on rating, commercial and interaction term of commercial and time. Because total loss percentage and rating have endogeneity problem, OLS is lack of consistency and thus not valid for our estimation. Instead, we use the time order of the data (partitioned episode) as the instrumental variable. The intuition is that time only affects total loss percentage via rating.

## 3.1 Introduction

Now let's consider the hypothesis. The dependent variable chosen here is total loss percentage, which could help us predict the dynamic of audience loss. Note the number of viewers who join the watching during the show is not available to the research, so it is impossible to estimate the real number of audience that are leaving this show, but we can still aim to manage the viewers loss according to that it is always more expensive to earn a new customer than to prevent losing an old customer or viewer.

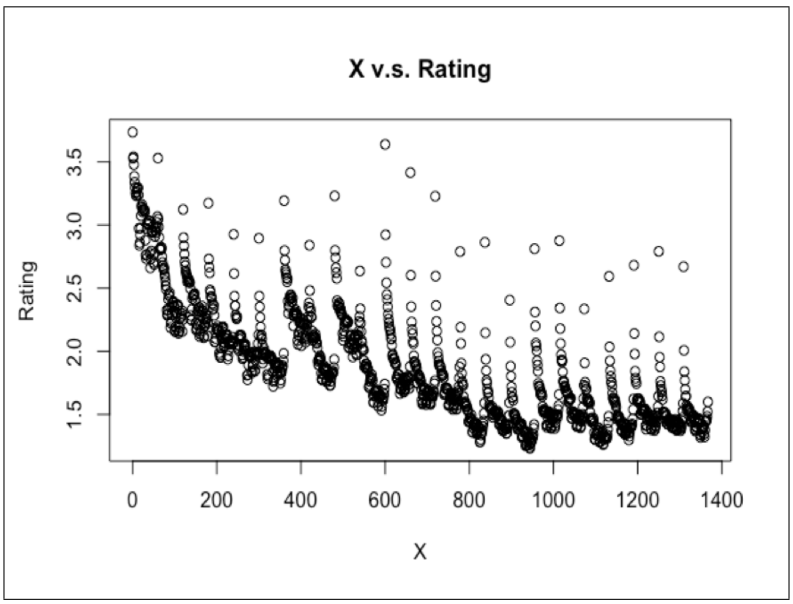
Next we want to consider the independent variables that could have an effect on the total loss percentage to find the primary drive behind it. We want to assume the rating stands for the accumulated evaluation of narratives from audience, then we can see the rating as an explanatory variable for analyzing total loss percentage, which is plausible explanation. But we also pay attention to the sudden fluctuations in total loss percentage, which is largely corresponding to dummy variable commercial. And we assume the endogeneity between total loss percentage and rating from Figure 1, we need an instrumental variable to solve the problem.

## 3.2 Instrumental Variable

The endogeneity problem lies in the correlation between our response variable total loss percentage and rating. An instrumental variable that is related to rating but not to total loss percentage can help reduce the correlation between rating and error terms.

The time order is chosen as the instrumental variable. Firstly, the time order has a significant relationship with rating. This tendency can be shown in Figure 2, and it is obvious that rating is decreasing as time goes further.

**Figure 2: Relationship between rating and time order**

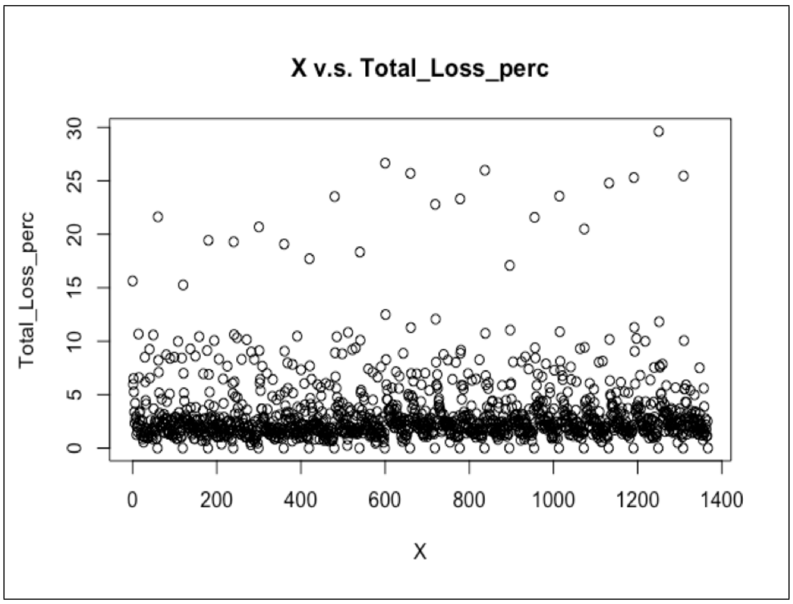



Thus, the assumption between time and rating is established as follows. The more correlated between time and rating, the stronger time can explain rating.

$$Cov(X, Rating) \neq 0$$

How to explain the correlation between rating and time? Both rating and time are condensed variables that contains much information. Assume the rating stands for appreciation from audience, which could be decreasing with more and more narrative defects appear in the series, along with other factors. We may agree that audience leaving the show largely due to the defects of narratives, and those lost audience would be highly unlikely to return back after they given up watching the show. Further, we can assume that time order stands for negative narrative quality, and the defects are always accumulating across the broadcasting period. This well explained that why rating is decreasing as time passes by. Figure 3 shows relationship between total loss percentage and time.

**Figure 3: Relationship between total loss percentage and time order**




Secondly, we found that the time order does not have a relationship with total loss percentage, indicating the percentage of people leaving this show is not affected by the time. Thus we have the assumption of:

$$Cov(X, Totallosspercentage) = 0$$

Besides, we can find as time goes by, the outliers of total loss percentage have a upward tendency, although it does not affect the lack of correlation based on the result of significant test.

Based on different relationships between time and rating/loss in the long run, we can justify using time as the instrumental variable.

### 3.3 Two-Stage Least Squares (2SLS) Model

Using rating as endogenous variable and time as instrumental variable, the Two-Stage Least Squares (2SLS) Model is built to estimate what is affecting the total loss percentage.

At the first stage, the endogenous variable rating is regressed on instrumental variable as well as other predictors to produce the fitted values of rating. The part unrelated to the error term in the endogenous variable is extracted through this process.

$$\begin{aligned} &Rating \\ &\quad = \alpha + \beta_1 X + \beta_2 MinuteInCommercial + \beta_3 X * MinuteInCommercial \end{aligned} \tag{1}$$

At the second stage, the total loss percentage is regressed on rating values unrelated to error terms from stage one, in place of the actual values of the problematic rating to compute the consistent estimation of coefficients. Applying fitted values of rating as instrumental variable is also viable here because we only have one instrumental variable corresponding to one endogenous variable.

$$\begin{aligned} &TotalLossPercentage \\ &\quad = \theta + \pi_1 Ra\hat{t}ing + \pi_2 MinuteInCommercial + \pi_3 X * MinuteInCommercial \end{aligned} \tag{2}$$

We can prove that under assumption of two correlation assumptions, the estimation is consistent in 2SLS. The results of first stage and second stage estimation are shown in Table 2 and Table 3. These results can be seen as biased estimation under small samples, but the bias would be eliminated with large sample. Since the data used here is large enough, we can accept the estimation here as approximately unbiased.

# 4 Result

## 4.1 Estimation of 2SLS model

The results of first and second stage regression is shown below:

**Table 2: First stage estimation**

| Coefficients | Estimate | Std. Error | t-value |
|---|---|---|---|
| Intercept | 2.584*** | 0.019 | 135.900 |
| X | -0.096*** | 0.0024 | -40.052 |
| Commercial | -0.220*** | 0.032 | -6.478 |
| Interaction Term | 0.013** | 0.0042 | 3.222 |

* Notes. Calculated under R. All codes disclosed on the Github. *** p¡.01, ** p¡.05, * p¡.1.

**Table 3: Second stage estimation**

| Coefficients | Estimate | Std. Error | t-value |
|---|---|---|---|
| Intercept | 3.839*** | 0.567 | 6.776 |
| Rating | -0.490* | 0.289 | -1.695 |
| Commercial | 1.437*** | 0.350 | 4.110 |
| Interaction Term | 0.013* | 0.0045 | -1.935 |

* Notes. Calculated under R. All codes disclosed on the Github. *** p¡.01, ** p¡.05, * p¡.1.

The endogeneity make the simple division of dependent variable invalid. Based on that, R-squared statistic in instrumental variable method is not meaningful. Due to the same reason, the F test is invalid for the second stage, although F test is useful for examining the effect of instrumental variable in the first stage. As a result, results here do not include R-squared or F-statistic for the second stage.

The coefficient of dummy variable commercial is 1.437, indicating the presence of advertisement would cause 1.437% of audience loss during the broadcasting of *Blindspot*. It is very significant at the 0.001 significance level. The coefficient of rating is -0.490, indicating the total loss would be 0.49% less when rating are one unit higher. It is only significant on the 0.1 significance level. Besides, due to that the commercial has too strong influence on the total loss percentage, the rating's effect is not so significant. The interaction term has rather small influence on the total loss percentage.

## 4.2 Diagnostic tests

According to our hypothesis, only one instrumental variable is applied to the model, the problem of over-identification do not exist in this case. Two major diagnostic tests used here is Weak Instruments test and Wu & Hausman test.

**Table 4: Diagnostic tests**

| Coefficients | df1 | df2 | statistic |
|---|---|---|---|
| Weak Instruments | 1 | 1364 | 1604.1*** |
| Wu & Hausman | 1 | 1363 | 529.1*** |

* Notes. Calculated under R. All codes disclosed on the Github. *** p¡.01, ** p¡.05, * p¡.1.

Weak instruments use F-test on the instruments at the first stage. The null hypothesis is essentially that we have weak instruments, so a rejection means our instruments are not weak, which is good. Thus, the instrument variable time does not have problem of weak instruments.

Wu&Hausman test examines the consistency of the OLS estimates under the assumption that the IV is consistent. The rejection of Wu&Hausman test means OLS is not consistent, suggesting endogeneity is present. This suggests that we should use IV regression on this problem, since the endogeneity problem matters in this case.

## 4.3 Instrumental Variable vs. OLS

To compare the estimation of Two-Stage Least Squares and Ordinary Least Squares (OLS), we graphed the residual of two models in the Figure

From above plots of residual v.s. fitted value of OLS and IV regression, we can see that the residuals have a significant negative relationship with the fitted value in

Figure 4: **Comparison between OLS and IV Regression: Residual v.s. Fitted Plot of IV**

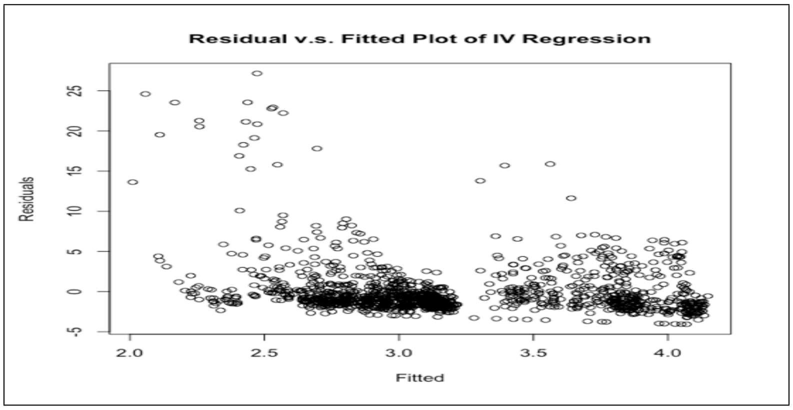
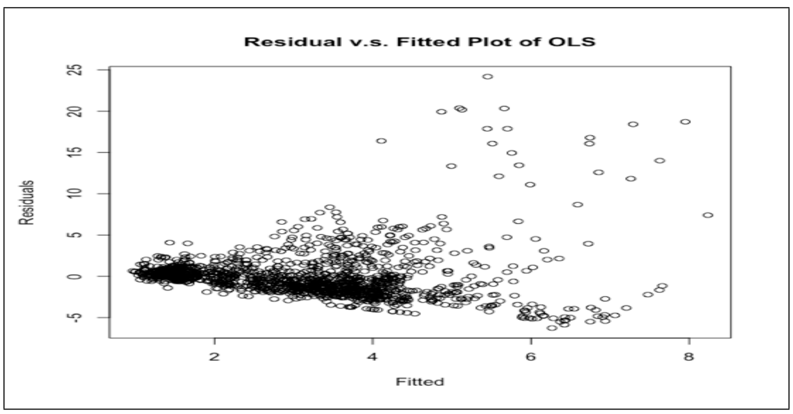



Figure 5: **Comparison between OLS and IV Regression: Residual v.s. Fitted Plot of OLS**




OLS model, but the relationship is much weaker in IV regression model. Thus, we conclude that the IV regression is a better model.

However, the points in both graphs is dispersed from zero, indicating both our estimation is affected by the omitted variables. Due to the lack of direct measurement of audience behavior, it would be difficult to fully explain the variations in total loss percentage.

## 4.4 Limitations, Alternatives & Future work

An important concern with our method is endogeneity and proper choice of instrumental variable to reduce the unwanted correlation. Although our instrumental variable shows significance on the influence, the choice of time can still be improved by combining even more data sources, especially those variables that can directly reflects audience behavior to reveal the omitted effects.

The other limitation of this study is caused by outliers. For the outliers of total loss percentage, they are not caused by input error. These outliers are left in our data in the end. We can find that from the exploratory analysis is a large proportion of audience leave in the beginning of each episode of *Blindspot*. A possible explanation is the audience quickly found they are not interested in the series in the start. However, this pattern goes the same with every episode. Considering the existence of "Previously On" and consistency of narratives between last and next episode, this is probably caused by other factors in the short run.

It is observed that loss percentage decreases with time during each episode, indicating audience are much easier to leave in the former stages of watching. The commitment of watching the show is an accumulated choice, and the cost for commitment is much higher in the beginning of each episode. On the other hand, the audience holds a different belief in the short run. At the later stages, people have paid for the sunk cost of watching the previous part, and it made them unlikely to leave the show even the proceeding is boring.

This study can be extended in several directions. Most fundamentally, it is important to determine a valid instrumental variable that can explain the variations in rating. For example, active audience may discuss the TV-related topics on Internet in real-time, but lost audience will not. With the advent of online social networks that facilitate status updates, moments can be instantly shared in real-time using mobile phone creating a second screen for interaction with TV. Combining with online heat data from Twitter or Facebook could be a possible method to help enhance the IV. Secondly, the problem of outliers with total loss percentage indicates omitted short-run pattern in audience behavior, which may require using Bayesian method and audience expectation to analyze.

# 5 Conclusion

Television advertising is the earliest, and also an important topic of marketing that applies quantitative methods to analyze advertising effects. In many advertisement settings, identifying the dynamic between audience attention and many other factors is critical, beyond identifying advertising investment strategies overall. This study not only allows us to identify endogeneity problem with rating and total loss percentage, but also focus on the real-time audience loss dynamic, allowing us to provide evidence that time and commercial influences the audience loss through distinct channels.

The findings indicate that the major factor that directly affects the total audience loss is commercials. It may, in some instances, lower the price of advertisement for consecutive commercials broadcasting in a short period. On the other hand, as the airing time of TV shows goes, its attraction is decreasing with time significantly. By the method of instrumental variable, the time order/air history of television series influences the loss percentage by ratings. The ratings has been proved to have a rather slighter effect on the total loss percentage in the long run.

Importantly, it is suggested to producers to maintain the balance of commercials in the television series to prevent the permanent loss of audience, especially when there are crucial attention spots like "Previously On". It also provides a method to predict the audience over a specific spot to better price the advertisement for network provides. These findings would remain valid even in the context of digital ages, while online advertisement keep challenging the content providers to accustom the needs of audience for better attention and involvement.

# References


**Alavy, Kevin, Alison Gaskell, Stephanie Leach, and Stefan Szymanski**, "On the edge of your seat: Demand for football on television and the uncertainty of outcome hypothesis," *International Journal of Sport Finance*, 2010, *5* (2), 75.

**Becker, BV, Daniel Gambaro, Aline Crisnir, and Samara Coutinho**, "Migration of Television Audience to Digital Media: Impacts on TV Schedule and Journalism," *Athens Journal of Mass Media and Communications*, 2015, *1* (4), 275–288.

**Dmochowski, Jacek P, Matthew A Bezdek, Brian P Abelson, John S Johnson, Eric H Schumacher, and Lucas C Parra**, "Audience preferences are predicted by temporal reliability of neural processing," *Nature communications*, 2014, *5*.

**Harrington, Stephen, Tim Highfield, and Axel Bruns**, "More than a backchannel: Twitter and television," in "Audience Interactivity and Participation," COST Action ISO906 Transforming Audiences, Transforming Societies, 2012, pp. 13–17.

**Kanazawa, Mark T. and Jonas P. Funk**, "Racial Discrimination in Professional Basketball: Evidence from Nielsen Ratings," *Economic Inquiry*, 2001, *39* (4), 599–608.

**Lochrie, Mark and Paul Coulton**, "Sharing the viewing experience through second screens," in "Proceedings of the 10th European conference on Interactive tv and video" ACM 2012, pp. 199–202.

**Lynch, Kate and Horst Stipp**, "Examination of qualitative viewing factors for optimal advertising strategies," *Journal of Advertising Research*, 1999, *39* (3), 7–7.

**Meurs, L. Van**, "Zapp! A study on switching behavior during commercial breaks," *Journal of Advertising Research*, 1998, *38* (1), 43–44.

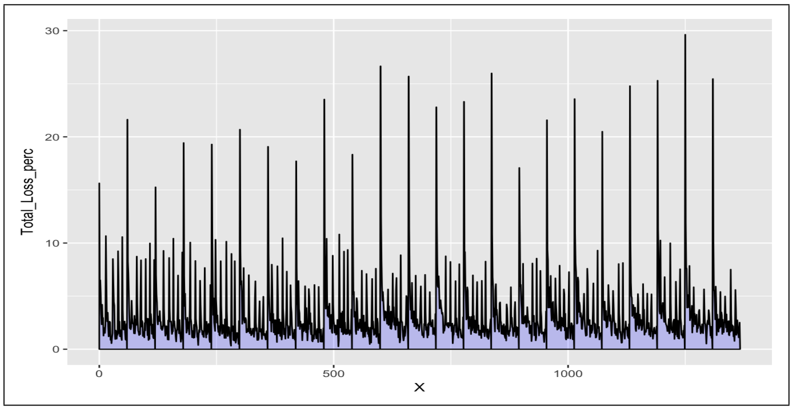
**Tainsky, Scott**, "Television broadcast demand for National Football League contests," *Journal of Sports Economics*, 2010, *11* (6), 629–640.

**Wilbur, Kenneth C, Linli Xu, and David Kempe**, "Correcting audience externalities in television advertising," *Marketing Science*, 2013, *32* (6), 892–912.

# APPENDIX

## A-1 Exploratory figures

**Figure 6: Dependent Variable: Audience loss percent tendency**




## A-2 Variable distribution

**Figure 7: Distribution of Rating**

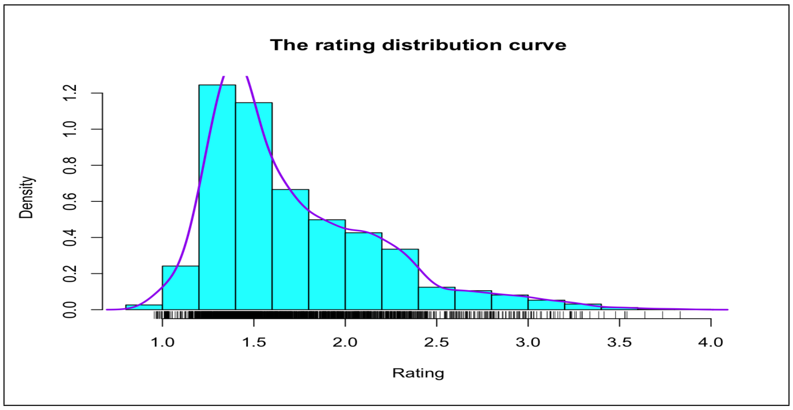


Figure 8: Distribution of Total Loss Percentage

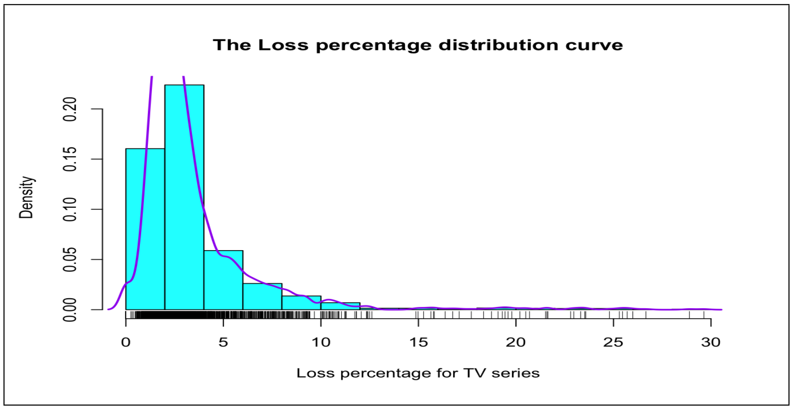



Table 5: ADF Test and PP Test

| Variables | Dickey-Fuller | Dickey-Fuller Z(alpha) |
|---|---|---|
| Rating | $-6.9171^{**}$ | $-238.09^{**}$ |
| Minute In Commercial | $-13.53^{**}$ | $-538.02^{**}$ |
| Loss Percentage | $-12.75^{**}$ | $-1574.7^{**}$ |

* Calculated under R.