There's No Free Lunch Conversation:
The Effect of Brand Advertising on Word of Mouth

Mitchell J. Lovett

Simon Business School
University of Rochester
mitch.lovett@simon.rochester.edu

Renana Peres

School of Business Administration
Hebrew University of Jerusalem, Jerusalem, Israel 91905
peresren@huji.ac.il

Linli Xu

Carlson School of Management
University of Minnesota
linlixu@umn.edu

March 2018

Acknowledgment: We thank the Keller Fay Group for the use of their data and their groundbreaking efforts to collect, manage, and share the TalkTrack data. We gratefully acknowledge our research assistants at the Hebrew University--Shira Aharoni, Linor Ashton, Aliza Busbib, Haneen Matar, and Hillel Zehavi—and at the University of Rochester--Amanda Coffey, Ram Harish Gutta, and Catherine Zeng. We thank Daria Dzyabura, Sarah Gelper, Barak Libai, and Ken Wilbur for their helpful comments. We thank participants of our Marketing Science 2015, INFORMS Annual Meeting 2015, Marketing Science 2017, Marketing Dynamics 2017, NYU 2017 Conference on Digital, Mobile Marketing and Social Media Analytics sessions and at the Goethe University Seminar Series.

This study was supported by the Marketing Science Institute, Kmart International Center for Marketing and Retailing at the Hebrew University of Jerusalem, the Israel Science Foundation, and the Carlson School of Management Dean's Small Grant.

There's No Free Lunch Conversation:

The Effect of Brand Advertising on Word of Mouth

Abstract

Advertising is often purchased with the expectation that the ads will generate additional social impressions that will justify the high price of advertising. Yet academic research on the effect of advertising on WOM is scarce and shows mixed results. We examine the relationship between monthly Internet and TV advertising expenditures and the total (offline and online) word of mouth (WOM) for 538 U.S. national brands across 16 categories over 6.5 years. We find that the average implied advertising elasticity on total WOM is small: 0.016 for TV, and 0.010 for Internet. Even the categories that have the strongest implied elasticities are only as large as 0.05. Despite this small average effect, we do find that advertising in certain events may produce more desirable amounts of WOM. Specifically, using a synthetic control approach, we find that being a Super Bowl advertiser causes a moderate increase in total WOM that lasts one month. The effect on online posts is larger, but lasts for only three days. We discuss the implications of these findings for managing advertising and WOM.

Keywords: word of mouth, advertising, brands, dynamic panel methods, paid media, earned media, synthetic control methods.

1 Introduction

Paid advertising is often purchased with the expectation to increase earned media exposures such as social media posts and word of mouth (WOM, hereafter). Perhaps most prominently, the expectation to boost earned mentions has become a key justification for spending on high priced ad spots in programs like the Super Bowl (Siefert et al. 2009; Spotts, Purvis, and Patnaik 2014). "Television is like rain and we catch the rain in buckets and re-deploy it to the social channels to make our sales opportunity and brand grow (George Haynes, an executive from Kia motors, on an interview to Forbes magazine about Kia advertising on Super Bowl 2013, in Furrier 2013)."

Some practitioners in the advertising industry believe that paid advertising generates a substantial influence on brand equity and sales by increasing the WOM a brand receives. Brand conversations are reported to commonly reference advertisements with estimates ranging from 9% (Gelper, Peres and Eliashberg 2016) to 15% (Onishi and Manchanda 2012) of online buzz about movie trailers and 20% for all WOM referencing TV ads (Keller and Fay 2009). Further, some industry reports claim that the impact of advertising on WOM is considerable (Graham and Havlena, 2007; Nielsen 2016; Turner 2016), and that the impact on total WOM (online and offline) can amplify the effect of paid media on sales by 15% (WOMMA 2014).

However, scholarly research on this topic is scarce. As illustrated in Figure 1, the current literature either focuses on the influence of advertising on sales (Naik and Raman 2003; Sethuraman, Tellis, and Briesch 2011; Danaher and Dagger 2013; Dinner, Van Heerde, and Neslin 2014), WOM on sales (Chevalier and Mayzlin 2006; Liu 2006; Duan, Gu, and Whinston 2008; Zhu and Zhang 2010), or their joint influence on behaviors (Hogan, Lemon, and Libai 2004; Chen and Xie 2008; Moon, Bergey, and Iacobucci 2010; Stephen and Galak 2012; Onishi and Manchanda 2012; Gopinath, Chintagunta, and Venkataraman 2013; Lovett and Staelin

2016). Research on how advertising induces WOM is mostly conceptual (Gelb and Johnson 1995; Mangold, Miller, and Brockway 1999), or theoretical (Smith and Swinyard 1982; Campbell, Mayzlin, and Shin 2017). Existing empirical studies that measure the effect of advertising on WOM, are sparse, and focus on case studies for a single company (Park, Roth, and Jacques 1988; Trusov, Bucklin and Pauwels 2009; Pauwels, Aksehirli, and Lackman 2016) or specific product launches such as Onishi and Manchanda (2012) and Bruce, Foutz and Kolsarici (2012) for movies, and Gopinath, Thomas, and Krishnamurthi (2015) for mobile handsets, and Hewett et al. (2016) for US banks. Tirunillai and Tellis (2012) studied the effect of online WOM for 15 firms from 6 markets but the main focus was on firms' stock market performance. All these studies focused on online social media and did not incorporate offline WOM, although offline WOM is estimated to be 85% of WOM conversations (Keller and Fay 2012). The results from these studies are mixed, with some positive effects (Onishi and Manchanda 2012; Tirunillai and Tellis (2012); Gopinath, Thomas, and Krishnamurthi 2015), non-significant effects (Trusov, Bucklin, and Pauwels 2009; Onishi and Manchanda 2012; Hewett et al., 2016; Pauwels, Aksehirli, and Lackman 2016), and even negative effects (Feng and Papatla 2011).

-------*Insert Figure 1 about here* ------

The main goal of this paper is to evaluate the effect of advertising on WOM. A key component of the analysis is information on the brand mentions that is drawn from the Keller Fay TalkTrack. This dataset includes comprehensive information about individuals' online and

offline conversations about brands. From this dataset, we include information on 538 US national brands across 16 broad categories and over 6.5 years.

We use two distinct analysis approaches to evaluate the effect of advertising on WOM. Our main analysis leverages monthly WOM and advertising expenditures on Internet, TV, and other media (from Kantar Media's Ad$pender database) to quantify the relationship between advertising expenditures and WOM. We use panel regressions that include brand fixed effects and time effects (trends), while also controlling for past WOM, advertising expenditures in other media, and news mentions. All variables have brand-level heterogeneous effects.

We find that the relationship between advertising and WOM is significant, but small. The average implied elasticity of WOM is 0.016 for TV advertising expenditures and 0.010 for Internet display advertising expenditures. Our findings suggest that these relationships are weaker than some of the industry expectations. For the average monthly spending on TV advertising in our sample, approximately 58 million ad exposures are generated. Based on our estimates, a 10% increase in TV advertising expenditure is associated with less than 58,000 additional impressions from WOM.

We find significant heterogeneity across brands and categories in the estimated relationship between advertising and WOM. For instance, categories with the largest implied elasticities to TV advertising are Sports and Hobbies, Media and Entertainment, and Telecommunications. However, the average implied elasticity, even for these largest categories, is still relatively small (e.g., average elasticity between 0.02 and 0.05).

We conduct a series of robustness tests and find our results are consistent across these specifications. These tests include ones where we use instrumental variables (costs and political advertising). Although the results are consistent, we find the instruments are weak. Hence, our

main analysis does rely on a conditional independence (i.e., an exogeneity) assumption. However, as we discuss in more detail later, most of the typical concerns regarding endogeneity in advertising effects are upward biasing. Since such biases would indicate our estimates are too large, this supports the credibility of our small effect sizes.

Our second set of analyses uses a different approach to causal inference and studies the effect of advertising on WOM where the effect is expected to be large—Super Bowl advertising. We conduct an analysis using the generalized synthetic control technique (Abadie, Diamond, and Hainmeller 2010; Bai 2013; Xu 2017), which constructs a difference-in-difference type estimator by matching the treatment group to a control group synthesized from a weighted combination of the non-treated brands. This causal inference technique can assess in non-experimental data the causal impact of a treatment (in this case, advertising on the Super Bowl) on the outcome (WOM).

We find that being a Super Bowl advertiser increases monthly WOM by 16% in the month of the Super Bowl and by 22% in the week after the Super Bowl. This increase suggests "free" impressions of the order of 10%-14% of the average monthly ad impressions, a sizable contribution especially because most evidence suggests the impact of WOM engagements on consumer choices is larger than that of advertising exposures (Sethuraman, Tellis, and Briesch 2011; You et al., 2015; Lovett and Staelin 2016). Further, we find that online social media posts respond even more than total WOM including an average increase of 68% on the day of the Super Bowl.

Our findings portray a world in which "there is no free lunch." Paid advertising developed for TV and the Internet should not *automatically* be associated with meaningful increases in WOM. If a brand has the goal of increasing WOM, and uses advertising as the vehicle to do so,

then care must be taken both to design the campaign for this goal (Van der Lans et al., 2010) and to monitor that the design is successful. While our results demonstrate that some campaigns for some brands such as Super Bowl advertisements generate far higher WOM response, the small average implied elasticity and low heterogeneity across brands and categories suggest that these larger effects are relatively rare and are not obtained without a focused investment of considerable resources.

2 Existing Theory and Evidence on the Advertising-WOM Relationship

Marketing theory provides a foundation for both a positive and a negative advertising-WOM relationship. On the positive side, engaging in WOM is driven by the need to share and receive information, have social interactions, or express emotions (Lovett, Peres, and Shachar 2013; Berger 2014). Advertising can trigger these needs and potentially stimulate a WOM conversation about the brand. Four routes through which advertising might trigger these needs include attracting attention (Batra, Aaker, and Myers 1995; Mitra and Lynch 1995; Berger 2014), increasing social desirability and connectedness (Aaker and Biel 2013; Van der Lans and van Bruggen 2010), stimulating information search (Smith and Swinyard 1982), and raising emotional arousal (Holbrook and Batra 1987; Olney, Holbrook, and Batra 1991; Lovett, Peres, and Shachar 2013, Berger and Milkman 2012).

However, advertising can also have a negative influence on WOM. Dichter (1966) argues that advertising decreases involvement, and if involvement has a positive influence on WOM (Sundaram, Mitra, and Webster 1998), advertising would cause a decrease in WOM. Feng and Papatla (2011) claim that talking about an advertised brand may make an individual look less unique, and may harm her self enhancement. Similarly, if advertising provides sufficient

information so that people have the information they need, they will tend to be less receptive to WOM messages (Herr, Kardes, and Kim 1991), which diminishes the scope for WOM.

The overall balance between the positive and negative influences is not clear. Scholarly empirical research on this issue is limited and the available results are mixed. Onishi and Manchanda (2012) estimated the advertising elasticity of TV advertising exposures on blog mentions for 12 movies in Japan, and found an elasticity of 0.12 for pre-release advertising, and a non-significant effect for post-release advertising. Gopinath, Thomas and Krishnamurthi (2015) studied the impact of the number of ads on online WOM for 5 models of mobile phones and estimated elasticities of 0.19 for emotion advertising and 0.37 for "attribute" (i.e. informational) advertising. Feng and Papatla (2011) used data on cars to show both positive and negative effects of advertising on WOM. Using a model of goodwill for movies, Bruce, Foutz and Kolsarici (2012) found that advertising has a positive impact on the effectiveness of WOM on demand, but did not study the effect on WOM volume. Bollinger et al. (2013) found positive interactions between both TV and online advertising and Facebook mentions in influencing purchase for fast moving consumer goods, but did not study how one affects the other. Tirunillai and Tellis (2012) studied 15 firms from 6 markets and estimated the elasticity of online WOM on advertising expenditures to be 0.09. Hewett et al. (2016) find that advertising spend by four banks do not affect online Twitter posts, and Pauwels, Aksehirli and Lackman (2016) find that for one apparel retailer the effects of advertising on electronic brand WOM are relatively large in the long-term, but small in the short-term.

Thus, both marketing theory and scholarly empirical research offer mixed guidance about the direction and size of the advertising-WOM relationship. Our focus is to quantify this relationship using data that cuts across many industries and brands, spans a long time-period, and

captures a wide set of controls. Our setting is mostly large established brands with relatively large advertising budgets. We next describe the main dataset used in our analysis.

3 Data

Our dataset contains information on 538 U.S. national brands from 16 product categories (the list is drawn from that of Lovett, Peres, and Shachar 2013), and detailed description appears in Web Appendix A. The categories include: beauty products, beverages, cars, children's products, clothing products, department stores, financial services, food and dining, health products, home design and decoration, household products, media and entertainment, sports and hobbies, technology products and stores, telecommunication, and travel services. The brands in the list include products and services, corporate and product brands, premium and economy brands. For each brand from January 2007 to June 2013, we have monthly information on advertising expenditures, word of mouth mentions, and brand mentions in the news. We elaborate on each data source and provide some descriptions of the data below.

3.1 Advertising expenditure data

We collect monthly advertising expenditures from the Ad$pender database of Kantar Media. For each brand, we have constructed three categories of advertising—TV advertising, Internet advertising, and other advertising. For TV advertising, we have aggregated expenditures across all available TV outlets (DMA-level as well as national and cable). For Internet advertising expenditures, we include display advertising (the only Internet advertising available in Ad$pender). Display advertising is appropriate since it is more often used as a branding tool, whereas search advertising is more closely connected with encouraging purchases directly. Hence, display advertising is more closely aligned with the goal of obtaining WOM. We focus

on these TV and Internet advertising expenditures for three reasons. First, for our brands, together they form the majority of the expenses at around 70% of the total expenditures according to Ad$pender. Second, TV advertising is the largest category of spending and has been suggested to be the most engaging channel (Drèze and Hussher 2003) and often cited as generating WOM. Third, Internet advertising is touted as the fastest growing category of spending among those available in Kantar and reflects the prominence of "new media." That said, we also collect the total advertising expenditures on other media, covering the range of print media (e.g., newspapers, magazines), outdoor, and radio advertisements.

3.2 Word of mouth data

Our primary word of mouth data is drawn from the TalkTrack dataset of the Keller-Fay Group. The dataset contains the number of mentions for each brand every week across a sample of respondents, who are recruited to self report for a 24-hour period on all their word of mouth conversations. During the day they record their brand conversations and list the brands mentioned in the conversation. Note that a list of brands is not provided to respondents – i.e., they can mention any brand. These conversations can happen both online and offline. The inclusion of offline WOM is important, since it is estimated to be 85% of WOM conversations (Keller and Fay 2012).

The sample includes 700 individuals per week, spread approximately equally across the days of the week. This weekly sample is constructed to be representative of the U.S. population (see Lovett, Peres, and Shachar (2013) for a detailed description). The company uses a scaling factor of 2.3 million to translate from the average daily sample mentions to the daily number of mentions in the population. We aggregate the WOM data to the monthly level to match with the monthly advertising data on all brands in our main analysis.

3.3 News and press mentions data

WOM may be triggered by news media, which might also proxy for external events (e.g., the launch of a new product, a change of logo, product failure or recall). Such events could both lead the firm to advertise and consumers to speak about the brand, so that the WOM is caused by the event not the advertising. To control for such unobserved events and news, we use the LexisNexis news and press database to collect the monthly number of news and press mentions for each brand.

3.4 Descriptive statistics

Table 1 presents category specific information about the advertising, media mentions, and WOM mentions data. This table communicates the large variation across categories in the use of the different types of advertising and in the number of media mentions. For example, the highest spender on TV ads is AT&T, the highest spender on Internet display ads is TD AmeriTrade, and the brand with the highest number of news mentions is Facebook. The average number of mentions for a brand in the sample is 15.8 (equivalent to 36 million mentions in the population), and the brand with the highest WOM is Coca Cola. In Web Appendix A, we present time series plots for four representative brands as well as descriptive statistics and correlations for the data.

-------- *Insert Table 1 about here* ----

4 Model

In our main analysis, we focus on relating advertising expenditures to WOM. Our empirical strategy is to control for the most likely sources of alternative explanations and evaluate the

remaining relationship between advertising and WOM. Hence, causal inference requires a conditional independence assumption. We are concerned about several important sources of endogeneity due to unobserved variables that are potentially related to both advertising and WOM and, as a result, could lead to a spurious relationship between the two. The chief concerns and related controls that we include are 1) unobserved (to the econometrician) characteristics at the brand level that influence the advertising levels and WOM, which we control using brand fixed effects (and in one robustness test, first differences), 2) WOM inertia that is spuriously correlated with time variation in advertising, controlled for by including two lags of WOM, 3) unobserved product introductions and related PR events that lead the firm to advertise and also generate WOM, which we control using media mentions of each brand, and 4) seasonality and time varying quality of the brand that leads to both greater brand advertising and higher levels of WOM. For seasonality and time-varying quality, we use a (3rd order) polynomial function of the month of year and of the year. This mitigates the effect of a high and low season (within year) and longer time trends across years. We also introduce common time effects in a robustness test.

With these controls in mind, our empirical analysis proceeds as a log-log specification (where we add one to all variables before the log transformation).[1] Under the conditional independence assumption, this specification imposes a constant elasticity for the effect of advertising expenditures on WOM and implies diminishing returns to levels of advertising expenditures. For a given brand *j* in month *t*, the empirical model is defined as

$$(1)\ \log(WOM)_{jt} = \alpha_j + \gamma_{1j}\log(WOM)_{jt-1} + \gamma_{2j}\log(WOM)_{jt-2}$$

[1] We also test adding alternative constants (0.1 and 0.01). The relative magnitudes and statistical significance are consistent with the reported results, and qualitative conclusions remain the same. The results are available from the authors.

$$+\beta_{1j} log(AdTV)_{jt} + \beta_{2j}\log(AdInternet)_{jt} + X_{jt}\beta_{0j} + \varepsilon_{jt}$$

where α_j are brand fixed effects, log(*AdTV)* and log*(AdInternet)* relate to the focal variables, logged dollar expenditures for TV and Internet display ads, and X_{jt} contains control variables that include the logged dollar expenditures for other advertising (print, outdoor, and radio), logged count of news and press articles mentioning the brand and polynomials (cubic) of month of year and year. The $\gamma_{1j}, \gamma_{2j}, \beta_{0j}, \beta_{1j}, \beta_{2j}$ are random coefficients for, respectively, the effect of lagged word-of-mouth variables, X_{jt}, and the two focal advertising variables.

In what follows, we focus on the average relationship between advertising and WOM across brands. In one set of results we also allow observable heterogeneity in brand coefficients in the form of category-level differences.[2] For the models that include both random coefficients and fixed effects we use proc mixed in SAS with REML. For the models without random coefficients we use plm in R, which estimates the model using a fixed effects panel estimator, noting that in both models our longer time-series implies negligible `Nickell bias' in the lagged dependent variables (Nickell 1981).[3]

5 *Results*

We organize the results from our main analysis into three sections. The first section presents our results related to the magnitude of the average relationship between advertising and WOM and interpreting this magnitude in the broader context of advertising. The second section explores

[2] We note that we also examined whether the WOM effects varied by brand characteristics using the data provided by Lovett, Peres, and Shachar (2013). The relationships we found suggested there were few significant relationships, so few that the relationships could be arising due to random variation rather than actual significance.
[3] In robustness checks, we also conduct several two-stage least squares analyses to evaluate the extent of remaining endogeneity bias after our controls. These are also done in R using plm.

how much heterogeneity in the advertising-WOM relationship exists across brands and categories. The third section sheds light on whether some types of advertising campaigns or special events might exhibit larger relationships between advertising and WOM, through an analysis of Super Bowl advertising.

5.1 The advertising-WOM relationship

The first set of columns in Table 2 (Model 1) presents the results from estimating Equation (1). In this section, we focus on the parameters related to the population mean for Model 1. We find that the advertising variables indicate significant positive coefficients for both TV (0.016, s.e. =0.002) and Internet display ad expenditures (0.010, s.e. =0.002). The difference between the two coefficients is significant (0.0058, s.e. diff 0.0027), indicating that at the point estimates the relationship between TV advertising and WOM is 60% stronger than that of Internet display advertising and WOM.

The control variables take the expected signs, are significant, and have reasonable magnitudes. Based on the estimated effects for the lagged dependent variables, WOM has a low level of average persistence in WOM shocks that diminishes rapidly between the first and second lag[4], keeping in mind that these effects are net of the brand fixed effects. News mentions have a much larger significant and positive estimate, but we caution against interpreting this effect as arising due to news per se, since this variable could also control for new product introductions which typically are covered in the news. The variance parameters for the heterogeneity across

[4] We have also tested the effect of adding lagged TV ads, Internet ads, other ads and news mentions. These model results do not substantially alter our conclusions, but sharply increase the expositional difficulty. We report the simpler current advertising version for ease of exposition. For these models, the first lags are significant for all but Internet ads, and much smaller than the current variables. The magnitude of the current variable reduces and the total impact including all lags is similar in size. The second lags for all variables were found to be insignificant.

brands are also all significant.[5] We discuss the heterogeneity related to the brand advertising variables in more detail in section 5.2.

------- *Insert Table 2 about here* ---------

How big are these estimated advertising effects on WOM? Since the analysis is done in log-log space, the estimated coefficients on advertising are constant advertising elasticities under the causal interpretation of the coefficient. The implied elasticity of WOM to TV advertising expenditures is 0.016 and to Internet advertising expenditures is 0.010.

We offer some perspective on the magnitude of this relationship. First, the relationship is quite modest even in absolute magnitudes. For instance, in our sample, the average number of conversations about a brand in a month is 15.8. Given the sampling procedure of Keller-Fay, they project that one brand mention in their sample equals 2.3 million mentions in the United States. This suggests there are 36.4 million conversations about the average brand in our dataset in a month. Our elasticity estimate implies that a 10% increase in TV advertising corresponds to around 58,000 additional conversations about the brand per month. For the large, high WOM national brands that we study, this number of brand conversations is quite small. Consider the average spending of $5.89 million on TV advertising. A 10% increase in spending at 1 cent per advertising impression on average generates 58.9 million advertising impressions. In this case, the additional WOM impressions associated with advertising is orders of magnitude smaller than the advertising impressions, only one thousandth.

[5] We note that we include only heterogeneity in the linear time and seasonality terms of the cubic functions. This was necessary due to stability problems with estimating such highly collinear terms as random effects.

Second, the translation to sales based on the estimated WOM elasticities in the literature are quite small, too. For instance, You et al. (2015) in a meta-study of electronic WOM find an overall elasticity of 0.236 on sales. At this elasticity for WOM on sales, the average impact of advertising through WOM would be less than 0.004. Further, the 0.236 eWOM elasticity of You et al. (2015) is relatively large compared to recent studies that find elasticities between 0.01 and 0.06 (Lovett and Staelin 2016; Seiler, Yao, and Wang 2017). With these lower elasticities, the effect would be an order of magnitude smaller. Given that the meta-studies on the influence of advertising on sales (e.g., Sethuraman, Tellis, and Briesch 2011) reveal average advertising elasticities of 0.12, the implied impact of advertising on sales through WOM is only a very small part of the overall advertising influence.

How do these elasticities relate to the elasticities reported in the specific cases studied in the scholarly literature? As mentioned above, reported results are mixed, with some analyses showing a positive effect (Onishi and Manchanda 2012; Tirunillai and Tellis (2012); Gopinath, Thomas, and Krishnamurthi 2015; Pauwels, Aksehirli and Lackman 2016), some showing no significant effect (Trusov, Bucklin, and Pauwels 2009; Onishi and Manchanda 2012; Hewett et al., 2016), and some even showing negative effects (Feng and Papatla 2011). The comparison, even in the cases of positive elasticities is not very direct. For example, Onishi and Manchanda (2012) provide an estimated elasticity of 0.12 for daily advertising exposures on pre-release WOM, where the WOM is blogs about 12 different movies in Japan. For five models of mobile phones Gopinath, Thomas, and Krishnamurthi (2015) find elasticities between 0.19 and 0.37 for monthly online WOM to the number of advertisements. Pauwels et al. (2016) finds long-term brand electronic WOM elasticities of 0.085, 0.149, 0.205, and 0.237 for TV, print, radio, and paid search ads for weekly data about one apparel retailer. We differ notably in two ways. First,

our measure is the response of total *monthly* WOM, which may smooth some of the daily variation captured in Onishi and Manchanda (2012) and the weekly variation in Pauwels et al. (2016). Second, our data covers over 500 brands, spans 6.5 years, and covers all types of WOM, not just online. With these broader definitions and sample, it appears the estimated average relationship between advertising and WOM is much smaller than what is currently reported in the literature.[6] Hence, in absolute terms and relative to the positive findings in the literature, we find a weak average advertising-WOM relationship.

In Web Appendix B, we provide details on a range of model tests that support the robustness of the main results presented above. First, we drop or add different components to the model to evaluate robustness to specification. We find that as long as either lagged WOM or brand fixed effects are included in the model, the small advertising-WOM relationships described above maintain. Importantly, the brand fixed effects are critical controls since without them the relationship between WOM and advertising budgets (e.g., due to sales) would appear to be stronger than it actually is.

Second, we evaluate instrumental variables specifications. Our empirical strategy leverages control variables to reduce potential endogeneity concerns related to seasonality, unobserved brand effects, secular trends, and new product/service launches. The causal interpretation of our results relies on a conditional independence assumption. The main concerns about measuring advertising causal effects typically involve positive biases (e.g., brands advertise in the high season of sales that might falsely be attributed to the advertising). We have attempted to control for these concerns and show that our control variables do not overly influence the results.

[6] Our small effect size appears similar in some respects to Du and Wilbur's (2016) small correlation between advertising and brand image measures using weekly data.

However, we also note that failing to account for endogeneity of advertising is usually expected to produce *larger* effect sizes. Since we find a small effect size, this suggests the typical concerns are not a major threat. One main argument specific to our context could lead to a downward bias—if advertising and WOM are substitutes. Since the advertising for large established brands tends to be planned well in advance, advertising cannot easily respond to short-term fluctuations in WOM. Hence, we can narrow the substitutes concern to planning to cut advertising when WOM is high and vice versa. For example, when the product is on consumers' minds and being talked about (e.g., summer for ice cream), the firm chooses not to advertise. On the face, this seems like a counter-intuitive and counter-factual argument. Even so, our brand level seasonality and secular trend controls are intended to address exactly this kind of concern.

Nonetheless, because we recognize our analysis relies on conditional independence, we also examine whether our results are robust to an instrumental variables approach to solving any remaining endogeneity. We find that the main estimates do not shift meaningfully under an alternative model where we use instrumental variables as an explicit source of exogenous variation. Unfortunately, the instruments we were able to obtain (costs and political advertising) are weak.[7]

Together, these additional analyses presented in Web Appendix B provide support for the robustness of our main results, and in particular the small average effect. The only main result that is not robust is the finding that the TV advertising effect is larger than the Internet advertising effect. In the next section, we discuss whether the average advertising-WOM relationship covers up heterogeneity in the relationship across brands and categories.

[7] We also examined whether WOM that mentions advertising has a stronger relationship with advertising expenditures. We find that it is not meaningfully different in magnitude. These results are in Web Appendix C.

5.2 Does the average effect mask larger effects for some brands or categories?

We now turn to how much stronger the effects for some brands and categories are than the average effect we reported thus far. Brand level heterogeneity in the relationship between advertising and WOM could lead some brands to have strong relationships and others to have weak relationships, resulting in the small average coefficients described above. For instance, this variation could arise from different customer bases, different brand characteristics, different degrees of engagement with the brand, or different types or quality of advertising campaigns between brands. Heterogeneity variances for Model 1 in Table 2 shows that the standard deviations for the heterogeneity in advertising coefficients are roughly the same size as the coefficients themselves, indicating that brands differ meaningfully in the relationship between WOM and advertising. However, the cross-brand variation does not produce an order of magnitude shift in the point estimates. For example, for the TV ads effect, a two standard deviation shift implies that a few brands have point estimates as large as 0.054. Although the max of these point estimates is larger than the overall average, 0.054 is still less than half the size of the typical sales elasticity to advertising. This suggests that even for the brands with the largest relationships between advertising and WOM, the magnitudes are relatively modest.

To understand whether the relationships systematically differ across categories, we incorporate category dummy variables and interact them with the variables in Equation (1). Figure 2 presents the category level estimates with +/− one standard error bars for both TV and Internet dollar spend. As apparent, the automobiles category has the smallest average TV advertising-WOM relationship (-0.004, but not significantly different from zero), whereas the highest estimate is 0.041 for Sports and Hobbies, significantly larger than zero and the coefficient for automobiles. Also, on the high-end are Telecommunications, which includes

mobile handset sellers, and Media and Entertainment, which includes movies. These latter two categories are ones that past research has found to have significant, positive effects of advertising on WOM (mobile handsets and movies). Hence, the category variation we find is directionally consistent with the categories that have been studied in the past being exceptionally large. For Internet display advertising expenditures, we find that Sports and Hobbies have one of the weakest relationships, whereas Media and Entertainment has the highest. Again, overall, we find that the categories with the largest advertising elasticities are still relatively small.

------- *Insert Figure 2 about here* ---------

5.3 Does the average effect mask larger effects for some events or campaigns?

While the heterogeneity in categories and brands described in the last section suggests that persistent differences do not lead to large magnitudes for the advertising-WOM relationship, it is possible that some events, periods, or specific campaigns might do so. One leading possibility is that certain campaigns or events are simply better at generating conversation than others. To evaluate this potential, we examine one of the most often cited sources of incremental WOM impressions from advertising—the Super Bowl.[8] We collected information on which of the brands in our dataset advertised in the Super Bowl in each of the years in our sample. We then incorporated this data into our model by including both a main effect of being a Super Bowl advertiser in the month of the Super Bowl (February) and interaction terms between this variable

[8] We also collected data on advertising awards including, for instance, the EFFIE, CANNES, and OGILVY awards. Interacting the award winners in a year with their advertising expenditure produced no statistically significant results nor systematic pattern.

and the logged advertising spending variables. If the Super Bowl increases the effectiveness of advertising spending on WOM impressions, we would expect the coefficients on the interaction terms to be positive.

The second set of columns in Table 2 (Model 2) presents the results. We find that none of the Super Bowl interaction terms is large or significant. In fact, the term for TV advertising, which one would expect to be positive if Super Bowl advertising is more efficient, is actually negative and small.[9] While this finding suggests that advertising on the Super Bowl does not lead to stronger relationships between advertising expenditures and WOM, the main effect potentially tells a different story. In particular, the main effect of being a Super Bowl advertiser is positive, large (0.24) and significant (t-stat = 2.04). This indicates that although Super Bowl advertising expenditures are not more efficient per dollar than at other times, Super Bowl advertisers have on average 24% higher WOM in the month of the Super Bowl than in other periods. This large effect size could suggest that advertising is more effective in the Super Bowl for creating WOM, but that the variation in advertising spending on Super Bowl ads is insufficient to attribute that gain to advertising expenditures. Since such an increase could translate to a much larger effect than what we find in the small average elasticity, this result seems to provide an opportunity for advertising to play a much larger role in creating WOM than our previous findings suggest. Further, this finding is consistent with both the popular press and practitioner literature arguing that Super Bowl advertisements lead to a large increase in social media impressions.

If the Super Bowl main effect is causal then advertising may generate WOM in some campaigns or when combined with specific events. However, because this finding is a main

[9] The Super Bowl main effect and interaction effects do not have random coefficients, because they are not separately identified from the brand fixed effects and the brand-specific advertising random coefficients.

effect with a discrete time variable, the threats to causal inference are more severe including concerns about the non-random identity of Super Bowl advertisers and the potential for anticipated, unobserved brand-time WOM shocks. In the next section, we examine in more detail this main effect using techniques specifically aimed at addressing these threats to causal inference.

5.4 The Causal Effect of Advertising in the Super Bowl on WOM

Unlike in the main analysis, where we observe multiple continuous advertising expenditure variables, the analysis in this section focuses on whether being a Super Bowl TV advertiser causes an increase in WOM. In this case, we have a discrete "treatment" variable, *Super Bowl*, which takes a value of 1 for Super Bowl advertisers in the time period(s) when we test for an effect, and 0 otherwise. In this section, we present evidence about the causal effect of this Super Bowl treatment.

To measure this causal effect, we would like to calculate the difference between the realized WOM for the Super Bowl advertisers as compared to the counterfactual case, i.e., the WOM these brands would receive had they not advertised in the Super Bowl. Of course, by definition, we do not (and cannot) observe the counterfactual case for the same brands, and instead seek a way to generate the missing counterfactual WOM data. Ideally, we would run a field experiment that randomizes the assignment of Super Bowl advertising slots to brands in order to justify using the non-treated brands as the counterfactual measure. This is infeasible.[10]

[10] We note that some recent papers have used other strategies that leverage geographic variation and the surprise of who plays in the Super Bowl (Hartmann and Klapper forthcoming). We could not employ this approach due to national level data.

To construct the prediction for this missing counterfactual data, we use a recently developed technique, the Generalized Synthetic Control Method (GSCM) of Xu (2017). This method is a parametric approach that generalizes to multiple treatment units the synthetic control method developed by Abadie, Diamond, and Hainmueller (2010). The synthetic control method was originally developed for comparative case studies, and has been used and extended broadly including in economics (Doudchenko and Imbens 2016), finance (Acemoglu et al., 2016), political science (Xu 2017), and, recently, in marketing (e.g., Vidal-Berastain, Ellickson, and Lovett 2017).

The intuition behind these methods is to use the non-treated cases—so called "Donors"—to create a "synthetic control" unit for each treatment unit. The synthetic control unit is developed by using a weighted combination of the donor pool cases, where the weights are selected so that they create a synthetic control that closely matches the pre-treatment data pattern of the outcome variable (in our context, logged WOM) for the treated cases. The synthetic control's post-treatment pattern is then used as the counterfactual prediction for the treated cases. Because the synthetic controls method uses the pre-treatment outcome variable, it naturally conditions on both observables and unobservables. As the pre-treatment time-series increases in length, the level of control increases. Thus, the synthetic control approach can account for unobserved variables that might otherwise invalidate causal inference.

In the GSCM, a parametric model of the treatment effect and data generating process follows the interactive fixed effects model (see Bai 2009) and is assumed to be

$$(2)\ Y_{it} = \delta_{it} D_{it} + x_{it}'\beta + \lambda_i' f_t + \varepsilon_{it},$$

where

D_{it}: binary treatment variable for a brand *i* in a Super Bowl in period *t*

δ_{it}: The brand-time specific treatment effect

x_{it}: Fixed effect for every brand/Super Bowl-year and period

β: The vector of common coefficients on the control variables

f_t: The unobserved time-varying vector of factors with length *F*

λ_i: The brand-specific length *F* vector of factor loadings

ε_{it}: stochastic error, assumed uncorrelated with the D_{it}, x_{it}, f_t, and λ_i

The method requires three further assumptions related to only allowing weak serial dependence of the error terms, some (standard) regularity conditions, and that the error terms are cross-sectionally independent and homoscedastic. Given these assumptions, the average treatment effect on the treated, ATT_t, for the set of N_{Tr} Super Bowl advertising brands, $\mathcal{T}$, can be estimated based on the differences between *i*'s observed outcome $Y_{it,i\in\mathcal{T}}$ and the synthetic control for *i*, $Y_{it,SC}$.

$$(3)\ ATT_t = \frac{1}{N_{Tr}} \sum_{i\in\mathcal{T}} \left[Y_{it,i\in\mathcal{T}} - Y_{it,SC} \right]$$

Estimation proceeds in three steps. First, we estimate the parameters β, the λ_i vectors for all donor pool cases, and the vector f_t. These are estimated using only the data from the pre-treatment period for the donor pool. Second, the factor loadings, λ_i for each of the treated units are estimated using the pre-treatment outcomes for the treatment cases conditioning on the β and f_t estimates. Third, the synthetic control for the treated counterfactuals, $Y_{it,SC}$, are calculated using the β and f_t estimates from step one and the λ_i estimates from step two. This then allows calculating the ATT_t for each period. The number of factors, *F*, is selected via a cross-validation procedure in which some pre-treatment observations are held back and predicted. The three-step

procedure is used for each number of factors and the number of factors with the lowest mean squared prediction error is chosen. Inference proceeds using a parametric bootstrap. See Xu (2017) for details on the procedure and inference.

We implement the procedure using the available software package in R, gsynth. We estimate the causal effects including two-way fixed effects (time and brand-year). Our standard errors are clustered at the brand-year level and we use 16,000 samples for bootstrapping the standard errors. We report analyses for both the Keller-Fay WOM measure, which is a representative sample of online and offline WOM, and Nielsen-McKinsey Insight (NMI), which is a tool that provides counts of online posts about brands. The two datasets overlap from 2008 onward and so we use this common period to make the analyses comparable. We note that for the Keller-Fay measures the reported subsample and the full available time period have quite similar effect sizes and significances.

We report the average treatment effects in Table 3 along with the number of factors used and the number of pre-periods, post-periods, and total observations. In most cases, the number of factors reported is the optimal number selected by the cross-validation technique. In the Keller-Fay WOM cases, the optimal number of unobserved factors was zero suggesting no meaningful remaining interactive fixed effects in the data. This indicates that the fixed unit and time effects already control for the unobserved time-varying influences. This finding provides indirect support for our conditional independence assumption used in the main analysis section. In these cases with zero optimal factors, we also present solutions where we forced the model to have one unobserved factor to ensure robustness against more factors.

We begin with the monthly data that most closely approximates our main analysis. We include the last six months prior to the Super Bowl as pre-treatment periods and consider the

Super Bowl treatment beginning in February (time 0) and continues through March. We find a significant and positive average causal effect of being a Super Bowl advertiser for the month of and after the Super Bowl. The average ATT for the two months is 10.8% (s.e.=0.043,p-value=0.026) with the best fitting number of factors (zero) and 10.3% (s.e.=0.050,p-value=0.035) with one factor. The ATT for the month of the Super Bowl, February, is estimated to be 15.9% (s.e.=0.054, p-value<.01) with the optimal zero factors and 15% with one factor (s.e.=0.062, p-value=0.013), but this effect rapidly declines. Already in March, the effect is insignificant with the ATT estimated to be 6% (s.e. 0.054, p-value=0.246) with zero factors. Panel A of Figure 3 shows the time-varying estimated ATT for each month of the data, showing the only individually significant month is the month of the Super Bowl. Thus, the effect on total WOM caused by being a Super Bowl advertiser is relatively large, but only lasts approximately one month.

One major concern with this analysis is that, if the Super Bowl advertiser effect is actually shorter-lived than one month, monthly data could have an aggregation bias. To examine this possibility, we conduct the analysis on *weekly* Keller-Fay measures, which is the finest periodicity our dataset contains.[11] We use 16 weeks prior to the Super Bowl week as pre-treatment periods, and a total of 4 weeks of treatment periods including the week of and three weeks after the Super Bowl. Panel B of Figure 3 shows the weekly pattern of the effects. The week of the Super Bowl has no increase in WOM (0.1%, s.e.=0.056), which may not be too surprising since the Super Bowl airs on the last day of the week. We find the first week following the Super Bowl has a 22.1% increase (s.e.=0.057, p-value<.01) in WOM, but that the

[11] Note that we have access to the Keller-Fay WOM at the weekly level, but not our other measures, in particular, the Kantar advertising data, so that we are unable to conduct our main panel regression analysis at the weekly level.

following weeks have lower effect sizes of 10.9% (s.e.=0.056, p-value<.061), 14.3% (s.e.=0.058,p-value=0.012), and 10.4% (s.e.=0.058,p-value=0.068) respectively for weeks 2-4. The average ATT across the first four weeks is estimated to be 11.8% and significant (s.e.=0.033, p-value<.01). While the weekly data indicate a higher peak of WOM effect in the week following the Super Bowl, the general patterns do not suggest the monthly data dramatically understate the average effect. In particular, the effect stays significant for the entire month (4 weeks). Overall, these results indicate that being a Super Bowl advertiser causes a sizable increase in WOM of 16% in the first month of and 22% in the first week after the Super Bowl.

These results speak to the potential for aggregation bias in this WOM data. First, the point estimate for the peak weekly effect is less than 50% larger than that of the monthly average. Second, the estimated ATT for February from the monthly data has a 95% confidence interval of (5.2%, 26.6%). This interval actually covers the maximum weekly estimated value, suggesting we cannot statistically distinguish them. These results suggest that our small result in the main analysis that uses monthly data is unlikely to be explained away by short-lived WOM effects. Although there might be aggregation bias, the aggregation bias appears to not be large enough.

Both the above Super Bowl causal analysis and our main analysis consider total WOM including online and offline, taken from a representative sample. However, the studies that show larger effect sizes of advertising on WOM tend to focus on the narrow part of WOM that is online, and use the overall count of brand-related posts from social media outlets such as Twitter, or user blogs. We now examine whether the Super Bowl effect is larger for such online posts,

and whether the effect on these online posts is shorter-lived than that of the overall WOM on the representative sample.

To examine this question, we apply the same analysis to the counts of online posts from the Nielsen-McKinsey Insight user-generated content search engine and Panels C and D of Figure 3 present the effect patterns. In the monthly analysis, the measured ATT for the month of the Super Bowl is significant and 26.6% (s.e.=0.039,p-value<.01), and in the month following the Super Bowl, the effect size falls to be insignificant at 4.9% (s.e.=0.044,p-value=0.240). Thus, the effect does appear to be larger for online posts than total WOM, but lasts at most one month. Considering weekly data, the ATT for the week of the Super Bowl is significant and 48.0% (s.e.=0.042,p-value<.01), and the three weeks after the Super Bowl are all insignificant at 4.1% (s.e.=0.048), 1.8% (s.e.=0.048), and 2.3% (s.e.=0.051), respectively. This analysis suggests that the Super Bowl has a much larger but shorter effect on counts of online posts than on representative, total WOM mentions.

Because the Nielsen-McKinsey Insight data come daily, we can perform the analysis at this even more fine-grained level. For this analysis, we use 60 days prior to the Super Bowl as the pre-treatment period. Panel E of Figure 3 indicates that the incremental posts concentrate heavily on the first few days with significant causal estimates of 67.7% (s.e.=0.062,p-value<.01) for the day of the Super Bowl, 62.8% (s.e.=0.058,p-value<.01) for the day after, 39.7% (s.e.=0.068,p-value<.01) for the second day after, 25.2% (s.e.=0.081,p-value<.01) for the third, 12.3% (s.e.=0.084,p-value=.179) and insignificant for the fourth, and dropping to below 10% and insignificant thereafter. These causal effects on online posts for the first three days are much larger than the effects on total WOM measured with a representative sample. This analysis also

reaffirms the concentration of incremental impressions close to the Super Bowl for online posts.[12]

How should we interpret these results for the online posts from Nielsen-McKinsey Insight compared to the total WOM from Keller-Fay? First, the effects for online posts are larger for a short duration (few days for daily or one week for weekly). In contrast, the effect on the total WOM persists for approximately the full month. These shorter-term, stronger effects in the online data might explain why studies that focus on online posts alone may find larger effects of advertising on WOM. Second, the total WOM from Keller-Fay is measured with a representative sample of the U.S. population and can be interpreted as impressions. In contrast, the online posts have only a vague connection to impressions with some posts never seen by anyone and others seen by many people and are not collected to be representative. Thus, for generalizations to impressions that advertising creates, the Keller-Fay data has a stronger foundation.

6 Discussion

We conducted an empirical analysis to evaluate the relationship between advertising expenditures and WOM conversations about brands. The belief that this relationship is strong and positive is used to justify advertising buys and influences the level of investment in advertising. Yet, while some practitioners appear to assume advertising increases WOM meaningfully, scholarly empirical research on this influence is scarce, is based on a few product launches, and shows mixed results. Our dataset contains information on 538 U.S national brands across 16 categories over a period of 6.5 years. Our main analysis controls for news mentions,

[12] Interestingly, this analysis also suggests that unlike the total WOM from the Keller-Fay data, data on online posts would exhibit meaningful aggregation biases, even at the weekly level.

time lagged WOM, seasonality, secular trends, brand fixed effects and random coefficients, and checks robustness against model misspecification. In a second set of analyses, we apply a causal inference technique (Bai 2013; Xu 2017) on Super Bowl advertisers to evaluate the possible impact of large, WOM-focused advertising campaigns on WOM. Together, these analyses present a compelling story. Our main findings include:

1. The relationship between advertising and WOM is positive and significant, but small. Assuming causality, the average implied elasticity of TV advertising is 0.016, and that of Internet advertising is 0.010. Projecting from our sample to the entire US population, for an average brand in our dataset this implies that a 10% increase in TV advertising leads to 58,000 additional conversations about the brand per month. This amounts to approximately 0.1% of the paid advertising exposures for the same advertising spend.

2. Cross-brand and cross-category heterogeneity in the advertising-WOM relationship is significant. The categories with the largest implied elasticities to TV advertising are Sports and Hobbies, Media and Entertainment, and Telecommunications. However, even for these categories, the average implied elasticity is relatively small, with values between 0.02 and 0.05. Similarly, the "best" brands are estimated to have average elasticities of only around 0.05. This implies the brands with the most effective brand advertising for WOM would be associated with increases in WOM conversations that are less than 1% of the increase in advertising exposures.

3. Certain events and campaigns are able to achieve higher impact on WOM. Our causal analysis of the Super Bowl advertisers indicates that WOM increases 16% in the month of the Super Bowl and 22% in the week after the Super Bowl. This implies an increase of 10-13% of the average advertising impressions.

4. The Super Bowl advertiser impact on online posts, harvested from the Internet (instead of using a representative sample) is even higher, but much shorter-lived. The causal effect is 27% for the month of, 48% for the week of, and 68% for the day of the Super Bowl.

These results imply that the advertising-WOM relationship is small on average, but that a larger effect is possible for certain campaigns. Further, the effect of specific campaigns can be relatively large and very short-lived when measuring the effect on online social media posts instead of the total WOM for a representative sample of the population. We take this to imply that one should be cautious about generalizing the impact of advertising on WOM based only on online post data collected by crawling the web.

What are the managerial implications of our findings? Our findings suggest, as the title of this paper implies, "there is no free lunch." Mass TV and Internet display advertising expenditures do not *automatically* imply large gains in WOM. More precisely, across 538 brands and many campaigns per brand over the 6.5-year observation window, high advertising expenditures **on average** are not associated with a large increase in WOM. Similarly, based on our analysis, no single brand or category appears to generate large average effects across the 6.5 years. We do find, for Super Bowl advertisers, where expenditures are very large and the event is a social phenomenon with the advertisements playing a relatively central role in media attention about the event, the causal effect on WOM is larger. However, such successful WOM campaigns must be relatively rare to still find the average advertising effects to be so small.

Does the small average effect we find imply that investing in advertising to generate WOM is foolish? Not necessarily. Our results suggest that if marketers seek to enhance WOM through advertising, they will likely need to go beyond the typical advertising campaigns contained in our dataset. Our analysis reveals that managers are unlikely to generate meaningful increases in

WOM unless they obtain deeper knowledge of which expenditures and campaigns generate WOM on which channels. We suggest that for managers to pursue the goal of generating WOM from advertising, they need to be able to track WOM carefully and use methods that can assess the effectiveness of advertising in generating WOM at a relatively fine-grained level (e.g., campaign or creative). Importantly, because of the disconnect between online posts and overall WOM, it is critical to evaluate both to understand the true picture of impressions gained from advertising.

References

Aaker, David A. and Alexander Biel (2013), *Brand equity & advertising: advertising's role in building strong brands*, Psychology Press.

Abadie, Alberto, Alexis Diamond, and Jens Hainmeller (2010), "Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program," *Journal of the American Statistical Association*, 105 (490), 493-505.

Acemoglu, Daron, Simon Johnson, Amir Kermani, and James Kwak (2016), "The Value of Connections in Turbulent Times: Evidence from the United States," *Journal of Finanial Economics*, 121, 368-391.

Angrist, Joshua and Jörn Steffen Pischke (2008), *Mostly Harmless Econometrics: An Empiricist's Companion*, Princeton University Press.

Bai, Jushan (2009), "Panel Data Models with Interactive Fixed Effects," *Econometrica*, 77(4), 1229-1279.

Bai, Jushan (2013), "Notes and Comments: Fixed Effects Dynamic Panel Models, A Factor Analytical Method," *Econometrica*, 81(1), 285-314.

Batra, Rajeev, David A. Aaker, and John G. Myers (1995), *Advertising Management*, 5th Edition, Prentice Hall.

Belloni, Alexandre, Daniel Chen, Victor Chernozhukov, and Christian Hansen (2012), "Sparse models and methods for optimal instruments with an application to eminent domain," *Econometrica*, 80 (6), 2369-2429.

Berger, Jonah (2014), "Word of mouth and interpersonal communication: A review and directions for future research," *Journal of Consumer Psychology*, 24 (4), 586-607.

Berger, Jonah and Katherine L. Milkman (2012), "What makes online content viral?" *Journal of marketing research*, 49 (2), 192-205.

Bollinger, Bryan, Michael Cohen, and Lai Jiang (2013), "Measuring Asymmetric Persistence and Interaction Effects of Media Exposures across Platforms," *working paper*.

Bruce, Norris I., Natasha Zhang Foutz, and Ceren Kolsarici (2012), "Dynamic effectiveness of advertising and word of mouth in sequential distribution of new products," *Journal of Marketing Research*, 49 (4), 469-486.

Campbell, Arthur, Dina Mayzlin, and Jiwoong Shin (2017), "Managing Buzz", *The RAND Journal of Economics*, 48 (1), 203-229.

Chen, Yubo and Jinhong Xie (2008), "Online consumer review: Word-of-mouth as a new element of marketing communication mix," *Management Science*, 54 (3), 477-491.

Chevalier, Judith A. and Dina Mayzlin (2006), "The effect of word of mouth on sales: Online book reviews," *Journal of marketing research*, 43 (3), 345-354.

Danaher, Peter J., and Tracey S. Dagger (2013), "Comparing the relative effectiveness of advertising channels: A case study of a multimedia blitz campaign," *Journal of Marketing Research*, 50 (4), 517-534.

Dichter, Ernest (1966), "How Word-of-mouth Advertising Works," *Harvard Business Review*, 16 (November-December), 147-166.

Dinner, Isaac M., Harald J. Van Heerde, and Scott A. Neslin (2014), "Driving online and offline sales: The cross-channel effects of traditional, online display, and paid search advertising," *Journal of Marketing Research*, 51 (5), 527-545.

Doudchenko, Nikolay and Guido Imbens (2016), "Balancing, Regression, Difference-in-Difference and Synthetic Control Methods: A Synthesis," working Paper.

Draganska, Michaela, Wes Hartmann, and Gena Stanglein (2014), "Internet vs. Television advertising: A brand-building comparison," *Journal of Marketing Research*, 51 (5), 578-590.

Drèze, Xavier and François-Xavier Hussherr (2003), "Internet advertising: Is anybody watching?" *Journal of Interactive Marketing*, 17 (4), 8-23.

Du, Rex and Kenneth C. Wilbur (2016), "Advertising and Brand Image: Evidence from 575 Brands over 5 Years," working paper.

Duan, Wenjing, Bin Gu, and Andrew B. Whinston (2008) "The dynamics of online word-of-mouth and product sales: An empirical investigation of the movie industry," *Journal of Retailing*, 84 (2), 233-242.

Feng, Jie and Purushottam Papatla (2011), "Advertising: stimulant or suppressant of online word of mouth?" *Journal of Interactive Marketing*, 25 (2), 75-84.

Furrier, John (2013) "Innovative Advertising Is About Integrating TV with Social - Kia Motors Uses Social Media to Reach the New Audience," *Forbes*, Feb-25-2013.

Gelb, Betsy and Madeline Johnson (1995), "Word-of-mouth communication: Causes and consequences," *Marketing Health Services*, 15 (3), 54.

Gelper, Sarah, Renana Peres, and Jehoshua Eliashberg (2016), "Talk Bursts: The Role of Spikes in Pre-release Word-of-Mouth Dynamics," working paper.

Gopinath, Shyam, Pradeep K. Chintagunta, and Sriram Venkataraman (2013), "Blogs, advertising, and local-market movie box office performance," *Management Science*, 59 (12), 2635-2654.

Gopinath, Shyam, Jacquelyn S. Thomas, and Lakshman Krishnamurthi (2014), "Investigating the relationship between the content of online word of mouth, advertising, and brand performance," *Marketing Science*, 33 (2), 241-258.

Graham, Jeffrey, and William Havlena (2007), "Finding the "missing link": Advertising's impact on word of mouth, web searches, and site visits," *Journal of Advertising Research*, 47 (4), 427-435.

Hartmann, W. and D. Klapper (forthcoming), "Super Bowl Ads," *Marketing Science*.

Herr, Paul M., Frank R. Kardes, and John Kim (1991), "Effects of word-of-mouth and product-attribute information on persuasion: An accessibility-diagnosticity perspective," *Journal of Consumer Research*, 17 (4), 454-462.

Hewett, Kelly, William Rand, Roland T. Rust, and Harald J. van Heerde (2016), "Brand buzz in the echoverse," *Journal of Marketing*, 80 (3), 1-24.

Hogan, John E., Katherine N. Lemon, and Barak Libai (2004), "Quantifying the ripple: Word-of-mouth and advertising effectiveness," *Journal of Advertising Research*, 44 (3), 271-280.

Holbrook, Morris B. and Rajeev Batra (1987), "Assessing the role of emotions as mediators of consumer responses to advertising," *Journal of Consumer Research*, 14 (3), 404-420.

Keller, Ed and Brad Fay (2009), "The role of advertising in word of mouth," *Journal of Advertising Research*, 49 (2), 154-158.

Keller, Ed and Brad Fay (2012), *The Face-To-Face Book: Why Real Relationships Rule In a Digital Marketplace*, Simon and Schuster.

Liu, Yong (2006), "Word of mouth for movies: Its dynamics and impact on box office revenue." *Journal of Marketing* 70 (3), 74-89.

Lovett, Mitchell J., Renana Peres, and Ron Shachar (2013), "On brands and word-of-mouth," *Journal Marketing Research*, 50 (4), 427-444.

Lovett, Mitchell J. and Richard E. Staelin (2016), "The Role of Paid, Earned, and Owned Media in Building Entertainment Brands: Reminding, Informing, and Enhancing Enjoyment," *Marketing Science*, 35(1), 142-157.

Mangold W. Glynn, Fred Miller, and Gary R. Brockway (1999), "Word-of-mouth communication in the service marketplace," *Journal of Services Marketing*, 13(1), 73-89.

Mitra, Anusree and John G. Lynch Jr. (1995),"Toward a reconciliation of market power and information theories of advertising effects on price elasticity," *Journal of Consumer Research*, 21 (4), 644-659.

Moon, Sangkil, Paul K. Bergey, and Dawn Iacobucci (2010), "Dynamic effects among movie ratings, movie revenues, and viewer satisfaction," *Journal of Marketing*, 74 (1), 108-121.

Naik, Prasad A. and Kalyan Raman (2003), "Understanding the impact of synergy in multimedia communications," *Journal of Marketing Research*, 40 (4), 375-388.

Nickell, Stephen (1981), "Biases in dynamic models with fixed effects," *Econometrica*, 49 (6), 1417-1426.

Nielsen (2016), "Stirring up buzz: How TV ads are driving earned media for brands," http://www.nielsen.com/us/en/insights/news/2016/stirring-up-buzz-how-tv-ads-are-driving-earned-media-for-brands.html

Olney, Thomas J., Morris B. Holbrook, and Rajeev Batra (1991), "Consumer responses to advertising: The effects of ad content, emotions, and attitude toward the ad on viewing time," *Journal of Consumer Research*, 17 (4), 440-453.

Onishi, Hiroshi and Puneet Manchanda (2012), "Marketing activity, blogging and sales," *International Journal of Research in Marketing*, 29 (3), 221-234.

Park, C. Whan, Martin S. Roth, and Philip F. Jacques (1988), "Evaluating the effects of advertising and sales promotion campaigns," *Industrial Marketing Management*, 17 (2), 129-140.

Pauwels, Koen, Zeynep Aksehirli, and Andrew Lackman (2016), "Like the ad or the brand? Marketing stimulates different electronic word-of-mouth content to drive online and offline performance," *International Journal of Research in Marketing*, 33 (3), 639-655.

Seiler, Stephan, Song Yao, and Wenbo Wang (forthcoming), “Does Online Word of Mouth Increase Demand (and How?): Evidence from a Natural Experiment,” *Marketing Science*.

Sethuraman, Raj, Gerard J. Tellis, and Richard A. Briesch (2011), "How well does advertising work? Generalizations from meta-analysis of brand advertising elasticities," *Journal of Marketing Research*, 48 (3), 457-471.

Siefert, Caleb J., Ravi Kothuri, Devra B. Jacobs, Brian Levine, Joseph Plummer, and Carl D. Marci (2009), "Winning the Super “Buzz” Bowl," *Journal of Advertising Research*, 49 (3), 293-303.

Sinkinson, Michael and Amanda Starc (2017), "Ask your doctor? Direct-to-consumer advertising of pharmaceuticals," working paper.

Smith, Robert E., and William R. Swinyard (1982), "Information response models: An integrated approach," *The Journal of Marketing*, 46 (1), 81-93.

Spotts, Harlan E., Scott C. Purvis, and Sandeep Patnaik (2014),"How digital conversations reinforce super bowl advertising," *Journal of Advertising Research*, 54 (4), 454-468.

Stephen, Andrew T. and Jeff Galak (2012), "The effects of traditional and social earned media on sales: A study of a microlending marketplace," *Journal of Marketing Research*, 49 (5), 624-639.

Stock, James and Motohiro Yogo (2005), "Testing for weak instruments in linear IV regression," in chapter 5 in *Identification and inference for econometric models: Essays in honor of Thomas Rothenberg.*

Sundaram, D.S. Kaushik Mitra, and Cynthia Webster (1998), "Word-Of-Mouth Communications: A Motivational Analysis", in *Advances in Consumer Research*, Vol. 25, Joseph W. Alba, and J. Wesley Hutchinson, eds. Provo, UT: Assoc. for Consumer Research, 527-531.

Tirunillai, Seshadri, and Gerard J. Tellis (2012), "Does chatter really matter? Dynamics of user-generated content and stock performance," *Marketing Science*, 31 (2), 198-215.

Trusov, Michael, Randolph E. Bucklin, and Koen Pauwels (2009), "Effects of word-of-mouth versus traditional marketing: findings from an internet social networking site," *Journal of Marketing*, 73 (5), 90-102.

Turner (2016), "Television advertising is a key driver of social media engagement for brands," http://www.4cinsights.com/wp-content/uploads/2016/03/4C_Turner_Research_TV_Drives_Social_Brand_Engagement.pdf

Van der Lans, Ralf and Gerrit van Bruggen (2010), "Viral marketing: What is it, and what are the components of viral success," in *The Connected Customer: The Changing Nature of Consumer and Business Markets*, New York, 257-281. Eds: Stefan Wuyts, Marnik G. Dekimpe, Els Gijsbrechts, Rik Pieters.

Van der Lans, Ralf, Gerrit van Bruggen, Jehoshua Eliashberg, and Berend Wierenga (2010), "A viral branching model for predicting the spread of electronic word of mouth," *Marketing Science*, 29 (2), 348-365.

Vidal-Berastain, Javier, Paul Ellickson, and Mitchell Lovett (2017), “Understanding the Impact of Entry of Alternative Retailer Types on Consumer Grocery Shopping Habits,” working paper.

WOMMA (2014), Return on Word of Mouth. https://womma.org/wp-content/uploads/2015/09/STUDY-WOMMA-Return-on-WOM-Executive-Summary.pdf

Xu, Yiqing (2017), “Generalized Synthetic Control Method: Causal Inference with Interactive Fixed Effects Models,” *Political Analysis*, 25, 57-76.

You, Ya, Gautham G. Vadakkepatt, and Amit M. Joshi (2015), "A meta-analysis of electronic word-of-mouth elasticity," *Journal of Marketing*, 79 (2), 19-39.

Zhu, Feng and Xiaoquan Zhang (2010), "Impact of online consumer reviews on sales: The moderating role of product and consumer characteristics," *Journal of Marketing*, 74 (2), 133-148.

Table 1: Monthly spending on advertising (in thousand dollars) on TV and Internet, and number of news and press mentions (in thousands) per category.

Category	Avg TV $K/mo	Max TV $K/mo	Brand with max spending TV	Avg Internet $K/mo	Max Internet $K/mo	Brand with max spending Internet	Avg news K/mo	Max news K/mo	Brand with max news	Avg WOM/mo	Max WOM/mo	Brand with max WOM
Beauty products	355.0	3601.9	L'oreal	17.5	87.0	L'oreal	0.9	7.0	Chanel	9.9	69	Dove
Beverages	358.4	3496.2	Pepsi	12.4	168.6	Pepsi	1.3	14.1	Coca-Cola	22.9	394	Coca Cola
Cars	1168.3	5961.2	Ford	109.7	701.7	Chevrolet	16.1	171.3	GM	24.8	284	Ford
Children's products	166.5	994.7	Mattel	10.0	48.7	Lego	0.7	4.4	Mattel	10.4	71	Toyes R Us
Clothing products	174.1	1218.6	GAP	10.1	70.0	Kohls	3.9	24.1	GAP	13.2	138	Nike
Department stores	640.4	3122.7	Walmart	58.0	380.2	Target	6.0	26.3	Walmart	41.5	375	Walmart
Financial services	557.2	3108.7	Geico	204.4	1219.7	TD Ameritrade	24.6	154.2	Bank of America	10.6	104	Bank of America
Food and dining	497.8	4601.9	General Mills	21.5	254.0	General Mills	2.3	15.4	Banquet	12.2	200	McDonalds
Health	852.8	4953.0	Johnson & Johnson	45.8	261.6	Johnson & Johnson	4.7	19.5	Pfizer	10.7	48	KFC
Home design	453.7	1858.1	Home Depot	34.0	148.1	Home Depot	2.9	14.2	Home Depot	17.0	105	Home Depot
Household Products	355.2	1543.0	Clorox	13.3	94.9	Clorox	0.8	14.2	P&G	10.9	54	Tide
Media and entertainment	219.8	4710.6	Time Warner	55.8	652.2	Netflix	30.7	531.3	Facebook	8.4	133	American Idol
Sports and hobbies	36.6	195.3	NFL *	14.4	63.8	MLB *	188.	451.6	NHL*	18.1	194	NFL
Technology	258.0	2193.0	Apple	43.1	465.6	Microsoft	6.4	72.3	Apple	26.3	361	Apple
Telecom	1305.1	8700.1	AT&T	84.8	781.9	AT&T	26.0	140.8	iPhone	35.6	319	AT&T
Travel services	158.0	978.2	Southwest Airlines	43.5	244.6	Expedia	4.6	15.5	Holiday inn	10.1	83	American Express

*NFL=National Football League, MLB= Major Baseball League, NHL = National Hockey League

Table 2: Main Model with Dependent Variable Ln(WOM). N=40,888.

	Model 1			Model 2		
	Population Means			Population Means		
Variables	Estimate	Standard Error		Estimate	Standard Error	
Ln (Advertising $ TV)	0.016	0.002	**	0.017	0.002	**
Ln (Advertising $ Internet)	0.01	0.002	**	0.011	0.002	**
Ln (Advertising $ Other)	0.013	0.002	**	0.013	0.002	**
Super Bowl				0.241	0.118	*
Ln(Advertising $ TV)*SuperBowl				-0.027	0.016	
Ln (Advertising $ Internet)*SuperBowl				0.011	0.017	
Ln (Advertising $ Other)*SuperBowl				-0.005	0.018	
Ln (No of news mentions)	0.101	0.009	**	0.100	0.008	**
Ln (WOM(t-1))	0.129	0.009	**	0.136	0.009	**
Ln (WOM(t-2))	0.045	0.006	**	0.047	0.006	**
Month of Year	-0.317	0.081	**	-0.312	0.082	**
(Month of Year)^2	0.468	0.142	**	0.459	0.142	**
(Month of Year)^3	-0.201	0.072	**	-0.197	0.072	**
Year	0.865	0.181	**	0.907	0.181	**
Year^2	-1.257	0.506	**	-1.376	0.507	**
Year^3	0.412	0.426		0.505	0.426	
	Heterogeneity Variances			Heterogeneity Variances		
	Estimate	Standard Error		Estimate	Standard Error	
Ln (Advertising $ TV)	0.0004	0.0001	**	0.0004	0.0001	**
Ln (Advertising $ Internet)	0.0005	0.0001	**	0.0005	0.0001	**
Ln (Advertising $ Other)	0.0006	0.0001	**	0.0006	0.0001	**
Super Bowl						
Ln(Advertising $ TV)*SuperBowl						
Ln (Advertising $ Internet)*SuperBowl						
Ln (Advertising $ Other)(SuperBowl						
Ln (No of news mentions)	0.0293	0.0028	**	0.0293	0.0028	**
Ln (WOM(t-1))	0.0279	0.0024	**	0.0279	0.0024	**
Ln (WOM(t-2))	0.0082	0.0011	**	0.0082	0.0011	**
Month of Year	0.0115	0.0023	**	0.0115	0.0023	**
(Month of Year)^2						
(Month of Year)^3						
Year	0.3422	0.0295	**	0.3418	0.0294	*
Year^2						
Year^3						

[+]Spending is the log of $1,000's of dollars plus one per brand per month. * indicates p-value<.05; ** indicates p-value<.01.

Table 3: Average Treatment Effect (ATT) for overall WOM data (from the Keller-Fay data set), and for online posts (from the NMI data set), in various time resolutions.

Type of WOM Data	Data Frequency	Effect size (ATT.avg)	Standard Error	p.value	#Factors	#Pre Periods	#Treatment Periods
Overall WOM on a representative sample	week	0.1181	0.0335	0.0005	0	16	4
Overall WOM on a representative sample	week	0.1047	0.0444	0.0113	1	16	4
Overall WOM on a representative sample	month	0.1076	0.0431	0.0124	0	6	2
Overall WOM on a representative sample	month	0.1029	0.0505	0.0354	1	6	2
Online Posts	week	0.1405	0.0383	0.0003	3	16	4
Online Posts	month	0.1574	0.0370	0.0000	1	6	2
Online Posts	day	0.1511	0.0875	0.1789	10	60	31
Online Posts	day	0.2660	0.0638	0.0000	9	60	8

Figure 1: Overview of the literature of advertising and WOM

Figure 2: Effect of advertising on WOM per product category

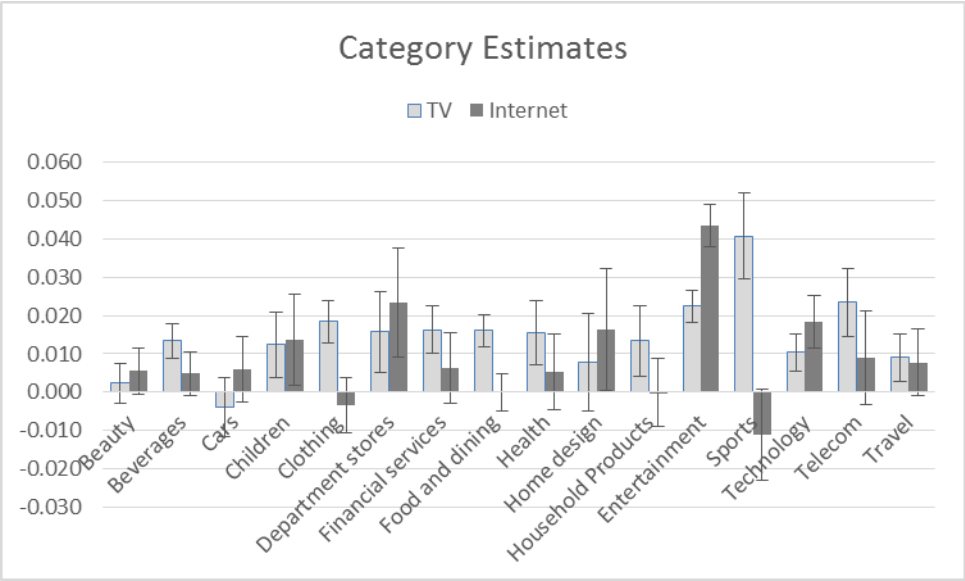
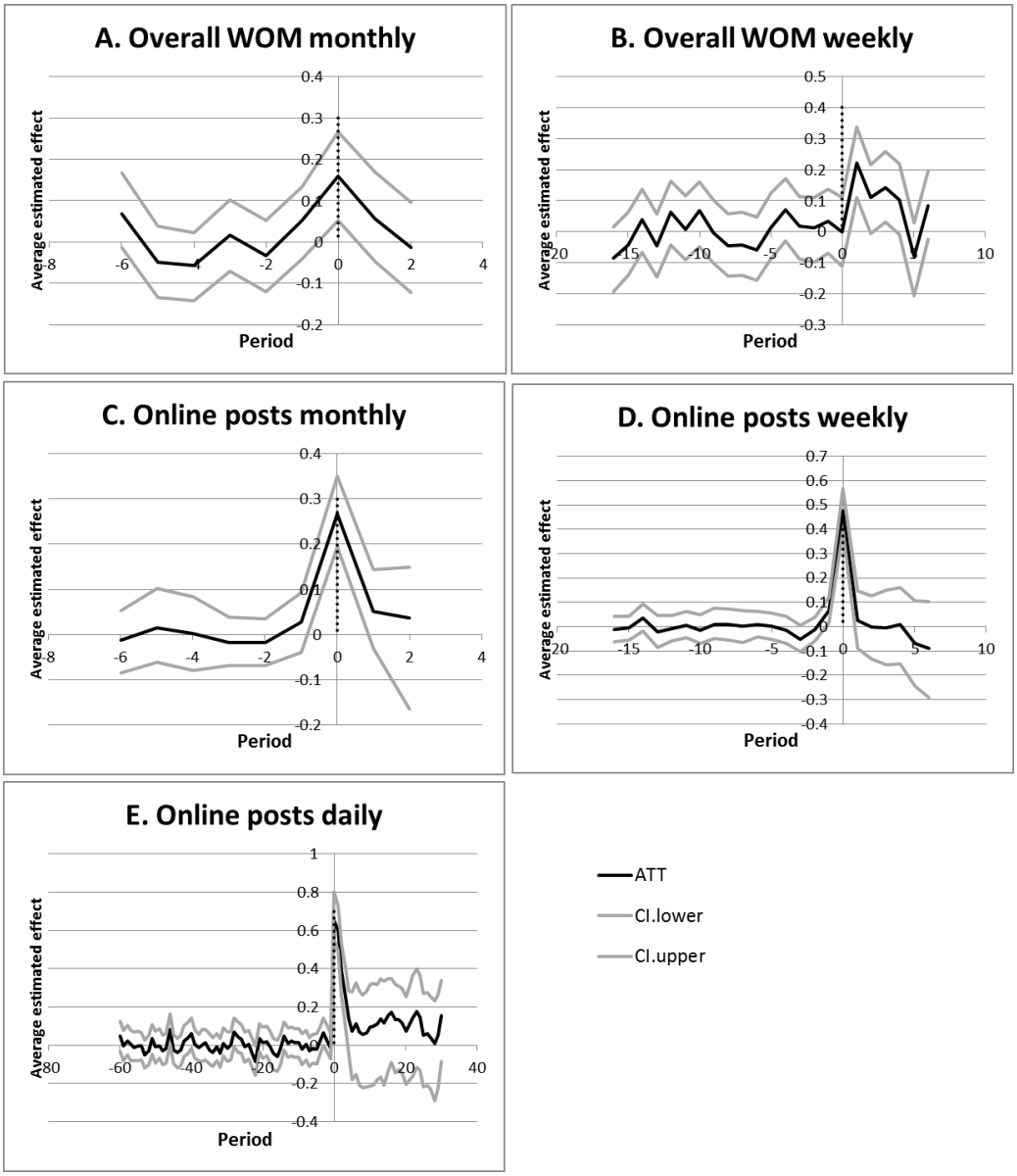


Figure 3: Time-varying estimated average treatment effect (ATT) for overall WOM data (from the Keller-Fay data set), and for online posts (from the NMI data set), in various time resolutions.



Web Appendix A: Data Description

Our brand list contains 538 brands from 16 product categories. The brand list is described in Table A1. Figure A1 presents time series plots for four representative brands in the dataset. Our main analysis uses these time series for the full set of brands to evaluate the relationship between advertising and WOM. These data patterns do not present a clear pattern indicating a strong advertising-WOM relationship.

---------- *Insert Table A1 about here* ---------

---------- *Insert Figure A1 about here* ---------

Table A2 presents descriptive information about the main variables in the study. We have 41,964 brand-month observations. The table indicates that the majority of advertising spending is on TV advertising. Internet display advertising is, on average, 10% of TV advertising. Brands greatly differ in their advertising spending. On average, a brand receives 205 news mentions per month. Some brands (e.g., Windex and Zest) do not receive any mentions in some months, and the most mentioned brand (Facebook) receives the highest mentions (18,696) in May of 2013. As for WOM, the average number of monthly mentions for a brand is 15 in our sample, which translates to an estimated 34.5 million average monthly conversations in the U.S. population. Table A3 presents similar descriptive information about the main variables, but in the log scales we use in estimation, along with the correlations across these key variables.

---------- *Insert Table A2 about here* ---------

---------- *Insert Table A3 about here* ---------

Figure A1: Illustration of the time series data - monthly advertising expenditure on TV and Internet, number of news mentions, and WOM, for four brands.

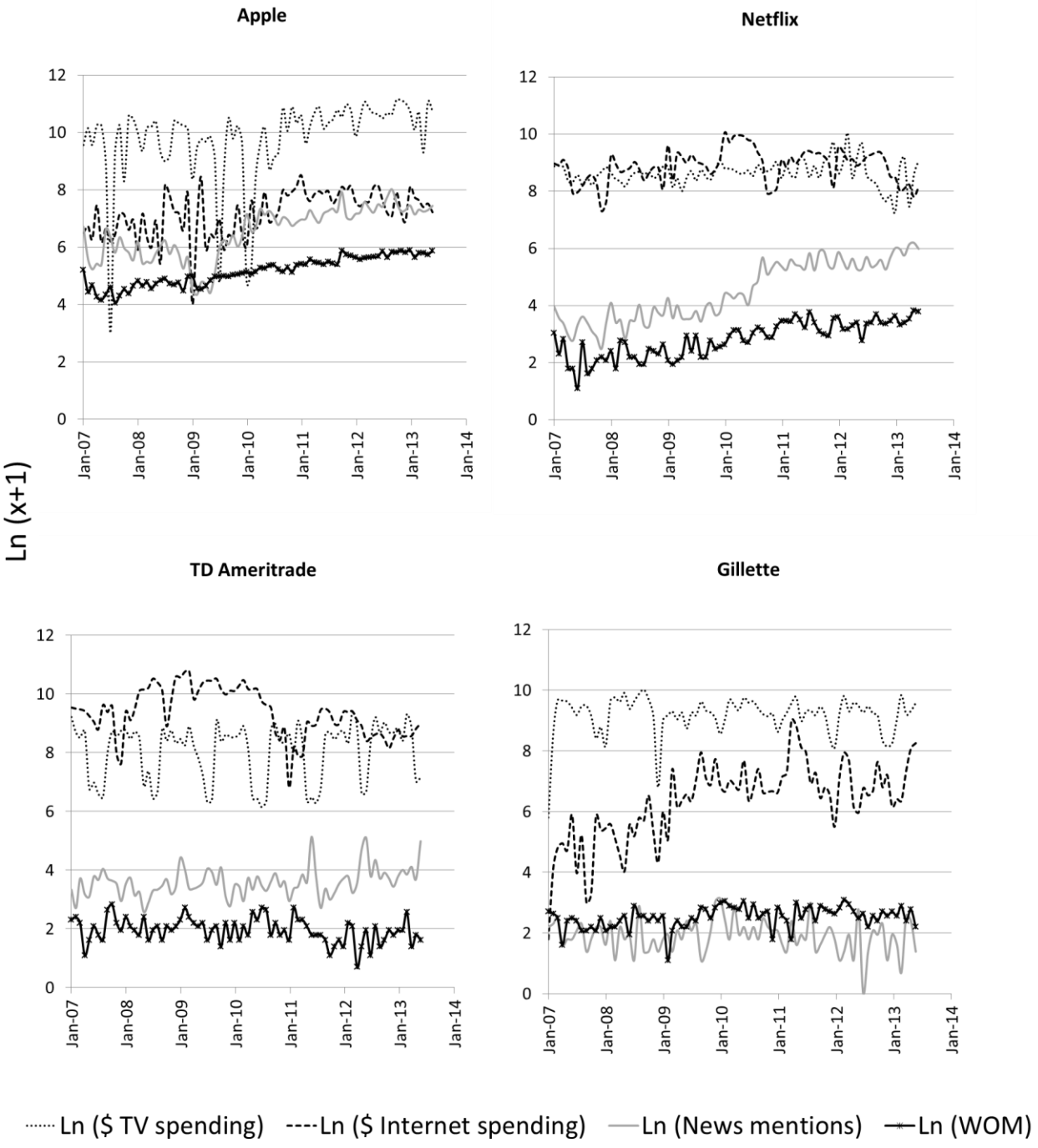


Table A1: Brand List

Beauty Products	Sephora	Minute Maid	Infiniti	**Clothing products**
Always	St. Ives	Monster Energy Drink	Jaguar	Adidas
Arm And Hammer	Suave	Mountain Dew	Jeep	Aeropostale
Aveeno	Tampax	Nestea	Jiffy Lube	American Eagle
Avon	Tresemme	Ocean Spray	Kia	Armani
Axe	Zest	Patron Tequila	Land Rover	Banana Republic
Bath & Body Works	**Beverages**	Pepsi	Lexus	Bloomingdales
Caress	A And W Root Beer	Poland Spring	Lincoln	Chicos
Chanel	Absolut	Propel Fitness Water	Mazda	Coach
Charmin	Anheuser Busch	Red Bull	Mercedes Benz	Converse
Clairol	Aquafina	Sam Adams	Mercury	Eddie Bauer
Clinique	Bacardi	Sierra Mist	Mini Cooper	Foot Locker
Colgate	Budweiser	Smirnoff	Mitsubishi	Gap
Covergirl	Canada Dry	Snapple	Nissan	Gucci
Crest	Captain Morgan	Sobe	Pep Boys	H&M
Degree	Coca-Cola	Sprite	Pontiac	Hot Topic
Dial Soap	Coors	Sunkist	Porsche	Jcrew
Dove (Personal Care)	Coors Light	Sunny Delight	Saab	Kohls
Estee Lauder	Corona	Tropicana	Subaru	Lane Bryant
Garnier Fructis	Crystal Light	Welch	Suzuki	Levis
Gillette	Dasani Water	**Cars**	Toyota	Louis Vuitton
Head & Shoulders	Diet Mountain Dew	Acura	Volkswagen	Lowes
Herbal Essence	Diet Pepsi	Audi	Volvo	Marshalls
Irish Spring	Dr Pepper	Autozone	Yamaha	New Balance
Ivory	Fanta	BMW	**Children's Products**	Nike
Jergens	Fresca	Buick	Carters	Nordstrom
Kotex	Gatorade	Cadillac	Enfamil	Old Navy
Lancome	Grey Goose	Chevrolet	Fisher Price	Pac Sun
Listerine	Guinness	Chrysler	Gerber	Payless
Loreal	Heineken	Dodge	Leapfrog	Polo
Mary Kay	Jack Daniels	ExxonMobil	Lego	Prada
Maybelline	Jose Cuervo	Firestone	Little Tikes	Ralph Lauren
Neutrogena	Juicy Juice	Ford	Luvs	Reebok
Nivea	Koolaid	GM	Mattel	TJ Maxx
Old Spice	Lipton	GMC	Oshkosh	Tommy Hilfiger
Pantene	Maxwell House	Good Year Tires	Pampers	Under Armour
Playtex	Michelob	Harley Davidson	Playskool	Wilson
Revlon	Mikes Hard Lemonade	Honda	Toys R Us	
Scott Tissue	Miller Brewing	Hyundai		
Secret	Miller Lite	Infiniti		

Department Stores	Td Ameritrade	Marie Callender	Velveeta	**Household Products**
Barnes & Noble	Trowe Price	Mcdonalds	Wegmans	Cascade
BJs	USAA	Nabisco	Whole Foods	Cheer
Borders	Vanguard	Nestle	Winn Dixie	Clorox
Costco	Visa	Olive Garden	Yoplait	Dawn
Kmart	Wachovia	Oreos	**Health**	Downy
Meijer	Wells Fargo	Oscar Mayer	Advil	Febreze
Office Depot	**Food And Dining**	Outback Steakhouse	Aetna	Gain
Sams Club	Albertsons	Panera	Aleve	Hoover
Sears	Applebees	Papa Johns	Band Aid	Kitchen Aid
Staples	Arbys	Perdue Chicken	Bayer	Lysol
Target	Banquet	PF Chang	Benadryl	Mr Clean
Walmart	Butterball	Pillsbury	Blue Cross/Blue Shield	P&G
Financial Services	Campbell	Pizza Hut	Cigna	Palmolive
AIG	Cracker Barrel	Popeyes	Claritin	Pine Sol
Allstate	Dannon	Prego	CVS	Pledge
American Express	Del Monte	Publix	Excedrin	Purex
Bank Of America	Dennys	Quaker Oats	GNC	Swiffer
BB&T Bank	Digiorno	Quiznos	Johnson & Johnson	Tide
Capital One	Dole	Ragu	Kaiser Permanente	Windex
Charles Schwab	Dominos Pizza	Ralphs Grocery	Lipitor	**Media & Entertainmer**
Citibank	Doritos	Red Lobster	Merck	24tvshow
Discover Card	Dunkin Donuts	Red Robin	Pfizer	ABC
Dow Jones	Frito Lay	Romanos Macaroni Grill	Prilosec	Amazing Race
Edward Jones	General Mills	Ruby Tuesday	Rite Aid	American Idol
Etrade	Giant Eagle	Safeway	Tylenol	America's Next Top Mode
Fidelity Investments	Giant Food	Sara Lee	Walgreens	BBC
Fifth Third Bank	Healthy Choice	Shaw's Supermarket	**Home Design**	Bet
Geico	Heinz	Slim Fast	GE	Big Brother
H&R Block	Hershey	Snickers	Home Depot	Blockbuster
HSBC	Hot/Lean Pockets	Sonic	Ikea	Cartoon Network
Ing Direct	Ihop	Starbucks	Kenmore	CBS
Mastercard	Jack In The Box	Stouffers	La-Z-Boy	CNBC
Merrill Lynch	Jello	Subway	Maytag	CNN
Metlife	Kelloggs	Swansons	Pier 1 Imports	Comedy Central
Morgan Stanley	KFC	Taco Bell	Whirlpool	CSI
Prudential	Kraft	Texas Roadhouse		Dancing With The Stars
Regions Bank	Kroger	TGI Fridays		Deal Or No Deal
Smith Barney	Lays Chips	Tostitos		Desperate Housewives
Suntrust	Long John Silvers	Tyson		DirectTV

Discovery Channel	PBS	YMCA	Wii Fit	**Travel Services**
E!	People Magazine	**Technology**	Xbox	Alamo
Ebay	Prison Break	Acer	Xbox 360	Alaska Air
ESPN	Scrubs	Apple	Zune	American Airlines
Everybody Loves Raymond	Shrek (Movie)	Best Buy	**Telecommunications**	Amtrak
Facebook	Simpsons	Bose	AOL	Best Western
Family Guy	Sirius	Brother	AT&T	British Airways
Food Network	Smallville	Canon	Blackberry	Budget Car Rental
Fox	South Park	Circuit City	Boost Mobile	Carnival Cruise Lines
Fox News	Spongebob Squarepants	Compaq	Charter Communications	Comfort Inn
Friends	Survivor	Dell	Cox	Continental Airlines
Fringe (TV Show)	The Office	Fuji	Dish Network	Days Inn
General Hospital	Time Warner	Garmin	Iphone	Delta Airlines
Google	TNT	Gateway Computer	Motorola	Enterprise Car Rental
Greys Anatomy	Two And A Half Men	Halo (Video Game)	Nokia	Expedia
Hallmark	Ugly Betty	HP	Qwest	Frontier Airlines
Harry Potter	VH1	iPod	Road Runner	Hampton Inn
HBO	Wall Street Journal	iTunes	TMobile	Hertz
Heroes (TV Show)	Wheel Of Fortune	Kodak	Virgin Mobile	Holiday Inn
House (TV Show)	Yahoo	Lexmark	Vonage	Hyatt
Incredible Hulk (Movie)	You Tube	LG		Jet Blue
Indiana Jones (Movie)	**Sports and Hobbies**	Microsoft		Marriott
Iron Man (Movie)	Atlanta Braves	Nikon		Orbitz
Jeopardy	Boston Celtics	Nintendo		Priceline.Com
Law And Order	Boston Red Sox	Palm/Treo		Royal Caribbean Cruises
Lifetime Television	Curves	Panasonic		Sheraton Hotels
Lost	La Lakers	Pioneer		Southwest Airlines
Money Magazine	MLB	Playstation 3		Travelocity
MSN	Nascar	Radio Shack		United Airlines
MSNBC	NBA	RCA		US Air
Mtv	New England Patriots	Samsung		
Myspace.Com	NFL	Sandisk		
NBC	NHL	Sanyo		
Ncis	NY Giants	Sharp		
Netflix	NY Mets	Sony Playstation		
Nickelodeon	NY Yankees	Super Mario Brothers (Video Game)		
NY Times	Pittsburgh Steelers	Tivo		
Oprah	WWE	Wii		

Table A2: Summary statistics of main variables

Variable/per brand per month	Descriptive Statistics			
	average	std.dev	min	max
Advertising Expenditures				
K$ TV spending	5890.46	12743.14	0	153886.6
K$ Internet spending	665.34	2002.29	0	47928.3
K$ Other ad spending	2828.46	6124.37	0	105786.9
News Mentions				
News mentions	205.31	778.21	0	18696
WOM				
WOM total mentions	15.81	31.11	0	394

Table A3: Summary statistics and correlations of main variables

	Variable/per brand per month	Descriptive Statistics				Correlations				
		average	std.dev	min	max	1	2	3	4	5
	Advertising Expenditures									
1	**Ln (K$ TV spending)**	5.407	3.825	0	11.94	1	0.56	0.56	0.06	0.42
2	**Ln (K$ Internet spending)**	3.777	2.781	0	10.78	0.56	1	0.60	0.31	0.39
3	**Ln (K$ Other ad spending)**	5.532	3.171	0	11.57	0.56	0.60	1	0.23	0.33
	News Mentions									
4	**Ln (News mentions)**	3.322	1.909	0	9.84	0.06	0.31	0.23	1	0.26
	WOM									
5	**Ln (WOM total mentions)**	2.142	1.088	0	5.98	0.42	0.39	0.33	0.26	1

Web Appendix B: Robustness checks

In this section, we provide evidence on the robustness of our main analysis results to different model specifications and to potential remaining endogeneity concerns. To illustrate the robustness of our results presented in Table 2, Table B1 presents six model specifications that delete or adjust variables or model components from the model of Equation (1). In Model 1a, we only include the advertising variables, the news mentions, and the time and seasonality controls (i.e., no lagged dependent variable, no brand fixed effects, no brand random coefficients). This model with very limited controls produces implied elasticities that are larger (0.09 for TV and 0.05 for Internet). However, without the additional controls, these estimates are likely to be spurious. Model 1b adds to Model 1a the two lags of Ln(WOM). In this model, the estimated elasticities are already quite small (0.017 for TV and 0.006 for Internet). Model 1c adds brand fixed effects to the model and we find that the implied elasticities actually grow slightly (0.018 for TV and 0.017 for Internet). Model 1d deletes News Mentions variable from the main model of Table 2. Again, we find the remaining coefficients are quite similar in size and significance. In Model 1e, we replace the fixed effects with first differences. In model 1f, we include time effects for each month in the data instead of cubic trends of month of year and year. In model 1g, we drop the lagged Ln(WOM) and include the brand fixed effects. Looking across these specifications, the implied advertising elasticities appear to be consistently small and of the relative magnitude reported in Table 2, whenever reasonable controls are included. Further, the main controls that are important are brand fixed effects (or first differences) and the lagged Ln(WOM). That noted, the conclusion that Internet advertising expenditures is statistically smaller than TV advertising expenditures appears to not be robust to model specifications.

---- *Insert Table B1 about here* ------

Although, as noted, we include controls for the main endogeneity concerns, one might remain concerned that brand managers anticipate some specific shocks to WOM and also plan in advance their advertising around those anticipated shocks. To examine whether our results are biased due to any such remaining endogeneity between, e.g., TV advertising and the unobserved term in the regression, we applied a two-stage least squares analysis. This analysis is applied to the model without random coefficients. As instruments, we use average national advertising costs per advertising unit obtained from Kantar Media's Ad$pender data. The argument for validity of the instrument comes from a supply-side argument that advertisers respond to advertising costs, and the exclusion here is that no single brand sets the price of advertising that prevails in the market. We were able to obtain these per unit costs for TV, magazines, and newspapers. For Internet display advertising, we include total political Internet display advertising expenditures. Here, we follow the argument made by Sinkinson and Starc (2017) that political advertising can crowd out commercial advertisers. We interact these cost and political advertising variables with the brand indicators, producing 2152=538*4 instruments.

We found that the Cragg-Donald statistic for this set of instruments (3.24 with 3 endogenous variables) failed to achieve the minimum thresholds suggested by Stock and Yogo (2005), suggesting these are weak instruments. Further, the first stage regression coefficients were counterintuitive for the total political Internet advertising variables, for example, with many brands having higher Internet display advertising expenditures when political advertising expenditures were larger. These results suggest that we should interpret this analysis using the instruments with caution since it could produce biased estimates due to weak instruments that are not operating as theoretically predicted. In principle, the indication of weakness and biasing

could arise because we include many potentially weak instruments that may not be helpful (Angrist and Pischke 2009). To examine this, we also estimated the model via two-stage least squares where we use a LASSO technique in the first stage to select the optimal instruments for each of the three endogenous variables (Belloni et al., 2012). In principle, if a subset of all instruments is strong, then this analysis would select the optimal set of instruments. The LASSO procedure, however, "deselects" less than 20% of the instruments.[13]

Table B2 presents the results of the two different instrumental variables analyses. The estimates for advertising expenditures still have effect sizes that are quite small with the largest being 0.04 for Internet display advertising. Although this estimate is larger than our main estimates reported in Table 2, it is still in the range of the results we discuss in the main paper. In addition, unlike our results from the main analysis, these results indicate that Internet advertising expenditures are significantly more effective than TV advertising expenditures in generating WOM. However, when combined with the inconsistent finding in the robustness checks for this difference and given the weakness of the instruments, we interpret this contradiction to suggest that the relative effect size is ambiguous. This is consistent with the results of Draganska, Hartmann, and Stanglein (2014), who find that advertising on TV and the Internet do not have significantly different effects on brand performance metrics.

--------- *Insert Table B2 about here* ----------

[13] Following Angrist and Pischke (2009), we also examined point estimates from a LIML estimator. The estimated values are quite similar to the LASSO-IV estimates and are available upon request. We also examined the instruments without the brand interactions and this similarly produced weak instrument results and unreasonable first stage estimates.

Table B1: Nested Models with dependent variable, Ln(WOM). Monthly data. N=40,888.

	Model1a			Model1b			Model1c			Model1d		
Variable	Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error	
Intercept	1.034	0.0118	**	0.103	0.0073	**						
Ln (Advertising $ TV)+	0.089	0.0016	**	0.017	0.0009	**	0.018	0.0012	**	0.020	0.0012	**
Ln (Advertising $ Internet)+	0.049	0.0023	**	0.006	0.0013	**	0.017	0.0016	**	0.019	0.0016	**
Ln (Advertising $ Other)+	0.013	0.0020	**	0.002	0.0011	*	0.015	0.0015	**	0.017	0.0015	**
Ln (#of news mentions)	0.110	0.0026	**	0.020	0.0015	**	0.122	0.0048	**			
Ln (WOM(t-1))				0.495	0.0046	**	0.271	0.0049	**	0.283	0.0049	**
Ln (WOM(t-2))				0.367	0.0046	**	0.161	0.0048	**	0.168	0.0048	**
Brand Fixed Effects?	No			No			Yes			Yes		
Brand Random Coefficients?	No			No			No			No		
Time Effects?	Cubic functions of month of year and year			Cubic functions of month of year and year			Cubic functions of month of year and year			Cubic functions of month of year and year		

	Model1e			Model1f			Model1g		
Variable	Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error	
Intercept									
Ln (Advertising $ TV)+	0.007	0.0014	**	0.018	0.0012	**	0.015	0.0017	**
Ln (Advertising $ Internet)+	0.009	0.0019	**	0.017	0.0016	**	0.011	0.0024	**
Ln (Advertising $ Other)+	0.009	0.0016	**	0.015	0.0015	**	0.015	0.0025	**
Ln (#of news mentions)	0.048	0.0046	**	0.120	0.0048	**	0.116	0.0113	**
Ln (WOM(t-1))	-0.543	0.0048	**	0.278	0.0049	**			
Ln (WOM(t-2))	-0.257	0.0018	**	0.160	0.0048	**			
Brand Fixed Effects?	First Differences			Yes			Yes		
Brand Random Coefficients?	No			No			No		
Time Effects?	Cubic functions of month of year and year			Time fixed effects			Cubic functions of month of year and year		

+Spending is the log of $1,000's of dollars plus one per brand per month. * indicates p-value<.05; ** indicates p-value<.01.

Table B2: Instrumental variables analysis for the model estimated in Table 2 (Eq 1)

	2SLS-All Instruments (Eq 1)			2SLS - LASSO-IV (Eq 1)		
Variable	Estimate	Std. Error		Estimate	Std. Error	
Intercept						
Ln (Advertising $ TV)[+]	0.017	0.0027	**	0.025	0.0039	**
Ln (Advertising $ Internet)[+]	0.032	0.0038	**	0.042	0.0064	**
Ln (Advertising $ Other)[+]	0.007	0.0036	*	0.010	0.0057	
Ln (#of news mentions)	0.270	0.0049	**	0.266	0.0066	**
Ln (WOM(t-1))	0.160	0.0048	**	0.159	0.0063	**
Ln (WOM(t-2))	0.121	0.0050	**	0.114	0.0061	**
Month of Year	-0.739	0.5214		-0.909	0.5214	
(Month of Year)^2	2.498	0.4998	**	2.510	0.4927	**
(Month of Year)^3	-1.131	0.4931	*	-1.184	0.4833	*
Year	1.621	0.6157	**	0.924	0.7396	
Year^2	-5.561	0.5043	**	-5.342	0.4914	**
Year^3	2.153	0.5005	**	2.276	0.4966	**
Brand Fixed Effects?		Yes			Yes	
Brand Random Coefficients		No			No	

[+]Spending is the log of $1,000's of dollars plus one per brand per month. * indicates p-value<.05; ** indicates p-value<.01.

Web Appendix C: WOM Mentioning Advertisements

The Keller-Fay TalkTrack dataset also includes information about whether a brand mention references advertising. Out of all the brand mentions a respondent provides, 10 are randomly selected for the respondent to provide additional information about the conversation surrounding the brand mention. Specifically, respondents were asked to indicate whether the conversation included a reference to media or marketing about the brand. The exact question, "Did anyone in the conversation refer to something about the brand from any of these sources?" used a multi-select format allowing up to two answers. The response categories include TV advertisements and Internet advertisements as options. We use this item to count the number of cases in which the brand conversation referred to an ad.

Figure C1 presents the percentage of brand conversations that reference ads for each brand (which we refer to as ad-WOM), including WOM with references to TV (top panel) and Internet (bottom panel) ads. First, the distribution suggests that a meaningful proportion of all brand conversations contain references to advertising. Unsurprisingly, far more of the conversations contain mentions of TV ads than Internet ads. For most brands, TV ads are referenced between 6% and 14% of the time, whereas Internet ads are only referenced between 2% and 6% of all conversations. Both distributions are skewed right, so that there are some brands for which advertising is referenced quite frequently during conversations.

-------- *Insert Figure C1 about here* -------

In our main analysis, we pooled all WOM together, which could cover up a stronger relationship between advertising expenditures and the number of brand conversations that

reference ads. To test whether this is the case, we estimate the same model but use as the dependent variable (and lagged dependent variables) the WOM that references either TV ads or Internet ads (ad-WOM).

The results of the two analyses are presented in Table C1. The TV ad-WOM analysis reveals that advertising coefficients have a similar magnitude and significance as those presented in the main analysis in Table 2. The relationship between the advertising variables and the Internet ad-WOM is estimated to be smaller than that found for the total WOM measures. Recall that the construction of the ad-WOM measure differs from that of the total WOM so that a direct comparison of the estimates is not possible. Yet we can conclude that these results provide no evidence that the advertising-WOM relationship is meaningfully stronger when considering only WOM that discusses advertising. Hence, although many brand conversations talk about the ads, the advertising did not necessarily "cause" the conversation about the ads. Instead, the advertising becomes part of the existing conversations that would have happened anyway.

------- *Insert Table C1 about here* --------

Table C1: Models with ad-WOM as dependent variable. Monthly data. N=40,888.

	DV: TV ad-WOM			DV: Internet ad-WOM		
Description	Estimate	Standard Error		Estimate	Standard Error	
Ln (Advertising $ TV) [+]	0.011	0.0014	**	0.003	0.0010	**
Ln (Advertising $ Internet) [+]	0.010	0.0018	**	0.003	0.0012	*
Ln (Advertising $ Other) [+]	0.007	0.0018	**	0.004	0.0012	**
Ln (#of news mentions)	0.057	0.0074	**	0.027	0.0044	**
Ln (DV(t-1))	0.033	0.0070	**	0.001	0.0066	
Ln (DV(t-2))	0.000	0.0058		-0.011	0.0063	**
Month of Year	-0.079	0.0785		0.031	0.0610	
(Month of Year)^2	0.057	0.1372		-0.050	0.1066	
(Month of Year)^3	0.000	0.0697		0.032	0.0542	
Year	0.626	0.1725	**	0.264	0.1337	*
Year^2	-0.500	0.4877		-0.066	0.3776	
Year^3	-0.090	0.4107		-0.159	0.3181	

[+]Spending is the log of $1,000's of dollars plus one per brand per month. The heterogeneity variances are similar in size and significance to those in Table 2. * indicates p-value<.05; ** indicates p-value<.01.

Figure C1: Percentage of WOM conversations mentioning TV advertising (top panel) or Internet advertising (bottom panel).