TV Gets Social:
Evaluating Social Media Data To Explain Variability Among Nielsen TV Ratings

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QMSS 5999

December 18, 2011

INTRODUCTION

Online social networking is not a fad. In current day, internet usage is quite prolific with an estimated universe[1] of 236 million individuals[2] in the United States during September 2010 ("NetView," 2010). Of those users, 62% (over 146 million unique individuals)[2] visited a member community which includes sites such as Facebook, Blogger, Twitter, and Tumblr ("NetView," 2010). This translates to nearly 4 in 5 active Internet users visiting social networking websites ("State of Social Media: The Social Media Report Q3 2011," 2011) which is a 30% increase from usage two years prior (September 2008) ("NetView," 2010). Additionally, 23% of Americans' time online is spent on social media sites ("State of Social Media: The Social Media Report Q3 2011," 2011). Of the content consumers create on these sites, 22% is about entertainment which includes television shows and movies, while a third of internet users claim that they consume the entertainment content online ("State of Social Media: The Social Media Report Q3 2011," 2011).

My focus in this paper is to explore how online word-of-mouth, WOM, impacts off-line behavior, specifically TV viewership. As WOM for a TV show builds online, it should have a direct impact on increased ratings. My research draws on three theoretical frameworks: a) the long tail (Anderson), b) the strength of weak ties (Granovetter, 1973), and c) exposure effect (Zajonc, 1968). I also review the research that has been conducted relating WOM to off-line behavior.

Many factors are known to influence a consumer's decision making (i.e., which TV program to watch). Number of options is commonly cited (Iyengar, 2010) yet not applied in the WOM space; therefore, I first examine a theory unnoted in academic discussion, "the long tail" (Anderson). The long tail refers to the numerous varieties of products available to consumers online. With millions of social media sources also available online, the impact of the long tail on consumer decision making is important to keep in mind when determining how to analyze WOM conversation. Since consumers can easily connect across long tail WOM sites, I subsequently examine network theory, specifically focusing on "the strength of weak ties" (Granovetter, 1973). Several research studies have revealed that weak ties, which are loosely connected social acquaintances, provide bridges for information to flow between groups (Brown & Reingen,

[1] Universe size is defined as any individual who is over two years of age and had access to an internet-enabled computer within the timeframe of evaluation, September 2010.
[2] Estimate acquired from Nielsen NetView September 2010 data.

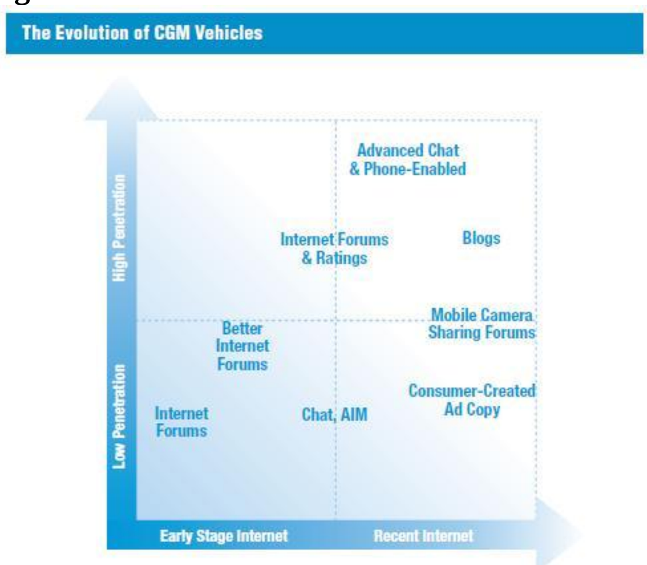
1987). Advances in technology have provided new means for weak ties to connect (Haythornthwaite, 2002), as a result, online weak ties can be highly influential in purchase decisions (Steffes & Burgee, 2009). Exposure to an object or idea also impacts consumers' decisions. It has been shown that there is a positive relationship between mere exposure to an object and an individual's attitude toward that object (Zajonc, 1968) such that exposure can influence brand choice (Becknell, Wilson, & Baird, 1963; Bornstein, 1989; Nedungadi, 1990). Thus, I investigate the concept of the "mere exposure effect" (Zajonc, 1968). Finally, I review prior work specifically focused on the correlations between online word-of-mouth and offline product sales. Both industry and academic researchers have primarily looked at how movie reviews impact box office sales (Asur & Huberman, 2010; Chintagunta, Gopinath, & Venkataraman, 2010; Duan, Gu, & Whinston, 2008b; Liu, 2006; Mishne & Glance, 2006), while two groups have investigated the outcome of online book reviews on book sales (Chevalier & Mayzlin, 2006; Gruhl, Guha, Kumar, Novak, & Tomkins, 2005). Only one paper focuses on TV ratings (Godes & Mayzlin, 2004) and my research specifically extends this study.

With a limited number of published studies linking online consumer-generated media to offline consumer decisions, I aim to add additional insight to this field of research. Previously, researchers used volume of messages; however, they had access to limited datasets often leading to questionable results for how the findings could be applied in a brand's marketing strategy. Additionally, tonality of discussion, often referenced as valence, has been a favored metric over raw volume of messages or dispersion of conversation. I plan to dive deeper into this space and directly extend research conducted by Godes and Mayzlin (2004) by gathering a broader and more robust dataset (capturing much of the long tail) than researchers have previously had access. I seek to show that variability in message volume and sound representation of message spread, regardless of conversation polarity, will have a meaningful effect on future TV ratings.

BRIEF OVERVIEW OF SOCIAL MEDIA

While the popularity of websites such as Twitter and Facebook has skyrocketed in recent years, virtual social communities have been in use since the 1990s, and probably earlier. At first, users could simply post and reply to messages, while in current day, in addition to these basic functions, users can create online personas by sharing their interests, hobbies, photos, videos, and location (Figure 1) (Blackshaw & Nazzaro, 2004). Many communities are more tailored with respect to content than the aforementioned examples. For instance, there are member communities that focus discussion on specific categories such as child care, weight loss, automobiles, movies, and consumer electronics, as well as more specifically focused forums to discuss products such as BMW cars, the iPhone, or the popular TV show, *Glee*. The significant volume of information shared by individuals online is frequently referenced as consumer-generated media (CGM) (Blackshaw & Nazzaro, 2004), and the publically accessible "digital trail" left behind enables the information to be captured and analyzed.

Figure 1: Evolution of Consumer-Generated Media



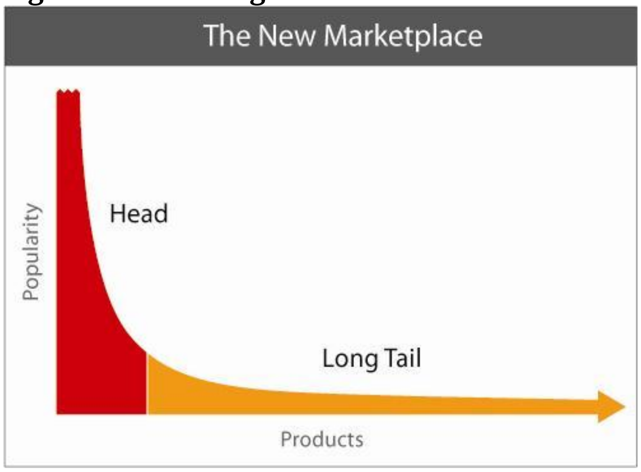
In addition to increased usage, trust in online word-of-mouth is also growing ("CONSUMER TRUST: Word of mouth rules," 2007). Among the messages posted online, there are millions of digital conversations between consumers discussing product attributes and providing recommendations for purchase decisions. According to The Nielsen Company's 2009 Global Online Consumer Survey, a survey of 25,000 internet users across 50 countries, 70% of respondents state that they trust consumer opinions posted online (Gianatasio, 2009). This is up nine percentage points from their 2007 survey. In the most recent study completed in March 2010, surveying 27,000 internet users in 55 countries, online reviews are found to be consulted by 57% of respondents before making a consumer electronics purchase decision followed by 45% of respondents seeking assistance in their automotive purchase decisions (*Global Trends in*

Online Shopping, 2010). With respect to the content of these online product opinions, 68% of North American respondents claimed that they are not more likely to share a negative review than a positive one. With both usage and trust in online word-of-mouth growing, social media's impact on consumer decision making needs to be explored and better understood.

THE LONG TAIL

While social media's impact on decision making is a research topic in its infancy, many factors are known to influence a consumer's purchase decisions such as framing, the means by which information is presented (Iyengar, 2010; Janiszewski, Silk, & Cooke, 2003; Levin, Schneider, & Gaeth, 1998), brand image (Gardner & Levy, 1955; Keller, 1993), marketing efforts (Iyengar, 2010, pp. 153-154; Royte, 2008), number of options from which to make a choice (Chernev, 2003; Iyengar & Lepper, 2000; Reutskaja & Hogarth, 2009), and the consumer's ability to recall the product (Bazerman & Chugh, 2006; Keller, Heckler, & Houston, 1998). An additional theory not traditionally mentioned in the decision-making literature, but is linked to social media, is the concept of the "long tail" (Anderson). It refers to the ever-growing long, narrow portion of the demand curve (Figure 2). For example, online retailers such as Amazon and iTunes offer practically an unlimited number of products; the quantity of niche products largely outnumbers the amount of popular items. Offering these niche items satisfy a significant number of consumer interests more specifically than the popular, "hit" items that typically are found on store shelves. As a result, the long tail is viewed as an important factor of the supply and demand model, particularly due to advances in new technology.

Figure 2: The Long Tail



This concept can further be extended to the world of online social media. While there are several "hit" sites that consumers will turn to for information, much of the social media world is comprised of the long tail (Figure 3). For example, in the wireless/mobile phone-enthusiast space, Android Forums[3], Apple Discussions[4], Gizmodo[5], and Engadget[6] are considered hits with large volumes of individuals visiting and conversing on the message boards and blogs. These sites cover many topics of mobile phone discussion including reviews of new phones, comparing features of various phones, discussing wireless networks, and troubleshooting technical problems on devices. Many highly knowledgeable individuals on the subject matter influence the dialogue on these sites, and as a result of the large amount of useful information being shared, these sites exist in the head of the demand curve, attracting many visitors and appearing most prominently among Google search results. Despite the low volume of discussion and few visitors to sites within the long tail, when aggregated across all sites within the tail, a significant volume of discussion persists. Additionally, within an early study of social media communities, valuable information was found when looking across many online communities as opposed to within any one of them (Godes & Mayzlin, 2004).

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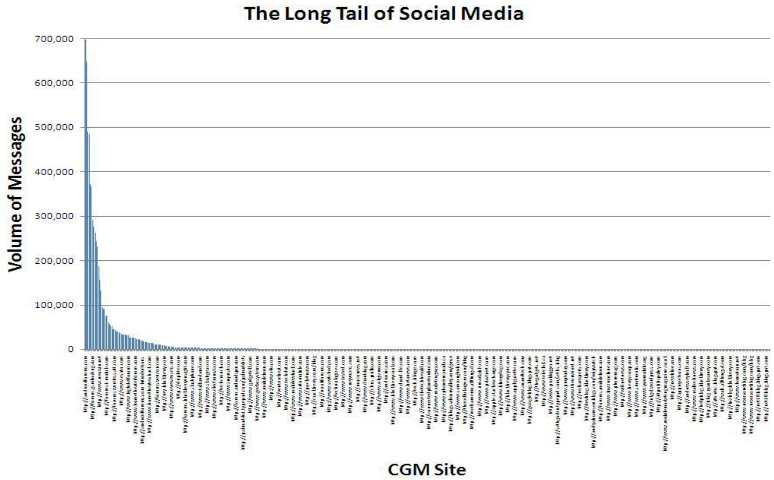
[3] Android Forums can be found at http://androidforums.com.
[4] Apple Discussions can be found at http://discussions.apple.com.
[5] Gizmodo can be found at http://gizmodo.com.
[6] Engadget can be found at http://www.engadget.com.

Figure 3: Volume of Messages per CGM Source Focused on Wireless and Mobile Phone Discussion Within North America



NETWORK TIES

The presence of millions of virtual communities within the long tail of social media amplifies Granovetter's (1973) theory on "the strength of weak ties." His theory claims that weak ties provide more access to information/subgroups that strong ties do not provide. Strong ties are considered a personal connection, a friend that engages in the "same world" as yourself – working with you, attending the same school, living in your neighborhood; however, weak ties, your acquaintances or someone who does not know you personally, do not engage in the same activities (Brown & Reingen, 1987; Gladwell, 2000). Weak ties are more likely to have information you, the decision maker, are not already aware of. Brown and Reingen tested this theory and found that weak ties provide bridges between groups where information can be exchanged. The theory holds for anything that is shared by word-of-mouth: finding a job, seeking out a new restaurant, adopting new consumer electronics, or even fashion trends. Gladwell surmises that this may be a reason that Hush Puppies became a fashion trend in women's shoes across the United States during the mid 1990's, due to word-of-mouth among weakly tied female consumers, whereas other trends simply never gain in popularity.

Furthering this concept, research shows that consumers are likely to use both strong ties and weak ties when seeking recommendation sources to aid purchase decisions (Duhan, Johnson, Wilcox, & Harrel, 1997). When the decision is perceived to be more difficult (having many alternatives and a large number of attributes to base the decision on), the consumer is more likely to rely on strong ties, while weak ties are often used when a consumer has some subjective/prior knowledge.

Technology advancements add new outlets for weak ties to connect. These additional communication streams (consider the many sources within the long tail of social media) can have a positive impact on weak ties, providing new opportunities for developing and strengthening the relationship (Haythornthwaite, 2002). In evaluating how traditional findings about social ties are maintained within the online word-of-mouth framework, Steffes and Burgee (Steffes & Burgee, 2009) found that online weak ties can be more influential in decision making than offline strong ties. They looked at college students' experiences in selecting which professors to study under, and found online professor reviews more helpful than friends' recommendations. While their findings are contradictory to traditional offline social tie theory, which claims strong tie referrals to be more influential than weak ties, I believe that Steffes and Burgee solidify Duhan et al.'s (1997) theory. Weak ties were likely to be more influential in this study because college students typically have prior knowledge of professors, and when prior knowledge exists, weak ties are more influential than strong ties. With this latter point in mind, it is not surprising that social media sources, a conduit to quickly connect weak ties, can influence the popularity and adoption of a TV show. The typical office place "water-cooler" conversations about TV shows have moved online, enabling buzz about a new show to spread faster across communities and throughout the long tail. This shifting dynamic is supported by an online field test conducted by Godes & Mayzlin (2009) where they found that online word-of-mouth across acquaintances was more effective than WOM across strong ties in a social network.

EXPOSURE EFFECT

In addition to the long tail and network ties, exposure to a brand or product also impacts purchase decisions. Where the long tail provides more avenues for consumers to connect, and weak ties facilitate the spread of information, exposure promotes familiarity and a positive attitude toward a product. Robert Zajonc (1968) defines his theory of "mere exposure" as "a condition which just makes the given stimulus accessible to the individual's perception" (p. 1). His research finds that brief, repeated exposure to a stimulus favorably increases a person's attitude toward the object. Succinctly put by Bornstein (1989), "familiarity leads to liking" (p.

265). Exposure frequency also significantly influences brand preference and choice (Becknell, et al., 1963) such that there is a positive relationship between the number of exposures and the magnitude of the effect (Bornstein, 1989, pp. 271-272). This gives supportive claims to why volume of online conversations likely impacts consumer decision making. As the number of messages online increases, as does the spread of the conversation across the long tail of social media sources, the probability of mere exposure increases through weak ties sharing information. It has been shown that consumers can be more comfortable with a brand over its competitors simply due to the fact that the consumer was exposed to the brand name (Baker, 1999). Consequently, the increased chances for exposure online may directly impact the sales of a product or number of viewers for a TV show.

ONLINE WORD-OF-MOUTH'S IMPACT ON PURCHASE DECISIONS

Thus far, all previously mentioned theories suggest that online word-of-mouth and the act of online social networking should have a direct effect on consumers' purchase decisions. Understanding this relationship is fundamental to how firms and consumers interact, such that providing insight into WOM as a leading indicator of sales is a primary focus of market researchers today. Interestingly, in this field of study there is a divide between industry researchers and academics. Industry researchers minimally control for potential confounding variables within their research. They primarily investigate correlations between two variables (Asur & Huberman, 2010; Gruhl, et al., 2005; Mishne & Glance, 2006) whereas academic researchers introduce greater controls into their analysis (Chintagunta, et al., 2010; Duan, et al., 2008b). I plan to emulate the latter group in my research.

Industry Research

Industry researchers have repeatedly illustrated that a meaningful relationship exists between online word-of-mouth and product sales. Initial research from IBM showed that raw volume of blog postings about specific books were correlated in a leading manner (by a few days) with changes in Amazon.com sales rank for the books (Gruhl, et al., 2005). Then researchers from Intelliseek (currently part of Nielsen) demonstrated that message polarity provided a higher correlation with movie sales prior to movie release than correlations between raw message volume and sales (Mishne & Glance, 2006). Nevertheless, these correlations are rather low and neither study implemented controls for external factors that may have a spurious relationship with sales such as press coverage or marketing efforts to promote the product. In 2010, researchers at HP Labs (Asur & Huberman, 2010) revisited the movies analysis looking at discussion rate (number of messages mentioning a specific movie per hour) as the explanatory variable. They found that movies with a higher rate of discussion had more tickets sold, but again used a simple correlation analysis with no control variables. In general, while a relationship is uncovered between various buzz metrics and product sales, industry researchers are not publishing statistically rigorous work to clearly identify social media's direct impact on sales after controlling for other marketing efforts.

Academic Research

Academic researchers have more rigorously explored the relationship between online word-of-mouth and product sales than industry researchers and continually investigate the connection in various manners. In 2004, researchers first found a link between online conversation and consumer viewing behavior using Nielsen TV ratings (Godes & Mayzlin, 2004). They investigated forty-four TV shows in their premiere season specifically focusing on online conversations within and between Usenet groups. They surmised that dispersion of online conversation was significantly correlated with a TV show's ratings early in the season while volume of conversation was significant later in the season. However, they did not account for factors that drive buzz volume such as prior season TV ratings or advertising spend to promote awareness of the show. In 2006, research confirmed a statistically meaningful relationship between WOM and consumer purchasing behavior by evaluating book reviews from two websites, Amazon.com and BN.com (Chevalier & Mayzlin, 2006), but again minimal controls were introduced to the model.

In the same year, 2006, volume of online movie discussion from Yahoo!Movies'[7] message board was shown to explain much variability in movie sales, whereas valence (the mean polarity score) was not significantly correlated with revenue (Liu, 2006). Two years later, the movie analysis was revisited (Duan, et al., 2008b). Unlike previous research, however, this model included fixed effects to account for movie-specific factors such as budget, marketing

[7] Yahoo!Movies can be found at http://movies.yahoo.com/.

expense, star power, the number of screens playing the movie, the number of days since release, and whether the movie had a weekend release date. Results found that box office sales and online review valence (reviews from Yahoo!Movies and Mojo[8]) drive future online review post volume, which in turn leads to increased sales. In short, online review volume correlated to subsequent increases in box office sales.

Duan et al, also looked at the data using a three-stage least squares method to account for the reciprocal causal relationship between online word-of-mouth and box office sales (2008a). They note that while previous studies only consider buzz as an exogenous variable, it is also endogenous in nature. As buzz volume increases, awareness for a movie will also increase leading to heightened sales. The increased sales will then lead to more buzz generation. This causal relationship has not been considered in any other studies previously noted and is important to specify when determining online word-of-mouth's direct impact on sales. From this analysis, Duan et al. concluded that the volume of posts is significantly associated with movie sales and that consumers are not influenced by the polarity of the messages.

Chintagunta, Gopinath, and Venkataraman (2010) also evaluated the relationship between online discussion of movies and box office sales. Also leveraging Yahoo!Movies for the online consumer reviews, they found that positive polarity of reviews (higher mean user rating) had a greater impact on predicting sales compared to volume of reviews. Unlike the prior study that leveraged fixed effects to control for movie-specific factors, this team specifically controlled for drivers of box office sales (such as marketing expense, number of theaters, days since initial release), movie characteristics (such as genre) as well as market characteristics (such as population). Additionally, they utilized geographic filters which aid reliability of their results. All previously mentioned research considered data to be at the aggregated national-level, whereas Chintagunta et al. point out that even nationally released movies have some markets release prior to others. As a result, online movie reviews can only stem from markets where the movie has released. This dynamic was accounted for in their analysis.

All of these academic studies discussed limit the review data to one or two sources, disregarding the significance of the long tail theory. While the websites utilized may be very popular, much of the online discussion about books and movies are not captured within their analyses.

[8] Mojo can be found at http://www.boxofficemojo.com.

Most recently, researchers have dived deeper into dissecting online word-of-mouth content effectiveness. Researchers have found that information specificity of messages impacts the effectiveness of WOM (Sung-Youl, Taihoon, & Aggarwal, 2011). Messages are stated to be specific, "pertains to a physical attribute of a product, it is measured on a universal scale, and it can be reported as a point of reference on that scale," or tensile, "information that is subject to interpretation because it is vaguely defined, lacks a universal measurement scale, or defies measurement because of its open-ended nature" (Sung-Youl, et al., 2011). The study revealed that tensile word-of-mouth is less effective in changing consumer opinions than specific word-of-mouth. The information specificity has a mediating role such that when the content is tensile, tie-strength and expertise matters, whereas when the content is specific these attributes are less important.

Effectiveness of message valence, or polarity of content, has also been evaluated, but with mixed results. Dellarocas, Xiaoquan, & Awad (2007) showed that volume and valence of online movie ratings corresponded to future box office sales. Chintagunta et al. (2010) concluded that valence had an effect on opening-day box office movie sales whereas volume and variance, the spread of conversation, had no effect. Sonnier, McAlister, & Rutz (2011) demonstrated that valence, broken out by three variables for volume of positive, negative and neutral comments, impacted daily sales performance for firms. However, Duan et al. (2008b) found only an indirect relationship for valence to movie sales through volume of messages (as previously discussed), and Chevalier and Mayzlin (2006) found that negative reviews online had a greater impact on book sales than positive reviews.

Unfortunately, when comparing results across studies, data sets do not align; some studies utilize consumer reviews while others used message board or blog data. While all of these sources are forms of online consumer-generated content, they are very different in nature. Reviews can only occur after a consumer interacts with the product whereas comments on message boards and blogs can occur at any stage of the product purchase decision cycle (pre- or post-purchase). Since Chintagunta et al. used Yahoo!Movie reviews only, their data was naturally filtered to only post-purchase discussion. This choice improves the reliability of their results with regard to implications that require temporal order[9] (Linden & Fillmore, 1985).

[9] According to Paul Lazarsfeld's criteria for causality, time order of events must be maintained.

Additionally, online review data is inherently cleaner and less noisy than blog data (Dey & Haque, 2009). Review sites categorize and organize the discussion (Yahoo!Movies has one listing under the movie's official title) while blog data is not standardized and requires text analytics tools to be used to sift through discussion and recall relevant messages[10]. This process of text analysis requires the development of keyword strings which are an art, rather than a science, to create. Balancing precision and recall within a keyword string is the foundation to any research project using blog data and is subject to issues of missing terminology. An incomplete list of terms and context rules will limit the extent to which the true volume of messages is recalled, and is a concern with any study using a keyword-based methodology. As previously noted, the long tail's impact on social media usage cannot be ignored. Many of the box office sales studies utilize only one review site. Although Yahoo!Movies is very popular[11], there are many alternative movie review sites online as well as blogs and message boards that discuss movies within the course of everyday conversation. Consequently, the affects of social media activity across the multitude of long tails sites have been ignored. Additionally, none of the studies to-date have considered the demographic composition of site users or behavioral skews that may exist among the users of Yahoo!Movies compared to the general population or target audience for the movies. Therefore, implications of previous results may not be reliable, and if these additional factors are taken into account, results could vary.

HYPOTHESES

Within my research, I focus on evaluating online conversation as a leading indicator of TV ratings, concentrating on the effect of buzz volume and dispersion after controlling for show-level factors such as genre, season, distribution channel, ad spend and prior ratings. I seek to find a statistically meaningful relationship one month prior to premiere episode airing and two weeks prior to in-season episodes as this leading relationship would provide time for marketers and show writers, in some cases, to make changes to their plans and still impact the current season. As a result of exposure effect and the subsequent positive relationship it generates for an

[10] Working as an industry researcher, these findings are based on my observations working in WOM research for Nielsen.

[11] According to The Nielsen Company's NetView database, Yahoo!Movies received approximately 14 million visitors a month within the first half of 2010.

object, I expect that higher message volume about a TV show will correspond to higher ratings for that show. Additionally, due to network theory and the strength of weak ties facilitating the spread of discussion, I posit that higher levels of dispersion for messages across social media sites will correspond to higher levels of awareness of the show which leads to increased ratings for the TV show. I accordingly test the following hypotheses in my analysis:

> **H1**: Number of messages about a TV show has a positive impact on TV ratings four weeks prior to premiere episode airing and two weeks prior to midseason and finale episode airing regardless of demographic age group.

> **H2**: Dispersion of messages for a TV show has a positive impact on TV ratings four weeks prior to premiere episode airing and two weeks prior to midseason and finale episode airing regardless of demographic age group.

While I posit that buzz volume may be a driver of TV ratings, it can then also be assumed that ratings will drive buzz volume. A TV show cannot be discussed online unless people watch the show. As viewership increases, buzz generation may increase, which in turn can spur more awareness for the show and subsequently increased viewership. Therefore, WOM and TV ratings have an endogenous relationship, as Duan et al. (2008a) previously called attention to, and a third hypothesis will be evaluated:

> **H3**: After accounting for the reciprocal relationship between buzz volume and TV ratings, the number of messages about a TV show will have a positive impact on TV ratings two weeks prior to midseason episode airing.

Despite academic researchers focus on message valence, I do not believe it is a reliable metric in modeling offline behavior as both a positive and negative relationship can be found between WOM and product sales. As previously discussed, researchers have found a positive relationship between WOM and offline behavior (Chintagunta, et al., 2010; Dellarocas & Narayan, 2006). But researchers have also demonstrated the inverse relationship to be true. For example, Berger, Sorensen and Rasmussen (2010) found negative publicity to increase sales by looking at the impact of *New York Times* book reviews. Also, negative buzz surged online when Tropicana changed the design of their packaging and juice logos in January 2009 (Elliot, 2009), and recently in 2010, when the clothing company Gap Inc. redesigned the logo on their website (Fredrix, 2010). Nevertheless, rather than negatively impacting the brand's reputation, loyal fans vocalized their concerns online and demanded the traditional logos be reinstated. This negativity online did not clearly correlate to decreased sales[12] likely as a result of the loyalty it evoked. The qualitative underpinnings of social media data cannot be ignored when trying to establish a quantitative relationship. If polarity was utilized as a filter for correlation to product sales, then the results would be confusing and misleading. Such examples showing mixed findings regarding the relationship between message valance and product sales support my theory that polarity is a confounding factor. Thus, I suggest focusing efforts on buzz volume and dispersion of discussion as a more meaningful method for explaining consumer purchase decisions and will not evaluate the effect of message valence.

DATA

I examined data on 250 TV shows with complete seasons airing within 2010 and/or 2011. Shows selected for analysis were randomly selected across four genres (comedy, drama, reality competition, and reality non-competition) to ensure representativeness and primarily occurred during prime time hours, between 7:00pm and 11:00pm. Sports shows and news programming were excluded from the analysis. All data came from Nielsen. Table 1 lists information about several example shows included in the analysis. (The full show list can be found in Appendix A.)

[12] According to Nielsen, while year-over-year sales declined during the timeframe of the logo change, the sales had been declining for at least six months prior to the marketing effort. Additionally, in the January/February timeframe, other juice brands such as V8, Sunkist, and Minute Maid also saw sales decline.

Table 1: Examples of Shows in the Sample

Show Name	Network	Broadcast/ Cable	New Series/ Returning	Genre	Episode Duration (minutes)	# Months in Season
American Dad	FOX	Broadcast	Returning	Comedy	29	8
Breaking Bad	AMC	Cable	Returning	Drama	62	4
Burn Notice	USA	Cable	Returning	Drama	60	2
Caprica	SYFY	Cable	New	Drama	60	2
Cleveland	FOX	Broadcast	New	Comedy	30	9
Cops	FOX	Broadcast	Returning	Reality: Non-Comp	30	11
Cupcake Wars	Food Network	Cable	New	Reality: Competition	60	3
Doctor Who	BBC – America	Cable	Returning	Drama	61	4
Entourage	HBO Prime	Cable	Returning	Comedy	27	4
How I Met Your Mother	CBS	Broadcast	Returning	Comedy	30	9
Jersey Shore	MTV	Cable	New	Reality: Non-Comp	60	4
Last Comic Standing	NBC	Broadcast	Returning	Reality: Competition	60	3
Losing It With Jillian	NBC	Broadcast	New	Reality: Competition	60	2
Mall Cops	TLC	Cable	New	Reality: Non-Comp	30	3
Millionaire Matchmaker	Bravo	Cable	Returning	Reality: Non-Comp	60	3
Office	NBC	Broadcast	Returning	Comedy	31	9
Psychic Kids	A&E	Cable	Returning	Reality: Non-Comp	60	2
Smallville	CW	Broadcast	Returning	Drama	60	7
So You Think Can Dance	FOX	Broadcast	Returning	Reality: Competition	60	3
Top Chef Masters	Bravo	Cable	New	Reality: Competition	60	0

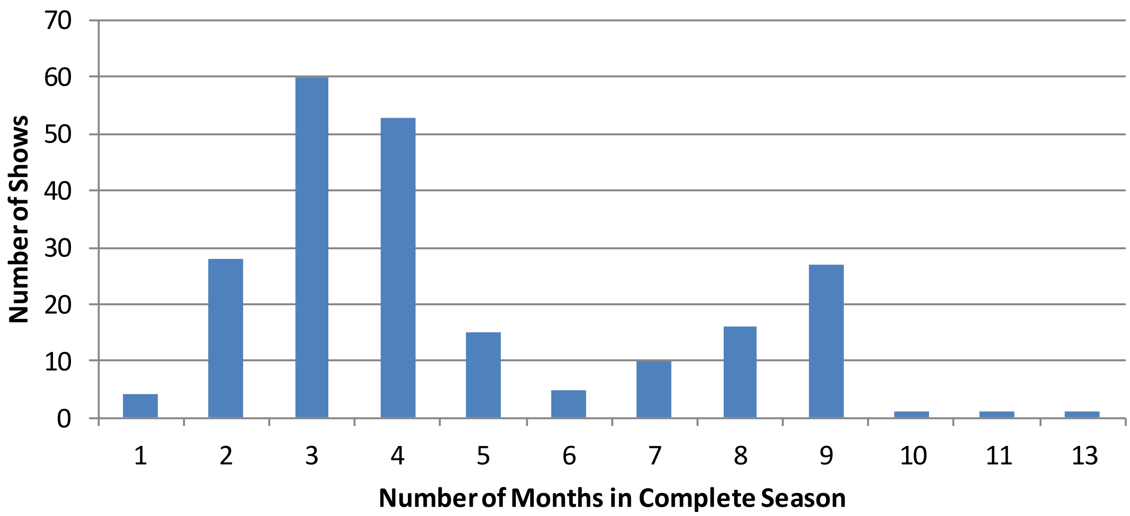
Shows stem from various networks across both broadcast and cable distribution channels, which are technically different methods of delivery but substantively air different types of shows that can be seen in language usage and plot lines (Gabler, April 4, 2010). The data also utilizes shows that are both new series and returning that primarily air for 30-60 minutes per episode as I expect WOM to have a positive impact on ratings regardless of these factors.

Table 2 summarizes the data by genre and Figure 4 presents the distribution of shows based on season length.

Table 2: Summary of Shows by Genre

Genre	# Shows	Avg Episode Duration (minutes)	Min Episode Duration (minutes)	Max Episode Duration (minutes)	Avg # Months in Season
Comedy	40	30	17	73	6
Drama	71	59	27	68	5
Reality: Competition	54	68	30	121	3
Reality: Non-Competition	67	51	30	120	4

Figure 4: Distribution of Shows by Months in Season



As seen above, the number of shows is not evenly distributed by genre; however, there is enough sample size per genre to conclude representativeness of prime time TV shows. There also is not even distribution for length of complete season. The average show length across all shows is 4.7 months with comedies having longer seasons on average than the other genres, and competitive reality shows having the shortest season (3 months on average).

Online Word-of-Mouth

Data was harvested from over 150 million social media sites including blogs, message boards, and UseNet groups from NMincite's My BuzzMetrics tool ("My BuzzMetrics," 2011). Public Facebook and Twitter data was excluded due to technical limitations with gathering historical data. A message was considered relevant about a TV show if it met two criteria: first, the message must contain terminology that matched a complex Boolean keyword about the show which contained items such as the TV show name, abbreviations for the name, common misspellings, actors' names and characters' names; and second, the message occurred within one month prior to the TV show's season airing and within one week after the finale episode aired. Three buzz metrics were generated from the WOM data: a) buzz volume, or the raw number of messages about a TV show, b) dispersion, the spread of discussion approximated by the average number of messages divided by the number of sources generating the discussion, and c) number of authors or individuals creating the online conversation.

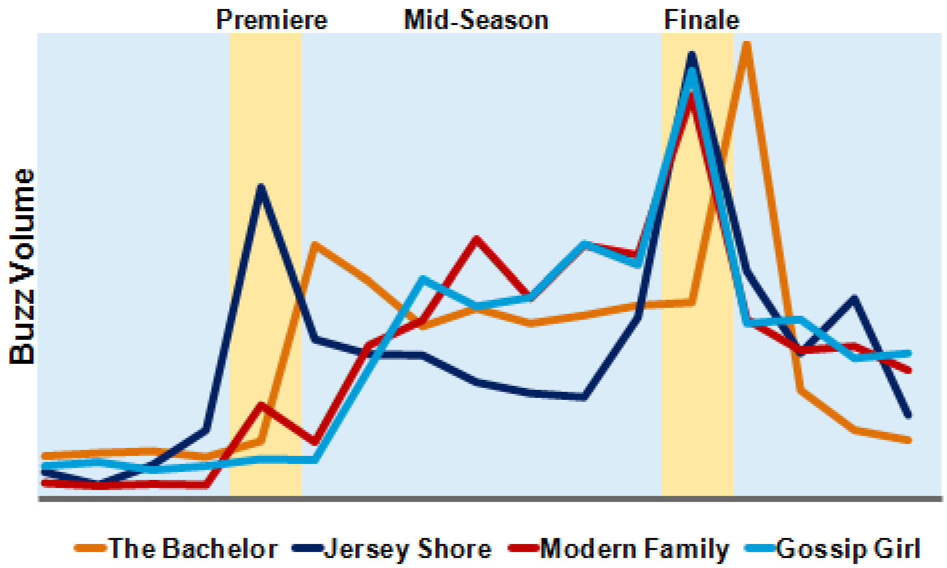
Table 3 displays summary statistics for buzz volume occurring two weeks prior to an episode airing, distributed by season segment (premiere, midseason and finale) and for the full season. Figure 5 illustrates the standardized buzz volume[13] trend for an average show in each genre over the course of the show's complete season.

Table 3: Summary Statistics for Buzz Volume by Season Segment

Season Segment	N	Mean	Std. Dev.	Min	Max
Premiere	151	391.09	1,028.12	1	8,270
Midseason	773	1,069.51	1,983.73	6	20,269
Finale	214	921.14	1,733.71	5	11,515
Full Season	1,138	951.59	1,850.89	1	20,269

[13] Buzz volume was standardized by taking the z-score of the weekly buzz volume for each show.

Figure 5: Standardized Buzz Volume Trended Weekly, by Genre



Buzz volume varies throughout the season. Regardless of the show, there is a surge of discussion volume during the premiere, a large spike during the finale, while the midseason garners relatively consistent buzz volume over time. The midseason earns more discussion volume on average than the other season segments; the mean buzz volume is more than double the premiere timeframe and 20% more than the finale segment. Due to the inherent difference in the amount of buzz occurring during each season segment, the analysis will be broken down by segment to examine how online word-of-mouth's impact on ratings varies in each of these stages.

Correlations of buzz volume with the other two WOM metrics, dispersion and number of authors, is shown in Table 4 for four weeks prior to premiere episode and two weeks prior to midseason and finale episode airing.

Table 4: Correlation for Buzz Volume by Season Segment

	Buzz Volume		
	Premiere: 4 weeks prior	**Midseason: 2 weeks prior**	**Finale: 2 weeks prior**
Dispersion	0.21*** (0.01)	0.23*** (0.00)	0.28*** (0.00)
Authors	0.96*** (0.00)	0.52*** (0.00)	0.51*** (0.00)

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

For premiere episode airing, buzz volume and authors are very highly correlated. As a result, authors will not be used in the model specification to ensure that collinearity among the independent variables is not problematic. For midseason and finale segments, buzz volume and authors are only moderately correlated and therefore the variable will remain in these two model specifications.

TV Ratings

Data was collected from Nielsen's audience measurement product ("Nielsen TV Audience Measurement: NPower," 2011) which collects data from a panel of 20,000 U.S. households which agree to have their TV viewing behavior monitored through a meter installed on all television sets in their household. The meter captures the channel being watched, who in the household is watching, and when the TV show is being watched, including "time-shifted" viewing (primarily from a DVR). TV ratings data, specifically live+3 days ratings, were used in this analysis, and is a share of all U.S. television households that watched a show within its first run and within three days of the original episode airing. Viewership from rerun episodes was excluded. Ratings were also examined by age (2+, 18-34, 35-49, 50+). From the TV meter data, additional descriptive information about each show was captured and utilized in the analysis such as a show's season number, episode duration, genre, and whether it was distributed on cable or broadcast television.

Table 5 displays summary statistics for live +3 days ratings, distributed by season segment (premiere, midseason and finale) and for the full season.

Table 5: Summary Statistics for Buzz Volume by Season Segment

Season Segment	N	Mean	Std. Dev.	Min	Max
Premiere	151	1.43	1.66	0.08	13.46
Midseason	773	1.92	1.68	0.05	9.52
Finale	214	1.66	1.58	0.06	8.65
Full Season	1,138	1.80	1.67	0.05	13.46

Similar to buzz volume, the data is distributed differently by season segment. The midseason tends to receive higher ratings than the premiere and finale episodes, but the premiere timeframe has a greater standard deviation between shows than the other season segments.

Advertising Spending

Nielsen's Monitor-Plus ("Nielsen Monitor-Plus," 2011) platform tracks information about advertising by brand (including TV shows), company, and product category. Data is collected across media types (i.e., TV networks, radio networks, internet, newspaper, magazines etc.) and reports on over three million brands for over 1.6 million companies in nearly 2,500 categories. Some key metrics captured include advertising spending, number of times an advertisement was aired, and audience viewership. For this analysis, advertising spending, total dollars spent to promote each TV show, was utilized as monthly expenditure from one month prior to TV season premiere through the finale episode.

68% (776 out of 1138 observations) of the data has ad spend available. Unfortunately, the data was not missing at random for the overall data set. When missing values were present, they tended to be for the full season of several shows rather than randomly missing months within a specific show's season. There are a few random shows not collected, however, the majority of the missing data is for the reality non-competition genre. For academic purposes to explore imputation methods, rather than throw away the observations with missing data, I imputed the missing values through both single imputation and multiple imputation techniques. Multiple imputation is said to be a sounder approach relative to single imputation because the method accounts for patterns in missingness as well as any uncertainty about the missing data, and accounting for these factors tends to lead to more appropriate standard errors on the imputed variables (Hill, Waldfogel, Brooks-Gunn, & Han, 2005; D.B. Rubin, 1987). Nevertheless, I am interested in exploring how the different imputation methods for missing data in my covariates changes the relationship between the dependent variable, TV ratings, and the explanatory variables I specifically investigate, buzz volume and dispersion. I expect to find that buzz volume and dispersion have a relatively stable relationship with TV ratings across these methods, confirming my hypotheses.

To impute the missing data a least squares dummy variable model with dummies for month effects was estimated for both single and multiple imputation (equation 1.1). Month effects were included because seasonality impacts advertising expenditure. For example, four times a year (February, May, July and November) Nielsen mails paper diaries to harder to reach local market areas to measure their TV viewing habits ("Nielsen “Sweeps” Months," 2010). As a result, many shows increase advertising spend and have dramatic plot lines to gain a larger viewing audience (Rocha, February 16, 2004). Season segment was also included in the imputation model to account for the fact that money spent to promote a show varies across the season and especially for premiere and finale episodes. Five imputations were included in the multiply imputed data set as only a small number of imputations are needed for efficiency of the estimate (D.B. Rubin, 1987; Donald B. Rubin & Schenker, 1991). The model utilized to singularly and multiply impute ad spend was as follows:

$$\begin{aligned} AD\ SPEND = \alpha + {} & \beta_1 \cdot TV\ RATINGS + \beta_2 \cdot BUZZ\ VOLUME_{t-2} + \beta_3 \cdot CABLE \\ & + \beta_4 \cdot DRAMA + \beta_5 \cdot REALITY\ COMPETITION \\ & + \beta_6 \cdot REALITY\ NONCOMPETITION + \beta_7 \cdot SEASON\ NUMBER \\ & + \beta_8 \cdot NEW + \beta_9 \cdot DURATION + \beta_{10} \cdot PRIOR\ SEASON\ TV\ RATINGS \\ & + \beta_{11} \cdot SEASON\ SEGMENT + \beta_X MONTH\ DUMMIES + u \end{aligned} \tag{1.1}$$

Table 6 contains summary statistics for ad spend across imputation methods. The mean for advertising spend is highest for the non-imputed data set, \$2,610,840. Single imputation and multiple imputation generate slightly different mean values, \$2,163,050 and \$2,348,060, respectively, however a t-test indicates that they are not statistically different from each other.

Table 6: Summary Statistics for Ad Spend by Imputation Method

Season Segment	N	Mean	Std. Dev.	Min	Max
Ad Spend (000), no imputation	776	2,610.84	3,187.22	0	25,399.40
Ad Spend (000), single imputation	1,138	2,163.05	2,851.23	0	25,399.40
Ad Spend (000), multiple imputation	1,138	2,348.06	n/a	0	25,399.40

Table 7 shows the summary statistics for all the variables discussed above that are included in the analysis.

Table 7: Summary Statistics for All Variables in the Analysis

Variable	Mean	St. Dev	Min	Max
Live +3 Day Ratings, People 2+	1.80	1.67	0.05	13.46
Buzz Volume 2 Weeks Prior	951.59	1,850.89	1.00	20,269.00
Dispersion 2 Weeks Prior	24.89	31.50	2.18	530.19
# Authors 2 Weeks Prior	70.86	194.04	0.14	2,750.36
Reality Competition Dummy	0.23	0.42	0.00	1.00
Reality Non-Competition Dummy	0.24	0.43	0.00	1.00
Drama Dummy	0.33	0.47	0.00	1.00
Cable Dummy	0.56	0.50	0.00	1.00
New Series Dummy	0.33	0.47	0.00	1.00
Ad Spend (000), single imputation	2,163.05	2,851.23	0.00	25,399.40
Ad Spend (000), multiple imputation	2,348.06	n/a	0.00	25,399.40
Prior Season Ratings, People 2+	1.47	1.90	0.00	9.18

There is significant variation in volume of online word-of-mouth relative to TV ratings. This is notable because a 1% increase in TV ratings is very meaningful to a TV network and often is equated to millions of dollars of revenue whereas a 1% change in buzz volume can be caused for many different reasons and is frequently of no significant consequence[14]. Since it is common to look at the data as a rate of change, I will log transform both TV ratings and buzz volume in my analysis.

The correlations between TV ratings, the dependent variable, and the other independent variables are presented in Table 8.

[14] This statement is industry knowledge I have gained from working in the media industry for Nielsen.

Table 8: Correlations for TV Ratings with All Independent Variables in the Analysis

	Live +3 Day Ratings, People 2+
Live +3 Day Ratings, People 2+	1.00
Buzz Volume 2 Weeks Prior	0.29*** (0.00)
Dispersion 2 Weeks Prior	-0.14*** (0.00)
Reality Competition Dummy	-0.01 (0.69)
Reality Non-Competition Dummy	-0.27*** (0.00)
Drama Dummy	0.25*** (0.00)
Cable Dummy	-0.67*** (0.00)
New Series Dummy	-0.16*** (0.00)
Ad Spend (000), single imputation	0.60*** (0.00)
Ad Spend (000), multiple imputation	0.54*** (0.00)
Prior Season Ratings, People 2+	0.70*** (0.00)

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Not surprisingly, Prior Season Ratings has the strongest relationship with current season ratings. A show that received an average rating of 2.0 in one season will likely have a similar rating the subsequent season as ratings do not vary greatly. Buzz Volume has a moderate, positive correlation with TV ratings illustrating that a relationship between the two variables exists such that buzz volume may help to explain future TV ratings as outlined in H1. Dispersion, on the other hand, has a weak, negative relationship. This suggests that shows with data spread across more sources have lower TV ratings, contradicting H2.

ANALYTICAL METHODS AND RESULTS

Analysis of the data focused on evaluating online conversation as a leading indicator of TV ratings, concentrating on the effect of buzz volume and dispersion after controlling for show-level factors such as genre, season, distribution channel, advertising spend and prior ratings (both episode and season). The data was divided into three segments based on temporal occurrence within a show's season (premiere, midseason, and finale), and models were estimated for each segment. Splitting the data in this manner was desirable as TV ratings, promotional efforts and online conversation about a show differ at each stage. The unit of analysis was the TV show.

Premiere and Finale Model Results

Ordinary least squares was utilized to estimate the premiere and finale TV show ratings among people ages 2+, 18-34, 35-49 and 50+. These age groups are standard reporting brackets for Nielsen TV ratings and since social media usage occurs primarily among the younger demographic of 18-34 year olds, it was of particular interest to see if buzz volume's relationship with TV ratings varies across these groups. The OLS model specification was chosen because it provides an unbiased estimate of the parameters since the data was linear in its parameters, perfect collinearity among the independent variables was not present, the error, u, had an expected mean of zero, and the error was uncorrelated with the independent variables (Wooldridge, 2009). The homoskedasticity assumption to ensure the best estimate of the parameters was not met; however, robust standard errors were utilized to correct for this issue (Wooldridge, 2009). Additionally, in the TV business ratings are considered to be a slow moving variable such that a one point increase is difficult to accomplish. Therefore, the ratings and buzz volume variables were log transformed to understand their relationship as a rate of change since media planners tend to focus on the percentage change in ratings. As previously noted, a 1% change in TV ratings can equal millions of dollars in revenue.

The following models were estimated using ordinary least squares regression with robust standard errors for the premiere and finale episode ratings, respectively:

<u>Premiere</u>

$$
\begin{aligned}
\log(RATINGS) = \alpha &+ \beta_1 \cdot \log(BUZZ\ VOLUME_{t-4}) + \beta_2 \cdot DISPERSION_{t-4} \\
&+ \beta_3 \cdot REALITY\ COMPETITION + \beta_4 \cdot REALITY\ NONCOMPETITION \\
&+ \beta_5 \cdot DRAMA + \beta_6 \cdot CABLE + \beta_7 \cdot NEW + \beta_8 \cdot AD\ SPEND \\
&+ \beta_9 \cdot PRIOR\ SEASON\ AVG\ RATING + u
\end{aligned}
\tag{2.1}
$$

Finale

$$\log(RATINGS) = \alpha + \beta_1 \cdot \log(BUZZ\ VOLUME_{t-2}) + \beta_2 \cdot DISPERSION_{t-2} \\ + \beta_3 \cdot AUTHORS_{t-2} + \beta_4 \cdot REALITY\ COMPETITION \\ + \beta_5 \cdot REALITY\ NONCOMPETITION + \beta_6 \cdot DRAMA + \beta_7 \cdot CABLE \\ + \beta_8 \cdot NEW + \beta_9 \cdot AD\ SPEND + \beta_{10} \cdot PRIOR\ SEASON\ AVG\ RATING \\ + \beta_{11} \cdot PRIOR\ EPISODE\ RATING + u \tag{2.2}$$

The estimation of the premiere model (2.1) using single imputation of advertising spend is presented in Table 9 while the multiple imputation of missing data is presented in Table 10. For both imputation models, the coefficient on buzz volume was positive and significant for people ages 18-35 and 35-49 at the $p<0.05$ level and $p<0.01$ level, respectively. Buzz volume was not statistically significant for the model including all people aged 2+ or the older demographic of people ages 50 and over. For the premiere models where buzz volume was statistically significant, a one percent change in buzz volume four weeks prior to episode airing corresponded to a 0.1 percent change in ratings, holding all other variables constant. Restating this finding to provide more clarity on the relationship by taking the inverse of the coefficient on buzz volume, a 10-11% change in buzz volume corresponds to a 1% change in premiere episode ratings, holding all other variables constant. Despite inclusion of dispersion, the variable was not statistically meaningful in any of the premiere models.

The estimation of the finale model (2.2) using single imputation for advertising spend is presented in Table 11 and the multiple imputation for missing data is displayed in Table 12. The coefficient on buzz volume for both the single and multiple imputation models was nearly the same; positive and significant at the $p<0.05$ level for ratings among 18-34 year olds and $p<0.01$ for all other age demographic groups. Using the inverse of the coefficient on buzz volume, a 9-17% change in buzz volume corresponded to a 1% change in finale episode ratings with the largest effect being present for the older demographic of people aged 50 and over and the smallest effect for people ages 18-34. This finding is unexpected as social media usage tends to be highest for younger individuals; however, social media is no longer a new concept and early adopters' parents and grandparents are joining in the online conversation (Musick, 2009). Dispersion was statistically significant at the $p<0.05$ level and had a negative relationship with ratings for all age groups except people 18-34 where it was insignificant.

While single and multiple imputation methods produced nearly identical estimation results, when the model was estimated without the imputed missing values for ad spend, and incomplete cases were dropped, the results changed slightly (Table 13). For the premiere model, 36% of the observations were dropped and the buzz volume coefficient became insignificant for all age groups. For the finale model, despite the same share of cases being dropped, the coefficient on buzz volume remained statistically significant for all age groups, except 35-49 year olds. The magnitude of the relationship also persisted such that a 9-16% change in buzz volume corresponded to a 1% change in TV ratings, ceteris paribus.

Table 9: Estimation Results – Premiere Model, Four Weeks Prior to Episode Airing, Buzz Volume and Ratings Log Transformed, Single Imputation for Ad Spend

	People 2+	People 18-34	People 35-49	People 50+
LOG (BUZZ VOLUME$_{t-4}$)	0.0362	0.0990**	0.0931***	0.0013
	(0.040)	(0.044)	(0.033)	(0.041)
DISPERSION$_{t-4}$	-0.0031	-0.0018	-0.0033	-0.0051
	(0.002)	(0.002)	(0.002)	(0.004)
REALITY COMPETITION	0.0453	0.0034	-0.0197	0.0396
	(0.080)	(0.087)	(0.074)	(0.091)
REALITY NON-COMPETITION	-0.0180	-0.0261	-0.0349	-0.0331
	(0.084)	(0.089)	(0.072)	(0.093)
DRAMA	0.1199	-0.1169	-0.0145	0.2705***
	(0.086)	(0.097)	(0.077)	(0.093)
CABLE	-0.2692****	-0.1289**	-0.2518****	-0.3833****
	(0.066)	(0.062)	(0.066)	(0.088)
NEW	0.0104	-0.0072	0.0427	0.0923
	(0.060)	(0.067)	(0.058)	(0.072)
AD SPEND	0.0000****	0.0000****	0.0000****	0.0000****
	(0.000)	(0.000)	(0.000)	(0.000)
PRIOR SEASON RATINGS	0.0712****	0.0654**	0.0539***	0.0879****
	(0.020)	(0.026)	(0.019)	(0.015)
CONSTANT	-0.0257	-0.1185	0.0184	0.0189
	(0.132)	(0.137)	(0.131)	(0.158)
N	149	149	149	149
R^2	0.609	0.426	0.607	0.639

Notes: Robust standard errors in parentheses

**** p<0.001, *** p<0.01, ** p<0.05, * p<0.1**

Table 10: Estimation Results – Premiere Model, Four Weeks Prior to Episode Airing, Buzz Volume and Ratings Log Transformed, Multiple Imputation for Ad Spend

	People 2+	People 18-34	People 35-49	People 50+
LOG (BUZZ VOLUME$_{t-4}$)	0.0393	0.1012**	0.0965***	0.0069
	(0.040)	(0.044)	(0.034)	(0.042)
DISPERSION$_{t-4}$	-0.0032	-0.0019	-0.0033	-0.0051
	(0.003)	(0.002)	(0.002)	(0.004)
REALITY COMPETITION	0.0531	0.0103	-0.0120	0.0492
	(0.081)	(0.088)	(0.075)	(0.092)
REALITY NON-COMPETITION	-0.0143	-0.0233	-0.0311	-0.0280
	(0.087)	(0.092)	(0.076)	(0.096)
DRAMA	0.1354	-0.1052	0.0023	0.2921***
	(0.088)	(0.099)	(0.079)	(0.094)
CABLE	-0.2898****	-0.1435**	-0.2750****	-0.4162****
	(0.067)	(0.064)	(0.066)	(0.089)
NEW	0.0196	-0.0011	0.0534	0.1059
	(0.060)	(0.066)	(0.059)	(0.073)
AD SPEND	0.0000****	0.0000***	0.0000****	0.0000***
	(0.000)	(0.000)	(0.000)	(0.000)
PRIOR SEASON RATINGS	0.0716****	0.0654**	0.0546***	0.0876****
	(0.019)	(0.025)	(0.018)	(0.014)
CONSTANT	-0.0161	-0.1127	0.0298	0.0364
	(0.133)	(0.138)	(0.131)	(0.160)
N	149	149	149	149
R^2	0.599	0.420	0.594	0.628

Notes: Robust standard errors in parentheses

****** p<0.001, *** p<0.01, ** p<0.05, * p<0.1**

Table 11: Estimation Results – Finale Model, Two Weeks Prior to Episode Airing, Buzz Volume and Ratings Log Transformed, Single Imputation for Ad Spend

	People 2+	People 18-34	People 35-49	People 50+
LOG (BUZZ VOLUME$_{t-2}$)	0.0681***	0.0598**	0.0855****	0.1096***
	(0.024)	(0.024)	(0.019)	(0.040)
DISPERSION$_{t-2}$	-0.0004**	-0.0001	-0.0009****	-0.0013**
	(0.000)	(0.000)	(0.000)	(0.001)
AUTHORS$_{t-2}$	-0.0001**	-0.0001	-0.0001***	-0.0002**
	(0.000)	(0.000)	(0.000)	(0.000)
REALITY COMPETITION	0.0787*	0.0966**	0.0591	0.1002
	(0.041)	(0.037)	(0.041)	(0.062)
REALITY NON-COMPETITION	0.0241	0.0637*	0.0301	0.0361
	(0.045)	(0.038)	(0.044)	(0.063)
DRAMA	0.0929**	0.0611*	0.0805**	0.1485**
	(0.040)	(0.035)	(0.037)	(0.060)
CABLE	-0.1386****	-0.1044****	-0.0965***	-0.2546****
	(0.030)	(0.021)	(0.034)	(0.052)
NEW	-0.0617*	-0.0740**	-0.0198	-0.0140
	(0.034)	(0.031)	(0.033)	(0.048)
AD SPEND	-0.0000	0.0000	-0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)
PRIOR SEASON RATINGS	-0.0218	-0.0150	-0.0098	-0.0054
	(0.015)	(0.012)	(0.012)	(0.013)
PRIOR EPISODE RATINGS	0.2242****	0.2332****	0.1918****	0.1341****
	(0.024)	(0.018)	(0.021)	(0.016)
CONSTANT	-0.3740****	-0.3782****	-0.3678****	-0.4016****
	(0.076)	(0.064)	(0.066)	(0.116)
N	214	214	214	214
R^2	0.842	0.835	0.837	0.750

Notes: Robust standard errors in parentheses

****** p<0.001, *** p<0.01, ** p<0.05, * p<0.1**

Table 12: Estimation Results – Finale Model, Two Weeks Prior to Episode Airing, Buzz Volume and Ratings Log Transformed, Multiple Imputation for Ad Spend

	People 2+	People 18-34	People 35-49	People 50+
LOG (BUZZ VOLUME$_{t-2}$)	0.0683***	0.0597**	0.0855****	0.1102***
	(0.023)	(0.023)	(0.019)	(0.040)
DISPERSION$_{t-2}$	-0.0004**	-0.0001	-0.0009****	-0.0013**
	(0.000)	(0.000)	(0.000)	(0.001)
AUTHORS$_{t-2}$	-0.0001**	-0.0001	-0.0001***	-0.0002**
	(0.000)	(0.000)	(0.000)	(0.000)
REALITY COMPETITION	0.0785*	0.0968**	0.0593	0.1006
	(0.041)	(0.038)	(0.042)	(0.062)
REALITY NON-COMPETITION	0.0259	0.0627	0.0309	0.0322
	(0.045)	(0.038)	(0.045)	(0.063)
DRAMA	0.0930**	0.0612*	0.0815**	0.1484**
	(0.040)	(0.036)	(0.038)	(0.060)
CABLE	-0.1370****	-0.1050****	-0.0951***	-0.2565****
	(0.030)	(0.021)	(0.034)	(0.052)
NEW	-0.0612*	-0.0741**	-0.0193	-0.0139
	(0.034)	(0.031)	(0.033)	(0.049)
AD SPEND	-0.0000	0.0000	-0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)
PRIOR SEASON RATINGS	-0.0218	-0.0150	-0.0099	-0.0055
	(0.015)	(0.012)	(0.012)	(0.013)
PRIOR EPISODE RATINGS	0.2245****	0.2332****	0.1930****	0.1352****
	(0.024)	(0.018)	(0.021)	(0.016)
CONSTANT	-0.3749****	-0.3774****	-0.3689****	-0.4017****
	(0.076)	(0.064)	(0.067)	(0.117)
N	214	214	214	214
R^2	0.843	0.836	0.838	0.750

Notes: Robust standard errors in parentheses

****** p<0.001, *** p<0.01, ** p<0.05, * p<0.1**

Table 13: Estimation Results – Premiere and Finale Models without Imputation for Missing Values of Ad Spend, Coefficient for Buzz Volume Only

	People 2+	People 18-34	People 35-49	People 50+
Premiere Model				
LOG (BUZZ VOLUME$_{t-4}$)	0.018 (0.047)	0.080 (0.054)	0.048 (0.042)	-0.022 (0.050)
N *R^2*	96 0.659	96 0.504	96 0.676	96 0.695
Finale Model				
LOG (BUZZ VOLUME$_{t-2}$)	0.064** (0.031)	0.041 (0.033)	0.075*** (0.026)	0.106** (0.048)
N *R^2*	139 0.865	139 0.861	139 0.876	139 0.784

Notes: Fully specified model was estimated. Detailed results available upon request.
Robust standard errors in parentheses
****** p<0.001, *** p<0.01, ** p<0.05, * p<0.1**

Midseason Model Results

Fixed effects was utilized to estimate the cross-sectional time series data for the midseason segment and was selected because it is useful when trying to understand the differences in behavior of individual unit effects for each TV show, assuming the same slope and constant variance across groups. It also controls for any unobserved differences across shows that are not explicitly included in the model (Wooldridge, 2009). Again, TV show ratings among people ages 2+, 18-34, 35-49 and 50+ were utilized.

The fixed effects specification was tested against pooled OLS using an F-test to evaluate the significance of the additional unit dummy variables. Utilizing ratings for people 2+, the F-statistic was equal to 5.43 with a p-value equal to 0.000 therefore the null hypothesis that OLS was the appropriate specification was rejected and the fixed effects specification was concluded to be the proper model (Wooldridge, 2009). I also verified that random effects was an inappropriate model specification using the Hausman test. The test resulted in a chi-square value of 483 with a p-value equal to 0.000. As a result, the null hypothesis that the random effects estimation method is appropriate was rejected (Wooldridge, 2009).

Homoskedasticity and serial correlation within the data was also examined and corrected for when present through the use of robust standard errors.

The following model was estimated using fixed effects regression with robust standard errors for the midseason episode ratings:

$$\log(RATINGS_{it}) = \alpha_i + \beta_1 \cdot \log\left(BUZZ\ VOLUME_{i,t-2}\right) + \beta_2 \cdot DISPERSION_{i,t-2} + \beta_3 \cdot AUTHORS_{i,t-2} + \beta_4 \cdot AD\ SPEND_{it} + \beta_5 \cdot PRIOR\ EPISODE\ RATING_{i,t-1} + u_{it} \tag{2.3}$$

Since a fixed effects estimator will not produce estimates for time invariant variables because of perfect collinearity with the dummy variables, all time invariant variables (genre dummies, cable dummy, and prior season average) were removed from the model specification as seen for premiere and finale episode models. The estimation of the midseason model (2.3) using single imputation of advertising spend is displayed in Table 14 and the multiple imputation for missing data is shown in Table 15.

The model estimation across the single and multiple imputation methods produced extremely similar results again. The coefficient on buzz volume for both models was positive and significant at the $p<0.05$ level for ratings among people 2+ and 35-49, and at the $p<0.01$ level for people 18-34 and 50+. A 14-25% change in buzz volume corresponded to a 1% change in midseason episode ratings with the largest effect being present for people 35-49 followed by people 50+. Also for people 35-49, dispersion was statistically significant at the $p<0.1$ level and had a negative relationship with ratings. For all other age groups, dispersion was insignificant.

Table 14: Estimation Results – Midseason Model, Two Weeks Prior to Episode Airing, Buzz Volume and Ratings Log Transformed, Single Imputation for Ad Spend

	People 2+	People 18-34	People 35-49	People 50+
LOG (BUZZ VOLUME$_{t-2}$)	0.0473***	0.0395**	0.0696****	0.0530**
	(0.017)	(0.020)	(0.019)	(0.023)
DISPERSION$_{t-2}$	-0.0001	-0.0000	-0.0002*	-0.0001
	(0.000)	(0.000)	(0.000)	(0.000)
AUTHORS$_{t-2}$	-0.0001	-0.0001**	-0.0001	-0.0000
	(0.000)	(0.000)	(0.000)	(0.000)
AD SPEND	0.0000**	0.0000*	0.0000*	0.0000*
	(0.000)	(0.000)	(0.000)	(0.000)
PRIOR EPISODE RATINGS	0.0341**	0.0322**	0.0271**	0.0233***
	(0.015)	(0.013)	(0.012)	(0.007)
CONSTANT	-0.0801	-0.0342	-0.0467	-0.0870
	(0.049)	(0.054)	(0.054)	(0.057)
N (Observations)	781	781	781	781
N (# TV Shows)	217	217	217	217
R^2	0.69	0.61	0.65	0.66

Notes: Robust standard errors in parentheses
**** p<0.001, *** p<0.01, ** p<0.05, * p<0.1**

Table 15: Estimation Results – Midseason Model, Two Weeks Prior to Episode Airing, Buzz Volume and Ratings Log Transformed, Multiple Imputation for Ad Spend

	People 2+	People 18-34	People 35-49	People 50+
LOG (BUZZ VOLUME$_{t-2}$)	0.0476***	0.0395**	0.0698****	0.0536**
	(0.017)	(0.020)	(0.020)	(0.023)
DISPERSION$_{t-2}$	-0.0001	-0.0000	-0.0002*	-0.0001
	(0.000)	(0.000)	(0.000)	(0.000)
AUTHORS$_{t-2}$	-0.0001	-0.0001**	-0.0001	-0.0000
	(0.000)	(0.000)	(0.000)	(0.000)
AD SPEND	0.0000	0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)
PRIOR EPISODE RATINGS	0.0345**	0.0325**	0.0274**	0.0235****
	(0.015)	(0.013)	(0.012)	(0.007)
CONSTANT	-0.0811*	-0.0351	-0.0478	-0.0878
	(0.049)	(0.054)	(0.054)	(0.057)
N (Observations)	781	781	781	781
N (# TV Shows)	217	217	217	217
R^2	n/a	n/a	n/a	n/a

Notes: Robust standard errors in parentheses
**** p<0.001, *** p<0.01, ** p<0.05, * p<0.1**

Given the fact that ratings are a slow moving variable and prior episode ratings are said to have the most significant impact on future ratings[15], a lagged dependant variable was utilized in my model specification. This follows work done by academic researchers on the impact of WOM (Chintagunta, et al., 2010; Duan, et al., 2008b; Godes & Mayzlin, 2004). When using a fixed effects approach, however, including an endogenous lagged dependent variable can lead to biased estimates. This occurs because the lagged variable induces correlation among the explanatory variables, x_{it}, and the error term, u_{it}, violating a key assumption (Wooldridge, 2009).

To correct for this issue, a dynamic panel model proposed by Arellano and Bond (1991) was also explored. Dynamic panel models are asymptotic in N, with fixed T, and utilize the panel structure of the data to find instruments to understand the correlation induced by the lagged dependent variable (Arellano & Bond, 1991). For a fixed effects model specification, this instrumental variable approach results in consistent and asymptotically normally distributed estimates (Hsiao, 2003).

The estimation of the midseason model (2.3) using the Arellano-Bond estimator with single imputation[16] of advertising spend is displayed in Table 16. Since the Sargan test for overidentifying restrictions cannot be produced when robust standard errors are used to correct for heteroskedasticity, the model was run with and without robust standard errors. The Sargan test showed the inclusion of the overidentifying restrictions are valid while the Arellano-Bond test for autocorrelation indicated that there was not any higher-order serial correlation concerns[17]. With these specification tests, the dynamic panel model is an appropriate estimator to utilize.

Using robust standard errors, the coefficient on buzz volume was positive and significant for all demographic groups except for people 35-49. A 16-20% change in buzz volume corresponded to a 1% change in midseason episode ratings. Dispersion was insignificant for all

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[15] This statement is industry knowledge I have gained from working in the media industry for Nielsen.

[16] Since multiple imputation better represents the uncertainty about the missing data relative to single imputation, I also ran the dynamic panel model on the multiple imputation dataset. However, the MI function in STATA would not produce the post estimation Sargan test or Arellano-Bond test which is why I presented the single imputation results in the body of this paper. The results of the dynamic panel model can be found in Appendix B and are substantively and statistically similar to the single imputation results.

[17] Details on the specification tests are available upon request.

age groups. In general, the dynamic panel models with and without[18] robust standard errors produced qualitatively equivalent results as the fixed effects approach confirming the relationship found between buzz volume, dispersion and TV ratings.

Table 16: Estimation Results – Midseason Model, Two Weeks Prior to Episode Airing, Buzz Volume and Ratings Log Transformed, Dynamic Panel Model, Single Imputation for Ad Spend

	People 2+	People 18-34	People 35-49	People 50+
LOG (BUZZ VOLUME$_{t-2}$)	0.0513**	0.0525*	0.0615	0.0511*
	(0.025)	(0.031)	(0.038)	(0.030)
DISPERSION$_{t-2}$	0.0001	0.0001	-0.0000	-0.0001
	(0.000)	(0.000)	(0.000)	(0.000)
AUTHORS$_{t-2}$	-0.0000	-0.0000	-0.0000	0.0001
	(0.000)	(0.000)	(0.000)	(0.000)
AD SPEND	0.0000**	0.0000	0.0000*	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)
PRIOR EPISODE RATINGS	0.5924****	0.4187***	0.4197***	0.3830***
	(0.112)	(0.154)	(0.140)	(0.135)
CONSTANT	-0.1167*	-0.0762	-0.0654	-0.0887
	(0.064)	(0.081)	(0.091)	(0.084)
N (Observations)	418	418	418	418
N (# TV Shows)	158	158	158	158

Notes: Robust standard errors in parentheses
****** p<0.001, *** p<0.01, ** p<0.05, * p<0.1**

The previously specified models are useful in addressing my first two hypotheses about buzz volume and dispersion's relationship with TV ratings. However, an unanswered question lingers with respect to the endogeneity of WOM and TV ratings as outline in H3. To investigate the interdependence of buzz volume and TV ratings over time, I developed a two equation system: one equation with TV ratings as the dependent variable (as previously investigated) and a second equation with buzz volume as the dependent variable. Fixed effects were utilized to capture the time invariant unit heterogeneity for each TV show and control for any unobserved

[18] Results for the dynamic panel model without robust standard errors are available upon request.

differences across shows. Following the method employed by Duan, et al. (2008a), a three-stage least squares (3SLS) approach was utilized to simultaneously estimate the system of two equations. This model specification produces consistent and efficient estimates, and according to Greene (1993, pp. 611-616) is preferable over a single-equation estimator such as OLS[19]. However, as previously discussed, since a fixed effects specification is being utilized in conjunction with a lagged dependent variable, the estimates may be biased due to correlation with the errors. Therefore, the results of this analysis will be used to confirm the previous findings that the relationship of TV ratings on buzz volume holds up under a more demanding model specification.

The following system of equations was estimated using 3SLS for the midseason episode ratings among people ages 2+ on the multiply imputed data set:

$$\begin{aligned}\log(RATINGS_{it}) = \alpha_i + \beta_1 \cdot \log\left(BUZZ\,VOLUME_{i,t-2}\right) + \ & \beta_2 \cdot DISPERSION_{i,t-2} \\ & + \beta_3 \cdot AUTHORS_{i,t-2} \ + \beta_4 \cdot AD\ SPEND_{it} \\ & + \beta_5 \cdot PRIOR\ EPISODE\ RATING_{i,t-1} + \ u_{it}\end{aligned} \tag{2.4a}$$

$$\begin{aligned}\log\left(BUZZ\,VOLUME_{i,t-2}\right) = \alpha_i + \beta_1 \cdot \log(RATINGS_{it}) + \ & \beta_2 \cdot AD\ SPEND_{it} \\ & + \beta_3 \cdot REALITY\ COMPETITION_i \ + \beta_4 \cdot DRAMA_i \\ & + \beta_5 \cdot REALITY\ NONCOMPETITION_i + \ \beta_6 \cdot CABLE_i \\ & + \beta_6 \cdot NEW_i \ + \ u_{it}\end{aligned} \tag{2.4b}$$

The model estimation results for (2.4a) and (2.4b) are presented in Table 17. The coefficients on buzz volume and TV ratings were both positive and significant at the p<0.001 level. After controlling for the interdependence between buzz volume and TV ratings, buzz volume's coefficient increased in magnitude such that a 5% change in buzz volume corresponded to a 1% change in midseason episode ratings meaning that there needs to be less movement in buzz volume to have the same impact on ratings. The percent change in buzz for people 2+ from the fixed effects and dynamic panel models were 21% and 19%, respectively.

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[19] OLS estimates would be inconsistent due to the lagged endogenous variable inducing correlation with the errors.

Table 17: Estimation Results – Midseason Model, 3SLS, Multiple Imputation for Ad Spend

	People 2+
LOG (BUZZ VOLUME$_{t-2}$)	0.1822****
	(0.039)
DISPERSION$_{t-2}$	-0.0000
	(0.000)
AUTHORS$_{t-2}$	-0.0000
	(0.000)
AD SPEND	0.0000
	(0.000)
PRIOR EPISODE RATINGS	0.0170***
	(0.006)
N (Observations)	781

	People 2+
LOG (RATINGS)	3.1186****
	(0.602)
AD SPEND	-0.0000
	(0.000)
REALITY COMPETITION	1.6799****
	(0.432)
REALITY NON-COMPETITION	2.0744****
	(0.421)
DRAMA	2.4505****
	(0.417)
CABLE	1.4883****
	(0.210)
NEW	1.1306***
	(0.379)
N (Observations)	781

Notes: Standard errors in parentheses
The fixed effects for each show used in estimating the model are not reported
****** p<0.001, *** p<0.01, ** p<0.05, * p<0.1**

DISCUSSION AND CONCLUSION

The objective of this paper has been to investigate how online word-of-mouth impacts off-line behavior, specifically TV viewership. With a limited number of published studies linking online consumer-generated media to consumer purchase decisions, I intended to add additional insight to this field of study. There are three major limitations that emerge within prior research studies: one, only one or two data sources among millions of alternatives on the web were utilized; two, minimal confounding factors impacting consumer purchase decisions were controlled for; and three, a minimal number of observations were used (for example, 44 TV shows (Godes & Mayzlin, 2004), 50 books (Gruhl, et al., 2005), 71 movies (Duan, et al., 2008a)).

Within my research, I focused on evaluating online conversation as a leading indicator of TV ratings, concentrating on the effect of buzz volume and dispersion, ignoring message valance, after controlling for show-level factors such as genre, season, distribution channel, ad spend and prior ratings. Relative to studies previously conducted in this field of research, I gathered a more robust dataset, capturing much of the long tail, by harvesting data from over 150 million social media sites. I also utilized a larger set of observations, harvesting data on 250 TV shows.

To explore and confirm my hypotheses, I utilized several modeling techniques (OLS, fixed effects, dynamic panel model, and 3SLS) to deeply explore the dynamics in my data to ensure my results were substantively and statistically meaningful. The results across all models presented provide consistent support of buzz volume's positive impact on TV ratings confirming H1 to be true. As the number of messages about a TV show increased, there was a positive impact on TV ratings four weeks prior to premiere episode airing and two weeks prior to midseason and finale episode airing regardless of demographic age group. This relationship can be quantified in a meaningful way. A 10-11% increase in buzz volume four weeks prior to premiere episode airing corresponded to a 1% increase in ratings. For finale episodes this relationship was similar but had a broader range spanning 9-17% increase in buzz volume two weeks prior to episode airing for the same change in ratings. The midseason revealed a slightly weaker relationship substantively speaking requiring a 14-25% increase in buzz volume two weeks prior to episode airing; however, this relationship was upheld and the range tightened using the dynamic panel model to 16-20%, hardly different from the finale estimation results. Due to the many lagged variables used as instruments, the dynamic panel model specification was more demanding on the data and tougher for statistically significant coefficients to arise relative to fixed effects and OLS specifications. When the 3SLS method was employed, also a demanding model on the data, the relationship became stronger for the midseason suggesting that only a 5% increase in buzz volume corresponded to a 1% increase in ratings. This finding supports H3 that after accounting for the reciprocal relationship between buzz volume and TV ratings, the number of messages about a show had a positive impact on ratings. Nevertheless, this model is likely biased due to the inclusion of a lagged dependent variable and should only be used as confirmation of a meaningful and persistent positive relationship between buzz volume and TV ratings.

I also explored the use of single and multiple imputation for missing data on my variable advertising spend. Despite multiple imputation being a preferred method to single imputation due to greater efficiency in the estimates and increased confidence coverage (Donald B. Rubin & Schenker, 1991), my analysis showed negligible differences in the statistical significance and magnitude of coefficient estimates through usage of single and multiple imputation. This convergence of findings confirmed the validity of the relationship between WOM and TV ratings.

A key limitation to this analysis is the method with which I operationalize dispersion. This concept regarding the spread of discussion was defined as the number of messages about a TV show divided by the number of sources generating those messages. Due to network theory and the strength of weak ties encouraging the spread of information, I intuitively thought that the greater the number of messages per source, or the more actively consumers are discussing a show online, would correspond to wider spread of discussion, increased likelihood of mere exposure, and ultimately more TV viewers. However, based on this definition, dispersion did not have the expected positive relationship with TV ratings. Alternatively, a negative relationship with ratings was found across all models presented, suggesting that shows with data spread across more sources have lower TV ratings, contradicting H2. Upon further consideration of this metric, number of messages per source, it may not truly be measuring spread of discussion but rather engagement in a TV show. Many shows have niche followings with very high engagement but mediocre ratings, such as *Parks and Recreation* or *Chuck*[20]. Therefore the weak, negative relationship seen here has sound footing in the fact that there could be more online engagement for shows with niche appeal rather than higher ratings.

To correct for this issue in future work, the use of the entropy metric as outlined by Godes and Mayzlin (2004) instead of my measure for dispersion may be a useful alternative. The entropy metric they used more soundly balances total volume of discussion and spread of discussion over sources, maximizing when discussion is more evenly spread across sites. This can be contrasted to my metric for dispersion which maximizes when discussion is concentrated on one source. The entropy metric is advantageous because it more appropriately operationalizes the theoretical concept of the strength of weak ties to generate more awareness about a topic. When discussion is more evenly spread across multiple sites, rather than concentrated on one or two sites, then more weakly tied individuals are connecting and the information can spread more

[20] These examples were selected by comparing Nielsen IAG's Program Engagement measure with Live+3 day TV ratings.

quickly. This also leads to greater exposure among individuals and a higher likelihood that a person will think favorably about the TV show and potentially lead to watching the show. This better captures the essence of the concept I was trying to test with H2.

A counter argument to using entropy, however, would be the inclusion of Facebook and Twitter data. These sites are known to be massive social networks with more weight and influence than a message board such as Television Without Pity[21]. The entropy metric weights all sites equally. If a topic is discussed on Facebook or Twitter it will likely have more exposure across many individuals. The exclusion of Facebook and Twitter is a limitation of the current analysis and would need to be explored as a build to the current analysis as well as in conjunction with using the entropy metric in future exploration.

Despite these limitations, having found a consistent relationship between buzz volume and TV ratings across all of the various estimation procedures strengthens the influence my findings have within the marketing industry. Specifically, the inclusion of a simultaneous equation system allowed me to model the dual causal relationship between WOM and TV ratings to reveal the true effect WOM has on explaining ratings. Since the coefficient on buzz volume remained statistically significant and within a similar range to the other model specifications, these findings confirm the need to invest in a social media strategy. Buzz volume impacts TV ratings and higher ratings leads to more advertising investment and revenue for the show. These results indicate that there is true return on investment for actively encouraging online word-of-mouth about a TV show. Additionally, the leading relationship found here provides time for marketers and show writers to make changes to their plans and still impact the current season. Marketers struggle to prove the value of their online efforts, and the outcomes demonstrated provide support for continued focus, emphasis and development of the evolving social world.

[21] Television Without Pity can be found at http://forums.televisionwithoutpity.com.

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APPENDIX A: ALL TV SHOWS IN SAMPLE

Show Name	Network	Broadcast/ Cable	New / Returning	Genre	Episode Duration (minutes)	# Months in Season
90210	CW	Broadcast	Returning	Drama	60	7
16 & Pregnant	MTV	Cable	Returning	Reality: Non-Competition	90	3
19 Kids and Counting	TLC	Cable	Returning	Reality: Non-Competition	30	8
24 Hour Restaurant Battle	Food Network	Cable	New	Reality: Competition	60	3
30 Rock	NBC	Broadcast	Returning	Comedy	30	8
Always Sunny In Philadelphia	FX	Cable	Returning	Comedy	31	4
Amazing Race	CBS	Broadcast	Returning	Reality: Competition	60	4
Amer Funn Home Videos	ABC	Broadcast	Returning	Reality: Non-Competition	60	8
American Dad	FOX	Broadcast	Returning	Comedy	29	8
American Idol	FOX	Broadcast	Returning	Reality: Competition	81	5
American Pickers	History	Cable	New	Reality: Non-Competition	60	8
America's Best Dance Crew	MTV	Cable	Returning	Reality: Competition	60	4
America's Got Talent	NBC	Broadcast	Returning	Reality: Competition	120	4
America's Most Wanted	FOX	Broadcast	Returning	Reality: Competition	60	13
America's Next Top Model	CW	Broadcast	Returning	Reality: Non-Competition	60	4
Apprentice	NBC	Broadcast	Returning	Reality: Competition	120	4
Archer	FX	Cable	New	Comedy	30	3
Are We There Yet	TBS	Cable	New	Comedy	30	1
Auction Kings	Discovery	Cable	New	Reality: Non-Competition	30	5
Bachelor	ABC	Broadcast	Returning	Reality: Competition	121	3
Bachelor Pad	ABC	Broadcast	New	Reality: Competition	121	2

Bad Girls Club	Oxygen	Cable	Returning	Reality: Non-Competition	60	4
Bbq Pitmasters	TLC	Cable	New	Reality: Competition	60	2
Bethenny Ever After	Bravo	Cable	New	Reality: Non-Competition	60	3
Big Bang Theory	CBS	Broadcast	Returning	Comedy	30	9
Biggest Loser	NBC	Broadcast	Returning	Reality: Competition	121	4
Bones	FOX	Broadcast	Returning	Drama	60	8
Boondocks, The	Adult Swim	Cable	Returning	Comedy	30	4
Breaking Bad	AMC	Cable	Returning	Drama	62	4
Brothers & Sisters	ABC	Broadcast	Returning	Drama	59	9
Burn Notice	USA	Cable	Returning	Drama	60	2
Cake Boss	TLC	Cable	Returning	Reality: Competition	60	6
Californication	Showtime Prime	Cable	Returning	Comedy	28	4
Caprica	SYFY	Cable	New	Drama	60	2
Castle	ABC	Broadcast	Returning	Drama	59	9
Celebrity Rehab	VH1	Cable	Returning	Reality: Non-Competition	60	2
Chefs vs. City	Food Network	Cable	New	Reality: Competition	60	5
Chopped	Food Network	Cable	Returning	Reality: Competition	60	5
Chuck	NBC	Broadcast	Returning	Drama	60	5
Cleveland	FOX	Broadcast	New	Comedy	30	9
Colony	Discovery	Cable	Returning	Reality: Competition	60	2
Community	NBC	Broadcast	New	Comedy	30	9
Cops	FOX	Broadcast	Returning	Reality: Non-Competition	30	11
Cougar Town	ABC	Broadcast	New	Comedy	31	9
Covert Affairs	USA	Cable	New	Drama	60	3
Criminal Minds	CBS	Broadcast	Returning	Drama	60	9
Criss Angel Mindfreak	A&E	Cable	Returning	Reality: Non-Competition	60	2
CSI	CBS	Broadcast	Returning	Drama	60	9
CSI: Miami	CBS	Broadcast	Returning	Drama	60	9
CSI: NY	CBS	Broadcast	Returning	Drama	60	9
Cupcake Wars	Food Network	Cable	New	Reality: Competition	60	3

Curb Your Enthusiam	HBO Prime	Cable	Returning	Comedy	32	3
Dancing With The Stars	ABC	Broadcast	Returning	Reality: Competition	92	3
Dating In The Dark	ABC	Broadcast	Returning	Reality: Competition	59	2
DC Cupcakes	TLC	Cable	New	Reality: Non-Competition	30	1
Deadliest Catch	Discovery	Cable	Returning	Reality: Non-Competition	60	4
Design Star	HGTV	Cable	Returning	Reality: Competition	60	3
Desperate Housewives	ABC	Broadcast	Returning	Drama	61	9
Dirty Jobs	Discovery	Cable	Returning	Reality: Non-Competition	60	5
Doctor Who	BBC - America	Cable	Returning	Drama	61	4
Dog The Bounty Hunter	A&E	Cable	Returning	Reality: Non-Competition	30	7
Drop Dead Diva	Lifetime	Cable	Returning	Drama	60	3
Eastbound & Down	HBO Prime	Cable	Returning	Comedy	27	3
Entourage	HBO Prime	Cable	Returning	Comedy	27	4
Eureka	SYFY	Cable	Returning	Drama	60	4
Extreme Makeover: Home Edition	ABC	Broadcast	Returning	Reality: Non-Competition	60	9
Family Guy	FOX	Broadcast	Returning	Comedy	31	9
Fashion Show	Bravo	Cable	Returning	Reality: Competition	60	3
Find My Family	ABC	Broadcast	New	Reality: Non-Competition	60	2
Flashpoint	CBS	Broadcast	Returning	Drama	60	3
Flipping Out	Bravo	Cable	Returning	Reality: Non-Competition	60	3
Football Wives	VH1	Cable	New	Reality: Non-Competition	30	3
For The Love Of Ray	VH1	Cable	Returning	Reality: Competition	60	3
Forgotten	ABC	Broadcast	New	Drama	60	7
Four Weddings	TLC	Cable	Returning	Reality: Competition	60	2
Friday Night Lights	NBC	Broadcast	Returning	Drama	60	4
Fringe	FOX	Broadcast	Returning	Drama	60	8
Futurama	Comedy Central	Cable	Returning	Comedy	30	4

Gangland	History	Cable	Returning	Reality: Non-Competition	60	2
Gates	ABC	Broadcast	New	Drama	60	4
Ghost Hunters	SYFY	Cable	Returning	Reality: Non-Competition	60	5
Ghost Hunters International	SYFY	Cable	Returning	Reality: Non-Competition	60	n/a
Ghost Lab	Discovery	Cable	New	Reality: Non-Competition	60	4
Glee	FOX	Broadcast	Returning	Drama	60	7
Good Wife	CBS	Broadcast	New	Drama	60	9
Gossip Girl	CW	Broadcast	Returning	Drama	60	7
Great Food Truck Race	Food Network	Cable	New	Reality: Competition	60	2
Grey's Anatomy	ABC	Broadcast	Returning	Drama	61	8
Hardcore Pawn	TRUTV	Cable	New	Reality: Non-Competition	30	3
Haven	SYFY	Cable	New	Drama	60	4
Hawthorne	TNT	Cable	Returning	Drama	60	3
Hell's Kitchen	FOX	Broadcast	Returning	Reality: Competition	60	4
Hoarders	A&E	Cable	New	Reality: Non-Competition	60	6
Hoarding: Buried Alive	TLC	Cable	New	Reality: Non-Competition	60	3
Holly's World	E! Entertainment	Cable	New	Reality: Competition	30	3
Hot In Cleveland	TV Land	Cable	New	Comedy	30	3
House	FOX	Broadcast	Returning	Drama	64	8
House of Payne	TBS	Cable	Returning	Comedy	30	4
How I Met Your Mother	CBS	Broadcast	Returning	Comedy	30	9
How To Make It In America	HBO Prime	Cable	New	Comedy	26	3
Human Target	FOX	Broadcast	New	Drama	60	4
I Want To Work For Diddy	VH1	Cable	Returning	Reality: Competition	60	3
In Plain Sight	USA	Cable	Returning	Drama	60	4
Iron Chef America	Food Network	Cable	Returning	Reality: Competition	60	10
J. Oliver's Food Revolutn	ABC	Broadcast	New	Reality: Non-Competition	60	2

Jersey Shore	MTV	Cable	New	Reality: Non-Competition	60	4
Justified	FX	Cable	New	Drama	62	4
Kate Plus 8	TLC	Cable	New	Reality: Non-Competition	60	5
Kathy Griffin: My Life On The D List	Bravo	Cable	Returning	Reality: Non-Competition	60	3
Keeping Up With The Kardashians	E! Entertainment	Cable	Returning	Reality: Non-Competition	30	3
King Of The Crown	TLC	Cable	New	Reality: Non-Competition	34	3
Kirstie Alley Big Life	A&E	Cable	New	Reality: Non-Competition	30	3
Kitchen Nightmares	FOX	Broadcast	Returning	Reality: Competition	60	5
Kourtney & Kloe Take Miami	E! Entertainment	Cable	New	Reality: Non-Competition	30	n/a
La Ink	TLC	Cable	Returning	Reality: Non-Competition	60	4
Last Comic Standing	NBC	Broadcast	Returning	Reality: Competition	60	3
Law & Order: Criminal Intent	USA	Cable	Returning	Drama	60	5
Law and Order	NBC	Broadcast	Returning	Drama	60	n/a
Law and Order:SVU	NBC	Broadcast	Returning	Drama	60	8
League	FX	Cable	New	Comedy	31	4
Let's Talk About Pep	VH1	Cable	New	Reality: Non-Competition	30	3
Leverage	TNT	Cable	Returning	Drama	60	4
Lie To Me	FOX	Broadcast	Returning	Drama	60	8
Little People, Big World	TLC	Cable	Returning	Reality: Non-Competition	30	4
Losing It With Jillian	NBC	Broadcast	New	Reality: Competition	60	2
Louie	FX	Cable	New	Comedy	31	3
Mad Men	AMC	Cable	Returning	Drama	62	4
Make It Or Break It	ABC Family	Cable	Returning	Drama	60	2
Mall Cops	TLC	Cable	New	Reality: Non-Competition	30	3
Man vs. Wild	Discovery	Cable	Returning	Reality: Non-Competition	60	5

Manhunters	A&E	Cable	Returning	Reality: Competition	30	3
Marriage Ref	NBC	Broadcast	New	Reality: Competition	60	4
Masterchef	FOX	Broadcast	New	Reality: Competition	120	3
Medium	CBS	Broadcast	Returning	Drama	60	9
Meet The Browns	TBS	Cable	Returning	Comedy	30	7
Melissa & Joey	ABC Family	Cable	New	Comedy	30	3
Melrose Place	CW	Broadcast	New	Drama	60	6
Memphis Beat	TNT	Cable	New	Drama	60	3
Men Of A Certain Age	TNT	Cable	New	Drama	60	2
Mentalist	CBS	Broadcast	Returning	Drama	60	9
Middle	ABC	Broadcast	New	Comedy	30	9
Millionaire Matchmaker	Bravo	Cable	Returning	Reality: Non-Competition	60	3
Minute To Win It	NBC	Broadcast	New	Reality: Competition	60	5
Modern Family	ABC	Broadcast	New	Comedy	30	9
Mythbusters	Discovery	Cable	Returning	Reality: Non-Competition	60	3
NCIS	CBS	Broadcast	Returning	Drama	60	9
NCIS: Los Angeles	CBS	Broadcast	New	Drama	60	9
Nurse Jackie	Showtime Prime	Cable	Returning	Comedy	28	4
Office	NBC	Broadcast	Returning	Comedy	31	9
Old Christine	CBS	Broadcast	Returning	Comedy	30	9
One Tree Hill	CW	Broadcast	Returning	Drama	60	8
Paranormal State	A&E	Cable	Returning	Reality: Non-Competition	30	2
Parenthood	NBC	Broadcast	New	Drama	60	3
Parks and Recreation	NBC	Broadcast	Returning	Comedy	30	9
Pawn Stars	History	Cable	Returning	Reality: Non-Competition	30	7
Plain Jane	CW	Broadcast	New	Reality: Non-Competition	60	3
Pretty Little Liars	ABC Family	Cable	New	Drama	60	5
Private Practice	ABC	Broadcast	Returning	Drama	59	8
Project Runway	Lifetime	Cable	Returning	Reality: Competition	60	4
Pros vs. Joes	Spike TV	Cable	Returning	Reality: Competition	60	3
Psych	USA	Cable	Returning	Drama	60	2

Psychic Kids	A&E	Cable	Returning	Reality: Non-Competition	60	2
Rachel Zoe Project	Bravo	Cable	Returning	Reality: Non-Competition	60	2
Real Housewives Atlanta	Bravo	Cable	Returning	Reality: Non-Competition	60	4
Real Housewives Beverly Hills	Bravo	Cable	New	Reality: Non-Competition	61	n/a
Real Housewives New Jersey	Bravo	Cable	Returning	Reality: Non-Competition	60	n/a
Real Housewives New York	Bravo	Cable	Returning	Reality: Non-Competition	60	n/a
Real Housewives Orange County	Bravo	Cable	Returning	Reality: Non-Competition	60	n/a
Real Housewives Washington D.C.	Bravo	Cable	New	Reality: Non-Competition	60	n/a
Real World	MTV	Cable	Returning	Reality: Non-Competition	60	4
Rescue Me	FX	Cable	Returning	Drama	61	3
Ricky Gervais Show	HBO Prime	Cable	New	Comedy	25	4
Rizzoli & Isles	TNT	Cable	New	Drama	60	3
Rob Dyrdeks Fantasy Factory	MTV	Cable	Returning	Reality: Non-Competition	30	7
Rookie Blue	ABC	Broadcast	Returning	Drama	60	4
Royal Pains	USA	Cable	Returning	Drama	60	2
Rules Of Engagement	CBS	Broadcast	Returning	Comedy	30	3
Sanctuary	SYFY	Cable	Returning	Drama	60	3
Saturday Night Live	NBC	Broadcast	Returning	Comedy	73	9
Say Yes To The Dress	TLC	Cable	Returning	Reality: Non-Competition	30	8
Say Yes To The Dress Atlanta	TLC	Cable	New	Reality: Non-Competition	30	n/a
Secret Life Of The American Teenager	ABC Family	Cable	Returning	Drama	60	4
Shaq vs.	ABC	Broadcast	New	Reality: Competition	60	1
Shark Tank	ABC	Broadcast	New	Reality: Non-Competition	60	3
Shear Genius	Bravo	Cable	Returning	Reality: Competition	60	3
Simpsons	FOX	Broadcast	Returning	Comedy	31	9

Sing-Off, The	NBC	Broadcast	New	Reality: Competition	121	1
Sister Wives	TLC	Cable	New	Reality: Non-Competition	30	2
Smallville	CW	Broadcast	Returning	Drama	60	7
So You Think Can Dance	FOX	Broadcast	Returning	Reality: Competition	60	3
Sons Of Anarchy	FX	Cable	Returning	Drama	68	3
South Park	Comedy Central	Cable	Returning	Comedy	30	4
Squad Prison Police	A&E	Cable	New	Reality: Non-Competition	30	2
Stargate Universe	SYFY	Cable	New	Drama	63	6
Steven Seagal: Lawman	A&E	Cable	New	Reality: Non-Competition	30	3
Storm Chasers	Discovery	Cable	Returning	Reality: Non-Competition	60	3
Supernanny	ABC	Broadcast	Returning	Reality: Non-Competition	60	6
Supernatural	CW	Broadcast	Returning	Drama	60	8
Survivor	CBS	Broadcast	Returning	Reality: Competition	60	4
Teen Mom	MTV	Cable	New	Reality: Non-Competition	120	4
Terriers	FX	Cable	New	Drama	61	4
The Big C	Showtime Prime	Cable	New	Drama	28	4
The Challenge	MTV	Cable	New	Reality: Competition	60	3
The Closer	TNT	Cable	Returning	Drama	60	4
The Hills	MTV	Cable	Returning	Reality: Non-Competition	30	4
Thintervention	Bravo	Cable	New	Reality: Competition	60	2
Til Death	FOX	Broadcast	Returning	Comedy	29	7
Titan Maximum	Adult Swim	Cable	New	Comedy	17	3
Toddlers & Tiaras	TLC	Cable	Returning	Reality: Competition	60	3
Top Chef	Bravo	Cable	Returning	Reality: Competition	60	4
Top Chef Just Desserts	Bravo	Cable	Returning	Reality: Competition	60	n/a
Top Chef Masters	Bravo	Cable	New	Reality: Competition	60	n/a

Top Shot	History	Cable	New	Reality: Competition	60	3
Tosh.O	Comedy Central	Cable	Returning	Comedy	30	5
True Beauty	ABC	Broadcast	Returning	Reality: Competition	58	2
True Blood	HBO Prime	Cable	Returning	Drama	54	4
Two and A Half Men	CBS	Broadcast	Returning	Comedy	31	9
Ugly Americans	Comedy Central	Cable	New	Comedy	30	4
Ultimate Cake Off	TLC	Cable	New	Reality: Competition	60	3
Undercover Boss	CBS	Broadcast	New	Reality: Non-Competition	60	3
United States Of Tara	Showtime Prime	Cable	Returning	Drama	27	4
Vampire Diaries	CW	Broadcast	New	Drama	60	8
Walking Dead	AMC	Cable	New	Drama	60	3
Warehouse 13	SYFY	Cable	Returning	Drama	60	4
Weeds	Showtime Prime	Cable	Returning	Drama	27	4
What Chilli Wants	VH1	Cable	New	Reality: Non-Competition	30	2
White Collar	USA	Cable	New	Drama	60	3
Who Do You Think You Are	NBC	Broadcast	New	Reality: Non-Competition	60	2
Wife Swap	ABC	Broadcast	Returning	Reality: Competition	60	5
Wipeout	ABC	Broadcast	Returning	Reality: Competition	61	4
Work Of Art	Bravo	Cable	New	Reality: Competition	60	3
Worst Cooks In America	Food Network	Cable	New	Reality: Competition	60	2

APPENDIX B: ESTIMATION RESULTS FOR DYNAMIC PANEL MODEL ON MIDSEASON MULTIPLEY IMPUTATED DATA

Estimation Results – Midseason Model, Two Weeks Prior to Episode Airing, Buzz Volume and Ratings Log Transformed, Dynamic Panel Model, Multiple Imputation for Ad Spend

	People 2+	People 18-34	People 35-49	People 50+
LOG (BUZZ VOLUME$_{t-2}$)	0.0514**	0.0519*	0.0588*	0.0467
	(0.026)	(0.032)	(0.034)	(0.030)
DISPERSION$_{t-2}$	0.0001	0.0001	-0.0000	-0.0001
	(0.000)	(0.000)	(0.000)	(0.000)
AUTHORS	-0.0000	-0.0000	-0.0000	0.0001
	(0.000)	(0.000)	(0.000)	(0.000)
AD SPEND	0.0000	0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)
PRIOR EPISODE RATINGS	0.6003****	0.4189***	0.4112***	0.3863***
	(0.127)	(0.157)	(0.145)	(0.133)
CONSTANT	-0.1185*	-0.0755	-0.0555	-0.0749
	(0.070)	(0.082)	(0.088)	(0.079)
N (Observations)	418	418	418	418
N (# TV Shows)	158	158	158	158

Notes: Robust standard errors in parentheses

**** p<0.001, *** p<0.01, ** p<0.05, * p<0.1**