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# DOES IT MATTER WHERE THE WORD-OF-MOUTH OCCURS?: AN EMPIRICAL STUDY ON THE SALES IMPACT OF THE DISTRIBUTION OF ONLINE USER REVIEWS

Wenqi Zhou
*Duquesne University*, zhouw@duq.edu

Wenjing Duan
*George Washington University*, wduan@gwu.edu

# DOES IT MATTER WHERE THE WORD-OF-MOUTH OCCURS?: AN EMPIRICAL STUDY ON THE SALES IMPACT OF THE DISTRIBUTION OF ONLINE USER REVIEWS

Wenqi Zhou, Division of Accounting and Information Systems Management, Palumbo-Donahue School of Business, Duquesne University, United States, zhouw@duq.edu

Wenjing Duan, Department of Information Systems and Technology Management, School of Business, The George Washington University, United States, wduan@gwu.edu

## Abstract

*Consumers consistently resort to online Word-of-Mouth (WOM) in online shopping, thanks to the reach of the Internet and various web tools. Nevertheless, they are confronting relatively different levels of search costs for WOM information available on the Internet, depending on the distribution of WOM across websites. This study investigates the sales impacts of dispersion of WOM volume and variation of WOM valence by using sales and WOM data of software programs from Amazon and download.com. Our results suggest that less evenly distributed WOM leads to more sales, conditional on the total number of WOM conversations across websites. And it is even more beneficial for a product's sales if having this less dispersed WOM distribution skewed towards retailing websites. In addition, more consistent consumer evaluations across websites encourage online purchasing decisions. By comparing the volume dispersion and variance variation, we find that receiving one hundred reviews of 5-star average rating on Amazon leads to sales almost six time greater than receiving fifty reviews of 5-star average rating on Amazon and another fifty reviews of 5-star average rating on download.com.*

*Keywords: Word-of-Mouth, Volume dispersion, Valence variation, Online retail sales.*

# 1 INTRODUCTION

The Internet and electronic commerce has unprecedentedly accumulated and spread Word-of-Mouth (WOM) information. Most retailing websites adopt online review communities to encourage consumers share their experience after consumptions; third-party websites serve as more independent sources to solicit user reviews and critics. A single product could receive hundreds of user feedback and product reviews in a variety of websites. For example, the software program *Norton 360* receives online user-generated reviews in multiple retailing websites, e.g. approximately 481 customer reviews at Amazon and 4,841 at Dell, and also in several third-party websites, e.g. 375 user reviews at CNET dwonload.com (CNETD) and 43 at pcmag.com.

In parallel with the flocking WOM available on the Internet, consumers are capable to reach almost every piece of all WOM information relevant to their interested products. Consumers are shown to intensely search before purchasing online (Zhang et al. 2006). They can certainly go beyond navigating the retailing websites where they are about to make purchasing decisions and resort to third-party websites for online WOM (Gu et al. 2012). Their internet experience could help them to automatically locate well-known third-party websites that are specialized on providing WOM in specific fields. For instance, CNETD is famous for eliciting user discussions and offering free trial versions of software programs; IMDB is the most leading online community for reviewing movies; Tripadvisor.com accumulates user conversations to help people schedule their vacations, such as attractions to visit, flights and hotels. Consumers could also utilize online search tools, e.g. search engines, to conveniently discover a collection of WOM information available on the Internet (Gu et al. 2012). A Pew Internet survey (2012) pointed out that 92% of people use search engines to find information on the Web while surfing online. Those displayed search results mostly direct consumers to major online retailers and third-party websites (Gu et al. 2012).

Although consumers have easy access to WOM on retailing websites and third-party websites before arriving at their purchasing decisions, little is known regarding how the distribution of WOM over multiple websites influences online retail sales. In practice, managers in a variety of industries have widely embraced the WOM marketing strategy, including online buzz marketing initiatives, as an alternative to traditional advertising (Mayzlin 2006). The power of WOM marketing is so attractive that some of them even aggressively solicit bogus reviews (The New York Times 2012). Nevertheless, managers are facing the challenge of selecting a few WOM sites from enormous available websites on the Internet and according setting a benchmark of an optimal mix of WOM on them. Therefore, there is an essential need to bring empirical evidence in academic research to bear on this issue.

In particular, this study tries to fill in this gap in our understandings of the sales impact of the distribution of WOM across websites, in terms of both volume and valence. WOM volume and valence are two prominent and widely discussed attributes of WOM. They represent the amount of WOM conversations and average customer evaluations respectively (Liu 2006). Specifically, we investigate how the *dispersion* of WOM volume and the *variation* of WOM valence across websites influence online retail sales. Dispersion of WOM volume indicates how different volume of WOM is across websites (Godes & Mayzlin 2004). A larger dispersion of WOM in volume implies a more evenly distributed WOM over websites. In terms of the distribution of WOM valence across websites, valence variation captures the disagreement of average product evaluations across different communities. A smaller variation of WOM in valence indicates more consistent consumer opinions on product evaluations hosted by multiple websites.

We construct a panel data of 62 software programs including sales ranks and online user reviews from Amazon and corresponding user reviews from CNETD over 18 weeks. To our best knowledge, this study is the first to reveal that the distribution of WOM across the Internet, both in volume and valence, matters to online sales. While more online WOM conversations on the Internet are better; conditional on total volume of WOM across websites, we find that one additional user review leads to a larger increase in online retail sales, if this review occurs on the website that has already garnered the larger portion of overall available WOM. More interestingly, a more favorable scenario for a retailing website is when most WOM activities available on the Internet take place on its own website. This finding on the negative relationship between dispersion of WOM volume and online sales contributes to WOM studies that, although the increase in volume of WOM on the Internet always boosts sales, where those additional reviews appear matters. In addition, we also find a more consistent product evaluation from customers on the Internet helps promote the relevant product's online sales. Conditional on the total volume of WOM and volume dispersion, receiving a 5-star average user rating on one website and a 1-star average rating on the other leads to only two thirds of the sales resulted from receiving the same average user rating on each website instead.

Our findings have some valuable practical implications. The effect of online WOM marketing strategy depends on the choice of websites to invest on and the nature of the products to promote. First, online marketers or retailers shall monitor the status of dispersion of WOM volume and, based on that, decide which website to invest on. To promote a new product just entering the online market, firms shall focus on encouraging WOM activities on retailing websites. For a more mature product that has already received user reviews on various websites, in the short run, marketers shall allocate marketing resources in stimulating consumer conversations on the website, which hosts the largest share of WOM currently available on the Internet. From this perspective, it supports the recent marketing trend of online retailers to invest in the content of third-party websites, in addition to their own content (Jupiter Research 2005), because generally third-party websites tend to accumulate more WOM. It would be, however, more beneficial for the long-term sales by investing on the retailing websites even if it stimulates less active consumer WOM interactions for the time being. Second, we suggest that online marketers or retailers carefully reconsider soliciting positive user feedback exclusively from one single website. Having positive reviews on one website and very contradictory consumer comments on others websites is actually a lot worse than receiving neutral evaluations from consumers on every website. Therefore, marketers shall implement a marketing strategy that delivers consumers consistent product information from WOM of various websites.

The rest of this paper is organized as follows. We review relevant literature in the next section, followed by our proposed research hypotheses. We then describe research context and variables. Afterwards, we present our empirical model and discuss the results. Finally, we make conclusions and discuss the implications, as well as identifying areas for future research.

## 2 RELATED LITERATURE

Recently an emerging stream of WOM literature have been working on understanding the differential impact of WOM information from multiple sources on user choices (Amblee & Bui 2007; Bickart & Schindler 2001; Gu et al. 2012; Senecal & Nantel 2004; Zhou & Duan 2010, 2012). Amblee and Bui (2007) compared the impacts of online user reviews and professional reviews and found no significant difference between them in magnitude. Zhou and Duan (2010) argued that it is misleading to treat WOM originated from multiple reviewer identities independent of each other. They identified that professional reviews influence online user choices through volume of user reviews. However, most of these previous studies investigate WOM hosted by one single site, which in essence compare the trustworthiness and information quality of WOM information according to reviewers' types (Amblee & Bui 2007; Bickart & Schindler 2001; Senecal & Nantel 2004; Zhou & Duan 2010). The only exceptions in this line of research are conducted by Chevalier and Mayzlin (2006), Gu et al. (2012) and Zhou and Duan (2012) that work on WOM information from multiple websites. Chevalier and Mayzlin (2006) is the first to study WOM from more than one website. However, they used WOM data from both Amazon and BN.com (BN) mainly to develop the difference-in-difference regression model to derive the causality from WOM to sales. They did not consider the possibility that consumers may read BN reviews and end up with purchasing on Amazon. Gu et al. (2012) conducted a more relevant study to ours by pointing out that online user reviews from three third-party websites are all more influential on Amazon sales than user reviews of its own. Recently, Zhou and Duan (2011) found that the existence of CNETD professional reviews moderates the feedback mechanism between Amazon user reviews and Amazon sales. The common underlying assumption of these two studies is that online search costs are so low that consumers would freely spend time and make efforts on searching WOM as much as they want on each website until they find enough information to pick their favourites. Unlike those two studies, we recognize that there should be a limit on the amount of searches for WOM information for consumers before reaching to their final decisions. Although consumers may use multiple websites for WOM information, the extent to which they explore WOM on those websites can be restricted to search costs of WOM information. Specifically, search costs of WOM information determine the degree to which consumers may read detailed user-generated comments, take reviewer backgrounds into consideration, compare contradictory opinions, and integrate all aspects of WOM information. We argue that the distribution of WOM over websites indicates the level of search costs of WOM information, which influences the amount of WOM searches consumers will make on those websites.

This research complements the literature on the distribution of WOM volume across online communities. A study conducted by Godes and Mayzlin (2004) nearly a decade ago is so far the first and the only one to examine the dispersion of WOM volume. It introduced dispersion of WOM volume to measure the extent to which WOM information is evenly distributed across online communities. They found the large dispersion of WOM over Usenet newsgroups has a positive impact on consumers' decisions of watching TV shows. The underlying reasoning is that more evenly distributed WOM in volume implies a more hetergenous population talking about this product. Thus more people can get informed of it and potentially purchase it. Our study attempts to update and complement the understandings on this measure in current online shopping context. We first introduce more types of communities by including both retailing websites and third-party websites, while Godes and Mayzlin (2004) considered third-party communities only. Second, the current Internet has gradually broken online community boundary and greatly strengthened the "weak tie" between them. The key presumption of Godes and Mayzlin (2004) is that consumers can be member of only one community and the interaction between two communities is very weak. Therefore members of one community are very hard to get to know the conversations taking place in another community through the "weak tie" between communities. However, during those ten years since their study, consumers have accumulated a great deal of Internet experience in surfing across websites and utilizing online search tools. To locate WOM information, they could either directly refer to well-known third-party and retailing websites or conveniently check out websites listed in the results from online search tools. There is literally no way to categorize one person to be member of only one community. Therefore, dispersion of WOM volume across websites shall not infer consumers' awareness any more as argued by Godes and Mayzlin (2004) ten years ago. Third, we conduct this research in pure online context. Godes and Mayzlin (2004) used online WOM as proxies for overall WOM to build up the foundation for the relationship between online WOM and consumers' offline decisions. This paper takes a more straightforward approach by directly linking online WOM with consumers' online purchasing decisions.

Our study is also related to prior research on the distribution of online WOM valence. There have been a very few studies on the disagreement of online consumer evaluations hosted by a single website. Sun (2012) found that variance of ratings indicates whether the product is a niche product. When a book receives average rating lower than 4.1 on Amazon, its higher variance of Amazon ratings leads to more sales relative to its sales on BN. Zhu and Zhang (2010) found that variation of ratings has a negative impact on sales of less popular online video games. We complement these studies by analyzing variation of online user ratings hosted by multiple websites. Meanwhile, previous studies either focus on consumers' attitudes to conflicting opinions or the reflected variation in consumer preferences (Sun 2012; Zhu & Zhang 2010). Alternatively, we look into the distribution of WOM valence from a different perspective that inconsistent consumer evaluations function as complicated information and influence consumer search costs.

# 3 RESEARCH HYPOTHESES

The Internet and advance in technology have facilitated online information exchange and thus accumulated a vast amount of product information (Kulviwat et al. 2004). Among them, WOM serves as a major source for consumers to gather product information without physical trials and thus influences their online purchasing decisions (Chevalier & Mayzlin 2006; Dhanasobhon et al. 2007; Duan et al. 2008; Forman et al. 2008; Godes & Mayzlin 2004; Liu 2006). Online consumers are shown to be demanding and utilitarian in their online searching process (Koufaris 2002), and search more intensely than expected (Zhang et al. 2006). They tend to get familiar with products through extensive WOM search across websites. By doing so, they can reduce their risks of shopping online and also help differentiate the genuine consumption experiences from bogus reviews. Thanks to various search tools (e.g. Google search engine and online recommendation systems), they are now very able to discover and reach the large WOM information pool hosted by various websites at their fingertips (Gu et al. 2012, Pew Internet 2012).

As implied by information economics and information search theory (Bakos 1997; Stigler 1961), consumers shall keep searching for WOM until the marginal utility resulted from one additional search equals its corresponding cost. Given the low enough search costs in current online shopping environment, information economics literature expect that consumers will look at almost all product information available on the internet and will purchase the product best satisfying their needs, improving market efficiency (Bakos 1997). The survey conducted by Pew Internet (2012) empirically supports this by showing that more than 90% people use search engines to search information online. Gu et al. (2012) also found that WOM hosted by multiple websites are all influential to Amazon sales. Therefore, we adopt this assumption as well and further argue that consumers use online WOM from both retailing websites and third-party websites to signal product quality (Gu et al. 2012). However, the amount and the depth of WOM searches consumers would conduct across websites shall depend on the level of search costs (Zhang et al. 2006). Consumers' WOM information search collects not only two widely discussed WOM attributes, valence and volume, but also the richer information conveyed by review text contents, reviewer characteristics, etc. Those information include improvements or advantages of the products, reviewers' personal preferences, reviewers' knowledge in the relevant fields, the clues of whether the reviews are disguised promotional chatting, and so on. Generally, lower search cost for WOM information leads to more comprehensive WOM searches and further more informed consumer decisions (Bakos 1997). This widely accepted understanding of consumer information search in the literature sets the ground for proposing the following three hypotheses.

We argue that dispersion of WOM volume across websites influences the level of online search costs for WOM information. Specifically, more evenly distributed WOM across the Internet indicates higher search costs for WOM information as compared to less dispersed WOM. In the latter scenario, to access the same amount of online WOM information, consumers can resort to fewer websites. This leads to the lower costs, because visiting more websites not only costs more searching time but also requires being able to get around with multiple websites. The overwhelmingly concentrated WOM information on one single website even provides consumers the convenience to instantly access most of WOM available on the Internet by merely visiting this website. In other words, search cost for one additional piece of WOM information from a less dispersed WOM pool across the Internet is lower.

Hence, lower search costs for WOM information, as a result of the less dispersed WOM, could encourage consumers to do more WOM information search about products. They could explore WOM more extensively and in-depth on each of visited websites, including reading more detailed text comments, checking reviewer identity information, as well as allowing more time on the cognitive process of making careful decisions. Theoretically more information collected from more searches shall help consumers to locate their favourites on retailing websites and make better purchasing decisions. If every consumer could find his best match, theoretically the product can reach its maximized sales by serving all of its targeted customers. Hence, the less dispersed WOM across websites is favourable to online retail sales. We propose:

H1. *More evenly distributed WOM across retailing and third-party websites has a negative impact on online retail sales*.

Consumers face even lower search costs if it is the retailing website that has attracted a larger share of WOM activities across the Internet, given the same volume dispersion across websites. In this case, consumers could easily get access to most of their needed product information from WOM directly on the retailing website. Since the retailing website is consumers' purchasing destination, first-time consumers would have to learn how to surf the website anyway, regardless of the amount of search they are going to conduct on the Internet. It is also reasonable to assume that existing customers are already familiar with retailing websites' layout and online review community. But all consumers would encounter a learning curve experience with exploring third-party websites for more WOM. The more they need to search on third-party websites, the more effort they need to make to acquaint themselves with those websites and locate WOM. Therefore, for the same amount of WOM information, consumers, no matter they are new to the retailing website or not, face lower search costs to explore WOM contents if they are hosted by the retailing website. Accordingly, the reduced search costs resulted from WOM skewed towards retailing websites are lower than the scenario where this concentration occurs on third-party websites. As we argued beforehand, lower search costs encourage more WOM information searches and thus increase consumers' likelihoods to find their best matches, which at the end helps each product approach its targeted consumer group.

In addition, when the concentration of WOM volume occurs on the retailing websites, consumers are also more likely to successfully shop online. Surfing on third-party websites can distract consumers from completing their purchases. Consumers can be accidentally attracted to other irrelevant user conversations on products, categories in which they are not interested at all, or social networking activities and external links offered by third-party websites. This can limit consumer concentration in purchasing tasks, leading to inefficient search process (Koufaris 2002; Novak et al. 1998). Consumers could end up with not purchasing the product they actually like and need. Therefore, more searches on third-party websites also lead to less chance for consumers to finally purchase any product.

From these two perspectives, when the distribution of WOM volume is skewed towards retailing websites, the product can more easily approach its targeted consumer group. We hence propose:

H2. *Conditional on dispersion of WOM volume across websites, having more WOM received on the retailing website has a positive impact on online retail sales*.

Prior studies suggest that evaluative disagreement of product information would deliver the ambivalence to consumers' attitude towards corresponding products (Kaplan 1972; Priester & Petty 1960, 2001). In front of conflicting information, consumers would generally try to reconcile them and finally achieve an integrated evaluation of their own (Hastie 1980; McGuire 1981; Srull & Wyer 1989). Therefore, in online WOM context, disagreed consumer feedback from WOM across websites can incur more cognitive costs to consumers for processing the inconsistency than relatively more consistent WOM evaluation. The resulted higher costs could discourage consumers to conduct extensive WOM search, which leads to a smaller chance for them to locate their best matches. Hence, products are less likely to serve all of their targeted consumers. Therefore, we propose:

H3. *More consistent user reviews across websites has a positive impact on online retail sales*.

# 4 DATA

## 4.1 Research Context

We collect data weekly on 62 software programs on Amazon and CNETD over 18 weeks during the period June 2011 through October 2011. In recent years, product variety of software programs offered through online channel has increased tremendously (Zhou & Duan 2012). As a typical type of experience goods, consumers often confront difficulties with evaluating software quality before consumption. Meanwhile consumers with intentions to purchase software programs naturally have some knowledge and experiences of surfing the Internet and utilizing online searching technology. Therefore abundant product choices and the nature of software program determine that consumers would have the need and capability to extensively search for product information across websites. This makes online software market an appropriate context to study the impact of distribution of WOM across websites on consumers' purchasing decisions by assuming that consumers will extensively check all available WOM information and purchase the product best meeting their needs. In addition, online distribution channels play an increasingly important role for software industry. According to IDC, online channels will account for over 70% total sales by 2015 (Revenue Architects 2012). Understanding the influencing factors of online retail sales is thus also practically meaningful.

Amazon is one of the leading online retailers and has been widely chosen by previous studies to examine online market outcome (Chevalier & Mayzlin 2006; Ghose & Sundararajan 2005; Gu et al. 2012). The conclusions drawn from Amazon data regarding the distribution of online WOM could directly offer practical guidance to its software suppliers and also be generalized to other online retailers. We choose CNETD as an important WOM site noticeably contributing to WOM information of software programs on the Internet. CNETD is a representative third-party website specialized in providing software samplings and consumers' shared experience. Its free trial service over a broad range of categories helps attract active WOM interactions. As a well-known information provider in online software market, CNETD is often displayed on the first page of search results whenever consumers look for software program information through search engines. Many experienced consumers may also naturally consider CNETD as a reliable source of their first choice for software information. Consumers who are about to purchase software programs on Amazon are thus very likely to be aware of CNETD WOM.

We collected weekly data on the top 100 software programs sold by Amazon during the period June 2011 through October 2011. Specifically, on Amazon, for each software program, we collect sales rank, number of online consumer reviews, average consumer rating, price, release date, eligibility for free-shipping service, and software category. However, we only keep observations on 62 best-selling software programs over those 18 weeks because they have the matched free trial versions available on CNETD. They also have generated considerable online discussions on both Amazon and CNETD due to their popularities, producing sufficient statistic power for our empirical analysis. For each corresponding CNETD free trial that is matched to each of 62 Amazon software, we collected the number of online user reviews, average user rating and weekly downloads at the beginning of every week. That finally leads to an unbalanced data set of overall 635 observations on 62 pairs of software programs on Amazon and CNETD over 18 weeks.

## 4.2 Variables

This study attempts to investigate the impact of the distribution of online WOM on online retail sales. As an alternative to the inaccessible true transaction data, we use Amazon sales rank as the proxy for Amazon sales. The Pareto relationship between Amazon sales and sales rank has been well established and widely applied in prior studies (Brynjolfsson et al. 2003; Chevalier & Mayzlin 2006; Ghose & Sundrararajan 2005; Gu et al. 2012). In particular, Ghose and Sundrararajan (2005) designed an experiment to empirically estimate actual quantities of software programs sold by Amazon given the negative linear relationship between log value of sales rank and log value of sales. Similarly, we use Amazon sales rank ($AmazonSalesRank_{i,t}$) with a log transformation to approximately measure the log value of actual sales.

One of the key independent variables is dispersion of WOM volume. We use number of online user reviews in each website as the WOM volume hosted by this website ($Vol_{i,t}^{j}$). Accordingly, the total WOM volume of those two websites ($TotalVol_{i,t}$) is simply the summation of WOM volume on each website. Dispersion of WOM volume represents how the number of all those WOM conversations spreads over two websites. Following Godes and Mayzlin's study (2004), we use entropy as the dispersion of WOM volume ($DispersionVol_{i,t}$), which is defined as follows:

$$DispersionVol_{i,t} = \begin{cases} -\sum_{j} \frac{Vol_{i,t}^{j}}{TotalVol_{i,t}} log\left(\frac{Vol_{i,t}^{j}}{TotalVol_{i,t}}\right) & if\ TotalVol_{i,t} > 0 \\ 0 & if\ TotalVol_{i,t} = 0 \end{cases}$$

where $j$ denotes each website, i.e. Amazon and CNETD, and $Vol_{i,t}^{j}$ denotes WOM volume on website $j$. If both of two websites do not receive reviews for software $i$, discussing the distribution of WOM volume in such case becomes meaningless. Therefore, we set the value of volume dispersion for this software $i$ as zero to ensure no impact of volume distribution on the sales. The larger value of entropy indicates a high level of dispersion and thus a more evenly distributed WOM across Amazon and CNETD. When product $i$ receives the same number of user reviews on Amazon and CNETD, $DispersionVol_{i,t}$ reaches its maximum, which is 0.301 in our two-site case. For software program $i$ receiving all its user reviews on one website, its $DispersionVol_{i,t}$ turns to be the minimum, zero, to indicate the lowest level of dispersion.

There are two main reasons to adopt entropy instead of variance to indicate how WOM volumes on two websites differ from each other. First of all, entropy does not vary over total volume of online user reviews from both Amazon and CNETD, as long as the ratio of WOM volumes between those two websites stays the same. We need to include total volume of online user reviews from Amazon and

CNETD as a control variable in our following empirical analysis. The reason is that more ongoing conversations available on the Internet, the more likely consumers would be aware of the corresponding products (Liu 2006). Therefore, using entropy to make $DispersionVol_{i,t}$ independent of $TotalVol_{i,t}$ helps disentangle examining the distribution of WOM volume from overall WOM volume. Godes and Mayzlin (2004) have clearly discussed the advantages of choosing entropy over variance in studying dispersion of WOM volume from this perspective. Second, generally, variance is not an indicator of measuring uncertainty (Ebrahimi et al. 2010). Variance is able to accurately capture uncertainty only when the relevant distribution is univariate. However, this study tends to measure the statistic uncertainty of WOM volume between two sites, as a result, variance is not appropriate. Instead, Ebrahimi et al. (2010) pointed out that entropy for dispersion matrix can capture the uncertainty in the multivariate case, as a natural extension of variance in the univariate case.

The other main independent variable is variation of WOM valence. The variation of WOM valence captures the extent to which consumers of Amazon and CNETD differ in their opinions. We use average rating as the WOM valence for each website ($Val_{i,t}{}^{j}$). Similarly, we still apply entropy, instead of the more common measure—variance, on average ratings from two websites as the variation of WOM valence ($VariationVal_{i,t}$) illustrated below. Therefore, this variable is independent of the average valence of WOM over Amazon and CNETD ($MeanRating_{i,t}$), which is simply the mean value of their average ratings ($(Val_{i,t}{}^{A}+ Val_{i,t}{}^{C})/2$).

$$VariationVal_{i,t} = \begin{cases} -\sum_{j} \dfrac{Val_{i,t}^{j}}{Val_{i,t}^{A} + Val_{i,t}^{C}} log\left(\dfrac{Val_{i,t}^{j}}{Val_{i,t}^{A} + Val_{i,t}^{C}}\right) & if\ both\ Val_{i,t}^{A}\ and\ Val_{i,t}^{C} > 0 \\ 0 & if\ Val_{i,t}^{A}\ or\ Val_{i,t}^{C} = 0 \end{cases}$$

where $j$ denotes each website, i.e. $A$ for Amazon and $C$ for CNETD and $Val_{i,t}{}^{j}$ denotes WOM valence on website $j$. For software program $i$ not receiving user reviews from both websites, the variation of WOM valence does not exist, thus its value of this term is set to be zero.

The larger value of $VariationVal_{i,t}$ actually denotes a smaller variation of WOM valence. It reaches its maximum when average user rating of product $i$ on Amazon is equal with its CNETD average rating. It reaches its minimum of 0.196 when product $i$ receives the lowest possible rating, one-star, on one website and the highest rating, five stars, on the other. The statistical attribute of entropy also assures that the variation of WOM valence does not change along with the value of $MeanRating_{i,t}$. We thus can safely include the average consumer evaluation over Amazon and CNETD ($MeanRating_{i,t}$) as another control variable (Chevalier & Mayzlin 2006) and avoid confounding the estimated impact of variation of WOM valence. There have been mixed conclusions in literature regarding the relationship between valence of WOM and user choices. Some researchers believe that higher valence of WOM persuades consumers to make purchasing or adoption decisions (Liu 2006; Zhou & Duan 2012). On the contrary, another a few studies find that online user reviews are not influencers of user choices at all (Duan et al. 2008, 2009; Liu 2006). Given the divergent opinions over the impact of WOM valence, it would also be interesting to see whether variation of WOM valence plays a more significant role in influencing consumers' online purchasing decisions than WOM valence.

In addition, we also use Amazon product prices, product age, CNETD weekly downloads and download license as control variables and control for product fixed effect and time fixed effect (Chevalier & Mayzlin 2006; Li & Hitt 2008; Zhou & Duan 2011). Table 1 provides a description of the variables used in the empirical analysis, and Table 2 presents the summary statistics of those variables. One can see from the Table 2 that online user reviews are far away from being evenly distributed over Amazon and CNETD. The mean value of $DispersionVol_{i,t}$ indicates that on average products receive at least four times more user reviews on one website than on the other. The mean statistic of $DummyVol_{i,t}$ further shows that more than 70% software programs receive more user reviews on Amazon than on CNETD. Hence, it seems Amazon attracts much more WOM activities for most of the products than CNETD. In addition, software programs tend to have relatively less prominent difference in user ratings between those two websites than in number of user reviews, indicated by a smaller mean value of $VariationVal_{i,t}$ than that of $DispersionVol_{i,t}$.

| Variables | Descriptions |
|---|---|
| $AmazonSalesRank_{i,t}$ | Sales rank of software *i* at week *t* on Amazon |
| $TotalVol_{i,t}$ | Total number of Amazon and CNETD reviews software *i* receives by week *t* |
| $DispersionVol_{i,t}$ | Dispersion of number of Amazon and CNETD reviews software *i* receives by week *t* |
| $DummyVol_{i,t}$ | A dummy variable measures if software *i* receives more reviews by week *t* on Amazon than on CNETD |
| $MeanRating_{i,t}$ | Mean value of Amazon and CNETD average ratings software *i* receives at week *t* |
| $VariationVal_{i,t}$ | Variation between Amazon and CNETD average ratings software *i* receives at week *t* |
| $Age_{i,t}$ | Days since Amazon has released software *i* by week *t* |
| $AmazonPrice_{i,t}$ | Price offered by Amazon for software *i* at week *t* |
| $CnetdDown_{i,t}$ | Weekly number of downloads of software *i* at week *t* |
| $CnetdLicense_{i,t}$ | A dummy variable if software *i* is free to download at week *t* on CNETD |

*Table 1. Description of Key Variables*

| | **Mean** | **Std. dev.** | **Min** | **Max** |
|---|---|---|---|---|
| $AmazonSalesRank_{i,t}$ | 43.035 | 26.857 | 1.000 | 100.000 |
| $TotalVol_{i,t}$ | 313.239 | 525.339 | 0.000 | 4985.000 |
| $DispersionVol_{i,t}$ | 0.126 | 0.109 | 0.000 | 0.301 |
| $DummyVol_{i,t}$ | 0.734 | 0.442 | 0.000 | 1.000 |
| $MeanRating_{i,t}$ | 2.841 | 0.962 | 0.000 | 4.800 |
| $VariationVal_{i,t}$ | 0.218 | 0.127 | 0.000 | 0.301 |
| $Age_{i,t}$ | 573.260 | 521.188 | 6.000 | 2930.000 |
| $AmazonPrice_{i,t}$ | 78.911 | 132.924 | 0.000 | 949.000 |
| $CnetdDown_{i,t}$ | 7544.659 | 41440.350 | 0.000 | 457049.000 |
| $CnetdLicense_{i,t}$ | 0.033 | 0.179 | 0.000 | 1.000 |

*Table 2. Summary Statistics of Key Variables*

# 5 EMPIRICAL ANALYSIS

## 5.1 Empirical Model

We estimate the following model to test our proposed hypotheses:

$$
\begin{aligned}
-Ln(AmazonSalesRank_{i,t}) &= \beta_0 + \beta_1 TotalVol_{i,t} + \beta_2 DispersionVol_{i,t} + \beta_3 DummyVol_{i,t} + \beta_4 MeanRating_{i,t} \\
&+ \beta_5 VariationVal_{i,t} + \beta_6 Age_{i,t} + \beta_7 AmazonPrice_{i,t} + \beta_8 Ln(CnetdDown_{i,t}) \\
&+ \beta_9 CnetdLicense_{i,t} + \mu_i + \rho_t + \varepsilon_{i,t}
\end{aligned}
$$

We use $-Ln(AmazonSalesRank_{i,t})$ as the dependent variable to denote the negative log value of Amazon sales rank of product *i* at week *t*. Given the negative log linear relationship between the sales rank and sales, this model can assess the sales impact of independent variables. We first include $DispersionVol_{i,t}$ and $DummyVol_{i,t}$ respectively to test Hypotheses 1 and 2. The coefficient on $DispersionVol_{i,t}$ ($\beta_2$) captures the impact of dispersion of WOM volume across Amazon and CNETD on Amazon sales. As the larger value of $DispersionVol_{i,t}$ indicates a more even distribution of WOM in volume, this coefficient ($\beta_2$) is expected to be negative according to hypothesis 1. The coefficient on $DummyVol_{i,t}$ ($\beta_3$) captures whether having more WOM activities on Amazon leads to greater Amazon sales. Hypothesis 2 suggests this coefficient ($\beta_3$) shall be positive. We also add $TotalVol_{i,t}$ to represent the total number of Amazon and CNETD user reviews software *i* receives by week *t*. Its coefficient $\beta_1$ thus controls for the impact of total WOM volume over websites on Amazon sales. By doing so, our conclusions regarding the WOM distribution are conditional on total WOM volume given the significant $\beta_1$. To test hypothesis 3, we include $VariationVal_{i,t}$ to capture the impact of variation of WOM valence across Amazon and CNETD on Amazon sales. Since we use entropy to construct this variable, its larger value actually indicates more agreed consumer opinions. According to hypothesis 3, its coefficient ($\beta_5$) is expected to be positive. We also include $MeanRating_{i,t}$ to measure the mean of

Amazon and CNETD average user ratings software *i* receives at week *t*. Its coefficient ($\beta_4$) controls for the impact of overall consumer evaluation from Amazon and CNETD on Amazon sales.

Following previous studies, we also include several other control variables. Product age $Age_{i,t}$ is included to control for product diffusion (Duan et al. 2009). Price effect is also controlled by current price $AmazonPrice_{i,t}$ of software *i* at week *t* (Chen et al. 2007). In addition, the log value of weekly downloads $CnetdDown_{i,t}$ software *i* receives at week *t* on CNETD is added, as free sampling of software program is shown to influence online sales (Zhou & Duan 2012). $CnetdLicense_{i,t}$ is a dummy variable to indicate the license difference of free trial software versions on CNETD (Zhou & Duan 2011). Finally, we include product fixed effects $\mu_i$ and time fixed effects $\rho_t$ to control for time-invariant product heterogeneity and time-variance omitted variables respectively (Duan et al. 2008). Product fixed effects $\mu_i$ are used to control for products' idiosyncratic characteristics and intrinsic quality (Duan et al. 2008). Rather than using product-specific dummies, we include 27 category-specific dummies to represent product fixed effects. As our sample consists of 635 observations on 62 software programs, adding 61 product-specific dummies would significantly reduce the degree of freedom for estimating the above regression equation. This can lead to low statistical power and misleadingly insignificant estimations. Instead, we use category differences to approximately capture the time-invariant product differences. Amazon applies a very detailed categorization on its listed software programs. For example, in this data set, those 62 software programs belong to 28 distinct categories. Therefore, we believe that category-specific dummies can well reflect uncaptured product attributes and, at the meantime, allow us to efficiently estimate the regression model. Similarly, we add a set of 17 week-specific dummies $\rho_t$ to captures the common demand shocks (e.g. website-wise promotion event) to all software programs at week *t*.

## 5.2 Results

Table 3 presents our estimation results. To highlight the importance of distribution of WOM in both volume and valence, we compare two specifications. In the first specification, WOM related variables include only total volume of WOM on Amazon and CNETD, whether Amazon receives more WOM, and the mean of Amazon and CNETD WOM valence. The second one adds two key variables that particularly address our research question: dispersion of WOM volume and variation of WOM valence over two websites.

| | (1) | (2) |
|---|---|---|
| Intercept | -2.855*** | -2.697*** |
| $TotalVol_{i,t}$ | 0.001*** | 0.001*** |
| $DummyVol_{i,t}$ | 0.661*** | 0.499*** |
| $MeanRating_{i,t}$ | -0.117** | -0.087 |
| $DispersionVol_{i,t}$ | | -2.712*** |
| $VariationVal_{i,t}$ | | 1.940*** |
| $Age_{i,t}$ | -0.001*** | -0.001*** |
| $AmazonPrice_{i,t}$ | -0.001 | -0.0002 |
| $CnetdDown_{i,t}$ | -0.008 | -0.015 |
| $CnetdLicense_{i,t}$ | -0.870*** | -1.294*** |
| Product fixed effect | Yes | Yes |
| Time fixed effect | Yes | Yes |
| Observations | 635.000 | 635.000 |
| $R^2$ | 0.559 | 0.585 |
| **p<0.05;***p<0.01 | | |

*Table 3. The Impact of Distribution of WOM over Websites on Online Sales*

Regarding the distribution of WOM over those two websites, we have the following observations from results in column (2). First, as expected, dispersion of WOM volume from Amazon and CNETD has a negative impact on Amazon sales, given the significantly negative coefficient on $DispersionVol_{i,t}$. Since a large value of $DispersionVol_{i,t}$ indicates a high level of dispersion, this suggests that products receiving more evenly distributed WOM over retailing and third-party websites tend to achieve fewer sales. Therefore, this finding supports hypothesis 1. The coefficient on $TotalVol_{i,t}$ is significant, indicating the importance of drawing conclusions based on the same level of total volume of WOM from websites.

Second, given certain level of dispersion of WOM volume over those two websites, having more WOM occurred on Amazon is shown to be more favorable to its sales. The coefficient on the dummy indicator $DummyVol_{i,t}$ is significantly positive. Combined with our first finding, it implies that while a less dispersed WOM increases online sales, the scenario would be even more beneficial to sales if the distribution of WOM volume across websites is skewed towards retailing websites. By mapping the sales rank to sales, we can show that which website accumulates the majority of WOM matters a lot. We adopt 0.828 from Ghose and Sundararajan's study (2005), which conducted an experiment to estimate Amazon software sales from sales rank, as the Pareto index in this study. All else being equal, having the larger portion of WOM on Amazon would lead to an increase of 0.499 in the negative log value of Amazon sales rank ($-Ln(AmazonSalesRank_{i,t})$) than otherwise receiving them on CNETD, which in fact infers an increase of nearly 160% in sales.

Third, we find that the disagreement in consumer evaluations between Amazon and CNETD WOM discourages Amazon sales, indicated by the positive coefficient on variation of WOM valence. We note that a large value of $VariationVal_{i,t}$ denotes a smaller variation of WOM valence. Therefore the positive estimate on its coefficient actually suggests a negative relationship between the variation of WOM valence and online sales, supporting hypothesis 3. Using the same approach to map sales from sales rank, we find that Amazon sales on products with completely consistent average consumer evaluations across two websites is one and a half times as great as that resulted from the largest possible variation in user opinions, while volume dispersion and total volume keep the same.

It is very interesting to answer a question about whether it is better for a product's sales to have one hundred of reviews with a five-star average rating all received by Amazon or fifty reviews with a five-star average rating on each of two websites. In the first scenario, the product receives WOM exclusively on Amazon, which results in its volume dispersion and its valence variation both reaching the minimum of zero. In the second scenario, the value of volume dispersion and the value of valence variation are both 0.301, the maximum of entropy in a two-website context. Similarly we can compare the sales of these two cases by comparing their Amazon sales ranks to infer the difference in their sales. We find that, all else being equal, this product's sales is significantly greater in the former case with an increase of more than 600%.

We also find some interesting results by comparing the estimations in two columns. The only significant difference between them is the coefficient on the mean value of Amazon and CNETD valence. It is estimated to be negatively significant in column (1) but becomes insignificant in column (2). Hence, if ignoring the distribution of WOM across websites, researchers may inappropriately reach a counter-intuitive conclusion that lower overall average ratings across websites result in more online sales. Based on our empirical evidence to support hypothesis 3, this insignificant estimate in column (2) further suggests that the variation of WOM valence across retailing and third-party websites plays a much more significant role in influencing sales than an overall consumer evaluation. In addition to changing the estimation of this coefficient, incorporating the distribution of WOM across websites also increases the $R^2$ value without affecting estimations on variables not relevant to WOM, e.g. product age. Therefore, the explanatory power of distribution of WOM in column (2) comes within the WOM, instead of the potential correlation with other control variables that are not related to WOM.

In both two specifications, total volume of Amazon and CNETD WOM leads to higher sales. This is consistent with our proposition that consumers are able to extensively search for and get aware of WOM information hosted by multiple websites in current online market. More WOM conversations available on the Internet, the more likely consumers would get informed of the corresponding products. It also supports our argument that dispersion of WOM volume does not represent consumer awareness any more as it was shown by Godes and Mayzlin's study (2004). Therefore, it is not surprising to find different conclusions regarding dispersion of WOM volume in our study with theirs. However, the insignificant results on Amazon price in both two columns are contradictory to our expectation. It could be partly caused by our sample choice of best-selling software programs. All the products are ranked among the most 100 popular software on Amazon when being collected. Consumers are very likely attracted to them more by their high quality instead of low prices and thus are insensitive to price. Another reason could be the small variation in software price during the data collection period. We observe that price for the same product rarely fluctuates over time. This could technically lead to low statistical power and end up with insignificant results.

# 6 DISCUSSION AND CONCLUSIONS

In this paper, we examine how distribution of WOM hosted by retailing websites and third-party websites influences online retail sales by focusing on volume dispersion and variation valence. Our findings offer some important implications for researchers. First, this study highlights the role of distribution of WOM in influencing online sales. Earlier studies agree that consumers conduct extensive information search on the Internet before purchases and thus are influenced by WOM information on both retailing websites and third-party websites (Gu et al. 2012; Zhou & Duan 2012). Our research goes a step further by recognizing the different extent to which consumers search for WOM information by its distribution across websites. We argue that the distribution of WOM across websites affects consumers' search costs during their information search process and accordingly influences a product's potential to reach all of its targeted consumers. Our empirical finding supports this proposition by identifying the negative relationship between distribution of WOM and online sales. It thus highlights the importance of taking WOM distribution into account while studying the impact of online WOM hosted by multiple websites.

Second, this study also contributes to our understandings on the magnitudes of WOM effects from multiple sources. Previous studies investigate the differential impact of WOM created by different reviewer identities or hosted by different websites (Amblee & Bui 2007; Bickart & Schindler 2001; Gu et al. 2012; Senecal & Nantel 2004; Zhou & Duan 2010). They in essence conducted empirical analyses to support their conclusions conditional on the specific distributions of WOM in their contexts. Our findings suggest that which WOM source is more influential is a context-specific related question. We find receiving one additional review on Amazon may lead to a larger increase of its sales than having one more review on CNETD if most of WOM activities across those two websites have occurred on Amazon. However, it would be the other way around that CNETD WOM volume is more influential than Amazon WOM volume if CNETD have already attracted a lot more user feedback. Therefore, without knowing the status of WOM distribution, there is no simple answer to the magnitude comparison of WOM effects from multiple sources.

Third, our study also sheds lights on identifying user-generated WOM metrics that significantly influence consumer decisions. The literature generally agree that WOM volume is an influencer of user choices yet have divergent conclusions on WOM valence. A simple WOM valence measure may not well signal product quality beyond all the potentially mixed consumer opinions in text reviews. This research echoes previous studies by showing that the variation of WOM valence, rather than the valence itself, play a more important role in impacting online sales. This finding suggests that WOM research shall not be restricted to one single WOM host website.

Finally, this research complements literature on the sales impact of WOM volume. Most of previous studies deal with WOM volume received by one single website (Liu 2006; Duan et al. 2008). The underlying rationale is that volume of WOM indicates consumers' awareness of products. More user reviews lead to a higher chance that consumers would get informed of corresponding products. And being informed is the first necessary step of final purchase. Our results show that, given consumers' easy access to and their extensive search on multiple websites, this reasoning for WOM volume also applies to total volume of WOM hosted by both retailing and third-party websites. It thus, on the other hand, also updates the interpretation of the boundaries among online communities. Total volume of WOM across the Internet is used to be believed as irrelevant to offline sales in a movie sales study conducted about a decades ago (Ghodes & Mayzlin 2004). Back then, consumers were less savvy to acknowledge how many on-going conversations about one specific product are happening on the Internet. This study finds evidence that the boundaries among websites are much weaker in current online environment. Total volume of WOM across websites, rather than dispersion of WOM volume, becomes the indicator of consumers' awareness of products. This also provides suggestions that research on electronic commerce needs to consistently adjust to the rapid changes on online market.

There are several limitations of this research as well as a few promising directions of future research. First, we assume the same weights on WOM from retailing websites and third-party websites while quantifying the distribution of WOM in this study. Identifying the factors to influence weights on WOM of each website would be an interesting extension to construct better measures for the distribution of WOM across websites. Second, future research could also incorporate more websites. A richer sample collected from more retailing websites and third-party websites would add to the robustness of our results. Third, there could exist more attributes of WOM that influence consumers' search costs in their information search process, in addition to volume dispersion and valance variation. As we briefly browse reviews on Amazon and CNETD, some reviews are very structured and informative while others are relatively poorly written. It would be thus interesting to apply text mining techniques or use reviewer characteristics to consider review quality in future research.

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