The Sales Impact of Word-of-Mouth Distribution across Retail and Third-Party Websites

Completed Research Paper

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Abstract

With online search tools and users' Internet experiences, online consumers are shown to rely on Word-of-Mouth (WOM) information hosted by both retail and third-party websites. Nevertheless, will online consumers conduct the same comprehensive level of WOM search, if the distribution of WOM across websites differs? This study is intrigued by this question to propose that the distribution of WOM across websites affects the search cost of WOM information during consumers' decision making, and thus influences online retail sales. By using sales and WOM data of software programs from Amazon and a third-party website download.com, we find negative sales impacts of WOM volume dispersion and valence variation. Our results show that less dispersed WOM leads to more sales. And it is even more beneficial for a product's sales if having this less dispersed WOM distribution skewed towards retail websites. In addition, more consistent consumer evaluations across websites encourage online purchase decisions.

Keywords: Word-of-Mouth, user-generated content, volume dispersion, valence variation, online retail sales

Introduction

The Internet and electronic commerce has unprecedentedly accumulated and distributed Word-of-Mouth (WOM) information. In particular, most retail websites adopt online user review systems to encourage consumers to share their experience after consumption; third-party websites generally serve as more independent sources to solicit user reviews and critics. Nowadays, it is quite common that one product receive hundreds of user feedback and product reviews from more than one website. For example, the software program *Norton 360* receives online user-generated reviews in multiple retail websites, e.g. approximately 481 customer reviews at Amazon and 21 at staple.com, as well as in several third-party websites, e.g. 520 user reviews at CNET dwonload.com (CNETD) and 43 at pcmag.com.

The abundant WOM information available on the Internet benefit online consumers learning product quality and making informed purchase decisions. Consumers are shown to utilize online user reviews from not only retail websites where they are about to make purchases, but also third-party websites (Gu et al. 2012). Various online search tools and consumers' Internet shopping experiences make it possible that consumers are now capable to reach almost every piece of all WOM information (Gu et al. 2012). A Pew

Internet survey (2012) points out that 92% of people use search engines to find information on the Internet while surfing online. Those search results mostly direct consumers to major online retail and third-party websites (Gu et al. 2012). Especially, well-known third-party websites are normally listed at the top of search engine results, and are frequently resorted to by experienced customer in the relevant market. For instance, CNETD is famous for soliciting user feedback by offering free trial versions of software programs; IMDB is the most leading online user community for reviewing movies.

Although consumers are aware of WOM information hosted by retail websites and third-party websites before arriving at their purchasing decisions, little is known regarding how the distribution of WOM across multiple websites can influence their purchase decisions. Will the product receive greater sales on the retail website, if the third-party website hosts more reviews than the retail website? Will the product sales on the retail website changes if consumer feedback turns to be more consistent across sites? Answers to those questions have significant implications to practitioners. Managers in a variety of industries have widely embraced the WOM marketing strategy, e.g. online buzz marketing initiatives, as an alternative to traditional advertising (Mayzlin 2006). Nevertheless, it is not feasible nor efficient to evenly distribute WOM market expenses toward every website that host WOM information in the relevant online market. Instead, it becomes a challenge for managers to select a limited number of websites to invest WOM contents. 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 by investigating the sales impact of WOM distribution in terms of both volume and valence across two different websites: retail websites where consumers purchase products, and third-party websites where consumers mainly come to look for product information. WOM volume and valence are two prominent and widely discussed attributes of WOM. They represent the amount of WOM conversations that have been taking places 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 the heterogeneity of WOM volume across websites (Godes and 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 among different websites.

To do so, we construct a panel data of 43 software programs including sales ranks and online user reviews from Amazon and corresponding user reviews from CNETD between Jun. 2011 and Jan. 2012 over 33 weeks. To our best knowledge, this study is the first to provide some insights that the distribution of WOM across third-party websites and retail websites, in both volume and valence, matters a lot to online sales. While more online WOM conversations on the Internet are always better; conditional on total volume of WOM from Amazon and CNETD, we find that a less dispersed WOM volume across Amazon and CNETD is more beneficial to retail sales. Receiving more WOM on one single website leads to greater sales than having the same number of user reviews on each website. In other words, one additional user review leads to a larger increase in online retail sales if it occurs on the website that has already garnered the larger portion of overall available WOM. More interestingly, an even more favorable scenario for a product's sales on the retail website takes place when most WOM activities available on the Internet occur on Amazon. Our results show that, given the same volume dispersion, having the larger portion of WOM hosted by Amazon would lead to sales by over 40% greater than otherwise receiving that larger portion of WOM on CNETD. 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 available on the Internet always boosts sales, which website those additional reviews are generated makes a difference. In addition, we also find a negative relationship between variation of WOM valence over Amazon and CNETD and Amazon sales. A more consistent product evaluation from customers, i.e. smaller valence variation, on the Internet helps promote the relevant product's online sales. This impact is quite substantial. All else being equal, receiving a 5-star average user rating on one website and a 1-star average rating on the other website leads to sales by nearly 70% fewer than receiving reviews at the same average rating, 3-star, on each website. After taking the valence variation into account, average valence over retail and third-party websites is found irrelevant to online retail sales. Although our findings are based on the data from one representative retail website, i.e. Amazon, and one representative retails website, i.e. CNETD, we believe they can be carefully applied to explain the sales impact of WOM distribution across other retail and third-party websites.

Our findings have some valuable practical implications. First, online marketers or retailers shall select websites to invest WOM contents based on the product age in the market, which generally determines the distribution of existing WOM across multiple websites. Although our results generally support the online retailer's current practice of encouraging user-generated conversations on the Internet, we find evidence that depending on how long the product has been on the market, decisions on which website to invest on can be very different. For instance, to promote a new product that just enters the relevant online market, firms shall focus on retail websites to encourage WOM activities. 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 that has already accumulated the largest share of available WOM across 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), as generally third-party websites tend to accumulate more WOM. It would be, however, more beneficial for the long-term sales by investing on retail websites, even if it stimulates less active consumer WOM interactions for the time being. Second, we suggest that online marketers or retailers be cautious about exclusively soliciting positive user feedback from one single website. Having positive reviews on one website and very contradictory consumer comments on other websites is in fact a lot worse than initiating neutral evaluations from consumers on every website. Overall, marketers shall implement a marketing strategy that delivers consumers consistent product information from WOM on 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.

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 and Bui 2007; Bickart and Schindler 2001; Gu et al. 2012; Senecal and Nantel 2004; Zhou and Duan 2015, 2016). 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 (2016) 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 and Bui 2007; Bickart and Schindler 2001; Senecal and Nantel 2004; Zhou and Duan 2016). The only exceptions in this line of research are conducted by Chevalier and Mayzlin (2006), Gu et al. (2012) and Zhou and Duan (2015) 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 derive the causality from WOM to sales by developing a difference-in-difference regression model. 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 more influential on Amazon sales than user reviews of its own. Recently, Zhou and Duan (2015) found that the existence of CNETD professional reviews moderates the feedback mechanism between Amazon user reviews and Amazon sales. The common underlying assumption of Gu et al. (2012) and Duan (2015) 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 favorites. Unlike those two studies, we recognize that there is a limit on the amount of searches for WOM information consumers can afford 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 could be restricted to search costs of WOM information. Specifically, search costs of WOM information shall determine the degree to which consumers 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 and the depth of WOM searches consumers will make on those websites.

Our research also 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 investigation on 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, i.e. more evenly distributed WOM, over Usenet newsgroups has a positive impact on consumers' decisions of watching TV shows. The key presumption of Godes and Mayzlin (2004) is that consumers can be members 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. The large dispersion of WOM in volume implies a more hetergenous population talking about this product. Accordingly, more people can get informed of it and potentially purchase it. Our study attempts to update and complement the understanding on the "ties" among online communities and the indicator of online consumer awareness of products. We first introduce more types of communities by including both retail websites and third-party websites, while Godes and Mayzlin (2004) considered third-party communities only. Second, we recognize that during the past decade the Internet has gradually broken online community boundary and greatly strengthened the "weak tie" between them. 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 automatically refer to well-known third-party and retail 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 a member of a single community. Therefore, dispersion of WOM volume across websites will not be able to infer consumer awareness any more as argued by Godes and Mayzlin (2004) a decade ago. Instead, we find evidence that total number of WOM hosted by all online communities can be an indicator of consumer awareness now. Third, we adopt a more straightforward approach to conduct this research in pure online context by directly linking online WOM with consumers' online purchasing decisions. Godes and Mayzlin (2004) measured consumers' offline decisions and used online WOM as proxies for overall WOM.

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 and Zhang 2010). Alternatively, we look into the distribution of WOM valence from a different perspective that inconsistent consumer evaluations are complicated information to interpret and integrate and thus increase consumer search costs.

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, user-generated WOM serves as one of the major and trustworthy sources for people to recognize product features and quality without physical trials and thus is shown to influence online purchase decisions (Chevalier and Mayzlin 2006; Dhanasobhon et al. 2007; Duan et al. 2008; Forman et al. 2008; Godes and Mayzlin 2004; Liu 2006). In online channel, consumers are armed with various search tools (e.g. Google search engine and online recommendation system) to locate and access this large pool of WOM information at their fingertips. As implied by information search theory (Stigler 1961), consumers will keep searching for WOM information until the marginal utility resulted from one additional search equals its corresponding cost. In other words, lower search costs of WOM information lead to more intensive and in-depth WOM searches, leading to more informed purchase decisions and greater sales. We recognize that consumers' WOM information search goes beyond simply checking two widely discussed WOM attributes, valence and volume. It also includes extracting, interpreting and consolidating the richer information conveyed by review text contents, reviewer characteristics, etc. Therefore, although consumers are shown to rely on online WOM from both retail websites and third-party websites (Gu et al. 2012), the amount of WOM search that consumers are able to conduct across websites depends on search costs, which further affect their online purchase decisions.

We argue that the distribution of WOM, in both volume and valence, across websites influences online search costs of WOM information and, therefore, influences online retail sales. First, in terms of volume dispersion, more evenly distributed WOM across the Internet indicates higher search costs of 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 time to find the relevant websites but also requires more time for online users to learn different interfaces of those websites. In addition, the scenario of having WOM information overwhelmingly concentrated on one single website provides consumers the convenience to instantly access most of WOM available on the Internet by visiting that website only. Hence, lower search costs of WOM information as a result of the less dispersed WOM across sites can encourage consumers to do more comprehensive WOM information search about products. This encourages consumers to explore WOM more extensively and in-depth on each of visited websites, including reading more detailed text comments and checking reviewer identity information as well as allowing more time on the cognitive process of making careful decisions. More information collected from more WOM searches shall help consumers to locate their favorites on retail websites and make more informed purchase decisions. Generally if every consumer could find his/her best match, the product is more likely to reach its maximized sales by serving all of its targeted customers. Hence, the less dispersed WOM across websites is favorable to online retail sales. We propose:

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

In addition, given the same level of volume dispersion across websites, consumers face even lower search costs if it is the retail website that has attracted a larger share of WOM activities than the rest websites. In this case, consumers can easily get access to most of their needed product information from WOM directly on the retail website, which is their online destination. First-time consumers would have to learn how to surf the retail website anyway, regardless of the amount of search they are going to conduct on each website. It is also reasonable to assume that old customers are already familiar with retail websites' layout and online review community. But consumers would encounter an additional learning curve if they need to visit other third-party websites for more WOM. The more they need to search on third-party websites, the more effort they would make to acquaint themselves with those websites and locate the needed WOM. Therefore, given the same amount of WOM information and the same level of volume dispersion, consumers incur lower search costs to explore those WOM contents if the majority of them are hosted by retail website. In other words, the reduced search costs resulted from WOM volume being skewed towards retail websites are lower than the scenario where it is skewed towards third-party websites. As we argued beforehand, lower search costs encourage more WOM information searches and more purchases. Hence, we propose:

H2. *Conditional on dispersion of WOM volume across websites, having more WOM received on the retail website than on the third-party 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 and 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 and Wyer 1989). Therefore, in online WOM context, disagreed consumer feedback from WOM across websites would incur more cognitive costs to consumers for processing the inconsistency than relatively more consistent WOM evaluations. The resulted higher costs can discourage consumers to conduct 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 customers. Therefore, we propose:

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

Data

Research Context

We conduct our empirical analysis in online software market by using data from Amazon and CNETD. In recent years, product variety of software programs offered through online channel has been increasing tremendously (Zhou and Duan 2012). As a typical type of experience goods, consumers often face difficulties with evaluating software quality before consumptions. Meanwhile consumers with intentions to purchase software programs naturally have relevant knowledge and experiences of utilizing various Internet tools, e.g. search engines. Therefore, the nature of online software market determines 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 WOM distribution across websites on consumers' purchase decisions.

Accordingly, we construct a weekly data set of observations on bestselling software programs hosted by both Amazon and CNETD during the period June 2011 through Jan 2012. Amazon is one of the online leading retailers and has been widely chosen by previous studies to examine online market outcome (Chevalier and Mayzlin 2004; Ghose and Sundararajan 2005; Gu et al. 2012). The conclusions drawn from Amazon data can offer practical guidance to its software suppliers and also be generalized to other online software retail websites. In the meantime, we also collect weekly WOM data on the same software programs hosted by CNETD. CNETD is a representative third-party site that is noticeable for its large collection of user-generated WOM and expert opinions (Gu et al. 2012). It provides free and free-to-try software sampling on four platforms including Windows, Mac, mobile device and webware to encourage consumers experience products and share feedback. As a well-known site hosting software information, CNETD is often displayed at the top of search results when consumers use search engines to look for software program information. Many experienced software consumers also naturally resort to CNETD as a reliable source for product information. Therefore, consumers, who are about to purchase software programs on Amazon, are very likely to be aware of CNETD WOM, as evidenced by prior research (Gu et al. 2012).

The challenge in this data collection is to identify or match software programs that are hosted by both two sites. To cope with this, we conduct a 2-stage matching using CNETD's search functionality and a manual check. At the initial round, for each collected top 100 bestselling software program on Amazon, every week we search for the exact software name using the search function on CNETD homepage and collect the first 50 most relevant CNETD software programs. Accordingly, one Amazon software program has fifty candidates for its exactly matched CNETD product. However, the algorithm of CNETD search function is by no means able to assure that the CNETD product precisely matched to the collected Amazon software program is displayed at the highest position of the search results. Some software program suppliers on Amazon may even not upload the free-trial versions on CNETD. We thus, as a second step, conduct a manual screening on the very first-week data over those approximately matched pairs collected from Amazon and CNETD. We try to pick up only one out of fifty CNETD software programs as the free-trial version precisely matched to each collected Amazon software program, if any. From the first-week data collected on June 7th, we are able to extract 43 Amazon software programs with their exactly matched CNETD products. We then only keep observations on those 43 pairs from the originally collected Amazon and CNETD sample. This matching can help us to get the accurate data with moderate effort, since manually checking each week is tedious and time-consuming. That finally leads to an unbalanced data set of totally 665 observations on 43 software programs over 33 weeks for the analysis.

In particular, on Amazon, every week we collect sales rank, number of online consumer reviews, average consumer rating, price, release date, eligibility for free-shipping service, and software category for each software program. On the same date of each week, we also collect number of online user reviews, average user rating and weekly downloads for the matched software program on CNETD.

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 and Mayzlin 2004; Ghose and Sundrararajan 2005; Gu et al. 2012). In particular, Ghose and Sundrararajan (2005) designed an experiment to empirically estimate the negative linear relationship between log value of sales rank and log value of sales as $\Delta Ln(AmazonSales) = 0.828 * -\Delta Ln(AmazonSalesRank)$. 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 follow the literature to use number of online user reviews in each website to measure the WOM volume hosted by this website ($Vol_{i,t}^{j}$) (Duan et al. 2009). 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 captures how the volume of WOM conversations spreads over two websites. Following Godes and Mayzlin's study (2004), we use entropy to measure the dispersion of WOM volume ($EntropyVol_{i,t}$) by applying the entropy definition in our context as below:

$$EntropyVol_{i,t} = \begin{cases} -\sum_{j} \frac{Vol_{i,t}^{j}}{TotalVol_{i,t}} ln\left(\frac{Vol_{i,t}^{j}}{TotalVol_{i,t}}\right) & if\ both\ Vol_{i,t}^{A}\ and\ Vol_{i,t}^{C} > 0 \\ 0 & if\ Vol_{i,t}^{A}\ or\ Vol_{i,t}^{C} = 0 \end{cases}$$

where j denotes each website, e.g. A for Amazon and C for CNETD in this study, and $Vol_{i,t}^{j}$ denotes WOM volume on website j. Godes and Mayzlin (2004) have clearly discussed the advantages of choosing entropy over variance in studying dispersion of WOM volume. The main reason is that entropy does not vary over total volume of online user reviews from both Amazon and CNETD. Instead, it mainly depends on the ratio of WOM volumes between those two websites. We need to include total volume of online user reviews from Amazon and CNETD as a control variable in our following empirical analysis. More ongoing conversations available on the Internet, 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 the overall WOM volume.

The larger value of $EntropyVol_{i,t}$ indicates a larger volume dispersion, and in other words a more evenly distributed WOM across sites. When product i receives the same number of user reviews on Amazon and CNETD, $EntropyVol_{i,t}$ reaches its maximum, which is 0.693 as the largest possible volume dispersion in the two-site case. On the other hand, if either of two websites does not receive any review for software i, the entropy value is zero due to the limit value of $0/TotalVol_{i,t}*Ln(0/TotalVol_{i,t})$ as zero, which is reasonable in our context. When software program i receive all its user reviews on one single website, its $EntropyVol_{i,t}$ turns to be the minimum value, zero, to indicate the lowest level of dispersion. In addition, we also recognize that if a software is not reviewed in any site, in essence there doesn't exist a distribution of WOM across sites. Thus this product should be excluded from our final data set.

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 to measure the variation of WOM valence ($EntropyVal_{i,t}$) as illustrated below.

$$EntropyVal_{i,t} = \begin{cases} -\sum_{j} \frac{Val_{i,t}^{j}}{Val_{i,t}^{A} + Val_{i,t}^{C}} ln\left(\frac{Val_{i,t}^{j}}{Val_{i,t}^{A} + Val_{i,t}^{C}}\right) & if\ both\ Val_{i,t}^{A}\ and\ Val_{i,t}^{C} are\ available \\ 0 & if\ Val_{i,t}^{A}\ or\ Val_{i,t}^{C} is\ not\ available \end{cases}$$

where j denotes each website, e.g. A for Amazon and C for CNETD, and $Val_{i,t}^{j}$ denotes WOM valence on website j. Similarly, the advantage of entropy over variance also allow us to safely include the average consumer evaluation over Amazon and CNETD, $MeanRating_{i,t}$, measured by $(Val_{i,t}^{A} + Val_{i,t}^{C})/2$), as another control variable (Chevalier and Mayzlin 2006). This can help avoid confound estimating the impact of variation of WOM valence. There have been mixed conclusions regarding the relationship between valence of WOM and user choices. Some researchers believe that higher valence of WOM persuades consumers to make purchase or adoption decisions (Liu et al. 2006; Zhou and Duan 2012). On the contrary, other studies find that online user ratings 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 is important and interesting to compare the impact of valence variation and merely valence on influencing consumers' online purchase decisions. If the product is only reviewed on one single site, the $MeanRating_{i,t}$ is simply the average rating of this product on that site.

According to the statistical attributes of entropy, a larger value of $EntropyVal_{i,t}$ actually denotes a smaller variation of WOM valence. $EntropyVal_{i,t}$ reaches its maximum, 0.693, when average user rating of product *i* on Amazon is equal to its CNETD average rating, indicating smallest valence variation. Since $EntropyVal_{i,t}$ is symmetric over the variable of $Val_{i,t}{}^{j}/(MeanRating_{i,t}*2)$ and concave, 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 site. That is the case of largest possible valence variation. However, when software program *i* does not receive any user review on one of two sites, its variation of WOM valence across websites basically does not exist, thus its value of this term is set to be zero.

In addition, we also use Amazon product prices, product age, CNETD weekly downloads, download license, product fixed effect, and time fixed effect as control variables (Chevalier and Mayzlin 2006; Li and Hitt 2008; Zhou and Duan 2015). Table 1 provides a description of the variables used in our empirical analysis, and Table 2 presents the summary statistics of those variables. We find that, in any week of the data collection period, all products are at least reviewed by one of the two sites, if not both, as indicated by the minimum value of $TotalVol_{i,t}$ being greater than 0 in Table 1. As a result, as mentioned above, all samples in our data set can be used properly to capture the distribution of WOM. Table 2 also shows that online user reviews are far away from being evenly distributed over Amazon and CNETD. The mean value of $EntropyVol_{i,t}$ indicates that, on average, products receive user reviews on one website about twice of the other website. The mean statistic of $DummyVol_{i,t}$ further shows that nearly 80% software programs receive more user reviews on Amazon than on CNETD. Hence, it seems Amazon attracts much more WOM activities for most products than CNETD. In addition, software programs tend to have relatively more prominent difference in user ratings between those two websites than in the number of user reviews, indicated by a greater mean values of $EntropyVal_{i,t}$ than that of $EntropyVol_{i,t}$.

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 at week *t*
$EntropyVol_{i,t}$	Dispersion of WOM Volume over Amazon and CNETD for software *i* at 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 of software *i* at week *t*
$EntropyVal_{i,t}$	Variation between Amazon and CNETD WOM Valence of 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
$AmazonSalesRank_{i,t}$	45	28	1	100
$TotalVol_{i,t}$	357	547	10	5109
$EntropyVol_{i,t}$	0.280	0.239	0	0.693
$DummyVol_{i,t}$	0.782	0.413	0	1
$MeanRating_{i,t}$	3.342	0.730	1.400	4.800

$EntropyVal_{i,t}$	0.525	0.283	0	0.693
$Age_{i,t}$	731	589	151	3042
$AmazonPrice_{i,t}$	62.644	58.447	0	249.980
$CnetdDown_{i,t}$	7993	4391	0	47895
$CnetdLicense_{i,t}$	0.047	0.211	0	1

Table 2. Summary Statistics of Key Variables

Empirical Analysis

Empirical Model

We estimate the following model to test our proposed hypotheses:

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

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 $EntropyVol_{i,t}$ and $DummyVol_{i,t}$ respectively to test Hypotheses 1 and 2. The coefficient on $EntropyVol_{i,t}$ (β_2) captures the impact of dispersion of WOM volume across Amazon and CNETD on Amazon sales. As the larger value of $EntropyVol_{i,t}$ indicates a less dispersed or more even distribution of WOM volume, this coefficient (β_2) is expected to be negative according to hypothesis 1. The coefficient on $DummyVol_{i,t}$ (β_3) captures whether having more WOM activities on Amazon than on CNETD leads to greater Amazon sales. Hypothesis 2 suggests this coefficient (β_3) 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 β_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 separated from total amount of WOM available from two sites. To test hypothesis 3, we include $EntropyVal_{i,t}$ to capture the impact of variation of WOM valence across Amazon and CNETD on Amazon sales. As discussed in the previous section, its larger value indicates more agreed consumer opinions across two sites, i.e. smaller valence variation. Hence, according to hypothesis 3, its coefficient (β_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 (β_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 for by current price $AmazonPrice_{i,t}$ of software i at week t (Chen et al. 2007). In addition, the log value of weekly downloads $LnCnetdDown_{i,t}$ software i receives at week t on CNETD is added, as free sampling of software program is shown to influence online sales (Zhou and Duan 2015). $CnetdLicense_{i,t}$ is a dummy variable to indicate the license difference of free trial software versions on CNETD (Zhou and Duan 2012). Finally, we include product fixed effects μ_i and time fixed effects ρ_t to control for time-invariant product heterogeneity, such as products' idiosyncratic characteristics and intrinsic quality, and other omitted time-variant variables respectively (Duan et al. 2008). Specifically, rather than using product-specific dummies, we choose to use 27 category-specific dummies to represent product fixed effects. As our sample consists of 665 observations on 43 software programs, adding 43 product-specific dummies would significantly reduce the degree of freedom for estimating the above 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 43 software programs belong to 28 distinct categories. Therefore, we believe that category-specific dummies should well reflect those uncaptured product attributes and enable us to efficiently estimate the regression model in the meantime. To add the time fixed effect, similarly we add 32 week dummies ρ_t in the equation to capture the common demand shocks (e.g. website-wise promotion event).

Results

Table 3 presents our estimation results. To highlight the contribution of WOM distribution across the Internet on online retail sales, we compare two specifications. In the first column of Table 3, we estimated a model without considering WOM distribution across Amazon and CNETD. In particular, the WOM related variables in this first specification only include three commonly used variables in prior research: total volume of WOM on Amazon and CNETD, whether Amazon receives more WOM, and the mean of Amazon and CNETD WOM valence. The second column of Tables 3, on the other hand, presents the estimations of our proposed model that adds two key variables to address our research question: dispersion of WOM volume and variation of WOM valence over two websites. Moreover, to avoid the small sample issue, we also tested both two models in Bayesian framework, which doesn't have a requirement on the sample. The results are qualitative similar, showing the robustness of our results. Due to the page limits, the detailed report of the Bayesian estimations is not included, yet readily available upon request. We have also conducted a Hausman test to examine the potential endogeneity of volume dispersion and valence variation and find no evidence for endogeneity issue.

Overall, the results in column (2) of Table 3 support all the three hypotheses. First, as expected, dispersion of WOM volume from Amazon and CNETD has a negative impact on Amazon sales, given the significantly negative coefficient on $EntropyVol_{i,t}$. Since a large value of $EntropyVol_{i,t}$ indicates a high level of volume dispersion, this suggests that products receiving more evenly distributed WOM over retail and third-party websites tend to achieve fewer sales. Hypothesis 1 is thus supported. Moreover, by mapping the sales rank to sales, we can reveal that the magnitude of this negative impact of dispersion of WOM volume is remarkable. As discussed earlier, we adopt 0.828 as our Pareto index for the negative log linear relationship between sales rank and sales, as estimated by Ghose and Sundararajan (2005) in the context of Amazon software sales. We hypothetically compare two extreme cases of volume dispersion, while all else are equal. In one scenario, a product receives most of user reviews on one website, leading to an approximately zero value of $EntropyVol_{i,t}$. In the other case, this product receives one more user review on this websites than the other, which makes the limit of $EntropyVol_{i,t}$ approach its maximized value of 0.693. Please note that this comparison assumes that total number of user reviews, which website receives more user reviews, and the variation of user ratings in both two cases are all kept the same. We find that this product's sales is significantly greater in the first scenario by over 50% than in the second scenario, calculated by $e^{(0.828*-0.693*\beta 2)}-1$. We also observe that, the coefficient on $TotalVol_{i,t}$ is significant, indicating the importance of interpreting our conclusions conditional on total volume of WOM from websites.

Second, given the level of dispersion of WOM volume over those two websites, having more WOM occurred on Amazon is favorable to its sales. The coefficient is significantly positive on the dummy indicator $DummyVol_{i,t}$ that measures whether the product receives more WOM on Amazon. Combined with our first finding, it implies that while a less dispersed volume of WOM increases online sales, the scenario would be even more beneficial to sales if the distribution of WOM volume across websites is skewed towards retail websites. Similarly by mapping the sales rank to sales using 0.828 as the Pareto index, we find that which website accumulates the majority of WOM matters a lot. All else being equal, having the larger portion of WOM accumulated on Amazon would lead to a sales increase of more than 40% as estimated by $e^{(0.828*\beta 3)}-1$ than otherwise CNETD receiving most reviews. As a result, hypothesis 2 is supported.

Third, we find that the disagreement in consumer evaluations between Amazon and CNETD WOM discourages Amazon sales, indicated by the positive coefficient on $EntropyVal_{i,t}$. We note that a large value of $EntropyVal_{i,t}$ 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. Consumers are more encouraged to make online purchasing decisions by consistent consumer-generated product evaluations across websites than by divergent consumer opinions. Using the similar technique to map sales from sales rank, we find a surprisingly large magnitude of this impact. A product's sales on Amazon in the case that have received the same average user ratings across two websites (i.e. $EntropyVal_{i,t} =0.693$) can be one and a half times as great as that resulted from having one star average rating on one site and having five store on the other (i.e. $EntropyVal_{i,t} = 0.196$), estimated by $e^{0.828*(0.693-0.196)}$, all else being equal.

We also find some interesting results by comparing the estimations in two columns. The main 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 average ratings result in more online sales. However, based on our empirical evidence that supports hypothesis 3, this insignificant estimate in column (2) suggests that the variation of WOM valence across retail and third-party websites plays a much more significant role in influencing sales than an overall consumer evaluation. An improvement on consumer feedback on one single website might not be helpful for online sales as conventionally expected, unless this improvement would move consumers across the Internet come to a consensus. In addition to the change of this coefficient estimation, incorporating the distribution of WOM across websites also increases the R^2 value in column (2) without affecting estimations on variables not relevant to WOM, e.g. product age. Therefore, we believe that 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.

	(1)	(2)
Intercept	-3.817***	-3.628***
$LnTotalVol_{i,t}$ (β_1)	0.340***	0.220***
$DummyVol_{i,t}$ (β_3)	0.605***	0.420***
$MeanRating_{i,t}$ (β_4)	-0.248**	-0.056
$EntropyVol_{i,t}$ (β_2)		-0.739***
$EntropyVal_{i,t}$ (β_5)		1.579***
$Age_{i,t}$ (β_6)	-0.001***	-0.001***
$AmazonPrice_{i,t}$ (β_7)	0.002	-0.001
$CnetdDown_{i,t}$ (β_8)	-0.056***	-0.158***
$CnetdLicense_{i,t}$ (β_9)	-1.558***	-2.169***
Product fixed effect	Yes	Yes
Time fixed effect	Yes	Yes
Observations	665.000	665.000
R^2	0.642	0.660
p<0.05;*p<0.01		

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

Based on the above finding, we try to answer a very practically interesting question that whether it is better for a product's online sales to have nighty nine of five-star reviews received by Amazon and only one 1-star review on CNETD or fifty 5-star reviews received on each of two websites. In the first scenario, volume dispersion is much smaller than that of the second scenario, however, valence variation is much larger. $EntropyVol_{i,t}$ and $EntropyVal_{i,t}$ are calculated as 0.024 and 0.196 respectively. The $DummyVol_{i,t}$ is larger, being 1. In the second scenario, volume dispersion and valence variation are measured by the maximum value of entropy in a two-website context, which is 0.693. 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 in the first scenarios is over two times as much as the sales in the second scenario, calculated by $e^{(-0.828)*[0.024*\beta 2+0.196*\beta 5+\beta 3-0.693*(\beta 2+\beta 5)]}$.

Finally, we also find supportive and indirect evidence for our proposition that consumers are able to extensively search for and be aware of WOM information hosted by multiple websites in online market. In both two specifications, the total volume of Amazon and CNETD WOM leads to higher sales. 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 theorized by Godes and Mayzlin in a study conducted a decade ago (2004). Online consumers are now savvy enough to utilize various online search tools to locate product information through the boundaries of online community. Therefore, it is not surprising and actually reasonable to find different conclusions regarding dispersion of WOM volume in our study with that prior research in 2004. On the other hand, the insignificant results on Amazon price in both two columns are contradictory to our expectations. We believe that it can be related with our sample being bestselling software programs. All the products are ranked among the top 100 most popular software when being collected. Consumers are very likely attracted to them mainly by their high quality instead of low prices and thus insensitive to price difference. Another reason can be the small variation in software price during our collection period. We observe that price for the same product rarely fluctuates over time. This can technically lead to low statistical power and produce insignificant results.

Discussion and Conclusions

In this paper, we examine how distribution of WOM hosted by retail 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 hosted by both retail websites and third-party websites (Gu et al. 2012; Zhou and Duan 2015). Our research goes a step further by recognizing the different extent to which consumers search for WOM information according to the WOM distribution across those two types of websites. Consumers visit multiple websites for WOM information, however search cost of WOM information across sites affect the extent and the depth of searches they conduct on each website. Consumers not only look into numerical attributes of WOM but also review contents, reviewer background, etc. for richer product information. We aruge that the distribution of WOM across websites affects consumers' search costs of WOM information and accordingly influences a product's possibility to reach all of its targeted customers. Our empirical finding supports this proposition by identifying the significant relationship between distribution of WOM and online sales. It thus highlights the importance of taking WOM distribution into account while studying the sales impact of online WOM hosted by multiple websites.

Second, this study also contributes to our understandings on the magnitudes of WOM's sales effects from multiple sources. Previous studies investigate the differential impact of WOM created by different reviewer identities or hosted by different websites (Amblee and Bui 2007; Bickart and Schindler 2001; Gu et al. 2012; Senecal and Nantel 2004; Zhou and Duan 2016). They in essence conducted empirical analyses to support their conclusions conditional on the specific distributions of WOM in the relevant contexts. Our findings suggest that which WOM source is more influential is context specific. We find evidence that reduced dispersion of WOM volume and smaller variation of WOM valence across websites increase online sales. Specifically, receiving one additional review on Amazon may lead to a larger increase of its sales than having this one more review received on CNETD, if most of WOM activities across those two websites have already occurred on Amazon. However, it would be the opposite that CNETD WOM is more influential than Amazon WOM, if CNETD have already attracted a lot more user feedback. Therefore, without knowing the distribution of WOM, there is no simple answer to the magnitude comparison of WOM effects across multiple sources.

Third, our study also sheds lights on identifying user-generated WOM metrics that can significantly influence consumer purchase decisions. The literature generally agree that WOM volume is an influencer of user choices. However, a simple average rating, as the most common WOM valence measure, has received divergent opinions on whether it well signals product quality beyond all mixed individual consumer opinions and eventually influences sales. This research echoes previous studies by showing that the variation of WOM valence, rather than the valence itself, play a more important role in influencing online sales. For example, in our research context, receiving one additional positive user review on Amazon may hurt a product's sales, if this product has already accumulated overwhelmingly negative user reviews on CNETD. On the contrary, receiving positive reviews on Amazon can result in a more consistent consumer evaluation and thus promote product sales, if CNETD has already received overwhelmingly positive user reviews.

Finally, this research complements literature on the sales impact of WOM volume. Most of previous studies investigate WOM volume by looking into WOM received by one single website (Liu 2006; Duan et al. 2008). The underlying rationale is that volume of WOM indicates consumers' awareness of products. And more user reviews lead to a higher chance that consumers would get informed of corresponding products, leading to more purchases. Our results show that, given consumers' easy access to and their extensive search on multiple websites, this reasoning for WOM volume also applies to the total volume of all WOM hosted by both retail 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 study on movie sales about a decades ago (Ghodes and Mayzlin 2004). Back then, consumers were less savvy in utilizing online search tools to locate multiple online communities providing WOM information. Hence, they generally were only able to access the WOM information from one single community, and had difficulties with acknowledging how many on-going conversations about one specific product are happening outside of that particular community. Since each consumer belonged to one single community, the dispersion of WOM across online communities is found to measure the heterogeneity of consumers who are aware of the product. This study finds evidence that the boundaries among online communities are much weaker in today's e-commerce. Total volume of WOM across websites, rather than dispersion of WOM volume, becomes the indicator of consumer awareness of products. This also provides suggestions that research conclusions related with the fast-changing e-commerce need to consistently be reexamined and updated.

There are inevitably several limitations of this research as well as a few promising directions of future research. First, we follow the literature to assume that consumers are able to locate WOM information on Amazon and CNETD when they intend to purchase software program (Gu et al. 2012). However, we didn't actually observe consumer's online footsteps. A few Amazon consumers may not pay attention to WOM data on CNETD or explored WOM data hosted by other websites. Incorporating consumers' online traffic data into answering our research question can add to the robustness and rigorousness of our conclusions. Second, future research could also incorporate more websites and more products. Current study only selects one website to represent retail websites or third-party websites. A richer sample collected from more retail websites and third-party websites would add to the robustness of our results. It can also help further investigate the potential different weights of WOM across the sites on retail sales. Third, this study uses a sample of best-selling products on Amazon, which may raise concerns on applying our conclusions to the whole spectrum of products on online market. We also recognize that the results may not be directly applied to explain the scenario, where the product is rarely reviewed on any website. Instead, our conclusions will be more appropriately adopted to interpret products that have received reviews already on the Internet. Conducting empirical investigations on products with a wide range of popularities may help strengthen the validity of our findings. Fourth, 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. Our underlying argument in this study is that the extent to which consumers conduct WOM search depends on the distribution of WOM across websites. In fact, some other factors, such as the helpfulness and informativeness of review content, can also influence consumers' search costs and may further affect the chance that consumers can make enough information searches to find their favorites. 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 explore reviewer characteristics to consider review quality in future research.

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