The Paradoxes of Word of Mouth in Electronic Commerce

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ABSTRACT: Challenging conventional wisdom, we unravel three paradoxes of word of mouth (WOM) in e-commerce. Specifically, *the WOM valence paradox* contends that higher WOM valence of a product results in a larger subsequent decrease in the WOM valence of the product, *the WOM volume paradox* propounds that higher WOM volume of a product results in a smaller subsequent increase in the WOM volume of the product, and *the WOM spillover paradox* proposes that an improvement in the WOM of a product also improves the WOM of connected products in a product network. These paradoxes caution online retailers that superior WOM may at times backfire and not boost further sales. Drawing theoretical support from expectation-confirmation theory and network theory, we collect data from China's largest business-to-consumer platform, Tmall.com, and use linear panel data models to examine WOM evolution in a product network, controlling for relevant factors at the individual product, product network, and time unit levels. Importantly, we base our identification strategies on the use of instrumental variables and the difference-in-differences estimation approach. Numerous statistical checks confirm the robustness and consistency of our findings. We contribute to a much richer theoretical understanding of WOM, by extending the applicability of expectation-confirmation theory and network theory to novel predictions and contexts, adding a dynamic perspective, unveiling three important WOM paradoxes, and offering practical insights.

KEY WORDS AND PHRASES: econometric analysis, electronic commerce, e-tail, eWoM, product network, product review, word of mouth.

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Electronic commerce (e-commerce) has burgeoned rapidly, with the global sales of business-to-consumer (B2C) e-commerce expected to reach $1.92 trillion in 2016 [65]. With the mounting popularity of e-commerce, businesses hope to better capitalize on word of mouth (WOM) either in the form of a star rating or a review text to boost their sales. Indeed, Local Consumer Review Survey reported that 85 percent of consumers do consult online reviews prior to their purchases and 65 percent of consumers claim that online reviews influence their purchase decisions [12]. Hence, prior research has primarily focused on the value of WOM on economic outcomes, and assumed a simple and monotonic role of WOM in influencing business performance (e.g., [19, 20, 22, 36]). Consequently, businesses become overzealous in expending more effort to enhance WOM to drive sales [18, 34, 48], but gravely overlook the possible paradoxes of WOM. The severe scarcity of current literature in unveiling possible paradoxes of WOM signals a strong need that motivates our paper.

First, we challenge conventional wisdom to elucidate the paradoxes of WOM over time, whether in valence or in volume. Expectation-confirmation theory [5] explains that product post-purchase satisfaction is a function of expectation, perceived performance, and disconfirmation of belief [56, 57]. A product's existing WOM often sets the initial expectation of the product's performance (e.g., quality and popularity), and the subsequent perceived performance determines the mismatch or gap between the two, to influence what a reviewer will eventually write for future WOM. Expectation-confirmation theory [5] hints that high existing WOM in terms of valence and volume signals a high level of product quality [32] and popularity [45], which may elicit a larger mismatch between expectation and perceived performance to result in unfavorable reviews whereas low existing WOM valence and volume might instead experience the opposite. A few studies have attempted to understand how WOM valence evolves over time, but with equivocal findings. For instance, two studies [35, 42] found a declining trend in WOM valence when examining book reviews from Amazon. However, another study [46] reported an increasing trend in WOM valence when studying Yelp reviews on businesses (e.g., restaurants) instead of specific products. Unfortunately, these studies have invariably focused solely on WOM valence, and overlooked the concurrent evolution of WOM volume, which might have resulted in the mixed research findings of the past. We thus contend that the possible paradoxes of WOM should be unraveled through the concurrent examination of WOM valence and volume over time.

Second, we propound the paradoxes of WOM in a product network. With the advent of product recommender systems in e-commerce, products are now placed in product networks [54].[1] Network theory [68] depicts the relationships between network members in terms of nodes and ties, and documents the interdependence between connected network members [6, 38, 53, 55]. In a human social network, connected network members are not independent of one another due to reasons such as "peer influence" [6] or "homophily" [13]. Likewise, in a product network, network theory [68] postulates potential interdependence between connected products.

Unlike in the past, when a product's WOM could be evaluated separately, this new arrangement incites consumers to compare the WOM between the product and its recommenders, in terms of both valence and volume. As a result, consumers may be psychologically influenced by these linkages. On one hand, consumers may be tempted to make a purchase because of a product's high WOM. On the other hand, consumers may be derailed from purchase, as network theory [68] suggests that high WOM of a product may exert similar "peer influence" or "homophily" to the WOM of other connected products in the network due to their interdependence. Given that connected products at times could be competing products, high WOM may "spill over" to pose a challenge to the original product, resulting in another possible paradox of WOM. A similar phenomenon has been observed in investment: economics and financial research (e.g., [8, 11, 14]) has reported that the benefits from research and development (R&D) investment in a firm often spill over to other firms despite being competitors in the same industry. Nonetheless, the possible paradoxes of WOM in a product network remain unknown. Studies that fail to examine a more convoluted influence (i.e., WOM of linked products) wane in explanatory power.

Third, the revelation of possible paradoxes of WOM (through the lens of expectation-confirmation theory [5, 56, 57] and network theory [68]) is critical toward addressing undue worry by businesses over some counterintuitive occurrences. For instance, poor WOM (i.e., low valence and volume) may actually generate sales due to poor WOM being deemed more credible than superior WOM [15], or negative WOM being able to spark product awareness [58]. Increasingly, consumers have developed a sense of skepticism or disbelief toward marketing messages and online information [28, 52]. Consumers have learned of businesses that may resort to unethical tactics to artificially create a high valence or volume to drive sales (e.g., manipulating WOM through the removal of negative WOM [2, 27] or the use of paid reviewers [47]). In essence, only by having a more nuanced and lucid understanding of how prior WOM may impact subsequent WOM paradoxically, in terms of both valence and volume, and in a product network context, will we prevent academic researchers from arriving at erroneous or incomplete conclusions. In view of these critical research gaps, we seek to answer two research questions:

1. How does prior WOM of a product paradoxically influence the subsequent growth of the product's WOM?
2. How is the WOM of a product influenced by the WOM of connected products in a product network?

To answer these research questions, we collect product WOM, recommendation and transaction data from a retail store on Tmall.com selling digital cameras.[2] We propose a set of linear panel data models to investigate our research questions. Our identification strategy is based on the use of instrumental variables and the difference-in-differences estimation approach. To validate the robustness of our findings, we also perform plentiful statistical checks.

After ruling out plausible alternative explanations (such as the ceiling effect[3]), a set of notable findings have been identified, especially *the three paradoxes of WOM*. First, we elucidate that higher prior WOM valence of a product will lead to a larger subsequent decrease in the product's WOM valence (i.e., *the WOM valence paradox*).[4] Second, we underscore that higher prior WOM volume of a product results in a smaller subsequent increase in the product's WOM volume (i.e., *the WOM volume paradox*).[5] Third, our results show that an increase in a product's WOM valence and volume will increase the subsequent valence of other connected products in a product network (i.e., *the WOM spillover paradox*).

Our research makes the following important contributions. First, it extends the applicability of expectation-confirmation theory [5, 56, 57] to the context of e-commerce WOM, and theoretically identifies and empirically validates the paradoxes of WOM evolution in the e-commerce context. Second, this study also extends network theory [68] to the context of WOM in e-commerce product networks, and reveals the paradoxes of WOM in the product network context. Third, our work challenges past works that assume a simplistic and monotonic influence of WOM, to enrich the literature with a more complex (but realistic) prediction. In addition, we also draw important implications for e-commerce retailers' product marketing strategies and the design of e-commerce platforms.

Literature Review

WOM is typically defined as "oral, person-to-person communication between a receiver and a communicator whom the receiver perceives as non-commercial, concerning a brand, a product, or a service" [7, p. 3]. Given its importance and impact on consumer decision making and product sales, it is not surprising that academic researchers from information systems, marketing, and economics are eager to better understand the role of WOM (e.g., [3, 9, 21, 23, 25, 32, 33, 59, 64]). Given the plethora of work in this area, we review the relevant studies and synthesize them as follows: (1) expectation-confirmation theory and WOM, and (2) network theory and WOM.

Expectation-Confirmation Theory and WOM

Expectation-confirmation theory is a cognitive theory that seeks to explain consumers' product post-purchase satisfaction [56, 57]. Rooted in psychology, its applicability has been extended to information systems and marketing. Essentially, the theory posits that the discrepancy (i.e., positive or negative disconfirmation) between consumers' expectations and perceived performance will influence post-purchase satisfaction. Positive disconfirmation occurs when a product outperforms expectations, resulting in satisfaction, whereas negative disconfirmation occurs when a product falls short of expectations, resulting in dissatisfaction [5].

Expectation-confirmation theory is highly relevant to our investigation of WOM in two aspects. First, before purchasing a specific product, consumers can observe the product's existing WOM. In the e-commerce context, WOM valence typically signals product quality [32] whereas WOM volume typically signals product popularity [45]. As a whole, existing WOM often shapes consumers' expectation of the product's performance. Second, consumers' satisfaction or dissatisfaction may be reflected in the product's subsequent WOM in terms of consumers' contribution to the WOM valence (i.e., review ratings) and the WOM volume (i.e., additional pieces of reviews) [4]. Indubitably, expectation-confirmation theory serves well as the underlying theory to examine the impact of prior WOM on subsequent WOM in terms of both valence and volume.

Existing WOM research pales in its investigation of the impact of prior WOM on subsequent WOM. Only a paucity of studies attempt to understand the dynamics of WOM. For instance, one study [42] investigated book review data from Amazon to show that initial product WOM is provided by the early consumers, but is consumed by the later consumers, which results in an increasing level of dissatisfaction and decreasing level of valence over time. Based on similar data, more recent findings [35] argued that WOM valence may decrease because of the decreasing ability of future consumers to assess similarity with past reviewers, which then leads to more purchase errors. In contrast, another study [46] investigated review data from Yelp on businesses (as opposed to specific products), and reported a positive impact of prior WOM valence on subsequent valence. Unfortunately, these studies have overlooked the concurrent investigation of WOM volume with WOM valence.

Instead of examining the evolution of WOM or unveiling the possible paradoxes of WOM, most extant studies have focused on the economic outcomes of WOM. Nonetheless, the synthesis of these studies is vital to establishing the importance of our focus on WOM valence and volume. Initial WOM studies have examined product reviews in the e-commerce context. For instance, prior research [19] investigating book reviews on Amazon.com and BN.com revealed that an increase in valence and volume of reviews results in an increase in book sales. Moreover, an investigation of online reviews of consumer electronics and video games on Amazon has revealed that review valence has a stronger effect on search products, whereas review volume is more important for experience products [23]. Interestingly, several researchers [37] also contrasted valence and volume of internal WOM (from Amazon) and external WOM (from Cnet, DpReview, and Epinions) to show that a retailer's internal WOM has a limited impact on its sales of high-involvement products, whereas external WOM has a significant impact on the retailer's sales.

The importance of WOM valence and volume should not be underestimated, and has been further corroborated as researchers investigate beyond e-commerce websites to those that amass product reviews, such as those for movies, beer, restaurants, and the like. A study [44] using Yahoo! movie reviews and box office data from *Variety* magazine found that review volume, but not review valence, offers significant explanatory power for both aggregate and weekly box office revenue. Using similar data, another study[25] reported that review volume rather than review valence positively impacts box office revenues of movies. However, when a different group of researchers [20] examined Yahoo! movie reviews at a different national-level aggregate box office data, they maintained that the valence, not the volume, seems to drive box office performance. At times, the influence may be more complex—as reported in prior literature [26], a movie's box office revenue significantly influences WOM volume, which in turn leads to higher box office performance, thereby forming a positive feedback mechanism. Researchers have also investigated reviews of other product categories. For instance, analyzing beer review data from Ratebeer.com and U.S. brewers' sales data, they found that the review ratings play a significant role in determining new product growth in the craft beer industry [22]. Moreover, a recent paper [45] studied restaurant reviews on Dianping.com, and concluded that both online reviews and promotional marketing have a significant impact on restaurant sales, and found a substitute relationship between WOM volume and coupon offerings, but a complementary relationship between WOM volume and keyword advertising.

Network Theory and WOM

Network theory is the study of graphs as a representation of a set of discrete objects and their relationships, where these objects are viewed as network nodes, and relationships are viewed as network links. Network theory, however, can be applied to WOM research in two different ways. First, researchers treat consumers as the nodes, and the relationship between potential consumers as the links. Hence, network theory is applied to better understand how these individuals may influence one another in regard to WOM (e.g., [6, 13, 30, 36]). Second, researchers treat products as the nodes, and the recommendation (if any) between the products as the links. Hence, network theory is applied to better understand how products may influence one another [16, 53, 54, 55].

Exemplifying how network theory applies in the first approach, a study conducted in the offline social network context demonstrated that social tie strength and homophily will affect the WOM referral behavior among social members [13]. In recent years, popularized by the advent of social media (e.g., Facebook, YouTube, Twitter, Instagram), the emphasis has shifted toward examining online social networks. For instance, a randomized field experiment on Facebook [6] identified WOM peer influence and social contagion effects on consumers' product adoption. Moreover, another study examining Facebook [36] contrasted WOM from consumers with messages from marketers in a Facebook fan page brand community to quantify their relative impact on consumer purchase expenditure.

More recently, in addition to social networks, researchers from information systems and marketing also gained interest in product recommendation networks in e-commerce (e.g., [16, 53, 54, 55]), exemplifying how network theory applies in the second approach. Product networks are created by recommender systems in e-commerce [31, 60, 61], which adopt algorithms such as content-based approach (based on the characteristics of an item), a collaborative filtering approach (based on the consumer's social environment), or a hybrid approach (combining the prior two methods) [62], to recommend products that might interest consumers [70]. It should be noted that, although several studies examine product networks, they do not focus on WOM. An earlier study [16] used data on books in Amazon to discover the spread of exogenous demand shocks through the product networks. Some researchers [54] associated the average influence of network centrality on each book category with inequality in the distribution of its sales on Amazon. In a related paper, the same researchers [55] showed that the explicit connection in a product network could lead to a threefold amplification of the influence that complementary products have on each others' demands. Another investigation [53], based on the PageRank algorithm, decomposed a product's value into its own intrinsic value, the value it receives from the network, and the value it contributes to the network. However, these studies have overlooked the vital role of WOM in influencing product networks in e-commerce, which is our focus.

To summarize, our research differs from prior studies by examining the impacts of a product's prior WOM on the product's subsequent WOM growth (in terms of both valence and volume), and investigating how the WOM of a product is influenced by the WOM of connected products in a product network. Drawing theoretical support from expectation-confirmation theory and network theory, we seek to make significant theoretical and practical contributions.

Hypotheses

WOM valence (or review rating) is commonly interpreted as an indication of consumers' general evaluations (positive or negative) of a product [36]. Hence, WOM valence of a product often serves as a proxy for product quality[32].[6] According to expectation-confirmation theory [56, 57], if the existing WOM valence of a product is higher, which implies a higher level of quality, future consumers' expectation of the product quality may inevitably be heightened and harder to match. Consequently, they may perceive a less than expected product quality, thereby resulting in a higher level of dissatisfaction [5] and fueling the larger decrease in WOM valence subsequently [4]. Indeed, online retailers concurred that maintaining a consistently high level of product quality can be challenging at times [67].

Furthermore, in line with expectation-confirmation theory [56, 57], over the years consumers have accumulated substantial "bad experience" and thus developed a general tendency toward skepticism, if not disbelief, regarding higher WOM valence. This may be attributed in part to the aforementioned mismatch between initial expectation and eventual perceived performance, but it may also have stemmed from the knowledge of online retailers who manipulate WOM through "paid reviewers," "friendly forces," and/or removing negative WOM to create artificially high valence [24]. Consequently, higher WOM valence of a product may trigger consumers' apprehension and increase their annoyance to incur negative reviews so as to decrease the valence to its supposedly "true" level.

Compounding the problem, consumers who spend time and effort to write reviews on a product often hope that their reviews can exert some influence on others' purchase decisions [49]. If the existing WOM valence of a product is higher, consumers may be less motivated to post additional positive reviews on this already highly rated product because the perceived impact of their reviews is lower [35], thereby rendering additional positive reviews less likely. However, consumers who defer and possess poorer evaluations of the product tend to perceive their contribution as more influential because it can deter subsequent purchases due to their deviation from existing valence, which may lead to a decrease in subsequent valence. Empirically, two studies [35, 42] have documented some evidence of the decrease of WOM valence over time, thus lending some support to our arguments. All these point to the likelihood that higher WOM valence of a product may result in a larger subsequent decrease in the product's WOM valence. Therefore, we propose:

> *Hypothesis 1: Higher WOM valence of a product results in a larger subsequent decrease in the WOM valence of the product.*[7]

While WOM valence signals product quality [32], WOM volume may indicate product popularity [45]. According to expectation-confirmation theory [56, 57], higher existing WOM volume of a product, which implies a higher level of popularity, may unwittingly heighten future consumers' expectation of product performance. As a result, after purchase and consumption, the chances of a larger degree of disconfirmation and dissatisfaction are likely [5]. Consumers may become less tempted to further boost the popularity of the product with additional WOM volume [4]. Thus, higher initial WOM volume would experience a smaller subsequent increase.

In addition, expectations of the products are set because WOM generated by consumers typically entails some product information, and WOM volume serves as a good indicator of the amount of information in the WOM pool [71]. As one study underscores [69], reviewing a product is "costly." Hence, one often evaluates whether the impact or benefit of the review will outweigh the cost of submitting it before composing the review. When the existing WOM volume is higher, which signals richer information in the WOM pool, consumers are less tempted to add additional information (i.e., reviews) as the information may be redundant and the expected impact is lower. Evidently, adding one additional review to a product (whether simple or complex) with thousands of existing reviews is perceived to be less useful and influential (regardless of its truth) than adding one to another product with only few existing reviews. This suggests that higher WOM volume may instead impede subsequent volume growth. We thus posit:

> *Hypothesis 2: Higher WOM volume of a product results in a smaller subsequent increase in the WOM volume of the product.*[8]

Rarely investigated in the past, WOM of a product not only affects the future WOM of the product itself, but also is likely to affect the WOM of other products. Specifically, a product on e-commerce platform is seldom "isolated," but has many recommenders recommending it, resulting in a network of products [54].

Network theory [68] hence comes into play, as it asserts that connected network nodes are often interdependent through the influence of the attributes of network nodes (e.g., [16, 29, 38, 40, 53, 55]). In the context of a product network, products are likely to influence one another through their WOM attributes, such as valence and volume. This concurs with studies on human judgment and decision making (e.g., [39, 50]), which have shown that consumers' product evaluations and perceptions of product preferences are determined largely by the "reference points" used, rather than by absolute values alone [17, 51].

When consumers have little knowledge about the focal product, references become necessary [41]. Network theory hints at the likelihood of consumers in associating or even equating the excellence level of the focal product to that of the recommenders in the incoming network. After all, it is noted that "Customers who bought this item also bought" (on Amazon), thereby signaling to consumers that the focal product and its recommenders actually belong to the same preference group purchased by consumers. As WOM valence signals product quality [32] and volume signals product popularity [45], an increase in the WOM valence or volume of incoming network products (i.e., higher perceived product quality or popularity) may enhance consumers' positive evaluations of the focal product, and consequently, result in an increase in the WOM valence. Likewise, an increase in the WOM valence or volume of incoming network products may help attract a larger group of potential consumers to arrive at the focal products because of higher perceived product quality and popularity. These incoming network products explicitly provide visible connections to the focal product to make it easily accessible [16]. Consequently, this heightened exposure may drive consumers' purchases and contributions to the WOM volume of the focal product. In essence, network theory helps predict the associative assessment of a product from its incoming product network links. Hence, we conjecture:

Hypothesis 3: An increase in the WOM (in terms of valence and volume) of incoming network products results in an increase in the WOM valence of the focal product.

Hypothesis 4: An increase in the WOM (in terms of valence and volume) of incoming network products results in an increase in the WOM volume of the focal product.

Empirical Method and Analysis

Data Description

We assembled our data set from Tmall.com, which is China's largest B2C e-commerce platform under the Alibaba Group. Indeed, it has been listed by Alexa as the most visited B2C online retail website in China [1]. In September 2014, Alibaba launched the largest IPO (initial public offering) in U.S. history. Thus, Tmall has attracted significant attention from both China and overseas.

Tmall, which complements Taobao's consumer-to-consumer (C2C) business, was launched in April 2008 but became independent in June 2011. As of March 2013, more than 70,000 international and Chinese brands or retailers have established retail stores on Tmall [66], and each retailer is in charge of the sales and customer service for all the products in his or her own store. Similar to products on Amazon, each product on Tmall is featured on its own designated webpage, including all relevant information such as WOM (i.e., product reviews), list price, inventory, and so on. Moreover, on each product webpage, Tmall also employs recommender systems based on the collaborative filtering approach (which is also adopted by Amazon) to provide relevant product recommendations. For instance, for each focal product, recommender systems will first identify the group of consumers who have purchased it. Then the systems will further identify what other products these consumers also purchased subsequently and provide these copurchased products as recommendations to the focal product. Thus, these recommendations establish links from the product on a page to those recommended products. In other words, these recommendation links jointly form a network of all the products in the store. Notably, recommender systems in a store recommend only products that are from the same store. Unlike other e-commerce platforms, Tmall also releases the transaction records for each product on its respective webpage. Thus, actual transaction information allows us to construct a direct measure for product sales, instead of using sales proxies as was the case in prior related studies.

We obtain data on all 235 products sold in an online flagship store selling Nikon products.[9] As it is infeasible to observe all real-time changes of product information, especially those of the product network structure, we collect data on product information and product network structure on a daily basis (12:00 midnight) from May to December 2012. Consequently, our data set includes three parts: (1) daily snapshots of product information (e.g., WOM, price), (2) daily snapshots of product network structure, and (3) detailed individual product transaction records (e.g., sales quantity, transaction time).

Empirical Models

Based on our data set, we operationalize all relevant variables at the product-day level.[10] Let subscript i denote each individual product and subscript t denote each day. In order to test our four hypotheses (H1, H2, H3, and H4), we denote four model specifications:

$$\begin{aligned}\text{To test H1: } VAL\_DEC_{it} = {} & \alpha_1 * VAL_{i,t-1} + \alpha_2 * VOL_{i,t-1} + \alpha_3 * QUAN_{it} \\ & + \alpha_4 * LP_{it} + \alpha_5 * PS_{it} + \alpha_6 * IN_{it} + \alpha_7 * BM_{it} \\ & + \alpha_8 * DC\_NW_{it} + \alpha_9 * QUAN\_NW_{it} \\ & + \alpha_{10} * LP\_NW_{it} + \theta_i + T_t + \varepsilon_{it}\end{aligned} \tag{1}$$

$$\text{To test H2: } VOL\_INC_{it} = \beta_1 * VAL_{i,t-1} + \beta_2 * VOL_{i,t-1} + \beta_3 * QUAN_{it} + \beta_4 * LP_{it} + \beta_5 * PS_{it} + \beta_6 * IN_{it} + \beta_7 * BM_{it} + \beta_8 * DC\_NW_{it} + \beta_9 * QUAN\_NW_{it} + \beta_{10} * LP\_NW_{it} + \theta_i + T_t + \mu_{it} \quad (2)$$

$$\text{To test H3: } VAL_{it} = \gamma_1 * VAL\_NW_{i,t-1} + \gamma_2 * VOL\_NW_{i,t-1} + \gamma_3 * QUAN_{it} + \gamma_4 * LP_{it} + \gamma_5 * PS_{it} + \gamma_6 * IN_{it} + \gamma_7 * BM_{it} + \gamma_8 * DC\_N\mathrm{W}_{it} + \gamma_9 * QUAN\_N\mathrm{W}_{it} + \gamma_{10} * LP\_N\mathrm{W}_{it} + \theta_i + T_t + \omega_{it} \quad (3)$$

$$\text{To test H4: } VOL_{it} = \lambda_1 * VAL\_NW_{i,t-1} + \lambda_2 * VOL\_NW_{i,t-1} + \lambda_3 * QUAN_{it} + \lambda_4 * LP_{it} + \lambda_5 * PS_{it} + \lambda_6 * IN_{it} + \lambda_7 * BM_{it} + \lambda_8 * DC\_NW_{it} + \lambda_9 * QUAN\_NW_{it} + \lambda_{10} * LP\_NW_{it} + \theta_i + T_t + \sigma_{it} \quad (4)$$

Specifically, to test how a product's WOM affects its subsequent WOM growth (H1 and H2), we use two *independent variables* $VAL_{i,t–1}$ and $VOL_{i,t–1}$, where $VAL_{i,t–1}$ indicates product *i*'s average rating of consumer reviews up to day $t – 1$, and $VOL_{i,t–1}$ indicates product *i*'s cumulative number of consumer reviews up to day $t – 1$. The two *dependent variables* are VAL_DEC_{it} and VOL_INC_{it}. VAL_DEC_{it} indicates the *decrease* of WOM valence of product *i* in day *t*, measured as the difference between $VAL_{i,t–1}$ and VAL_{it} (i.e., $VAL_{i,t–1} – VAL_{it}$), whereas VOL_INC_{it} indicates the *increase* in WOM volume of product *i* in day *t*, measured as the difference between VOL_{it} and $VOL_{i,t–1}$ (i.e., $VOL_{it} – VOL_{i,t–1}$).

Next, to investigate how a product's WOM is affected by the WOM of connected products in a network (H3 and H4), we used focal product *i*'s WOM valence and volume (i.e., VAL_{it} and VOL_{it}) as the *dependent variables*, to examine how they are influenced by the two *independent variables* $VAL\_NW_{i,t–1}$ and $VOL\_NW_{i,t–1}$, where $VAL\_NW_{i,t–1}$ ($VOL\_NW_{i,t–1}$) represents the average rating (average cumulative number) of consumer reviews (up to day $t – 1$) of all the products pointing to focal product *i* in the network.

Finally, we also have *control variables* gathered from our literature review and available in our data set, at the product, product network, and time unit levels. These include: (1) product sales quantity ($QUAN_{it}$),[11] (2) product *i*'s list price (inclusive of discounts, if any) (LP_{it}), (3) product past monthly sales quantity (PS_{it}),[12] (4) product inventory(IN_{it}),[13] (5) number of webpage bookmarks (BM_{it}),[14] (6) network degree centrality (DC_NW_{it}),[15] (7) average sales quantity of products in the network ($QUAN\_NW_{it}$),[16] (8) average list price of products in the network (LP_NW_{it}),[17] (9) product fixed effects (θ_i), and (10) time fixed effects at the daily level (T_t).

It should be noted that, based on our research questions and hypotheses, we consider the dependent variables in Equations (1) to (4) in the current time period (*t*), but the major independent variables in the previous time period ($t – 1$) to

Table 1. Descriptive Statistics

Variable	Mean	Std. dev.	Min	Max
VAL_DEC (WOM valence decrease)	–0.004	0.167	–5.000	4.800
VOL_INC (WOM volume increase)	0.071	0.359	0.000	9.000
VAL (WOM valence)	3.669	2.008	0.000	5.000
VOL (WOM volume)	27.048	61.235	0.000	385.000
VAL_NW (Network product WOM valence)	3.236	1.341	0.000	5.000
VOL_NW (Network product WOM volume)	19.469	22.669	0.000	248.000
QUAN (Product sales quantity)	0.269	1.138	0.000	28.000
LP (Product list price, in thousands)	6.496	10.112	0.376	47.000
PS (Product past monthly sales quantity)	8.411	22.418	0.000	223.000
IN (Product inventory, in thousands)	0.633	0.919	0.002	8.291
BM (Number of web page bookmarks)	529.617	1,560.595	0.000	12,623.000
DC_NW (Network degree centrality)	11.273	13.192	0.000	77.000
QUAN_NW (Network product sales quantity)	0.208	0.472	0.000	8.667
LP_NW (Network product list price, in thousands)	5.762	7.611	0.000	75.888

Note: Number of observations = 8,368. All variables are at the product-day level.

examine the evolution of WOM.[18] Moreover, we use this time lag to avoid potential simultaneity issues. Table 1 reports the descriptive statistics, and Table 2 reports the correlation matrix.

Empirical Results

Baseline results

We first estimate a fixed effects (FE) model of Equation (1) to investigate the impact of prior WOM valence ($VAL_{i,t-1}$) on the subsequent decrease of WOM valence (VAL_DEC_{it}). Table 3, column (1) summarizes the estimation results. As indicated, control variables such as $QUAN_{it}$, PS_{it}, $QUAN\_NW_{it}$ are statistically significant, suggesting that our control variables have explanatory power. More important, the coefficient of the independent variable $VAL_{i,t-1}$ is statistically significant and has the expected positive sign. This shows that higher prior WOM valence will result in a larger subsequent decrease of WOM valence.

We next estimate an FE model of Equation (2) to examine the impact of prior WOM volume ($VOL_{i,t-1}$) on the subsequent increase in WOM volume (VOL_INC_{it}). Table 3, column (2) reports the estimation results. As expected, the coefficient of the focus variable $VOL_{i,t-1}$ is negative and statistically significant. This shows that higher prior WOM volume will lead to a smaller subsequent increase in WOM volume.

Table 2. Correlations

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1 *VAL_DEC* (WOM valence decrease)	—													
2 *VOL_INC* (WOM volume increase)	–0.089	—												
3 *VAL* (WOM valence)	–0.024	0.108	—											
4 *VOL* (WOM volume)	0.012	0.327	0.231	—										
5 *VAL_NW* (Network product WOM valence)	–0.007	0.029	0.301	0.080	—									
6 *VOL_NW* (Network product WOM volume)	0.010	0.008	0.206	0.014	0.417	—								
7 *QUAN* (Product sales quantity)	–0.039	0.352	0.115	0.367	0.033	0.009	—							
8 *LP* (Product list price)	0.004	–0.081	–0.461	–0.176	–0.380	–0.264	–0.094	—						
9 *PS* (Product past monthly sales quantity)	0.007	0.534	0.194	0.647	0.022	–0.005	0.575	–0.148	—					
10 *IN* (Product inventory)	0.007	0.092	0.237	0.206	0.176	0.183	0.100	–0.247	0.150	—				
11 *BM* (Number of web page bookmarks)	0.010	0.266	0.170	0.817	–0.026	–0.078	0.326	–0.089	0.568	0.117	—			
12 *DC_NW* (Network degree centrality)	0.004	0.219	0.289	0.501	0.024	–0.089	0.234	–0.173	0.480	0.174	0.540	—		
13 *QUAN_NW* (Network product sales quantity)	–0.055	0.045	0.088	0.069	0.199	0.406	0.146	–0.126	0.081	0.063	–0.002	–0.024	—	
14 *LP_NW* (Network product list price)	–0.004	–0.083	–0.347	–0.177	–0.384	–0.274	–0.094	0.762	–0.148	–0.229	–0.091	–0.156	–0.137	—

Table 3. Baseline Results

Variable	(1) H1	(2) H2	(3) H3	(4) H4
VAL	0.018***	0.008**		
(WOM valence)	(0.002)	(0.004)		
VOL	0.000	–0.001***		
(WOM volume)	(0.000)	(0.000)		
VAL_NW			0.022**	0.180
(Network product WOM valence)			(0.010)	(0.123)
VOL_NW			0.003***	–0.003
(Network product WOM volume)			(0.001)	(0.007)
QUAN	–0.006***	0.009**	0.039***	–0.606***
(Product sales quantity)	(0.002)	(0.004)	(0.011)	(0.135)
LP	0.000	–0.004	0.040***	–0.174
(Product list price)	(0.002)	(0.003)	(0.011)	(0.129)
PS	0.000**	0.005***	0.010***	0.143***
(Product past monthly sales quantity)	(0.000)	(0.000)	(0.001)	(0.011)
IN	–0.001	–0.003	0.081***	–2.101***
(Product inventory)	(0.003)	(0.005)	(0.016)	(0.190)
BM	0.000	–0.000***	0.000***	0.026***
(Number of web page bookmarks)	(0.000)	(0.000)	(0.000)	(0.001)
DC_NW	–0.000	0.002***	0.014***	0.024
(Network degree centrality)	(0.000)	(0.000)	(0.001)	(0.016)
QUAN_NW	–0.015***	–0.008	0.050*	0.419
(Network product sales quantity)	(0.005)	(0.008)	(0.027)	(0.316)
LP_NW	0.000	0.000	–0.011***	0.033
(Network product list price)	(0.000)	(0.001)	(0.002)	(0.028)
Constant	–0.066*	0.369***	2.841***	18.741***
	(0.037)	(0.066)	(0.203)	(2.415)
Time dummies	-included-	-included-	-included-	-included-
Number of observations	8,268	8,268	8,268	8,268
R^2	0.0225	0.0169	0.0034	0.6888

Notes: Standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

To investigate the role of WOM in a product network, we further estimate an FE model of Equations (3) and (4) to explore how WOM valence and volume of products in the network ($VAL\_NW_{i,t-1}$ and $VOL\_NW_{i,t-1}$) affect the WOM valence and volume of the focal product (VAL_{it} and VOL_{it}). The results are summarized in Table 3, columns (3) and (4), respectively. As shown in column (3), both coefficients of $VAL\_NW_{i,t-1}$ and $VOL\_NW_{i,t-1}$ are significant and have a positive sign. This provides interesting evidence that both the WOM valence and WOM volume of connected products in the network will positively contribute to the WOM valence of the focal product. However, results in column (4) show that the WOM valence and WOM volume of connected products in the network have no significant impact on the WOM volume of the focal product.

Identification

With the above significant relationships identified, we further explain our identification strategies to establish further support for a causal influence interpretation. Specifically, we treat our major independent variables (i.e., *VAL* and *VOL* in Equations [1] and [2], *VAL_NW* and *VOL_NW* in Equations [3] and [4]) as potentially endogeneous variables. Our first identification strategy makes use of instrumental variables (IVs). Suitable instruments would be factors that have high correlations with our focus independent variables, but not the dependent variables. Based on this criterion, we construct the same set of independent variables as instruments using similar data from another three Nikon stores on Tmall. Specifically, a product can be sold in multiple stores with different product IDs on Tmall. Thus, for each focal product in each day in our focal store, we identify the corresponding values of *VAL* and *VOL* of the same product in the other three Nikon stores. We then compute the average values of *VAL* and *VOL* across the three stores as the instruments for *VAL* and *VOL* in Equations (1) and (2).

To reiterate, *VAL* and *VOL* from other stores would have high correlations with those of the same product in the focal store, because a product, although sold in different stores, is likely to be evaluated and preferred by Tmall consumers, and to experience a similar level of WOM (*VAL* and *VOL*) even across stores on Tmall. However, *VAL* and *VOL* from other stores are unlikely to shift *VAL_DEC* or *VOL_INC* of products in the focal store. Thus, we believe they could serve as valid instruments.

Likewise, we obtain similar instruments for *VAL_NW* and *VOL_NW* in Equations (3) and (4). We believe a product is likely to be recommended (i.e., connected in the network) by similar products in different stores due to similar consumer purchase patterns on Tmall, and thus *VAL_NW* and *VOL_NW* in different stores could be highly correlated. However, *VAL_NW* and *VOL_NW* from other stores are unlikely to be correlated with the WOM (*VAL* and *VOL*) of products in the focal store. Therefore, they also serve as reasonable instruments.

We perform FE two-stage least squares regression with IVs. As is customary, the endogenous independent variable is estimated using the instrumental variables in the first stage, and these estimated values are used as independent variables in the second stage. As our model includes two potentially endogenous variables (i.e., *VAL* and *VOL* in Equations (1) and (2), *VAL_NW* and *VOL_NW* in Equations (3) and (4)), we generate estimated values for both these variables in the first stage. The estimation results are summarized in Table 4, columns (2), (4), (6) and (8). For ease of reference, Table 4 columns (1), (3), (5), and (7) present the baseline results from Table 3. As indicated, all the significant relationships identified in our baseline analysis are further supported after the potential endogeneity has been accounted for.

Our second identification strategy is based on a difference-in-differences (DID) model estimation approach, similar to the one used in Chevalier and Mayzlin [19]. Specifically, we examine whether a change in independent variables over time for a particular product in the focal store relative to the other Tmall Nikon store predicts a

Table 4. Identification: Instrumental Variable

	H1		H2		H3		H4	
Variable	(1) Baseline	(2) IV	(3) Baseline	(4) IV	(5) Baseline	(6) IV	(7) Baseline	(8) IV
VAL	0.018***	0.009*	0.008**	0.001				
(WOM valence)	(0.002)	(0.005)	(0.004)	(0.008)				
VOL	0.000	0.000	–0.001***	–0.002***				
(WOM volume)	(0.000)	(0.000)	(0.000)	(0.000)				
VAL_NW					0.022**	0.136***	0.180	–0.421
(Network product WOM valence)					(0.010)	(0.037)	(0.123)	(0.452)
VOL_NW					0.003***	0.010***	–0.003	0.346***
(Network product WOM volume)					(0.001)	(0.003)	(0.007)	(0.042)
QUAN	–0.006***	–0.006***	0.009**	0.008**	0.039***	0.038***	–0.606***	–0.614***
(Product sales quantity)	(0.002)	(0.002)	(0.004)	(0.004)	(0.011)	(0.011)	(0.135)	(0.137)
LP	0.000	0.001	–0.004	–0.002	0.040***	0.038***	–0.174	–0.361***
(Product list price)	(0.002)	(0.002)	(0.003)	(0.004)	(0.011)	(0.011)	(0.129)	(0.135)
PS	0.000**	0.001***	0.005***	0.005***	0.010***	0.008***	0.143***	0.140***
(Product past monthly sales quantity)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.011)	(0.011)
IN	–0.001	0.001	–0.003	–0.002	0.081***	0.037**	–2.101***	–2.342***
(Product inventory)	(0.003)	(0.003)	(0.005)	(0.006)	(0.016)	(0.017)	(0.190)	(0.203)
BM	0.000	0.000	–0.000***	–0.000***	0.000***	0.000**	0.026***	0.026***
(Number of web page bookmarks)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
DC_NW	–0.000	0.000	0.002***	0.002***	0.014***	0.014***	0.024	0.031*
(Network degree centrality)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.016)	(0.016)
QUAN_NW	–0.015***	–0.015***	–0.008	–0.007	0.050*	0.094***	0.419	0.422
(Network product sales quantity)	(0.005)	(0.005)	(0.008)	(0.009)	(0.027)	(0.026)	(0.316)	(0.321)

(continues)

Table 4. Continued

Variable	H1 (1) Baseline	H1 (2) IV	H2 (3) Baseline	H2 (4) IV	H3 (5) Baseline	H3 (6) IV	H4 (7) Baseline	H4 (8) IV
LP_NW	0.000	–0.000	0.000	0.000	–0.011***	–0.010***	0.033	0.039
(Network product list price)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)	(0.002)	(0.028)	(0.029)
Constant	–0.066*	–0.035	0.369***	0.143	2.841***	3.187***	18.741***	12.494***
	(0.037)	(0.053)	(0.066)	(0.093)	(0.203)	(0.291)	(2.415)	(3.544)
Time dummies	-included-	-included-	-included-	-included-	-included-	-included-	-included-	-included-
Number of observations	8,268	7,911	8,268	7,911	8,268	7,911	8,268	7,911
R^2	0.0225	0.0232	0.0169	0.0157	0.0034	0.0063	0.6888	0.6959

Notes: Standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

change in the dependent variables of that product in the focal store relative to the other. By using this DID approach to focus on the differences across stores over time, we are able to eliminate unobserved fixed effects, if any, which might be correlated with our independent variables of interest and would bias the estimated coefficients if they are omitted. The DID model estimation results are presented in Table 5 columns (2), (4), (6) and (8). Table 5 columns (1), (3), (5) and (7) present the baseline results from Table 3. As indicated, the DID estimation results are generally consistent with the baseline results.

In sum, after accounting for the potential endogeneity and controlling for unobserved confounding factors, we identify several notable impacts. We summarize all hypothesis testing results in Table 6. First, prior WOM valence of a product ($VAL_{i,t-1}$) will result in a larger subsequent decrease of the product's WOM valence (VAL_DEC_{it}). Thus, H1 is supported. Second, prior WOM volume of a product ($VOL_{i,t-1}$) will lead to a smaller subsequent increase in the product's WOM volume (VOL_INC_{it}). Thus, H2 is supported. Last, the impacts of $VAL\_NW_{i,t-1}$ and $VOL\_NW_{i,t-1}$ are significant on VAL_{it} but not on VOL_{it}, suggesting that the WOM valence and volume of products connected in the network would drive the valence, but not the volume, of the focal product. Therefore, H3 is supported but H4 is not supported.

Robustness checks

We further corroborate our findings by checking the robustness in multiple ways. First, we dismiss alternative explanations for the ceiling effect when H1 is supported (i.e., higher WOM valence will result in a larger subsequent decrease of WOM valence). Some may rationalize that since the star ratings are bounded between 0 (lower ceiling) and 5 (upper ceiling) for WOM valence, it could be the case that a higher valence naturally has more margin to decrease (e.g., from 5 to 0) than a lower valence (e.g., from 3 to 0). To alleviate this concern, we separate our sample into two subgroups based on the mean of *VAL* (i.e., below mean group and above mean group), and then estimate our model based on these two subsamples. The results are summarized in Table 7, columns (2) and (3). For brevity, from this point onward, we report only the major variables of interest for hypothesis testing. Compared with the baseline results in column (1), the consistent positive effect of *VAL* in both subgroups affirms that our finding is robust across differences in the value of *VAL*. In other words, this implies that higher WOM valence will result in a larger subsequent decrease of WOM valence, regardless of the current level of WOM valence. Likewise, we also separate our sample into two subgroups based on the median of *VAL*. The consistent results are shown in Table 7 columns (4) and (5).

Second, we seek to rule out the potential concerns over confounding effects of valence variance. Specifically, some may rationalize that H1 is supported due to the possibility that the WOM valence of a product might fluctuate and eventually arrive at its "true" value (i.e., the actual WOM valence a product deserves). Thus, if the

Table 5. Identification: Difference-in-Differences

	H1		H2		H3		H4	
Variable	(1) Baseline	(2) DID	(3) Baseline	(4) DID	(5) Baseline	(6) DID	(7) Baseline	(8) DID
VAL	0.018***	0.882***	0.008**	1.009***				
(WOM valence)	(0.002)	(0.013)	(0.004)	(0.116)				
VOL	0.000	0.001***	–0.001***	–0.947***				
(WOM volume)	(0.000)	(0.000)	(0.000)	(0.003)				
VAL_NW					0.022**	–0.002	0.180	0.057
(Network product WOM valence)					(0.010)	(0.003)	(0.123)	(0.095)
VOL_NW					0.003***	0.000**	–0.003	0.002
(Network product WOM volume)					(0.001)	(0.000)	(0.007)	(0.003)
QUAN	–0.006***	–0.002**	0.009**	–0.005	0.039***	0.003***	–0.606***	0.016
(Product sales quantity)	(0.002)	(0.001)	(0.004)	(0.010)	(0.011)	(0.001)	(0.135)	(0.029)
LP	0.000	–0.006	–0.004	–0.074	0.040***	0.011	–0.174	–0.042
(Product list price)	(0.002)	(0.022)	(0.003)	(0.198)	(0.011)	(0.021)	(0.129)	(0.592)
PS	0.000**	0.000	0.005***	–0.009	0.010***	0.002**	0.143***	–0.038*
(Product past monthly sales quantity)	(0.000)	(0.001)	(0.000)	(0.007)	(0.001)	(0.001)	(0.011)	(0.020)
IN	–0.001	0.002	–0.003	–0.188	0.081***	0.050**	–2.101***	–0.808
(Product inventory)	(0.003)	(0.025)	(0.005)	(0.227)	(0.016)	(0.024)	(0.190)	(0.677)
BM	0.000	–0.002***	–0.000***	0.006***	0.000***	0.002***	0.026***	0.153***
(Number of web page bookmarks)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.002)
DC_NW	–0.000	0.001	0.002***	0.009	0.014***	0.001	0.024	0.024
(Network degree centrality)	(0.000)	(0.001)	(0.000)	(0.009)	(0.001)	(0.001)	(0.016)	(0.025)
QUAN_NW	–0.015***	0.001	–0.008	–0.015	0.050*	0.000	0.419	0.038
(Network product sales quantity)	(0.005)	(0.001)	(0.008)	(0.012)	(0.027)	(0.001)	(0.316)	(0.034)
LP_NW	0.000	–0.001	0.000	0.003	–0.011***	0.001	0.033	0.007

(Network product list price)	(0.000)	(0.001)	(0.001)	(0.008)	(0.002)	(0.001)	(0.028)	(0.023)
Constant	–0.066*	–0.002	0.369***	0.268	2.841***	–0.002	18.741***	–0.501
	(0.037)	(0.080)	(0.066)	(0.736)	(0.203)	(0.078)	(2.415)	(2.195)
Time dummies	-included-	-included-	-included-	-included-	-included-	-included-	-included-	-included-
Number of observations	8,268	6,687	8,268	6,687	8,268	6,687	8,268	6,687
R^2	0.0225	0.5351	0.0169	0.9307	0.0034	0.1411	0.6888	0.4818

Notes: Standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 6. Hypothesis Testing Results

Hypothesis		Support
H1	Higher WOM valence of a product results in a larger subsequent decrease in the WOM valence of the product.	Yes
H2	Higher WOM volume of a product results in a smaller subsequent increase in the WOM volume of the product.	Yes
H3	An increase in the WOM (in terms of valence and volume) of incoming network products results in an increase in the WOM valence of the focal product.	Yes
H4	An increase in the WOM (in terms of valence and volume) of incoming network products results in an increase in the WOM volume of the focal product.	No

valence largely departs from its "true" value, we may expect a larger fluctuation in the subsequent valence. To dismiss this alternative explanation that the larger subsequent decrease of WOM valence is due to this fluctuation, we construct the valence variance variable (i.e., *VAL_VAR*, the variance of valence across all the previous days) as a proxy of valence fluctuation. After controlling for this fluctuation impact in our model, our estimate in Table 7, column (6) remains consistent. Third, we next address the potential concern over ceiling effect of WOM volume in support for H2. Some may assume that as WOM volume of a product keeps increasing, it simply slows down as WOM has reached its "highest" level (i.e., ceiling), if any. The potential ceiling might exist because consumers have gradually lost interest in the product over time and thus become less likely to purchase, and less likely to contribute additional WOM subsequently. To rule out this alternative explanation for subsequently smaller WOM volume (due to lower sales/interests of products), we first highlight that we have already controlled for product sales quantity (*QUAN*) in all our models, thus sales quantity should not be a factor confounding the impact of prior WOM volume on subsequent volume increase. Nevertheless, to make our assertions and results even more compelling, we further address this concern by replacing the dependent variable, VOL_INC_{it} (the absolute number of WOM volume increase), with the WOM volume increase over product sales quantity (i.e., $VOL\_INC_{it}/QUAN_{it}$) to investigate the increase in WOM volume, conditional on product sales. As $QUAN_{it}$ may contain "zeros," we also construct another similar measure by adding "one" to the denominator to avoid dividing by zeros. We estimate our model using these two new measures and summarize the results in Table 8, columns (2) and (3), respectively. Compared with the baseline results in column (1), the significant and negative impact of *VOL* remains consistent. This corroborates our original findings that higher WOM volume will result in a smaller subsequent WOM volume increase, regardless of volume ceiling. In addition, as a robustness check on alternative measures, we replace the dependent variable, VOL_INC_{it}, with the percentage of volume increase compared to the previous day (i.e., $VOL\_INC_{it}/VOL_{i,t-1}$ and $VOL\_INC_{it}/(VOL_{i,t-1} + 1)$). The results

Table 7. Robustness Check: Valence Ceiling Effect and Valence Variance (H1)

Variable	(1) Baseline	By mean (2) Below mean	By mean (3) Above mean	By median (4) Below median	By median (5) Above median	(6) Variance
VAL	0.018***	0.337***	0.579***	0.018***	0.717***	0.016***
(WOM valence)	(0.002)	(0.017)	(0.007)	(0.002)	(0.008)	(0.003)
VOL	0.000	–0.388***	0.001***	–0.000*	0.001***	0.000
(WOM volume)	(0.000)	(0.022)	(0.000)	(0.000)	(0.000)	(0.000)
VAL_VAR						0.003
(WOM valence variance)						(0.002)
Constant	–0.066*	–0.027	–2.793***	–0.011	–3.557***	–0.059
	(0.037)	(0.113)	(0.041)	(0.025)	(0.058)	(0.037)
Control variables	-included-	-included-	-included-	-included-	-included-	-included-
Number of observations	8,268	1,982	6,286	4,821	3,447	8,268
R^2	0.0225	0.2406	0.4214	0.0027	0.6784	0.0234

Notes: Standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 8. Robustness Check: Volume Ceiling Effect and Alternative Measure (H2)

Variable	(1) Baseline	By *QUAN* (2) $\frac{VOL\_INC_{it}}{QUAN_{it}}$	By *QUAN* (3) $\frac{VOL\_INC_{it}}{QUAN_{it}+1}$	By *VOL* (4) $\frac{VOL\_INC_{it}}{VOL_{i,t-1}}$	By *VOL* (5) $\frac{VOL\_INC_{it}}{VOL_{i,t-1}+1}$
VAL	0.008**	0.008	0.005**	0.008*	–0.002***
(WOM valence)	(0.004)	(0.019)	(0.002)	(0.005)	(0.001)
VOL	–0.001***	–0.003***	–0.001**	–0.000***	–0.000***
(WOM volume)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Constant	0.369***	–0.195	0.157***	–0.019	0.032***
	(0.066)	(0.629)	(0.045)	(0.026)	(0.010)
Control variables	-included-	-included-	-included-	-included-	-included-
Number of observations	8,268	836	8,268	6,398	8,268
R^2	0.0169	0.0420	0.0912	0.0248	0.0270

Notes: Standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

are presented in Table 8, columns (4) and (5), and are again consistent with the baseline results, suggesting that higher WOM volume will result in a smaller WOM volume increase regardless of our adoption of absolute numbers as measures or relative percentages as measures.

Fourth, we attempt to account for the plausible effects, if any, of product life cycle (1) assuming a linear effect; and (2) assuming a nonlinear effect. First, some may be concerned that new products introduced into the market might attract more attention and WOM from consumers, relative to old or outdated products (i.e., a linear effect). In other words, product age in the market might influence product WOM. Although Tmall does not state the dates of product entrance into the market, we can gather this information from other websites (i.e., Amazon) that carry similar products using "Date first available at Amazon.com." With this information, we compute for each of our product its product age variable (i.e., number of days existing in the market). We include this variable in our Equations (1) to (4) and present the estimation results in Table 9, columns (2), (4), (6), and (8). Most important, after controlling for product age, the results remain consistent with our baseline results reported in columns (1), (3), (5), and (7). The negative impact of product age in columns (6) and (8) is as predicted and does not affect our original robust results. Second, some may assume the plausible effect of product life cycle, if any, to be nonlinear, rather than linear. They rationalize that, in the beginning, new products will capture increasing attention, but will soon plateau and dwindle as the product matures. However, when the product is about to become obsolete, attention may once again rise. Hence, we have also included a squared term of product age to capture its potentially nonlinear effect. Our findings are consistent and robust. The results are not given here due to space constraints, but are available upon request.

As mentioned in the previous paragraph, it should be noted that some may attribute the ceiling effect of WOM volume due to waning interest (or the introduction of new products). Hence, our current robustness checks that account for product age again help to rule out the alternative explanation of ceiling effect and to further validate H2.

Fifth, to make our results more convincing, we check the robustness of our findings across differences in data samples so as to rule out any possible sample selection bias. We initially focus on the digital camera category from the Nikon store so as to more precisely and cleanly arrive at an unambiguous investigation. We now include all the product categories as our new sample, and reestimate Equations (1) to (4) with product category fixed effects included. As reported in Table 10, columns (2), (4), (6), and (8), the results remain consistent.

Sixth, to boost the robustness of our findings, we further check whether our findings remain unchanged based on different product categories. Instead of using digital cameras, we now collect data on notebook computers, mobile phones, and hair-care products from three additional stores on Tmall. The results in Tables 11 to 13 report findings similar to those using the digital camera category, which lends credence to our original findings.

Finally, we also ensure the robustness of our findings across time differences. Specifically, our main sample is organized at the product-day level. We reorganize

Table 9. Robustness Check: Product Age

Variable	H1		H2		H3		H4	
	(1) Baseline	(2) Age	(3) Baseline	(4) Age	(5) Baseline	(6) Age	(7) Baseline	(8) Age
VAL	0.018***	0.018***	0.008**	0.008**				
(WOM valence)	(0.002)	(0.002)	(0.004)	(0.004)				
VOL	0.000	0.000	–0.001***	–0.001***				
(WOM volume)	(0.000)	(0.000)	(0.000)	(0.000)				
VAL_NW					0.022**	0.023**	0.180	0.230*
(Network product WOM valence)					(0.010)	(0.011)	(0.123)	(0.128)
VOL_NW					0.003***	0.003***	–0.003	–0.004
(Network product WOM volume)					(0.001)	(0.001)	(0.007)	(0.008)
AGE		0.000		0.000		–0.003***		–0.042***
(Product age)		(0.000)		(0.000)		(0.001)		(0.007)
Constant	–0.066*	–0.076	0.369***	0.324***	2.841***	3.794***	18.741***	36.712***
	(0.037)	(0.058)	(0.066)	(0.103)	(0.203)	(0.319)	(2.415)	(3.794)
Control variables	-included-	-included-	-included-	-included-	-included-	-included-	-included-	-included-
Number of observations	8,268	7,877	8,268	7,877	8,268	7,877	8,268	7,877
R^2	0.0225	0.0231	0.0169	0.0175	0.0034	0.0075	0.6888	0.6809

Notes: Standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 10. Robustness Check: All Categories

	H1		H2		H3		H4	
Variable	(1) Baseline	(2) All	(3) Baseline	(4) All	(5) Baseline	(6) All	(7) Baseline	(8) All
VAL	0.018***	0.020***	0.008**	0.000				
(WOM valence)	(0.002)	(0.001)	(0.004)	(0.001)				
VOL	0.000	0.000	–0.001***	–0.001***				
(WOM volume)	(0.000)	(0.000)	(0.000)	(0.000)				
VAL_NW					0.022**	0.018***	0.180	0.164***
(Network product WOM valence)					(0.010)	(0.005)	(0.123)	(0.032)
VOL_NW					0.003***	0.002***	–0.003	0.004
(Network product WOM volume)					(0.001)	(0.000)	(0.007)	(0.003)
Constant	–0.066*	–0.051**	0.369***	0.068***	2.841***	2.200***	18.741***	6.234***
	(0.037)	(0.022)	(0.066)	(0.020)	(0.203)	(0.118)	(2.415)	(0.831)
Control variables	-included-	-included-	-included-	-included-	-included-	-included-	-included-	-included-
Number of observations	8,268	34,763	8,268	34,763	8,268	34,763	8,268	34,763
R^2	0.0225	0.0037	0.0169	0.0235	0.0034	0.0476	0.6888	0.6704

Notes: Standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 11. Robustness Check: Notebook Computers

Variable	H1 (1) Baseline	H1 (2) Notebooks	H2 (3) Baseline	H2 (4) Notebooks	H3 (5) Baseline	H3 (6) Notebooks	H4 (7) Baseline	H4 (8) Notebooks
VAL	0.018***	0.057***	0.008**	–0.045***				
(WOM valence)	(0.002)	(0.004)	(0.004)	(0.008)				
VOL	0.000	0.004***	–0.001***	–0.023***				
(WOM volume)	(0.000)	(0.001)	(0.000)	(0.002)				
VAL_NW					0.022**	0.128***	0.180	0.148**
(Network product WOM valence)					(0.010)	(0.015)	(0.123)	(0.062)
VOL_NW					0.003***	0.007***	–0.003	–0.032***
(Network product WOM volume)					(0.001)	(0.002)	(0.007)	(0.007)
Constant	–0.066*	–0.293	0.369***	0.213	2.841***	0.336	18.741***	28.379***
	(0.037)	(0.290)	(0.066)	(0.601)	(0.203)	(0.887)	(2.415)	(3.744)
Control variables	-included-	-included-	-included-	-included-	-included-	-included-	-included-	-included-
Number of observations	8,268	8,207	8,268	8,207	8,268	8,207	8,268	8,207
R^2	0.0225	0.0821	0.0169	0.0064	0.0034	0.1242	0.6888	0.0324

Notes: Standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 12. Robustness Check: Mobile Phones

	H1		H2		H3		H4	
Variable	(1) Baseline	(2) Mobile phones	(3) Baseline	(4) Mobile phones	(5) Baseline	(6) Mobile phones	(7) Baseline	(8) Mobile phones
VAL	0.018***	0.065***	0.008**	0.031*				
(WOM valence)	(0.002)	(0.003)	(0.004)	(0.017)				
VOL	0.000	0.000	–0.001***	–0.003***				
(WOM volume)	(0.000)	(0.000)	(0.000)	(0.000)				
VAL_NW					0.022**	0.122***	0.180	–4.405***
(Network product WOM valence)					(0.010)	(0.008)	(0.123)	(1.300)
VOL_NW					0.003***	0.000**	–0.003	–0.007
(Network product WOM volume)					(0.001)	(0.000)	(0.007)	(0.006)
Constant	–0.066*	–0.183***	0.369***	–0.443	2.841***	2.253***	18.741***	–122.311***
	(0.037)	(0.041)	(0.066)	(0.283)	(0.203)	(0.126)	(2.415)	(19.639)
Control variables	-included-	-included-	-included-	-included-	-included-	-included-	-included-	-included-
Number of observations	8,268	16,417	8,268	16,417	8,268	16,417	8,268	16,417
R^2	0.0225	0.0089	0.0169	0.7296	0.0034	0.1072	0.6888	0.5746

Notes: Standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 13. Robustness Check: Hair-care Products

Variable	H1		H2		H3		H4	
	(1) Baseline	(2) Hair care	(3) Baseline	(4) Hair care	(5) Baseline	(6) Hair care	(7) Baseline	(8) Hair care
VAL	0.018***	0.045***	0.008**	–0.000				
(WOM valence)	(0.002)	(0.006)	(0.004)	(0.003)				
VOL	0.000	–0.008	–0.001***	–0.011**				
(WOM volume)	(0.000)	(0.009)	(0.000)	(0.004)				
VAL_NW					0.022**	0.060***	0.180	0.094***
(Network product WOM valence)					(0.010)	(0.019)	(0.123)	(0.013)
VOL_NW					0.003***	0.014*	–0.003	0.017***
(Network product WOM volume)					(0.001)	(0.008)	(0.007)	(0.006)
Constant	–0.066*	–0.067	0.369***	–0.014	2.841***	1.441**	18.741***	–2.463***
	(0.037)	(0.221)	(0.066)	(0.103)	(0.203)	(0.720)	(2.415)	(0.487)
Control variables	-included-	-included-	-included-	-included-	-included-	-included-	-included-	-included-
Number of observations	8,268	2,874	8,268	2,874	8,268	2,874	8,268	2,874
R^2	0.0225	0.0155	0.0169	0.0523	0.0034	0.0249	0.6888	0.2470

Notes: Standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

our data at the product-week level. We estimate Equations (1) to (4) based on this weekly time frame and summarize the results in Table 14, columns (2), (4), (6), and (8), and find that all the supported hypotheses remain consistent. Moreover, in addition to the one-day lag level used in Equations (1) to (4), we also estimate models using different time lag levels (i.e., from a two-day lag to a seven-day lag) and the findings are robust. The results are also available upon request.

In view of all our rigorous statistical tests, we are confident of the robustness and consistency of our findings, thereby dismissing alternative explanations and concerns over potential differences in variable measures, samples, product categories, and time frames.

Discussion and Contribution

Discussion of Findings

Through the lens of expectation-confirmation theory and network theory, we manage to investigate the evolution of WOM over time and the role of WOM in product networks. We identify our notable findings as *the three paradoxes of WOM*.

We term our first paradox *the WOM valence paradox*. It has been widely believed that higher WOM valence signals to consumers a higher degree of perceived product quality, and hence leads to higher product sales [32]. As a result, retailers have made significant efforts to increase the WOM valence of products. However, through our rationalization using expectation-confirmation theory, we determine that the impact of prior WOM valence of a product on the product's subsequent WOM valence is a larger decrease (i.e., positive and significant). This elucidation challenges retailers as they grapple with the fact that higher WOM valence, which is supposed to bring about better sales, will also bring forth a larger decrease in subsequent WOM, and thus may dampen sales. Hence, the paradox of WOM valence highlights a complex relationship that has been overlooked in the past.

We term our second paradox *the WOM volume paradox*. Likewise, it has been documented that higher WOM volume signals to consumers a higher level of perceived popularity, and hence leads to higher product sales [45]. Consequently, retailers have strived to increase WOM volume to boost sales. However, through our reasoning using expectation-confirmation theory, we reveal that the impact of prior WOM volume of a product on the product's subsequent WOM volume is a smaller increase (i.e., negative and significant). In other words, WOM volume, which is supposed to boost sales, will inevitably trigger less additional subsequent WOM volume to hurt product sales. Beyond a simplistic understanding of "the more the merrier," the paradox of WOM volume cautions retailers to be cognizant of the consequences of high WOM volume.

Finally, we term our third paradox *the WOM spillover paradox*. In the past, retailers have simply assumed that the impacts of WOM work in isolation to influence product sales. The failure to account for the WOM influence via product

Table 14. Robustness Check: Weekly

	H1		H2		H3		H4	
Variable	(1) Baseline	(2) Weekly	(3) Baseline	(4) Weekly	(5) Baseline	(6) Weekly	(7) Baseline	(8) Weekly
VAL	0.018***	0.006***	0.008**	0.003				
(WOM valence)	(0.002)	(0.001)	(0.004)	(0.002)				
VOL	0.000	–0.000	–0.001***	–0.001***				
(WOM volume)	(0.000)	(0.000)	(0.000)	(0.000)				
VAL_NW					0.022**	0.335***	0.180	1.133***
(Network product WOM valence)					(0.010)	(0.029)	(0.123)	(0.390)
VOL_NW					0.003***	0.004*	–0.003	0.014
(Network product WOM volume)					(0.001)	(0.002)	(0.007)	(0.032)
Constant	–0.066*	–0.016**	0.369***	0.003	2.841***	–0.858***	18.741***	–2.905
	(0.037)	(0.007)	(0.066)	(0.016)	(0.203)	(0.150)	(2.415)	(2.044)
Control variables	-included-	-included-	-included-	-included-	-included-	-included-	-included-	-included-
Number of observations	8,268	1,829	8,268	1,829	8,268	1,829	8,268	1,829
R^2	0.0225	0.0326	0.0169	0.5328	0.0034	0.5113	0.6888	0.7287

Notes: Standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

network is a grave omission. Through our explanation using network theory, we show that higher WOM valence and volume of a product will positively contribute to the WOM valence of other products connected in the network. Hence, when retailers try to promote the WOM of a product, in the hope of driving the product's sales, it will at the same time generate positive WOM spillovers that diffuse along the network links to other connected products (which unfortunately may be potential competing products), and paradoxically, hurt its own sales.

As to why H4 is not supported, a plausible reason might be that reviewers have the possibility of providing a star rating (i.e., WOM valence) without writing a textual review (i.e., WOM volume). It is not mandatory that a reviewer has to commit to both. On Tmall, a textual review determines the WOM volume, which does not change if reviewers only rate the product without providing a textual review. As writing a textual review is often much more tedious than giving a simple star rating, reviewers are often reluctant to write multiple textual reviews especially for products connected and purchased together. Consequently, the WOM volume increase is not salient (i.e., H4 is not supported). However, reviewers find it easy and are willing to give star ratings to each of the products connected and purchased, which significantly increases the WOM valence (i.e., H3 is supported).

Theoretical Contributions and Practical Implications

Our study offers several important theoretical contributions. First, we draw theoretical support from expectation-confirmation theory [5, 56, 57] to explain the dynamics of WOM in terms of both valence and volume. Although the theory may have some presence in marketing, it is entirely novel to use the theory to predict how prior WOM will affect subsequent WOM. Our paradoxical findings attest to the felicitous application of this underlying theoretical framework. We contribute by extending the applicability of expectation-confirmation theory to the context of e-commerce WOM. Notably, we enrich the theory with a dynamic perspective, as we trace reviewers not only from the initial "expectation" to their "confirmation," but also accentuate the role of how prior "confirmation" forms the basis of subsequent "expectation," to perpetuate cycles of "expectation" and "confirmation." Importantly, we contribute to existing information systems and marketing studies that seek to explore the determinants of WOM (e.g., [10, 43]) by identifying that WOM in itself can actually be an antecedent, which has resulted in three paradoxes. This theoretical elucidation cannot be downplayed. It challenges most extant WOM studies that simply presume a direct relationship between WOM and economic outcomes (e.g., [19, 20, 22, 36]). In essence, we contribute theoretically by challenging researchers and practitioners to reexamine the convoluted and dynamic relationship of WOM.

Second, while the use of network theory [68] is more prevalent in understanding the influence of consumers on social media (e.g., Facebook, YouTube, Twitter, Instagram) (e.g., 6, 36]), we are among the few to explore network theory in a product network (e.g., [16, 53, 54, 55]) to examine WOM. We thus contribute by extending the applicability of network theory to unveil the paradoxes of WOM in the product network context. This challenges conventional wisdom by propounding why improving a product's WOM may not boost its sales. Specifically, *the WOM spillover paradox* identified suggests that the desire to increase a product's WOM in terms of valence and volume, will also improve the WOM of other connected products (which may be potential competing products). While past WOM studies have simply claimed that product WOM may affect the sales of the product (e.g., [19, 20, 25, 44]), our findings critically highlight that a product's improved WOM can instead benefit its potential competitors, which backfires to hurt its own sales. We contribute to the advancement of network theory in WOM literature through our novel and revealing demonstration of the existence of WOM spillovers. More important, our findings call attention to adopting a "connective" perspective rather than an "isolated" perspective when future researchers want to more accurately assess the value of WOM.

Overall, our study contributes to a much richer understanding of WOM literature and its related theories (such as expectation-confirmation theory and network theory). We contribute by pioneering and underscoring the possible paradoxes of WOM, which is evidently lacking and amiss in extant literature. Prior research findings on WOM may have unwittingly resulted in the misconception that driving higher WOM valence or volume can always result in better product sales (e.g., [19, 20, 25, 44, 45]). We thus challenge conventional wisdom by elucidating how WOM may paradoxically hurt product sales. Specifically, *the WOM valence paradox* underscores that increased WOM valence may drive sales, but at the same time, it may lead to more reduction in subsequent valence and consequently subsequent sales. Likewise, *the WOM volume paradox* cautions that increased WOM volume may increase sales, but simultaneously, the increased volume may hinder subsequent WOM growth and thus subsequent sales. In sum, we contribute to a stronger theoretical foundation by challenging past works that assume a simplistic and monotonic influence to reveal a more complicated (but realistic) relationship between product WOM and sales.

Moreover, our work is among the few studies to examine product WOM impacts using actual product sales information from e-commerce retailers. Previous studies are often handicapped by nonavailability of data and hence, they either have to combine WOM and sales data from different sources (e.g., [20, 25, 44]), which may introduce noises and affect the precision of research findings, or they have to collect data from a single source (such as Amazon) but use sales proxies obtained through a log-linear transformation of sales rank (e.g., [19]), which may sacrifice the precision of research findings. However, for this study, we are fortunate to have WOM and actual sales data from the same source, thereby allowing us to contribute to the WOM literature with more accurate and reliable conclusions.

Our study also provides important practical implications for e-commerce retailers to drive product sales. Specifically, our findings suggest that it may be unwise and futile for retailers to continually channel valuable resources just to increase the already high WOM valence and volume in order to boost further sales, because both the WOM valence paradox and the WOM volume paradox hint at the possibility of "backfire." Instead, for products that already boast high WOM valence and volume, retailers could consider adopting a "defensive" (as opposed to "offensive") approach. In other words, they should conscientiously monitor how the WOM evolves subsequently, paying attention to potential new reviewers. Whenever WOM threatens to decline, retailers should be swift in reacting and rectifying it by seeking marketing strategies to please these potential new reviewers, so as to maintain their superior WOM. For instance, retailers can offer rebates or deliver small gifts after consumers' successful transactions online, to attract favorable WOM from them. Also, retailers should brainstorm on ways and tactics to promote low WOM valence or volume products (e.g., by linking products with low ratings to products with superior WOM (i.e., high volume and high rating) so as to enjoy valence increments, as demonstrated by the WOM spillover paradox).

Finally, many e-commerce platforms have simply adopted existing recommender systems such as the one used on Amazon. Given the popularity and ubiquity of such recommender systems, we hope that platform operators will continually seek ideas and innovations to enhance certain functions and features of the system. Acknowledging the complexity of adding or redesigning the recommender systems, we hope that the effort to do so will help boost retailers' product sales. For example, based on our findings, platform operators might want to consider (1) adding analytical graphs to help retailers better trace the rise and fall of WOM valence or volume; (2) more important, alerting and forewarning retailers of potentially declining WOM valence (especially after consistently high WOM valence and/or below a certain level of threshold); (3) assisting with the identification of reviewers that are prone to give poor WOM valence; or (4) providing analyses of competing products that manage to "steal" the purchase away from its focal product. In essence, more insightful analytical tools examining consumer online behavior, purchase history, and "linked" product relations would be most beneficial to retailers in growing their businesses and generating larger long-term revenues.

Conclusion

Although our research has highlighted several notable findings and contributions, we acknowledge some limitations.[19] First, there exist some subtle differences between the features of Tmall in China and those in other countries (e.g., Amazon in the United States). For instance, Tmall has many online retail stores and it is understandable that recommender systems in a store recommend only products from the same store. However, Amazon is commonly perceived as one megastore (i.e., Amazon itself), and thus its recommender systems recommend any product on Amazon. Also, WOM volume on Tmall captures the amount of textual review that does not change if reviewers only provide star ratings, whereas that on Amazon still increases. Given these subtle differences, caution should be exercised in generalizing. Another limitation can be attributed to our main sample (i.e., Nikon products). As Nikon may be a premium brand as compared to other overseas and domestic brands for digital cameras in China, the ratings of Nikon products might be higher than the average level of digital cameras. This would somewhat sacrifice the randomness of the data sample. Nonetheless, we hope our effort to perform robustness checks (i.e., with notebook computers, mobile phones, and hair-care products from different stores) help to alleviate some concerns.

Despite these limitations, we are confident of our findings, given the numerous rigorous statistical tests that we have conducted to dismiss plausible alternative explanations, as well as the affirmative results we managed to replicate using different products (including search and experience products as well as complex and simple products) from different online stores. Most important, our identification of three paradoxes challenges previous and contributes much to academia and practitioners, thereby charting new avenues for future research.

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Notes

1. On most e-commerce sites, each product is linked to relevant products (accompanied by the respective WOM) to assist consumers in their purchase decisions [63]. Thus, the recommendations create a visible directed product network (or WOM network) where products (or WOM) (i.e., network nodes) are explicitly connected by hyperlinks (i.e., network ties). An example is the copurchase network on Amazon.com, where recommended products are listed under the title “Customers who bought this item also bought.” Accordingly, we define the product that explicitly recommends additional products as the recommender, and products in the recommended set as the recommended products.
2. It is noteworthy that robustness checks using data from notebook computers, mobile phones, and hair-care products from different stores also reaffirm our findings.
3. Please refer to the robustness checks for more details.
4. Consistent with prior literature [20, 25, 45], WOM valence refers to the average rating of consumer reviews.
5. Consistent with prior literature [20, 25, 45], WOM volume refers to the cumulative number of consumer reviews.
6. We sincerely thank our anonymous reviewer for offering the insight that higher WOM valence of a product may imply the higher quality of customer service associated with the product, and thus may offset the impact that higher WOM valence results in a larger subsequent decrease in the WOM valence. However, as subsequently discussed in the data description, each Tmall retailer is in charge of the sales and customer service for all the products in the retailer’s store. Thus, the quality of customer service should remain relatively stable across different products in the same store. Therefore, if customer service is included as an explanatory variable to our main econometric model (i.e., fixed effects model), the estimate will be statistically omitted.
7. In our empirical analysis, we have ruled out several alternative explanations (e.g., the ceiling effect of WOM valence, the confounding effects of valence variance) to validate this hypothesis. Please refer to the robustness checks for more details.

8. In our empirical analysis, we have ruled out several alternative explanations (e.g., the ceiling effect of WOM volume, the product age) to validate this hypothesis. Please refer to the robustness checks for more details.

9. Although we focus on one major category (i.e., digital cameras) as the focal products in our empirical analysis, we also report robustness checks on the sensitivity of this operationalization by including all the related product categories (e.g., battery, lens) in our sample and find consistent results. Moreover, we also collect data on notebook computers, mobile phones, and hair-care products, and obtain similar findings. The results are reported as robustness checks.

10. For robustness checks, we also report on the sensitivity of this operationalization by organizing our data at the product-week level and find consistent results.

11. This is aggregated from the transaction records to indicate the total quantity of product *i* sold in day *t*.

12. This is shown on Tmall product web pages to indicate the sales quantity of product *i* during the past month prior to day *t*.

13. This is shown on Tmall product web pages to indicate the available quantity of product *i* for sale in day *t*.

14. This is shown on Tmall product web pages to indicate the cumulative number of product *i*'s web page bookmarked by consumers in day *t*.

15. This measures the number of products pointing to product *i* in the network in day *t*.

16. This measures the average sales quantity of products pointing to product *i* in the network in day *t*.

17. This measures the average list price of products pointing to product *i* in the network in day *t*.

18. The estimation results based on different time lag levels are consistent with those from our one-day lag models.

19. We sincerely thank our anonymous reviewers for pointing out these limitations.

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