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Not all digital word of mouth is created equal:

Understanding the respective impact of consumer reviews and microblogs on new product success

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Abstract

The expansion of the Internet and social media have triggered a differentiation of the word-of-mouth (WOM) concept, with consumer communication about brands and products now taking place in various settings and forms. Two important digital WOM types are microblogs and consumer reviews. To clarify their differential roles for product success, this study offers a theoretical framework of the influence of these two types of WOM, drawing from consumer information search theory and diffusion theory. The tests of the proposed framework use a longitudinal data set of video game sales and weekly information gathered from microblogs (i.e., over 13 million tweets from Twitter) and consumer reviews (i.e., more than 17,000 Amazon consumer reviews). Analyzing a system of equations provides evidence that the influence of microblogs and consumer reviews on new product success changes over time. Prior to launch, the volumes of microblogs and consumer reviews, together with advertising, represent primary sales drivers. After launch, the volume of microblogs is initially influential, then loses impact, whereas the impact of the volume of consumer reviews continues to grow. The valence of consumer reviews gains significance only near the end of the observation period, but the valence of microblogging is never influential.

Keywords: WOM; social media; consumer decision making; video games

1. Introduction

Word-of-mouth (WOM) communication is a well-established determinant of new product success (Berger & Schwartz, 2011; Godes & Mayzlin, 2004). The rise of the Internet and social media have created new digital channels for exchanging WOM, causing a fragmentation of the concept. In addition to traditional face-to-face WOM, substantial WOM communication thus takes place in the digital realm; a recent survey of more than 2,000 German consumers revealed that digital WOM accounts for approximately 54% of the total WOM they exchange (Digitalization Think:Lab, 2014). Digital WOM is not a homogenous concept though, because it gets shared through varied digital channels that fundamentally shape how consumers interact.

Most WOM research centers on two types of digital WOM: consumer reviews of products on retail platforms such as Amazon.com (Floyd, Freling, Alhoqail, Cho, & Freling, 2014; Purnawirawan, Eisend, De Pelsmacker, & Dens, 2015) and comments posted to microblogs that get shared in real time among connected members of a social network, such as Twitter (Hennig-Thurau, Wiertz, & Feldhaus, 2015; Toubia & Stephen, 2013). Some additional studies also consider social tags (Nam & Kannan, 2014) and Facebook messages (Eisingerich, Chun, Liu, Jia, & Bell, 2015). Such studies acknowledge that the characteristics and mechanisms of various WOM types differ substantially. For example, consumer reviews usually are “pulled” by receivers, whereas microblogs quickly push information into receivers’ accounts. These conceptual differences in turn likely influence how and when WOM influences consumers. For example, microblogs might be particularly important at the moment a new product is released, because they offer rapid dissemination of information through the social networks of close personal connections (Hennig-Thurau et al., 2015).

In turn, researchers call for a better understanding of the differences across WOM types and their specific impacts on consumer decision making and product success (e.g., Berger, 2014;

Berger & Iyengar, 2013; Dellarocas, 2003; Godes & Mayzlin, 2004; Hennig-Thurau et al., 2015; Meuter, McCabe, & Curran, 2013). Yet conceptual and empirical research on the actual, *differential* effects is limited. Several investigations of how a particular WOM type affects consumer behavior and market outcomes do not account empirically for the influences of other, simultaneous WOM types. Such an approach would be sufficient if all WOM types influenced decisions similarly, such that any unique type could serve as a proxy for WOM in general (e.g., Zhu & Zhang 2010). But if the conceptual differences between WOM types influence how consumers use the conveyed WOM information in their adoption decisions, then understanding the differential effects of these WOM types is critical for avoiding erroneous judgments about the sources of new product success (or failure) and achieving a better allocation of scarce resources across WOM types in marketing efforts (e.g., Godes & Mayzlin, 2004).

This research seeks to disentangle, both conceptually and empirically, the respective effects that the volume and valence of consumer reviews and microblogs, as two main types of digital WOM, exert on consumers' adoption of new products. We develop a conceptual framework based on consumer information search theory and diffusion theory. Because microblogs and consumer reviews, with their unique characteristics, carry specific information (social versus functional), they should affect different types of consumers (early versus later adopters) differently throughout the diffusion process, in conjunction with the specific information carried by their WOM volume and valence. To test these arguments, we collect rich data about both consumer reviews and microblogs and study their respective influences on the success of 100 video games released for the Microsoft Xbox 360 console between October 2011 and November 2012. The microblog data contain more than 13 million messages on Twitter, the largest global microblogging service; the consumer review data consist of 17,597 product reviews from Amazon. We measure WOM data on a weekly basis over 22 (12 pre-release and 10 post-release weeks) weeks, together with sales, key control variables (e.g., game advertising), and reviews by 4,896 professional critics. To control for the endogenous nature of consumer reviews and microblogs, we estimate their effects with a system of equations.

Our findings confirm that consumer reviews and microblogs have different effects on product success and shed light on how these effects change over time, from pre-release to immediately after release to the post-release periods. Our analyses further offer fine-grained insights into how the volume and valence dimension of each digital WOM type influences consumers' purchase decisions and product success over time. Our findings have important implications for WOM research, as well as for marketing management, because they can help companies focus on monitoring and managing the WOM types that consumers use most when making their purchase decisions at different points in time.

2. What we know: Digital WOM and its effects on customers

In this research, we focus on two main types of digital WOM: microblogs about a product and online consumer reviews on websites that have dedicated sections for such product reviews.[1] Extant research about microblogs often uses data as a proxy for online WOM (Rui, Liu, & Whinston, 2013) or WOM overall (Asur & Huberman, 2010). However, this perspective conflicts with research that shows that consumer reviews and microblogs differ on various aspects (Hennig-Thurau et al., 2015). Specifically, microblogs are exchanged by communicators who are identifiable and accountable (Eisingerich et al., 2015, who use the term "sWOM"). The sender

[1] The nomenclature applied to different types of digital WOM in previous research is not consistent. Consumer reviews also are called online WOM (e.g., Berger & Schwartz, 2011; Kozinets, De Valck, Wojnicki, & Wilner, 2010; Zhu & Zhang 2010), WOM on online social sites (Eisingerich et al., 2015), or online customer reviews (Ho-Dac, Carson, & Moore, 2013). Microblogs (Nam & Kannan, 2014; Schweidel & Moe, 2014; Toubia & Stephen, 2013) are also called microblogging word of mouth (Hennig-Thurau et al., 2015) or social media posts (Barasch & Berger, 2014). Some scholars simply use "EWOM" as a synonym for all kinds of digital WOM (Babic, Sotgiu, Valck, & Bijmolt, 2016; Jansen, Zhang, Sobel, & Chowdury, 2009; You, Vadakkepatt, & Joshi, 2015).

and receiver often maintain some personal connection and are part of a "network of friends for social or professional interaction" (Trusov, Bucklin, & Pauwels, 2009, p. 92). Microblogs thus tend to involve personal, continuous conversations (Hennig-Thurau et al., 2015) that are informal, spontaneous, and length-restricted (Zhao & Rosson, 2009). In contrast, consumer reviews generally do not involve personal connections and instead are read by an anonymous audience, and they are not length-restricted, so they can provide more, and more differentiated, information about a product (Hennig-Thurau et al., 2015; Vasquez, 2014).

In addition, microblogs are pushed by senders to their networks in real time, whereas consumer reviews are pulled by readers in ways that the sender cannot control (Hennig-Thurau et al., 2015). Another difference involves the presence of summary signals that express WOM valence: The valence of consumer reviews often is displayed prominently as a summary (e.g., star) rating, reflecting the average sentiment of consumer opinions across all posted opinions. Such summary signals are not available for microblogs. Instead, each message on a microblog requires processing, so consumers cannot easily assess the average sentiment about a new product across their social network.

Considering these conceptual differences, scholars call for research into the different WOM types and their relative effects, instead of WOM in general, because "the communication channel … play[s] an important role in moderating the functions of word of mouth.… [M]uch more work remains to be done, and this is an open area for further investigation" (Berger, 2014, p. 601). In Table 1, we provide an overview of previous empirical studies that use market data to investigate the impact of consumer reviews and microblogs on product success; we also position our study in this context.[2] For each study, we indicate whether it includes the volume and/or valence of consumer reviews and/or microblogs and if it estimates effects over time. We also list whether articles distinguish between pre- and post-release periods (because WOM effects tend to differ over time) or account for the potentially endogenous role of WOM volume, which might result from the previous success of a product (e.g., Duan, Gu, & Whinston, 2008).

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

As this table shows, few published articles consider the relatively newer phenomena of microblogs. Most digital WOM studies also fail to account for the potentially endogenous character of WOM volume or variations in the impact of consumer reviews and microblogs over time, including pre- and post-release periods. Although several studies consider dynamic effects, no study investigates temporally different effects of microblogs on product success after the release week, and the few studies that investigate the effect of consumer reviews over time report conflicting findings.

Regarding the relative importance of volume versus valence of microblogs and consumer reviews in driving product success, existing findings are inconclusive. For microblogs, Rui et al. (2013) report that both the volume and valence influence demand, whereas Hennig-Thurau et al. (2015) only find an effect of negative tweets on the share of a movie's opening weekend box office revenues. For consumer reviews, Liu (2006) and Cui, Lui, and Guo (2012) find decreasing impacts of the volume of consumer reviews on sales over time, but Bruce, Foutz, and Kolsarici

[2] We identified these studies in three steps. First, we collected relevant articles from current meta-analyses (e.g., Floyd et al., 2014; You et al., 2015) and literature overviews (e.g., King, Racherla, & Bush, 2014). Second, we conducted manual searches of leading marketing journals (*International Journal of Research in Marketing*, *Journal of Marketing*, *Journal of Marketing Research*, *Marketing Science*, *Journal of Consumer Research*, *Journal of the Academy of Marketing Science*, *Journal of Retailing*, and *Journal of Interactive Marketing*). Third, to include related research disciplines and current working papers, we conduced keyword searches of electronic databases, such as Google Scholar, Science Direct, and EBSCOhost/Business Source Premier.

(2012) indicate an increasing effect. Similarly, Hu, Liu, and Zhang (2008) and Moon, Bergey, and Iacobucci (2010) identify decreasing effects for the valence of consumer reviews, whereas Gopinath, Thomas, and Krishnamurthi (2014) and Sonnier, McAlister, and Rutz (2011) find increasing effects over time. Liu (2006) and Duan et al. (2008) note greater explanatory power due to the volume of consumer reviews than their valence, but more recent studies that account for the endogenous character of this volume (due to the success of the new product) tend to find a stronger impact of the valence than of the volume of consumer reviews with increasing consumer product experience (e.g., Chintagunta, Gopinath, & Venkataraman, 2010; Gopinath et al., 2014).

To the best of our knowledge, no published research includes different types of WOM in a joint model. Thus, it is unclear which effects of consumer reviews or microblogs can be attributed to their respective type and which digital WOM types exert an impact on sales at the respective time. Shedding light on these questions is the main purpose of this research.

3. Effects of different digital WOM types over time: Conceptual framework and hypotheses

3.1. Theory and conceptual framework

Figure 1 depicts our conceptual framework. We consider a product sales context, because both types of digital WOM—microblogs and consumer reviews—exist and potentially affect new product success. We also address both the volume and valence dimensions of both types of WOM, such that we investigate how each combination of WOM type and WOM dimension influences product sales over time. Several time-variant (e.g., advertising spending, pricing over time, expert reviews) and time-invariant (e.g., product characteristics, publishing strategy) covariates also help us rule out a potential omitted variable bias.

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

To anticipate the relative sizes of the effects that the WOM types and their volume and valence dimensions exert at different phases of the release process, we build on consumer information search theory (Moorthy, Ratchford, & Talukdar, 1997) and diffusion theory (Mahajan, Muller, & Bass, 1995). First, information search theory notes that consumers rely on various information sources to reduce their pre-purchase uncertainty about how well a product can meet their consumption needs (Ratchford, Talukdar, & Lee, 2007; Urbany, Dickson, & Wilkie, 1989). Second, diffusion theory distinguishes early from later adopters, noting their different needs for social and functional information about a product to make decisions.

The conceptual differences between consumer reviews and microblogs may determine the capacity of each WOM type to provide early versus later adopters with valuable information at a certain point in a new product's diffusion process. That is, the impact of WOM information on consumers should depend on the respective WOM type (microblogs versus consumer reviews) and WOM dimension (volume versus valence). With our hypotheses, we begin by considering how the WOM type and WOM dimension characteristics separately provide value for adopter groups. We then integrate these arguments to offer hypotheses about how each combination of type and dimension influences product success over time.

3.2. Relative roles of consumer reviews and microblogs over time (WOM type)

Due to their personal, informal, spontaneous nature and limited capability to transmit functional or complex analyses, length-restricted microblogs mainly contain social information, reflecting buzz, excitement, or general interest in a new product. Consumer reviews instead can provide extensive, differentiated feedback about products—that is, functional information. However, the lack of personal connection between senders and receivers of this type of WOM makes it less well suited for transmitting social information (Vasquez, 2014).

The differential capacity of consumer reviews and microblogs to provide functional versus social information may determine the point in time when the new product information available in these two types of WOM is most relevant for various consumers. In particular, the social information shared through microblogs should be relevant mostly for early adopters in a new product's release week. Lambrecht, Tucker, and Wiertz (2015) argue that among early adopters of trends on Twitter, being the first to know and tweet about a new trend is an important way to gain status among followers and thus increase their image-related utility (Toubia & Stephen, 2013). Similarly, being among the first to tweet new product reviews helps senders signal that they are early adopters who are "in the know." It also can be beneficial for readers' image to comment on early new product–related statements.

Because WOM between strongly tied senders and recipients tends to be more influential (Brown & Reingen, 1987), we expect that the influence expressed through microblogs is particularly relevant in the release week, when buzz about a new product is still high. Information substitution dynamics (Risselada, Verhoef, & Bijmolt, 2014) suggest that microblogs lose some incremental importance in subsequent weeks, when the majority of adopters—who are less interested in interactive, self-representative social information—begin to purchase the new product. Consistent with this argument, Berger and Schwartz (2011) postulate that consumers lose interest as more similar, immediate WOM messages spread, so they talk less about them.

In contrast, consumer reviews offer a narrower product focus, functional information, and lower rates of self-presentation or social interactions (Nam & Kannan, 2014). Later adopters are more risk averse and delay purchase until functional information about the new product has spread throughout the market. Therefore, we predict that consumer reviews become increasingly influential over time, after other consumers have had opportunities to experience the product and articulate their detailed opinions. Bruce et al. (2012) compare the influence of consumer reviews (on Yahoo Movies and IMDb) with advertising and conclude that, over time, consumer reviews reduce the impact of advertising and become more relevant for the later-stage buying decisions of consumers who turn to this source of functional product-related information. Gopinath et al. (2014) confirm these findings in general and argue (drawing on diffusion theory) that not only do consumers have different propensities to rely on advertising and consumer reviews but that this reliance changes over time, as other consumers gain experience with the product.

Information from consumer reviews is stored in cumulative, summary ratings. The reliability of these signals depends on the number of ratings that constitute the cumulative score, in contrast with microblogs that are processed on a "per message" basis. More consumer reviews mean more robust and thus more valuable information for receivers (Godes & Silva, 2011; Moe & Trusov, 2011), so they should grow more relevant to consumer decision processes as time passes. Compared with microblogs, consumer reviews are not directed toward specific social relations and require pull from consumers, instead of being instantly pushed to computers or smartphones. Consumer review information thus spreads more slowly across a population of potential adopters than does microblog information (Hennig-Thurau et al., 2015). If a later adopter actively searches for such detailed review information though, it could be more influential than the pushed tweets.

In conclusion, we expect microblogs to be more influential when a new product is released, because the social information they provide is interesting to early adopters, but their influence fades over time. Consumer reviews instead should be least influential immediately after the new product is released, but their influence should grow over time as later adopters increasingly use the functional information they provide to make purchase decisions.

3.3. Relative roles of volume and valence over time (WOM dimension)

When reading microblogs, a consumer retains a vague impression of the aggregate tone of the few messages read (e.g., negative, neutral, or positive). The lack of summary signals makes it difficult for consumers to determine the overall valence of comments on microblogs about a new product though. For valence to have an effect on sales, consumers must be able to make accurate, cognitive aggregations of heterogeneous microblog information, which is difficult. Therefore, we expect the valence effect of microblogs to be limited, or nonexistent, when we also account for the effect of consumer reviews. In contrast, the process required to evaluate the volume of microblogs should be easier and faster for consumers (i.e., estimating the number of relevant microblogs).

In addition, when a new product is released, consumers' general interest in it may depend mainly on the volume, rather than valence, of the microblogs and consumer reviews. In other words, consumers base their decisions more on the buzz about the new product than its quality ratings. Early adopters even might buy products expressly so that they can talk about them online and increase their image-related utility (Toubia & Stephen, 2013) or self-enhancement (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004), regardless of the new product's quality. Volume also communicates more social information about how many other people find a new product interesting, which can serve as a basis for action-based cascades (Bikhchandani, Hirshleifer, & Welch, 1992), which tend to be particularly important at the moment the new product launches. This importance is particularly notable for products with an exponentially decaying adoption function, such as experiential media products, which attract a very large pool of early adopters just after their release.

In later product lifecycle stages, functional information should become more important than social information, because early adopters already will have moved on to another new product.

Later adopters probably buy, not to increase their image-related utility (e.g., recognition as a first adopter) but rather to minimize their risk and maximize functional-related product utility. Therefore, they compare the valence of different product alternatives. In addition, growing WOM volume in later product lifecycle stages makes the valence more reliable. For example, when 800 of 1000 (= 80%) consumers rate a product as excellent in later lifecycle stages, it appears far more reliable than when 4 of 5 (= also 80%) consumers in early lifecycle stages offer the same valence. Moreover, valence consensus increases over time (Moe & Trusov, 2011), making it easier for later adopters to select a product on the basis of strong quality expectations.

Therefore, we expect volume (of microblogs and consumer reviews) to be more influential when a new product is released, but its influence should fade over time. Valence (of microblogs and consumer reviews), conversely, should be least influential when a new product is released, but then its influence should grow over time.

3.4. Hypotheses about the respective WOM type/dimension combinations on product success over time

By integrating the arguments about the relative roles of different WOM types and dimensions over time, we can offer hypotheses for each WOM type/dimension combination. Table 2 summarizes the key arguments and conclusions for each respective combination.

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

Our previous discussion has led us to expect that the influence of microblogs decreases over time, but the influence of consumer reviews increases with the time that has passed since a new product's release. Moreover, the influence of volume should generally decrease over time, whereas the influence of valence generally increases. Combining these mechanisms and assuming that the power of both mechanisms is equivalent, we derive four hypotheses. That is, we expect that the influence of microblogs and the influence of volume in general both decrease with the time passed since a new product's release, so these effects reinforce each other. In contrast, even as the influence of microblogs decreases, the influence of valence in general should increase, so these effects compensate for each other, with no change in influence over time. Formally:

H_{1a}: The influence of microblogs' volume decreases over time after the product release.

H_{1b}: The influence of microblogs' valence does not change over time after the product release.

Furthermore, the influence of consumer reviews generally increases with the time passed since a new product's release, but the influence of volume information in general decreases, so these effects might balance each other out, with no change in influence over time. Finally, we argue that the influence of consumer reviews and the influence of valence in general both increase over time, which prompts us to expect a reinforcing effect for such a combination. Thus:

H_{2a}: The influence of consumer reviews' volume does not change over time after the product release.

H_{2b}: The influence of consumer reviews' valence increases over time after the product release.

4. Testing the differential effects of digital WOM types and dimensions: An empirical study of video games

4.1. Data

To test our hypotheses, we use video games as product examples. Despite the rather general nature of our framework, some of the arguments we make work best in an experiential media context, which is why we chose video games as the study category. Similar to other experiential products, such as movies, music, and books, the quality of video games is difficult for consumers to judge before consumption (Marchand & Hennig-Thurau, 2013). The diffusion of video games also is generally characterized by exponentially decaying patterns, such that demand for the new product (or product generation) is highest at the moment of its release.[3]

Our data set covers all 100 stand-alone, non-arcade video games released for the Microsoft Xbox 360 between October 2011 and November 2012. We control for other console releases, such as on the PS3 or Wii, but we focus on the Xbox 360 as the most popular platform in 2011 and 2012, with the highest global software sales (= 287,322,965 unit sales; cf. PS3 = 275,965,947 unit sales, Wii = 207,107,460 unit sales) according to vgchartz.com. In contrast with movies, for which consumers' access is restricted by the number of movie theaters, video games are nearly always distributed through online and offline retail stores using a ubiquitous distribution strategy, so access shortages are unlikely, and simultaneity does not bias the results. The short time frame of our data period and the introduction of the console six years prior to its start (i.e., the console already had reached its satiation phase) also imply that the installed base (total number of Xbox 360 consoles sold) is relatively stable, so software demand should not be distorted by hardware demand. Nevertheless, we control for cumulative hardware sales up to the respective week for which we collect sales data for each game. In addition, the chosen time frame ensures that our analyses are not affected by large price fluctuations, which we also control for. The data encompass 12 pre-release and 10 post-release weeks; the logic for this cut-off period is that demand for a game diminishes considerably after it has been in the market for 10 weeks.

[3] We concur with an anonymous reviewer that for some product categories with lower excitement or buzz levels at product launch, such as consumer durables, the importance of early adoption and the difference between the impact of microblogs and consumer reviews might not be as strong as that for video games or other experiential products.

4.2. Empirical model

Because of the structural differences between information that is available about new games in the release week and in the weeks that follow, we ran two separate equations to test our hypotheses. In both cases, we included several covariates, in addition to the WOM variables that are at the core of this research. Our selection of covariates is guided by extant research in games (e.g., Marchand, 2016) and related experiential media industries, such as movies (e.g., Clement, Wu, & Fischer, 2014). We log-transformed all non-binary variables to avoid distorting the estimation by outliers (Elberse & Eliashberg, 2003).

Formally, the sales equation for the release week (t = 0) is:

$$(1)\ ln\_sales_{g0} = \beta_1\ ln\_pre\text{-}release\_MB\_volume_g + \beta_2\ ln\_pre\text{-}release\_MB\_valence_g + \beta_3\ ln\_pre\text{-}release\_advertising_g + \beta_4\ ln\_prequel\_sales_g + \beta_5\ ln\_no\_of\_platforms_g + \beta_6\ ln\_age\_rating_g + \beta_7\ ln\_price_g + \beta_8\ ln\_hardware_g + \beta_9\ major\_publisher_g + \beta_{10}\ christmas\_release_g + \beta_0 + \varepsilon_{1g},$$

where g = 1, …, N is the index for the video games titles; *ln_sales* is weekly game sales; and *ln_pre-release_MB_volume* is the log-transformed cumulative volume of pre-release microblogs about a game prior to its release. In addition, *ln_pre-release_advertising* is the log-transformed cumulative advertising prior to the release (which is not endogenous; see Clement et al., 2014), *ln_prequel_sales* is the log-transformed sum of prequel sales (brand awareness) for a game,[4] *ln_no_of_platforms* is the log-transformed number of platforms on which a game is released,[5] *ln_age_rating* is a log-transformed restrictiveness score in the form of the Entertainment

[4] We also tested the number of prequels and a prequel dummy variable; the results were essentially the same. We select prequel sales as the most accurate and information-rich variable.
[5] This value ranges from 1 for games released only for the Xbox 360 to 8 for games released for the Xbox 360 and simultaneously for seven other platforms: PS2, PS3, PSP, PS Vita, Wii, Wii-U, and Nintendo 3DS.

Software Rating Board (ESRB) rating (from 1 = all ages to 4 = only ages 17 and above), *ln_price* is the log-transformed price of the particular game at release on Amazon.com (ranging from $39.99 to $74.99), and *ln_hardware* is the log-transformed global unit sales of the Xbox 360 console at release of the particular game. As binary variables, we include *major_publisher*, equal to 1 if the publisher is one of the top ten biggest publishers, with high distribution power in the release year of the game, and *christmas_release*, equal to 1 if the game was released between October and December and 0 otherwise. We do not include consumer reviews, which are available only in later weeks, after some consumers have experienced the product. (We also tested a constellation in which customer reviews exist prior to the new product's release and report these results in Web Appendix C.) For microblogs, we include volume and valence information but do not expect valence to be influential in the pre-release period, because this information is speculative rather than evaluative and likely provides little value to information recipients. The rate of neutral statements in microblogs is 60%, even prior to the release, with a strong social character (e.g., "The new game looks awesome, can't wait to try it"). We also do not include expert reviews by professional critics, which are not available for games at their release.[6]

In the post-release sales equation, we add consumer reviews (n = 17,597) and weekly data about expert reviewers' quality judgments (n = 4,896) as regressors. Because no summary values are available for the volume and valence of microblogs for consumers, we use the microblogs from the preceding week instead. Summary ratings are available for the volume and valence of

[6] Unlike in a film context, where professional reviews often appear *before* a film is released in theaters, professional reviews of video games are almost exclusively published only *after* the new game has been released (Kuchera, 2014; see also metacritic.com). Game publishers generally do not send their products to experts in advance or activate game servers prior to the release day. Rather, they provide first-day online patches that technically prevent early testing of the final game (Stuart, 2014).

consumer reviews though, so we use cumulative reviews up to and including the preceding week. The sales model for the weeks after the release week (t > 0) thus is:

$$(2)\ ln\_sales_{gt} = \delta_1\, ln\_lag\_MB\_volume_{gt} + \delta_2\, ln\_lag\_MB\_valence_{gt} + \delta_3\, ln\_lag\_CR\_volume_{gt} + \delta_4\, ln\_lag\_CR\_valence_{gt} + \delta_5\, ln\_lag\_experts_{gt} + \delta_6\, ln\_lag\_advertising_{gt} + \delta_7\, ln\_prequel\_sales_g + \delta_8\, ln\_no\_of\_platforms_g + \delta_9\, ln\_age\_rating_g + \delta_{10}\, ln\_price_{gt} + \delta_{11}\, ln\_hardware_{gt} + \delta_{12}\, major\_publisher_g + \delta_{13}\, christmas\_release_g + \delta_0 + \varepsilon_{2g},$$

where *t* denotes the particular week for time-variant variables, *ln_lag_MB_volume* is the log-transformed volume of microblogs from the previous week (t – 1),[7] *ln_lag_MB_valence* is the log-transformed valence of microblogs from the previous week, *ln_lag_CR_volume* is the log-transformed volume of consumer reviews until the preceding week, *ln_lag_CR_valence* is the log-transformed valence of consumer reviews until the preceding week, *ln_lag_experts* is the log-transformed valence of professional reviews (critics) from game experts (journalists) until the previous week, and *ln_lag_advertising* is log-transformed advertising spending in the previous week. The variable *ln_price* is the log-transformed weekly price of the particular game on Amazon.com, and *ln_hardware* is the log-transformed cumulative global unit sales of the Xbox 360 console until (and including) the preceding week of the particular game. The time-invariant variables (*ln_prequel_sales*, *ln_no_of_platforms*, *ln_age_rating*, *major_publisher*, *christmas_release*) are the same as those in Equation 1.

Because the volume of WOM is influenced by previous sales of the product, following its release, endogeneity could bias the results (e.g., Chintagunta et al., 2010). To address this

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[7] We also collected the volume of retweets, but its correlation coefficient with the volume of microblogs was .975 ($p < .001$), so we used only the volume of tweets.

endogeneity and the positive feedback (i.e., “success breeds success”), we use a dynamic, simultaneous equation system for the post-release period that encompasses three interdependent equations: a main equation with product sales as the dependent variable and two instrumental equations with the volume of microblogs and consumer reviews as dependent variables. For the release week equation, because the product has not been sold previously, endogeneity is not a concern.[8] We assume that the instruments do not correlate with the error term of Equation 2 because it contains unobserved variables such as strategic manager decisions about the game story, its flow, and in-game characters.

As instruments for the volume of microblogs, we use a binary variable indicating whether a game is based on a movie (*based_on_movie*) and the game’s log-transformed lagged buzz from the previous week (*ln_lag_buzz*), measured as the volume of product-related searches on Google divided by the total number of searches of the most popular game in the data set (i.e., *Call of Duty*), which provides a 100% benchmark (Kulkarni, Kannan, & Moe, 2012). If a game is based on a movie, more consumers are aware of the game’s brand will talk about it more likely, because the brand and related content already have appeared in the movie. For buzz, we expect that if more people search about a product, they will talk about it more likely. Both instruments meet the conditions of relevance and exogeneity (Wooldridge, 2013). They correlate with the endogenous variable *ln_lag_MB_volume* (F(*based_on_movie*) = 32.81, $p < .001$; F(*ln_lag_buzz*) = 239.34, $p < .001$) but not with the error term of Equation 2 (F(*based_on_movie*) = 2.13, $p = .15$; F(*ln_lag_buzz*) = 2.99, $p = .08$).

[8] We tested the release week model for potential endogeneity using the Durbin–Wu–Hausman test for the same instruments described in the text for the post-release model (cf. previous sales). The results affirmed our argument that the model is not affected by endogeneity: $\chi^2 = 2.73$, $p > .10$ for the volume of microblogs and $\chi^2 = .13$, $p > .10$ for the volume of consumer reviews.

As instruments for the cumulative volume of consumer reviews, we use a binary variable (*genre_shooter*) that indicates whether the game is a first-person shooter game, and another binary variable (*multiplayer*) that reveals if the game provides an online multiplayer feature (Marchand, 2016). The shooter game genre targets mainly young men who tend to be very active in consumer review forums, which could increase the volume of consumer reviews. Multiplayer games involve up to millions of consumers in joint play and enables communication during the game that may be about the game situation but also could express evaluative assessments. Moreover, multiplayer games lack some typical elements that critics tend to highlight, such as story flow or artificial intelligence, because the in-game characters mostly are represented by humans who create their own stories. Because players thus encounter unique game situations every time they play, consumers may be less likely to write detailed reviews. Both these instruments correlate with the endogenous variable *ln_lag_CR_volume* (F(*genre_shooter*) = 47.99, $p < .001$; F(*multiplayer*) = 6.62, $p = .01$) but not with the error term of Equation 2 (F(*genre_shooter*) = .54, $p = .46$; F(*multiplayer*) = .86, $p = .35$). All equations contain more unique independent than endogenous variables.

4.3. Measures

The data sources for the microblogs in both the pre- and post-release periods are the messages about each specific game sent through Twitter. With more than 300 million monthly active users (Twitter, 2016), Twitter is the largest microblogging network in the Western hemisphere and a standard data source for microblogs (e.g., Hennig-Thurau et al., 2015; Nam &

Kannan, 2014). We analyze all 13,522,031 English-language messages on Twitter.com,[9] without retweets, sent by the service's global user base about the video games in our sample over the relevant time period. We received these data from the social media monitoring firm Crimson Hexagon, which generated relevant search term combinations, including Twitter-specific acronyms for hashtags, handles, and exclusion words, for each game. It also eliminated identical tweets and spam (for more details, see Hitlin 2015). The collected messages then can be classified as positive, neutral, or negative tweets, using a proprietary support-vector machine learning algorithm by Crimson Hexagon for Twitter. The algorithm is based on an automated nonparametric content by Hopkins and King (2010) and classifies microblogs with a 92% accuracy rate relative to human-coded results (Crimson Hexagon, 2014; Hopkins & King, 2010).

The positive-to-negative ratio of game-related tweets in our data set is 3.32:1. Except for the release week, when we use all previously articulated microblogs, we rely on microblogs from week t – 1 instead of aggregate information. Thus, we can account for the short-term "per message" character of microblogs and the absence of cumulative summary measures for them. For the valence of microblogs, we calculate the quotient of positive/(positive + negative) tweets for each game, so the valence score ranges from 0 to 1. For the volume of microblogs, we count all (positive, negative, and neutral) tweets for each game.

To measure consumer reviews, we use customer articulations about a game posted on the website of the online retailer Amazon.com.[10] Amazon accounts for about 20% of all physical

[9] This count includes commercial tweets. But even the most popular game in our data set (*Call of Duty*) prompted between 1 and 6 commercial tweets from the publisher per day (6 around the release date). The total number of tweets was 3,035 during the release and 820 at the end of our observation period, so the ratio of commercial tweets is very small. Moreover, according to alexa.com, as of February 29, 2016, the share of twitter.com visitors from the United States is only 22%, suggesting that this site is a global attraction.

[10] We tested different measures for consumer reviews, such as the user reviews on metacritic.com and gamespot.com, and obtained similar results. We decided to use the Amazon.com reviews because of the retailer's

entertainment-related sales, including video games (Kantar Worldpanel, 2014), and represents a major forum for consumer reviews in this product category.[11] Amazon also has been well established as an appropriate source for consumer reviews (e.g., Chen, Wang, & Xie, 2011; Chevalier & Mayzlin, 2006; Ho-Dac et al., 2013; Li & Hitt, 2008). After a game's release, customers can publish their reviews on the game's page and rate its quality using a five-point scale (higher values indicate higher quality levels). Therefore, we include all consumer reviews by consumers on the respective Amazon.com page as the source for post-release consumer reviews (n = 17,597). Before the launch of a new game, anonymous discussions among consumers take place in the forum section for that game, but no consumer reviews are published (please also see footnote 14).

The cumulative number of reviews written up to and including week t – 1 provides the volume measure for consumer reviews, which also accounts for summary signals for this WOM type. The valence measure of consumer reviews integrates all consumer reviews written up to and including week t – 1 in a cumulative average (star) score (Liu, 2006). Both measures represent what consumers see when they visit the Amazon.com site for a specific game at a given point in time. In Table 3, we provide detailed information on the operationalization and data sources for the different digital WOM variables and controls. Table 4 contains the descriptive statistics.[12]

------------------ *Insert Tables 3 and 4 about here* ------------------

vast reach and general relevance. Amazon.com reviews also correlate strongly with the reviews on regional websites such as Amazon.co.uk, Amazon.it, or Amazon.fr.

[11] The reviews on Amazon.com are accessible on a global level, and Amazon.com delivers globally. On its additional regional websites, Amazon sometimes just repeats the Amazon.com reviews, or else it features reviews in the respective local language. We compared the volume and variance proportions of these regional sites with the Amazon.com site and found no substantial differences.

[12] Please see Web Appendix A for a correlation matrix that includes all sales, microblogs, and consumer reviews for the post-release periods and Web Appendix B for an autocorrelation figure.

4.4. Empirical estimation approach

To estimate the pre-release Equation 1, we use an ordinary least squares (OLS) regression, the most efficient estimator for models with only exogenous variables. For the post-release Equation 2, we employ three-stage least squares regression (3SLS) to account for endogeneity in the post-release model; 3SLS is superior to 2SLS because it captures contemporaneous cross-equation error correlations. It is also superior to OLS for models in which endogeneity exists. A Durbin–Wu–Hausman test provides evidence of endogeneity ($85.602 \leq \chi^2 \leq 117.305$ for $1,2,3 \leq t \leq 7,8,9$ with $p < .01$) in the post-release equations and confirms our a priori rationale for a simultaneous system of equations. In the pre-release equation, we find no indication of endogeneity. We report both 3SLS and OLS results for the post-release equation but focus on the former, which also corrects for a possible heteroskedasticity bias. For the pre-release equation, the OLS and 3SLS results do not differ with regard to the key variables of interest.

For the post-release period, we choose a moving windows approach (Bronnenberg, Mahajan, & Vanhonacker, 2000; McAlister, Srinivasan, & Kim, 2007) and compute changing parameter values instead of weekly analyses. Specifically, we condense the nine-week post-release period into three-week increments (e.g., weeks 1–3, 2–4). With this moving windows approach, we can identify important structural effects by extracting key information content and smoothing any outliers.

5. Results

5.1. Distribution of key variables over time

In Figure 2, we show the distribution of the volume of key variables over time. Advertising and the volume of microblogs peak one week before release. After the release, the variable scores generally decline over time.[13] Moreover, 68% of all experts' reviews are published in the release week or the subsequent week.

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

5.2. Estimation results

We report the regression coefficients for the release week in Table 5.[14] For the subsequent weeks, the results are displayed in Table 6; Table 7 contains the OLS results for the post-release models for comparison. In addition, in Figure 3 we plot the regression coefficients of the microblogs and consumer review variables over time.

------------------ Insert Tables 5, 6, and 7 and also Figure 3 about here ------------------

Because the variance inflation factors (VIF) are less than 2.9 in all models, we conclude that multicollinearity does not bias the results. A Chow test ($F_{11, 178} = 223.03$, $p < .01$) reveals significant differences and therefore a structural change in the 3SLS regression parameters between the first and last three weeks after the product release. The model is on a log scale, so the coefficients can be interpreted as elasticities. For example, a 1% increase of the volume of microblogs in weeks 0–2 corresponds to a .622% change in sales in weeks 1–3 (all else being equal).

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[13] An exception is the bump in Amazon volume and advertising in week 4. Here, the higher volume of evaluations reflects the product-specific characteristics of video games: Consumers usually play games for 10 to 50 hours (howlongtobeat.com), which is achieved in about four weeks for most players. The advertising bump in week 4 can be explained by the release of many big titles in the beginning of November, with increased advertising expenditures again a few weeks before Christmas. We therefore control for Christmas releases (i.e., any release between October and December) in our model.

[14] Although consumers have not yet been able to experience the product before release, we extended the analyses with pre-release forum activities on the respective Amazon.com page (n = 15,928). Of these pre-release forum posts, 74% contain neutral speculations about technical aspects of the game, such as resolution and framerate, or in-game features, such as the number of online multiplayer slots or levels. We operationalized *ln_pre-release_forum_volume* as the log-transformed cumulative volume of all pre-release discussion forum messages for a game prior to its release and *ln_pre-release_forum_valence* as the log-transformed valence of these forum messages. No major differences arise relative to the model in Table 4; we report the findings of this extended model in Web Appendix C.

The volume of microblogs is positively associated with sales in the release week and the six following weekly periods, before the coefficients decrease and become insignificant. This finding is consistent with our expectation that the impact of microblogs in general, and their volume in particular, fade over time, in support of H_{1a}. We find no significant effect of the valence of microblogs across the whole observation period, in support of H_{1b}. Therefore, the decrease of microblogs' influence in general and the increase of their valence compensate for each other.[15] These results align with our expectation that the volume of microblogs is more influential than their valence when studied together with consumer reviews. Without summary signals for microblogs, consumers must process each post individually to detect its valence, which explains why our measure of the valence of microblogs cannot offer additional quality-related information to consumers beyond that offered by the volume of microblogs before (and immediately after) a new product's release or other information sources after the product's release.

For consumer reviews, the results show a positive effect of their volume in the release week, which persists over the whole observation period without substantial changes, in support of H_{2a}. The valence of consumer reviews becomes associated positively with sales only in the final two observation periods, indicating an increasing influence of the valence of consumer reviews over time, in support of H_{2b}. We conclude from these results that the signaling power of the volume of consumer reviews is stronger than what previous research has suggested.

[15] We also tested the model with only one of the valence variables and with the raw (i.e., not log-transformed) valences. The results again showed no significant effect.

5.3. Omitting one WOM type

Our results point to the differing roles that consumer reviews and microblogs play as information sources in consumer decision-making processes. Therefore, it is important to consider the correlations of both types of WOM with purchases, instead of using one or the other as a proxy for a general WOM concept. However, the two WOM types, with their unique roles, also might exhibit some overlap, which we investigate further by re-specifying our post-release models to include only microblogs or only consumer reviews in separate analyses.

Omitting the consumer reviews leads to a significant volume of microblogs for the entire observation period, including the final period (t = 7,8,9), with strongly increasing parameters. The valence of microblogs remains insignificant though. If studied in isolation, the effect of the volume of microblogs would be exaggerated, because it actually contains effects that should be attributed to the volume of consumer reviews. This incorporation of effects does not exist for the valence of microblogs, which reinforces our argument that the two types of WOM valence contain different information and serve different functions for consumers. Microblogs are better suited to transmit social information, whereas consumer reviews can provide functional information, and there is limited overlap between the two types once a product has been released and its quality can be assessed by consumers. If we omit the microblog measures in the post-release periods, the volume of consumer reviews remains significant, with higher z-values[16] than when we include microblogs. In addition, the valence of consumer reviews becomes significant in the early periods after release (t = 1, 2, 3, again with higher z-values).

[16] For the release week equation, we applied OLS, using t-statistics. For the post-release equations, we used 3SLS, with z-statistics.

These findings thus shed additional light on the two digital WOM types and suggest asymmetry between the valence of consumer reviews and microblogs. In contrast with the valence of microblogs—which does not capture effects that should be attributed to the valence of consumer reviews—the valence of consumer reviews seems to absorb some of the impact of the valence of microblogs (and possibly volume too).[17]

6. Conclusion

6.1. Discussion of results

Previous research on WOM, and particularly digital WOM, mostly treats the different types of WOM as one and the same, rarely addressing differences across digital WOM types. This study responds to calls for a deeper understanding of different WOM types and offers the first simultaneous examination of two dominant types of digital WOM, namely, online consumer reviews on websites that have dedicated sections for such reviews and consumer communication about a new product through social media that use microblogs. With extensive data about video games over a 22-week period around their respective product launches and accounting for endogeneity, we shed light on the different roles that each type of digital WOM plays in the consumer decision-making process for video game purchases.

The volumes of both consumer reviews and microblogs significantly drive purchases in the release week, reaffirming the importance of digital WOM for creating awareness about a new product. In the 10 weeks after a new product release, the exogenous part of the volume of

[17] To test whether consumer reviews and microblogs might complement each other, we included interaction terms in our models with consumer reviews/microblog and volume/valence. Specifically, we tested four different specifications that differ in the data transformation (raw versus log-transformed values) and the creation of the interaction terms (product terms versus residual centering; Lance, 1988). We found no significant interaction effects for any of the four model specifications, indicating that information provided by consumer reviews and microblogs does not provide value in a non-linear way.

consumer reviews is relevant for consumer decision making for the whole time frame; the valence of consumer reviews becomes relevant only after six weeks. We consider it important that the effect of the volume of consumer reviews coexists with that of the volume of microblogs—a strong indicator of their different roles for consumers.

Our findings suggest that functional information included in consumer reviews needs time to become relevant for consumer decision making, because a high volume of consumer reviews can increase the credibility of their valence. In contrast, the social nature of the volume of microblogs makes it a relevant driver only in the first weeks of the post-release period, whereas we do not find an impact of the valence of microblogs on product sales throughout the entire observation period. This interesting finding might be explained by the difficulty consumers have assessing the overall valence of microblogs. As a more general observation, the valence of microblogs and consumer reviews do not drive sales at the beginning of a new product lifecycle. We speculate that early adopters, who care about the social recognition they earn from being first to purchase and talk about a product, are more influenced by how many people are interested in a new product than by what they actually say about it. Early trend propagators get their status from having the product early and then evaluating it themselves; they want to be opinion makers rather than opinion followers. Therefore, they are influenced by volume, not by valence.

The additional analyses in which we omit either consumer reviews or microblogs indicate that it is advantageous to consider the two types jointly to understand the effects of consumer interactions on sales and to avoid biased parameters. For example, if the volume of consumer reviews is omitted from the analysis, the results suggest that the volume of microblogs might influence sales over the entire post-release period, whereas it loses significance in the medium term, after $t = 6, 7, 8$, when accounting for both digital WOM types, as our analyses reveal.

By studying both consumer reviews and microblogs jointly, this research provides support for our argument that the conceptual differences between these two types of WOM affect the role they each play for different types of consumers, resulting in differential impacts on product adoption over time. As a result, the two digital WOM types should not be used as proxies for each other but rather to capture related yet distinct marketplace phenomena.

6.2. Managerial implications

Our findings have implications for marketing managers of experiential media products and can help companies focus their marketing and monitoring efforts on the information sources that consumers use most when making decisions at different points in time. In the pre-release period, the volumes of microblogs affect new product success. A consumer cannot judge the quality of the new product at this point, so the main goal of marketing campaigns should be to create awareness. Later, marketers should allocate their marketing budgets in a way that stimulates both microblogs and consumer reviews. The recent trend to engage more in content marketing and create separate, original content around a new experiential product release to spark consumers' interest suggests that the industry is starting to recognize this dynamic (Batchelor, 2013).

We also find that the exogenous volumes of consumer reviews and microblogs correlate with product sales *after* the new product release. Most marketing campaigns for experiential products focus on the pre-release period (Elberse & Anand, 2007), but our results indicate that it might be worthwhile to continue supporting games with activities that generate post-release digital WOM, such as by explicitly incentivizing consumers to spread WOM or creating additional sharable content. When formulating these strategies, marketers need to realize that the impact of microblogs is more short-lived than that of consumer reviews. Industry trends are shifting toward social media campaigns, including Twitter (Batchelor, 2013), but our results indicate that consumer reviews still offer more longevity and remain important throughout the entire 10-week, post-release observation period.

Moreover, the valence of consumer reviews becomes more important as time passes. When consumers have time to experience and engage with the new product, they can write rich, informative reviews that other consumers use to make their decisions. Because it is often displayed as an aggregate indicator, such as a star rating, the valence of consumer reviews offers an important signal of new product quality that helps late adopters make quick evaluations. Managers therefore should monitor the main forums on which consumer reviews about their product are shared, then use this information as an important source of feedback and market intelligence. For video games and other digital products, it might be possible to address this feedback by fixing bugs or errors, even after the initial product release. The valence of microblogs has no such impact on product success, making it less important to invest in sentiment analyses of Twitter messages. These findings should be helpful in guiding managerial budget allocations across measures linked to the stimulation of specific WOM types.

6.3. Further research and limitations

This study sheds initial light on the differential roles of digital WOM types, but a vast scope remains for expanding our knowledge about microblogs and consumer reviews, especially with regard to how different types of consumers engage with these different types of WOM. For example, early adopters who like to be “in the know” might be concerned primarily with the speed of information dissemination and prefer to use microblogs. Later adopters instead tend to be more cautious and keen to minimize their purchase risk, resulting in a focus on information richness and thus a preference to use consumer reviews. Early adopters probably do not want “second-hand” product evaluations from unknown reviewers, because they engage in WOM for their own identity-signaling reasons and feel compelled to avoid being duped by potentially fake company reviews, but they might prefer personal microblogs. By the time the early majority has evaluated products extensively, early adopters already might have moved on to another product.

Another topic that deserves more research attention is the importance of “owned” versus “earned” social media (e.g., Poor, Duhachek, & Krishnan, 2013; Trusov et al., 2009). Many companies invest in their own social media channels (e.g., Twitter feeds, Facebook pages), and some host discussion forums on their own websites. We considered only “earned” microblogs and consumer reviews in this research; it would be interesting to discern the role of company-owned microblogs and consumer review channels in the communication strategy for a new product. Taking this notion a step further, what effects would closely targeted native advertising have, such as sponsored tweets targeted at different types of users, according to the interests that these users have expressed in previous tweets?

Further studies could expand our findings to other sources of consumer articulations, such as posts on other social media sites (e.g., Facebook, WhatsApp, Pinterest, G+, LinkedIn, Renren, Snapchat), blogs, social tags, and other sources of product reviews (e.g., YouTube, Epinions, CNET), as well as “traditional” face-to-face WOM. We expect the results for Facebook messages to be similar to those for microblogs, because both are used mainly on mobile devices (cf. computers with keyboards and large screens) and seem similar in nature (Smith, 2016a, 2016b). Mobile usage makes it inconvenient to write extensive, complex reviews, so mobile consumers usually offer relatively short messages (Nierhoff, 2013). Moreover, games depend on a console, and controlling for other hardware (e.g., motion-sensing input devices, virtual reality headsets) could extend the product-specific boundary conditions of platforms and network effects.

Studies also might also study the existence of cultural differences and other forms of heterogeneity more deeply. Our measure of global customer reviews comes from Amazon.com, and we provide several arguments for why this data source is an appropriate proxy. Still, researchers might want to test our model on a regional or local level, which could provide insights into potential cultural differences in the role of different digital WOM types.

Finally, the valence of microblogs does not correlate with purchases in any time period. We argue that because there is no summary signal, such as a star rating, of the aggregate-level valence of microblogs, their valence does not provide any additional social information that is not already expressed through their volume. Yet the valence of microblogs should exert an influence on an individual level, because consumers process each social media post on a per message basis, so they could be strongly influenced by a very positive or very negative post from someone in their network whom they trust. Additional research thus could study how microblogs and consumer reviews get processed on an individual level (e.g., in laboratory experiments).

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Table 1: Extant studies of the impact of digital WOM on sales

Authors	Consumer review volume	Consumer review valence	Microblog volume	Microblog valence	Consumer reviews & microblogs jointly	WOM volume endogenous?	Dynamic effects over time	Pre-release WOM
Amblee & Bui, 2011	✓	✓	✗	✗	✗	✓	✗	✗
Archak, Ghose, & Ipeirotis, 2011	✓	✓	✗	✗	✗	✓	✓	✗
Asur & Huberman, 2010	✗	✗	✓	✗	✗	✗	✓	✓
Bruce, Foutz, & Kolsarici, 2012	✓	✓	✗	✗	✗	✗	✓	✓
Chen, Wang, & Xie, 2011	✓	✓	✗	✗	✗	✓	✓	✗
Chevalier & Mayzlin, 2006	✓	✓	✗	✗	✗	✗	✓	✗
Chintagunta, Gopinath, & Venkataraman, 2010	✓	✓	✗	✗	✗	✓	✓	✗
Clemons, Gao, & Hitt, 2006	✓	✓	✗	✗	✗	✗	✗	✗
Cui, Lui, & Guo, 2012	✓	✓	✗	✗	✗	✓	✓	✗
Dellarocas, Zhang, & Awad, 2007	✓	✓	✗	✗	✗	✗	✓	✗
Dhar & Chang, 2009	✓	✓	✗	✗	✗	✓	✓	✗
Duan, Gu, & Whinston, 2008	✓	✓	✗	✗	✗	✓	✓	✗
Forman, Ghose, & Wiesenfeld, 2008	✓	✓	✗	✗	✗	✗	✗	✗
Gong, Zhang, Zhao, & Jiang, 2014	✗	✗	✓	✗	✗	✗	✗	✗
Gopinath, Chintagunta, & Venkataraman, 2013	✓	✓	✗	✗	✗	✓	✗	✓
Gopinath, Thomas, & Krishnamurthi, 2014	✓	✓	✗	✗	✗	✓	✓	✗
Gu, Park, & Konana, 2012	✓	✓	✗	✗	✗	✓	✓	✗
Hennig-Thurau, Fuchs, & Houston, 2013	✗	✓	✗	✗	✗	✗	✓	✓
Hennig-Thurau, Houston, & Walsh, 2006	✗	✓	✗	✗	✗	✗	✓	✗
Hennig-Thurau, Marchand, & Hiller, 2012	✗	✓	✗	✗	✗	✗	✓	✗
Hennig-Thurau, Wiertz, & Feldhaus, 2015	✗	✗	✓	✓	✗	✗	✗	✗
Ho-Dac, Carson, & Moore, 2013	✓	✓	✗	✗	✗	✓	✓	✗
Hu, Liu, & Zhang, 2008	✓	✓	✗	✗	✗	✗	✓	✗
Karniouchina, 2011	✓	✓	✗	✗	✗	✓	✓	✓
Kim, Park, & Park, 2013	✓	✓	✗	✗	✗	✗	✗	✗
Kumar, Bhaskaran, Mirchandani, & Shah, 2013	✗	✗	✓	✗	✗	✓	✓	✗
Lee, Lee, & Shin, 2011	✓	✓	✗	✗	✗	✗	✓	✗
Li & Hitt, 2008	✓	✓	✗	✗	✗	✗	✓	✗
Liu, 2006	✓	✓	✗	✗	✗	✗	✓	✓
Moe & Trusov, 2011	✓	✓	✗	✗	✗	✓	✓	✗
Moon, Bergey, & Iacobucci, 2010	✓	✓	✗	✗	✗	✗	✓	✗
Moul, 2007	✓	✓	✗	✗	✗	✓	✓	✗
Nam & Kannan, 2014	✗	✗	✓	✓	✗	✗	✓	✗
Rui, Liu, & Whinston, 2013	✗	✗	✓	✓	✗	✓	✓	✗
Sonnier, McAlister, & Rutz, 2011	✓	✓	✗	✗	✗	✓	✓	✗
Sun, 2012	✓	✓	✗	✗	✗	✗	✗	✗
Wong, Sen, & Chiang, 2012	✗	✗	✗	✓	✗	✗	✗	✓
Yang, Hu, Winer, Assael, & Chen, 2012	✓	✗	✗	✗	✗	✓	✗	✗
Ye, Law, Gu, & Chen, 2011	✗	✓	✗	✗	✗	✗	✗	✗
Zhang, Craciun, & Shin, 2010	✓	✓	✗	✗	✗	✗	✗	✗
Zhou & Duan, 2012	✗	✓	✗	✗	✗	✗	✓	✗
Zhu & Zhang, 2010	✓	✓	✗	✗	✗	✓	✓	✗
This study	✓	✓	✓	✓	✓	✓	✓	✓

Table 2: Combination of WOM types and dimensions

<table>
<tr><td colspan="3"></td><td colspan="2">WOM TYPE</td></tr>
<tr><td colspan="3"></td><td>Microblogs</td><td>Consumer Reviews</td></tr>
<tr><td colspan="3"></td><td>• Social, sender-focused, short information
• Medium to strong sender–recipient relationship
• Per message rating basis, difficult to evaluate (no summary signals)
• Push (quick, real-time) distribution
• Relevant for early adopters</td><td>• Functional, product-focused, detailed information
• Weak sender–recipient relationship
• Cumulative rating basis, easy to evaluate (summary signals)
• Pull (slow, synchronous) distribution
• Relevant for later adopters</td></tr>
<tr><td rowspan="2">WOM DIMENSION</td><td>Volume</td><td>• Social information (how many people find a new product interesting)
• Correspondence with risk aversion: low/medium
• Reliability (consensus): less relevant
• Relevant for early adopters</td><td>WOM volume of microblogs is relevant for early adopters
⇒ Decreasing influence on product demand over time</td><td>Consumer review volume is partially relevant for early and later adopters
⇒ No influence change over time</td></tr>
<tr><td>Valence</td><td>• Functional information (product quality)
• Correspondence with risk aversion: high
• Reliability (consensus): increases over time with higher volume
• Relevant for later adopters</td><td>WOM valence of microblogs is partially relevant for early and later adopters
⇒ No influence change over time</td><td>Consumer review valence is relevant for later adopters
⇒ Increasing influence on product demand over time</td></tr>
</table>

Table 3: Operationalization and data sources for the model variables

Variable	Operationalization	Data Source
Time-variant variables		
ln_sales	Log-transformed number of video game units sold globally during the respective week.	vgchartz.com
ln_lag_sales	Log-transformed number of video game units sold globally during the preceding week.	vgchartz.com
ln_lag_sales_cum	Log-transformed sum of the number of video game units sold globally up to and including the preceding week.	vgchartz.com
ln_pre-release_MB_volume	Log-transformed sum of all (positive, negative, and neutral) microblogs for a game sent through Twitter until its release.	twitter.com
ln_lag_MB_volume	Log-transformed number of all (positive, negative, and neutral) microblogs for a game sent through Twitter during the preceding week.	twitter.com
ln_pre-release_MB_valence	Log-transformed quotient of positive/(positive+negative) microblogs for a game sent through Twitter until its release.	twitter.com
ln_lag_MB_valence	Log-transformed quotient of positive/(positive+negative) microblogs for a game sent through Twitter during the preceding week.	twitter.com
ln_lag_CR_volume	Log-transformed sum of all consumer reviews for a game up to and including the preceding week.	Amazon.com
ln_lag_CR_valence	Log-transformed mean Amazon star rating (accounting for all ratings to this point) displayed in the preceding week.	Amazon.com
ln_lag_experts	Log-transformed composite metascore of experts' quality judgments for a game in the preceding week.	metacritic.com
ln_pre-release_advertising	Log-transformed sum of all advertising expenses for the game in thousands of US$ until its release.	kantarmedia.com
ln_lag_advertising	Log-transformed advertising expenses for the game in thousands of US$ during the preceding week.	kantarmedia.com
ln_lag_buzz	Log-transformed search buzz, measured as relative Google trends index for a game in comparison with the top selling game *Call of Duty: Modern Warfare 3* during the preceding week.	google.com
ln_price	Log-transformed weekly price of the particular game on Amazon.com.	camelcamelcamel.com
ln_hardware	Log-transformed cumulative global unit sales (installed base) of the Xbox 360 console until (and including) the preceding week.	vgchartz.com
Time-invariant variables		
ln_prequel_sales	Log-transformed sum of global prequel sales for a game.	vgchartz.com
ln_no_of_platforms	Log-transformed number of platforms on which the game was released (e.g., 2 when released for Xbox 360 and PS3).	vgchartz.com
ln_age_rating	Log-transformed restrictiveness score, which is equal to 1 if the game's ESRB rating is E (everyone, all ages); 2 if it is E10+ (everyone ages 10+); 3 if it is T (teen, ages 13+); 4 if it is M (mature, ages 17+).	gamespot.com
major_publisher	Binary variable; 1 if the publisher of the game is one of the top ten biggest publishers in the release year of the game (with high distribution power); 0 otherwise.	gamasutra.com
christmas_release	Binary variable; 1 if the game was released between October and December; 0 otherwise.	vgchartz.com
genre_shooter	Binary variable; 1 if the particular game is classified as shooter genre; 0 otherwise.	vgchartz.com
based_on_movie	Binary variable; 1 if the game is based on a movie; 0 otherwise.	imdb.com
multiplayer	Binary variable; 1 if the game can be played simultaneously with other players from different locations through the Internet; 0 otherwise	gamespot.com

Table 4: Descriptive statistics

Metric Variables	**Mean**	**Median**	**SD**	**Min**	**Max**
ln_sales	9.975	10.054	1.835	.000	15.831
ln_lag_sales	10.040	10.130	1.850	.000	15.830
ln_lag_sales_cum	10.934	12.087	4.032	.000	16.360
ln_pre-release_MB_volume	9.474	9.661	1.520	4.700	12.950
ln_lag_MB_volume	7.034	7.050	1.414	2.080	11.270
ln_pre-release_MB_valence	-.218	-.151	.201	-1.100	.000
ln_lag_MB_valence	-.291	-.166	.385	-3.880	.000
ln_lag_CR_volume	3.191	3.178	1.445	.000	7.110
ln_lag_CR_valence	1.347	1.386	.204	.000	1.610
ln_lag_experts	4.304	4.353	.175	3.620	4.570
ln_pre-release_advertising	1.835	.000	2.910	.000	10.390
ln_lag_advertising	.715	.000	1.845	.000	8.330
ln_lag_buzz	1.449	1.386	1.231	.000	4.620
ln_prequel_sales	10.781	14.250	6.618	.000	17.170
ln_no_of_platforms	1.035	1.099	.532	.000	2.080
ln_age_rating	.949	1.099	1.390	.000	1.390
ln_price	3.942	3.970	.223	3.401	4.320
ln_hardware	18.010	18.014	.070	17.773	18.139

Categorical Variables	**Sum**	**Share**
major_publisher	53	53 %
christmas release	48	48 %
genre_shooter	18	18 %
based_on_movie	21	21%
multiplayer	59	59%

Notes: MB = microblogs, CR = consumer reviews.

Table 5: Results for the release week

Week (0 = release week) ***DV = ln_sales***	**B**	**SE**
ln_pre-release_MB_volume	.825*	(.113)
ln_pre-release_MB_valence	-.306	(.723)
ln_pre-release_advertising	.133*	(.050)
ln_prequel_sales	.026	(.023)
ln_no_of_platforms	-.045	(.275)
ln_age_rating	.302	(.290)
ln_price	2.065	(1.065)
ln_hardware	-2.827	(2.003)
major_publisher	-.246	(.301)
christmas_release	.615	(.325)
constant	44.557	(36.486)
R^2	*.649*	
F	*16.42**	

* Significant at $p < .05$.
Notes: MB = microblogs, B = unstandardized OLS coefficients, SE = standard error. The positive coefficient of the price control variable is to be expected, because the best-selling games are usually AAA titles, which combine the highest production budgets with the highest technological standard available and thus sell at high retail prices.

Table 6: 3SLS results for the post-release period

Method	3SLS													
Weeks (0 = release week)	**1,2,3**		**2,3,4**		**3,4,5**		**4,5,6**		**5,6,7**		**6,7,8**		**7,8,9**	
	B	**SE**	**B**	**SE**	**B**	**SE**	**B**	**SE**	**B**	**SE**	**B**	**SE**	**B**	**SE**
DV = ln_sales														
ln_lag_MB_volume	.622*	(.113)	.332*	(.126)	.614*	(.159)	.698*	(.149)	.584*	(.167)	.441*	(.152)	.229	(.208)
ln_lag_MB_valence	-.006	(.188)	.038	(.167)	.110	(.151)	.211	(.146)	.212	(.132)	.023	(.133)	-.033	(.141)
ln_lag_CR_volume	.729*	(.108)	.913*	(.138)	.673*	(.167)	.644*	(.150)	.710*	(.168)	.706*	(.161)	.892*	(.231)
ln_lag_CR_valence	.445	(.281)	.299	(.269)	-.028	(.325)	.213	(.339)	.441	(.365)	.768*	(.298)	1.110*	(.405)
ln_lag_experts	-.065	(.471)	-.328	(.439)	.320	(.475)	-.097	(.432)	-.289	(.430)	-.833*	(.356)	-.614	(.424)
ln_lag_advertising	.060*	(.024)	.053*	(.023)	.009	(.028)	.000	(.029)	-.007	(.031)	.047	(.027)	.072*	(.032)
ln_prequel_sales	.002	(.009)	.006	(.009)	.002	(.009)	-.001	(.009)	.000	(.009)	.003	(.008)	.001	(.009)
ln_no_of_platforms	.094	(.118)	.075	(.116)	-.041	(.129)	-.045	(.122)	-.001	(.134)	.011	(.125)	.064	(.178)
ln_age_rating	-.445*	(.140)	-.510*	(.154)	-.373*	(.177)	-.433*	(.163)	-.535*	(.169)	-.703*	(.148)	-.790*	(.168)
ln_price	.304	(.402)	-.070	(.351)	-.222	(.182)	-.215	(.178)	-.066	(.181)	.790*	(.308)	.951*	(.334)
ln_hardware	-.524	(.864)	-.033	(.859)	-.345	(.946)	-.473	(.893)	.060	(.951)	.259	(.829)	1.719	(1.047)
major_publisher	-.096	(.124)	-.127	(.118)	.085	(.130)	.127	(.126)	.190	(.127)	.063	(.102)	.069	(.106)
christmas_release	.326*	(.130)	.568*	(.125)	.746*	(.145)	.945*	(.137)	1.133*	(.144)	1.287*	(.114)	1.262*	(.145)
constant	11.333	(15.490)	6.662	(15.042)	9.076	(16.513)	12.313	(15.904)	3.112	(16.925)	-1.000	(14.677)	-28.731	(18.046)
R^2	*.506*		*.495*		*.446*		*.481*		*.555*		*.703*		*.680*	
χ^2	*490.12**		*503.17**		*442.50**		*507.36**		*566.28**		*890.16**		*785.07**	
DV = ln_lag_MB_volume														
based_on_movie	.432*	(.122)	.471*	(.129)	.482*	(.126)	.504*	(.130)	.488*	(.140)	.456*	(.142)	.397*	(.149)
ln_lag_buzz	.253*	(.047)	.342*	(.049)	.311*	(.050)	.311*	(.053)	.390*	(.057)	.429*	(.058)	.504*	(.063)
ln_lag_sales	.440*	(.034)	.420*	(.039)	.449*	(.036)	.460*	(.036)	.388*	(.037)	.382*	(.039)	.311*	(.042)
constant	2.240*	(.344)	2.313*	(.371)	2.104*	(.341)	1.925*	(.339)	2.478*	(.345)	2.412*	(.360)	3.024*	(.382)
R^2	*.496*		*.495*		*.429*		*.421*		*.436*		*.473*		*.448*	
χ^2	*345.74**		*324.94**		*321.24**		*318.35**		*273.83**		*274.09**		*224.34**	
DV = ln_lag_CR_volume														
genre_shooter	.349*	(.121)	.295*	(.117)	.349*	(.126)	.381*	(.130)	.430*	(.133)	.443*	(.135)	.409*	(.129)
multiplayer	-.145	(.092)	-.189*	(.088)	-.205*	(.095)	-.217*	(.098)	-.238*	(.101)	-.243*	(.102)	-.191	(.101)
ln_lag_sales_cum	.494*	(.027)	.555*	(.029)	.591*	(.031)	.616*	(.033)	.609*	(.034)	.590*	(.035)	.565*	(.036)
constant	-2.890*	(.317)	-3.510*	(.344)	-3.912*	(.373)	-4.200*	(.398)	-4.062*	(.415)	-3.795*	(.438)	-3.473*	(.448)
R^2	*.577*		*.572*		*.562*		*.557*		*.553*		*.538*		*.521*	
χ^2	*416.51**		*435.56**		*436.40**		*426.41**		*396.18**		*343.95**		*299.19**	

* Significant at $p < .05$.

Notes: MB = microblogs, CR = consumer reviews, B = unstandardized 3SLS coefficients, SE = standard error.

Table 7: OLS results for the post-release period

Method	OLS													
Weeks (0 = release week)	**1,2,3**		**2,3,4**		**3,4,5**		**4,5,6**		**5,6,7**		**6,7,8**		**7,8,9**	
	B	**SE**	**B**	**SE**	**B**	**SE**	**B**	**SE**	**B**	**SE**	**B**	**SE**	**B**	**SE**
DV = ln_sales														
ln_lag_MB_volume	.342*	(.062)	.328*	(.061)	.360*	(.069)	.385*	(.066)	.397*	(.063)	.362*	(.050)	.357*	(.049)
ln_lag_MB_valence	-.120	(.202)	-.053	(.185)	.100	(.174)	.203	(.168)	.189	(.145)	-.083	(.127)	-.139	(.127)
ln_lag_CR_volume	.494*	(.071)	.475*	(.070)	.462*	(.076)	.478*	(.070)	.491*	(.067)	.453*	(.053)	.451*	(.056)
ln_lag_CR_valence	.741*	(.310)	.634*	(.303)	.367	(.366)	.541	(.371)	.804*	(.389)	1.025*	(.319)	1.299*	(.358)
ln_lag_experts	-.130	(.507)	-.310	(.460)	.304	(.512)	-.316	(.485)	-.519	(.456)	-.868*	(.348)	-.532	(.345)
ln_lag_advertising	.110*	(.026)	.073*	(.027)	.016	(.033)	.004	(.033)	-.012	(.034)	.047	(.028)	.058	(.030)
ln_prequel_sales	.014	(.011)	.022*	(.010)	.018	(.011)	.017	(.011)	.013	(.011)	.014	(.008)	.011	(.008)
ln_no_of_platforms	.267*	(.130)	.211	(.126)	.224	(.143)	.251	(.139)	.228	(.135)	.104	(.106)	.078	(.105)
ln_age_rating	-.442*	(.148)	-.504*	(.143)	-.392*	(.161)	-.483*	(.154)	-.569*	(.150)	-.694*	(.118)	-.786*	(.115)
ln_price	1.620*	(.443)	.855*	(.405)	.054	(.222)	.058	(.217)	.166	(.210)	1.278*	(.339)	1.474*	(.336)
ln_hardware	-1.676	(.950)	-1.133	(.933)	-.921	(1.076)	-.899	(1.062)	-.464	(1.067)	-.481	(.856)	.349	(.882)
major_publisher	-.175	(.142)	-.216	(.136)	.015	(.155)	.077	(.150)	.160	(.145)	.020	(.112)	.039	(.109)
christmas_release	.662*	(.145)	.941*	(.140)	1.240*	(.161)	1.513*	(.154)	1.617*	(.152)	1.652*	(.117)	1.578*	(.120)
constant	28.904	(17.136)	23.163	(16.697)	19.750	(19.265)	21.470	(19.132)	13.631	(19.251)	11.248	(15.513)	-6.237	(15.885)
R^2	*.635*		*.622*		*.566*		*.611*		*.645*		*.763*		*.768*	
F	*35.04**		*34.57**		*27.83**		*33.64**		*38.47**		*66.35**		*66.70**	
DV = ln_lag_MB_volume														
based_on_movie	.499*	(.135)	.477*	(.135)	.504*	(.141)	.520*	(.145)	.490*	(.150)	.422*	(.148)	.403*	(.152)
ln_lag_buzz	.443*	(.052)	.473*	(.051)	.515*	(.055)	.541*	(.058)	.553*	(.061)	.546*	(.060)	.537*	(.064)
ln_lag_sales	.289*	(.036)	.284*	(.038)	.253*	(.039)	.239*	(.037)	.244*	(.037)	.276*	(.038)	.294*	(.042)
constant	3.482*	(.343)	3.483*	(.360)	3.746*	(.357)	3.784*	(.341)	3.675*	(.343)	3.316*	(.348)	3.146*	(.389)
R^2	*.555*		*.517*		*.476*		*.462*		*.454*		*.472*		*.448*	
F	*122.92**		*105.57**		*89.51**		*84.29**		*79.66**		*83.87**		*73.69**	
DV = ln_lag_CR_volume														
multiplayer	.647*	(.159)	.661*	(.159)	.662*	(.156)	.661*	(.150)	.667*	(.146)	.656*	(.145)	.627*	(.143)
genre_shooter	-.103	(.117)	-.183	(.117)	-.203	(.114)	-.209	(.111)	-.218*	(.108)	-.195*	(.107)	-.171	(.106)
ln_lag_sales_cum	.475*	(.031)	.511*	(.033)	.542*	(.034)	.560*	(.034)	.561*	(.033)	.565*	(.033)	.570*	(.033)
constant	-2.896*	(.354)	-3.145*	(.394)	-3.436*	(.409)	-3.586*	(.409)	-3.518*	(.407)	-3.539*	(.414)	-3.556*	(.417)
R^2	*.538*		*.532*		*.548*		*.568*		*.574*		*.572*		*.573*	
F	*114.98**		*112.28**		*119.65**		*129.49**		*133.07**		*131.88**		*132.36**	

* Significant at $p < .05$.
Notes: MB = microblogs, CR = consumer reviews, B = unstandardized OLS coefficients, SE = standard error.

Figure 1: Conceptual framework

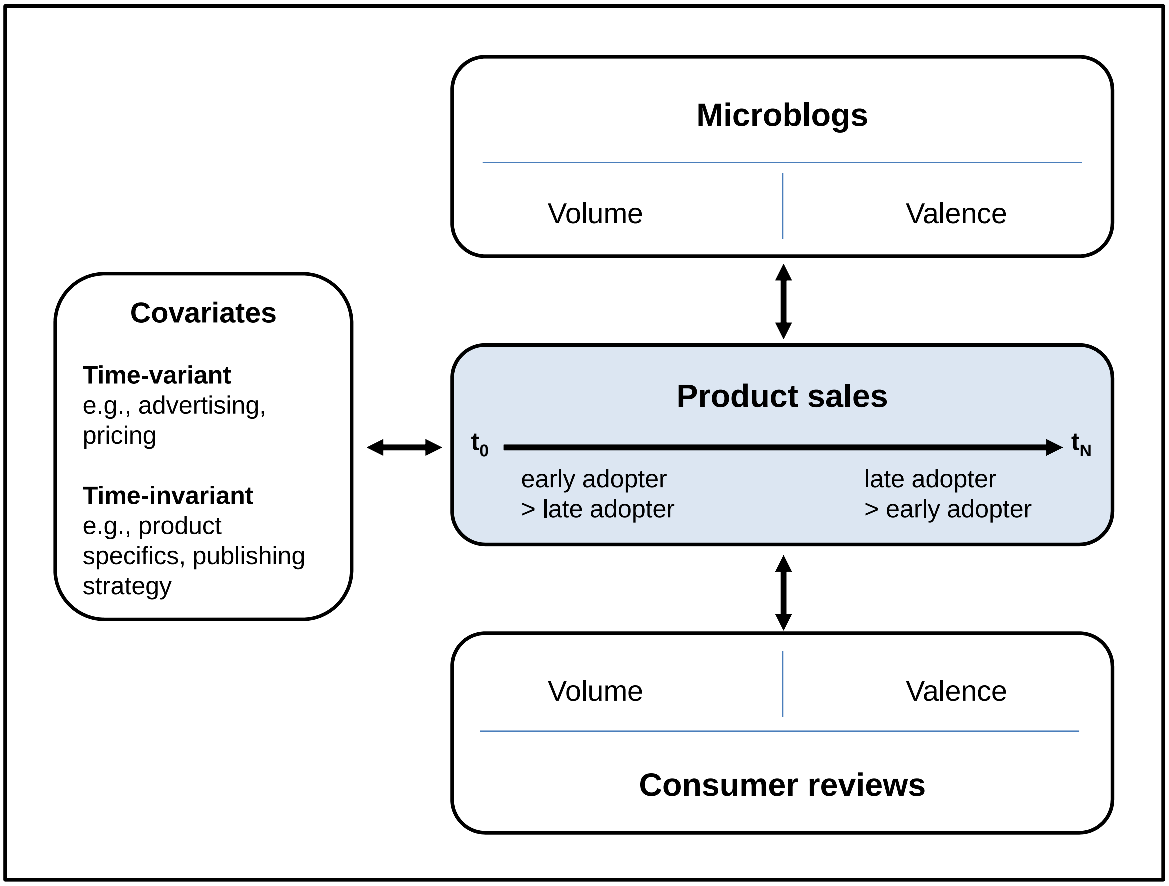


Figure 2: Normalized volume trends over time

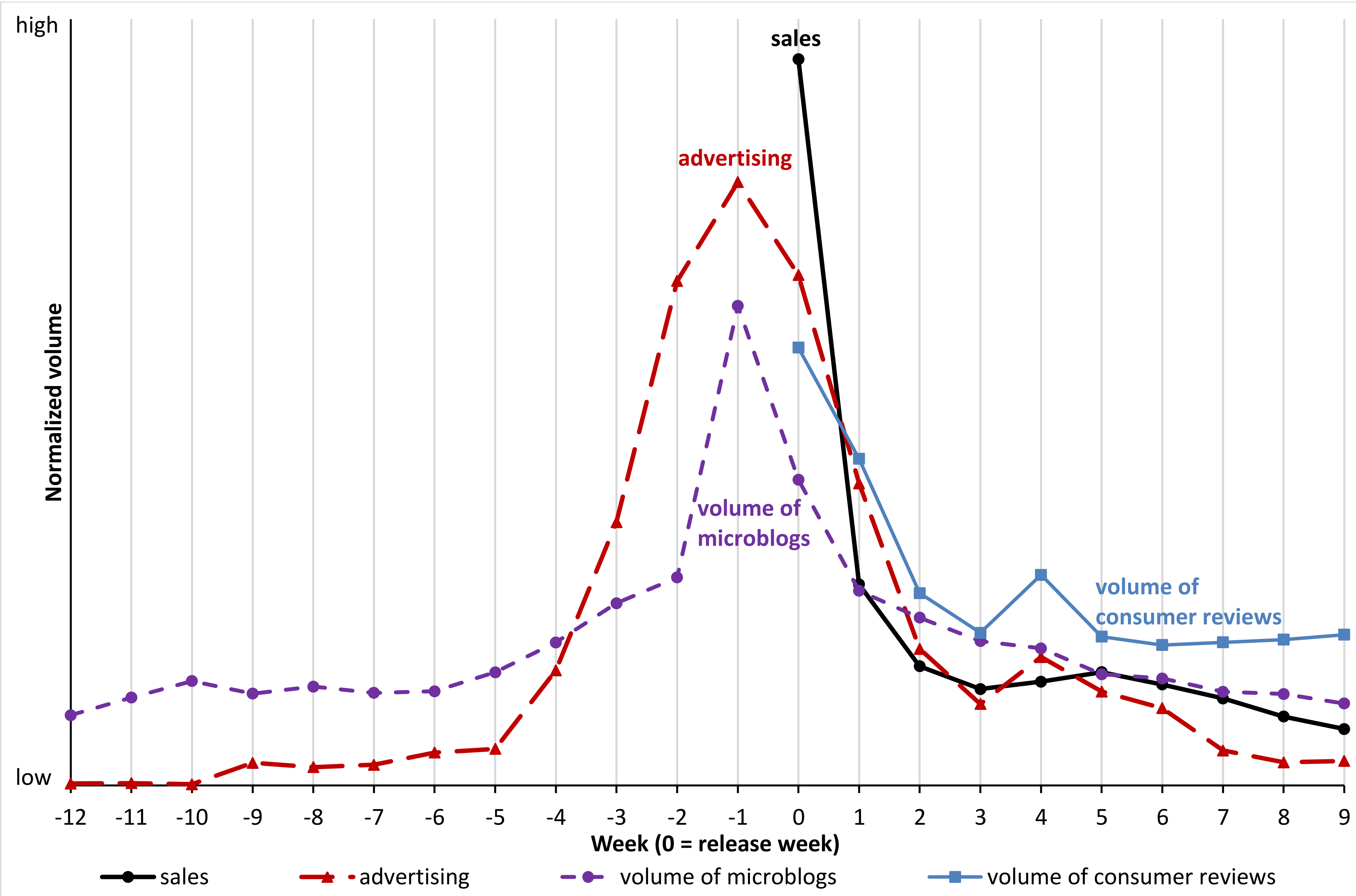
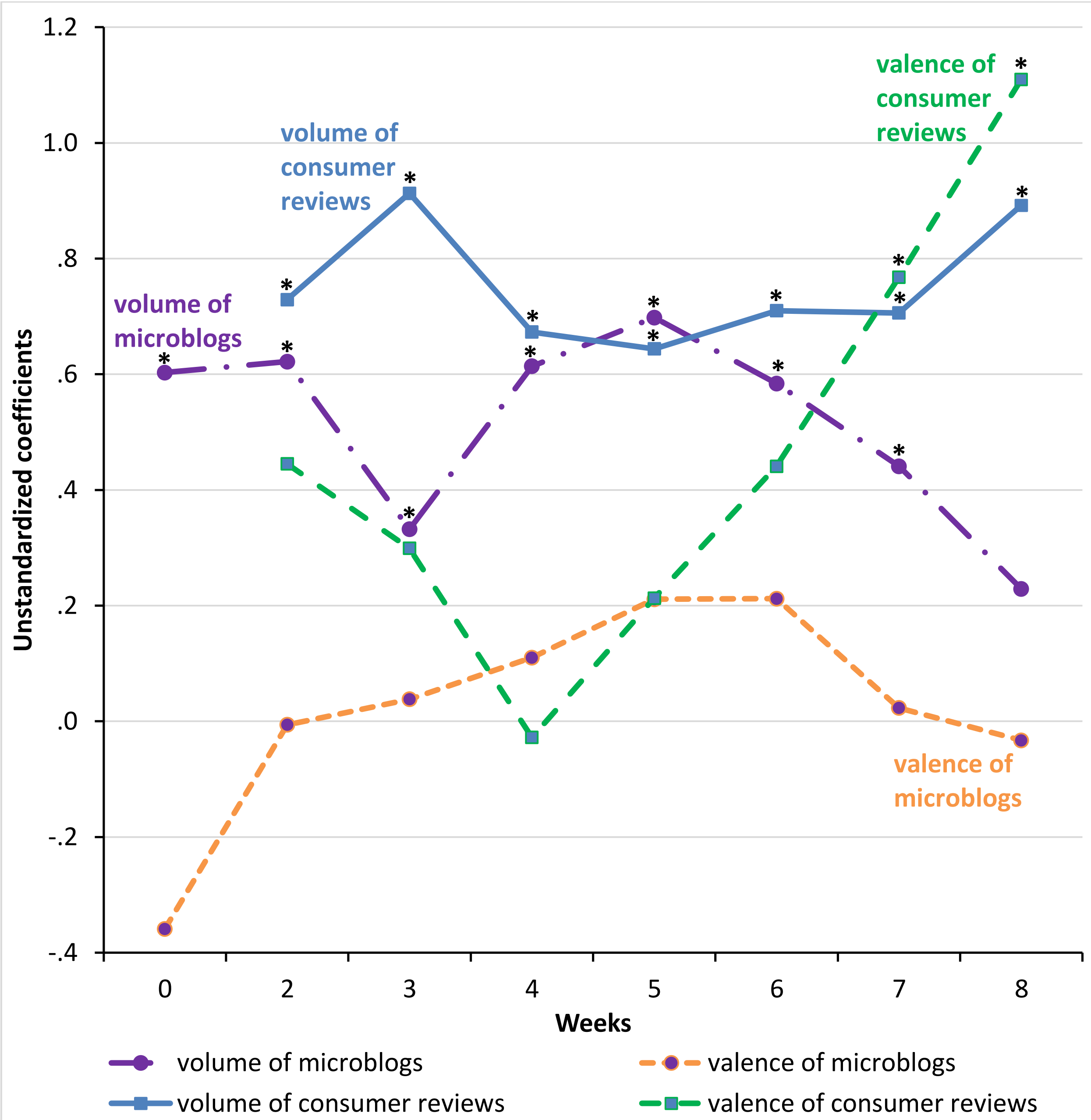


Figure 3: Unstandardized regression coefficients over time



* Significant at $p < .05$.

Notes: Coefficients for the release week are estimated with OLS, and those for the post-release weeks are estimated with 3SLS. Week 0 indicates the release week, week 2 refers to weeks 1, 2, and 3; week 3 is weeks 2, 3, 4; and so forth. Because of the log-transformation, the unstandardized coefficients can be interpreted as elasticities (e.g., a 1% increase of the volume of microblogs in weeks 0–2 corresponds to about .6% change in sales in weeks 1–3). The variables for the release week are the volume of microblogs = *ln_pre-release_MB_volume*, and valence of microblogs = *ln_lag_MB_valence*. For the post-release weeks, the variables are the volume of microblogs = *ln_lag_MB_volume*, valence of microblogs = *ln_lag_MB_valence*, volume of consumer reviews = *ln_lag_CR_volume*, and valence of consumer reviews = *ln_lag_CR_valence*.