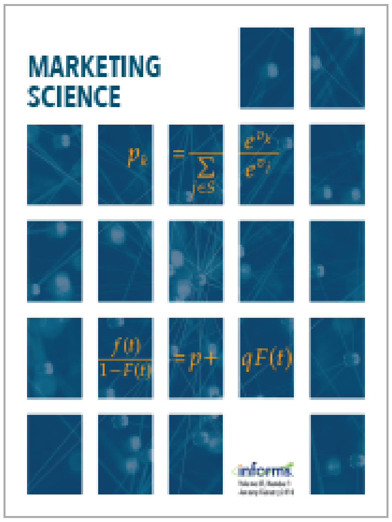


Marketing Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

Prerelease Buzz Evolution Patterns and New Product Performance

Guiyang Xiong, Sundar Bharadwaj

MARKETING SCIENCE
Vol. 33, No. 3, May–June 2014, pp. 401–421
ISSN 0732-2399 (print) | ISSN 1526-548X (online)
http://dx.doi.org/10.1287/mksc.2013.0828

Prerelease Buzz Evolution Patterns and New Product Performance

Guiyang Xiong, Sundar Bharadwaj
Terry College of Business, University of Georgia, Athens, Georgia 30602
{gyxiong@uga.edu, sundar@uga.edu}

This study examines the dynamics of online buzz over time before product release. Employing functional data analysis, we treat the curve of prerelease buzz evolution trajectory as the unit of analysis and find that the shape of the curve significantly adds power in predicting new product performance compared with using product characteristics and firm advertising alone. Moreover, daily prerelease buzz evolution data enable accurate sales forecasting long before product release, which allows sufficient time for managers to adjust product design and/or marketing strategy. For example, the forecasting accuracy using an early buzz evolution curve ending on the 61st day before product release is not only higher than that using accumulated buzz volume until then but also higher than that using the total volume of all buzz up until product release. Beyond the sales outcome, we find that prerelease buzz is quickly reflected in firm stock returns before product release and reduces the absolute amount of postrelease stock price correction. The model accounts for endogeneity, and the results are robust after controlling for buzz sentiment. We also explore the factors influencing prerelease buzz evolution patterns, thus generating insights into how to manage prerelease buzz dynamics to enhance new product performance.

Keywords: prerelease buzz dynamics; evolution pattern; functional data analysis; forecasting; new product sales; stock market value
History: Received: May 22, 2012; accepted: October 30, 2013; Preyas Desai served as the editor-in-chief and Gerard Tellis served as associate editor for this article. Published online in *Articles in Advance* February 10, 2014.

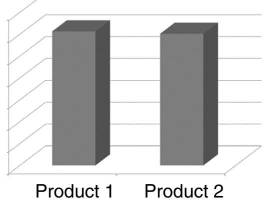
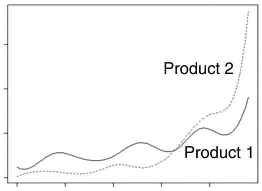
1. Introduction

Consumers frequently generate online blog and forum postings about products *before* their release, i.e., *pre*release buzz,[1] which reflects their interest in the forthcoming products (e.g., Houston et al. 2011). Not surprisingly, brands ranging from Ford to Mentos are paying increasing attention to prerelease buzz to maximize new product success. However, most existing studies have focused on *post*release online consumer conversations, i.e., consumer reviews or ratings generated *after* product release based on consumption experiences, and examined their relationship with product sales, replicating in the online context the long-standing research on the link between off-line word of mouth and product adoption (e.g., Brown and Reingen 1987, Chevalier and Mayzlin 2006, Coleman et al. 1966, Godes and Silva 2012, Moe and Schweidel 2012, Zhu and Zhang 2010).

It is critical for firms to forecast demand as early as possible to make necessary marketing mix changes and to wisely allocate resources, as it is extremely difficult to make up for lost sales later to recoup the significant costs already incurred in new product development, production, inventory, and marketing (e.g., Ainslie et al. 2005). However, accurate sales forecasting before product release has been a challenging task because of the lack of the product's prior sales history and the difficulty in collecting comprehensive data that represent the entire potential consumer base (Foutz and Jank 2010, Moe and Fader 2002). Although prerelease buzz data can be conveniently recorded and may help predict new product performance, research on their role is still nascent. Moreover, as shown in Table 1, the few existing studies that link *pre*release buzz with product sales have focused on examining *accumulated* buzz volume up until product release and neglected the history of

[1] Prerelease buzz is distinct from postrelease word of mouth. First, before product release, consumers do not have any consumption experiences with the actual product, and little is known about product quality. Hence, compared with postrelease consumer reviews, prerelease buzz mostly reflects consumer interest in the product rather than product evaluation. Second, postrelease word of mouth can have an immediate impact on purchase; however, when a potential consumer is exposed to prerelease buzz about product X, the product is not yet available on the market, and thus the impact of this buzz cannot be realized into actual purchase behavior until product release. Previous research suggests that consumer search of the product information online over time before product release can also indicate consumer interest in the upcoming product (e.g., Houston et al. 2011, Kulkarni et al. 2012). Hence, we also model prerelease search in comparison with prerelease buzz.

Table 1 Summary of Literature on *Prerelease* Buzz

	Prerelease buzz data or variables employed to explain new product performance		Consequences of prerelease buzz dynamics				Antecedents of prerelease buzz dynamics	
	Cumulative prerelease buzz 	Prerelease buzz dynamics 	Contrast of buzz versus search activity	Sales	Early forecasting of sales	Stock market value	Supplier-side factors	Demand-side factors
This study	**Yes**[a]	**Yes** (capture the entire history of daily buzz dynamics prior to release using nonparametric functional analysis)	**Yes**	**Yes**	**Yes**	**Yes**	**Yes** (advertising and marketing alliances)	**Yes** (preorder and viral effect)
Liu (2006)	Yes (total volume of Yahoo! movie messages before release)	No	No	Yes	No	No	No	No
Dhar and Chang (2009)	Yes (total volume of chatter four weeks before album release)	No	No	Yes	No	No	No	No
Gopinath et al. (2010)	Yes (cumulative number of prerelease blogs)	No	No	Yes	No	No	No	No
Chintagunta et al. (2010)	Yes (movie reviews from other markets before release in the focal market)	No	No	Yes	No	No	No	No
Onishi and Manchanda (2012)	Yes (cumulative number of blogs, including prerelease blogs)	No	No	Yes	No	No	Yes (advertising)	Yes (viral effect)
Kim and Hanssens (2012)	Yes (cumulative buzz up to one week before movie release)	No[b]	Yes	Yes	No	No	Yes (advertising)	No
Kulkarni et al. (2012)	No	Yes (simultaneously estimate a hazard model of weekly search and a separate sales model without search variable)	No	Yes	No	No	Yes (advertising)	No
Asur and Huberman (2010)	Yes (average number of tweets per hour during the week before movie release)	Yes (included the number of tweets on each of the seven days before release as seven separate variables in a linear regression to predict sales)	No	Yes	No	No	No	No

Notes. There is also a large body of research on *post*release buzz (consumer reviews or ratings generated after the associated product has been launched; see, e.g., Chevalier and Mayzlin 2006, Dellarocas et al. 2007, Duan et al. 2008, Tirunillai and Tellis 2012, and Zhu and Zhang 2010). We *only list the articles on prerelease buzz* to highlight the positioning and contributions of the current study, which focuses on the trajectory of *pre*release buzz dynamics over time in the period prior to product release.

[a]For comparison of model fit only.

[b]Kim and Hanssens (2012) use time-series models for *antecedents* of buzz dynamics over time. However, they only use cumulative buzz in the sales model.

buzz dynamics over the prerelease period (see §2.1 for further discussion of this research gap).

Against this backdrop, this study examines the relationship between *prerelease buzz dynamics* (i.e., the pattern or history of buzz growth or change over time prior to product launch) and *new product performance*. In particular, it addresses the following questions:

1. What is the link between prerelease buzz evolution patterns and postrelease new product performance?

2. (a) Does the forecasting accuracy of new product sales improve when using prerelease buzz evolution dynamics instead of cumulative or aggregated prerelease buzz measures?

(b) Do prerelease buzz dynamics help forecast new product sales over and above traditional marketing mix (e.g., advertising) and product features?

(c) Can partial prerelease buzz history, especially early buzz dynamics, help forecast sales accurately *well before* product release?

3. If prerelease buzz dynamics are important, what factors drive them?

Perhaps the technical difficulty in incorporating the *entire history* of prerelease buzz dynamics to explain postrelease sales could be a reason that previous studies mostly focus on accumulated prerelease buzz measures. In this study, we employ a flexible nonparametric method, functional data analysis (FDA), to analyze the daily buzz records of 681 new video game products before their launch. Treating each product's prerelease buzz evolution curve as the unit of observation, FDA allows us to examine what shapes of the curves are associated with superior new product performance. Functional regression shows that higher than average buzz volume throughout the prerelease period predicts greater sales, whereas a decreasing trend in prerelease buzz relative to the average has an inimical effect.[2] Moreover, using the shapes of prerelease buzz evolution curves significantly enhances model fit and forecasting accuracy compared with accumulated measures (e.g., total volume of prerelease buzz), indicating the important role of the *history* of buzz dynamics prior to product release. Although higher recent buzz is beneficial, it does not mean that early buzz dynamics are of no value to managers. We show that, at any time $-T$ before product release, one can use the shape of buzz evolution up until $-T$ to significantly improve the forecasting accuracy of new product sales more so than using advertising, preorder, or time-invariant product features alone. The accuracy of such *early forecasting* using partial buzz evolution dynamics (e.g., shape of buzz evolution ending on the 61st day before launch) is also higher than that using the total volume of *all* buzz before product release.

In addition, we look beyond sales and find that the stock market considers prerelease buzz in firm valuation. Before product launch, changes in prerelease buzz are quickly impounded in stock returns. In other words, prerelease stock prices already reflect the value of the forthcoming product based on prerelease buzz. As a result, prerelease buzz reduces "surprise" at the time of product launch, and thus it minimizes the size of abnormal change in firm value on product release day. Hence, we demonstrate the financial value relevance of prerelease buzz as an early indicator of new product performance.

Finally, if prerelease buzz dynamics drive new product performance, managers need to explore their antecedents. We systematically examine the effects of demand-side and supplier-side factors as well as product features on preprelease buzz dynamics over time.

In the rest of the paper, we first explain the importance of examining prerelease buzz evolution pattern and present theory about how it predicts new product performance. Next, we present the method, data, and results. We conclude with managerial and theoretical implications.

2. Prerelease Buzz Evolution Pattern and New Product Performance

2.1. The Meaningfulness of Examining Prerelease Buzz Dynamics

Existing research using *accumulated* prerelease buzz (summarized in Table 1[3]) is a good starting point, but it can be fruitful to examine the dynamics of prerelease buzz with disaggregated data over time for theoretical, statistical, and practical reasons. First, social psychology and political science literatures have documented the momentum effect that a person's attitude to subject X can be influenced by the *trend* in his or her peers' interest in or support for X (e.g., Bartels 1988, Kenny and Rice 1994). Hence, the trend in prerelease buzz dynamics can predict consumer perception and purchase. Second, Chintagunta and Lee (2012) find that the history of intentions prior to purchase matters and that intention growth pattern augurs sales. Prerelease buzz dynamics can continuously reflect and influence the dynamics of purchase intentions. As a result, Chintagunta and Lee call for future research to study "the trajectory of the buzz in the period leading up to the release" (p. 153). Third, two products with similar total volume of prerelease buzz could have very different trajectories of buzz dynamics (e.g., Figure 1). Finally, prerelease buzz dynamics are nonstationary for many products and may not follow a random walk (as visualized in Figure 2[4]). This further highlights that the *entire history* of prerelease buzz dynamics can contain additional information to forecast new product outcomes above and beyond the latest buzz or accumulated buzz prior to release.

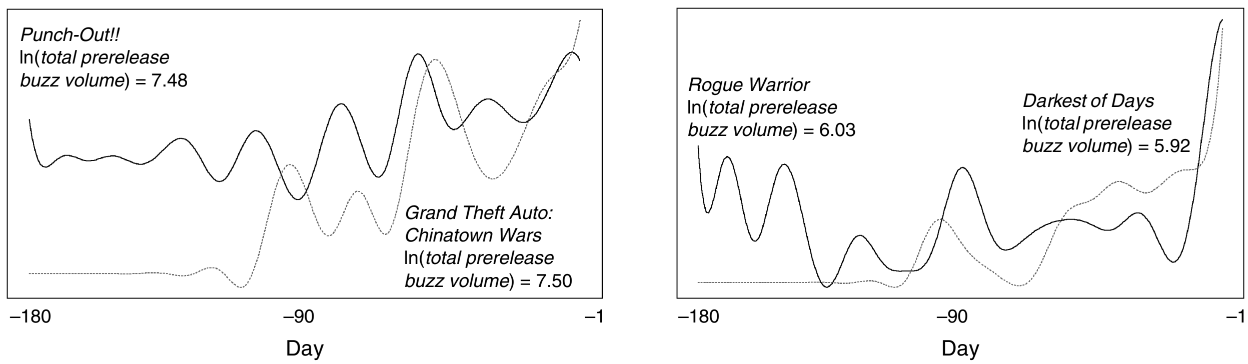
It is also of managerial interest to examine prerelease buzz dynamics. First, in contrast to off-line word of mouth, it is convenient to record and identify the

[2] Whereas existing research has ignored prerelease buzz dynamics over time, this result suggests the importance of considering the evolution pattern of prerelease buzz. Although the negative impact of a decreasing trend may not appear surprising, it serves as a foundation for which we generate nonintuitive insights into improving sales forecasting accuracy.

[3] One exception, Asur and Huberman (2010) treat seven days' of prerelease tweet volumes as seven separate variables in a cross-sectional regression, ignoring the statistical bias stemming from serial correlation (e.g., Wooldridge 2003). The other study using prerelease time-series data, Kulkarni et al. (2012), models the hazard (i.e., probability, instead of volume) of weekly online search over eight weeks before movie release but does not directly estimate the impact of prerelease search pattern on sales.

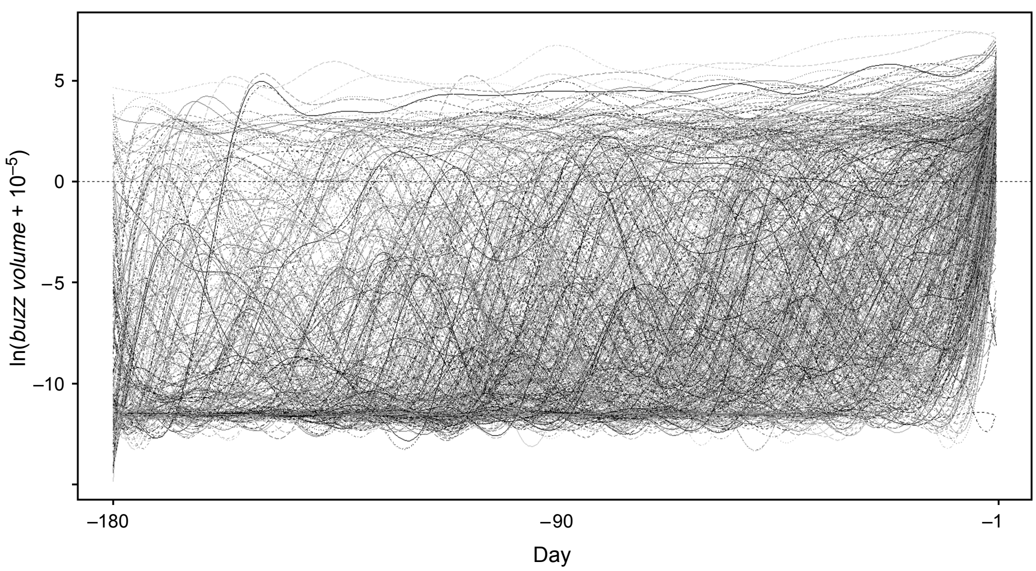
[4] The augmented Dickey–Fuller tests indeed suggest that the prerelease dynamics of most sample products are nonstationary.

Figure 1 **Examples of Video Game Products' Buzz Evolution Patterns *Prior to* Product Release**



Notes. Each graph includes two products with similar total volume of prerelease buzz. For example, whereas *Punch-Out*!! has a relatively steadily increasing pattern, *Grand Theft Auto*'s buzz has a steeper upward trend in the later stages and surpasses the buzz volume of *Punch-Out*!! right before product release day (on days −2 and −1).

Figure 2 **Smoothing Splines of Each Sample Product's Prerelease Buzz Volume (Logged)**



exact time at which online buzz occurs, and thus it is practical to model prerelease buzz dynamics. Second, managers are interested in forecasting new product performance *well in advance of* product release, since it allows them sufficient time before launch to modify the product and other marketing actions to maximize product success. The buzz evolution pattern in the earlier stages of the prerelease period can potentially enhance sales forecasting accuracy, and the predications can be updated as buzz evolves over time before product release.

2.2. Prerelease Buzz Evolution Pattern and New Product Sales

Consumers often refer to their peers when considering the purchase of a new product (Rogers 1983). Prerelease buzz volume can explain and predict new product sales for the following reasons.[5] First, it reflects the amount of consumer interest and engagement in the product before its launch (Kulkarni et al. 2012). High consumer interest in the prerelease period leads to eager anticipation (since the nonavailability of the product disrupts the goal of consumption), building up pent-up demand (Houston et al. 2011). Second, it increases the purchase likelihood of blog readers, forum participants, and other potential

[5] Prerelease buzz could foretell new product outcomes, because (1) it could influence consumer perception, which then affects new product performance, and (2) it could be reflective of consumer perception, which drives new product performance. Whereas both paths are possible and lead to the same final outcomes, we cannot distinguish between them with our data and empirical analysis. Hence we use "predict" and its synonyms (instead of "influence") to describe the relationship between prerelease buzz and new product outcomes. We thank the associate editor for this suggestion.

consumers by influencing their (1) awareness and (2) preference (Godes and Mayzlin 2009). For any new product to be purchased, awareness is a precondition. A large volume of buzz boosts awareness of the new product among potential consumers (Liu 2006). Beyond the awareness effect, (a) mere exposure to a brand name can promote favorable consumer attitude to the brand (Janiszewski 1993). Moreover, (b) when there is limited information about the product (typical for a prerelease period), the amount of buzz a product receives can be an indicator of its popularity and possibly high quality (Godes and Mayzlin 2004, Iyengar et al. 2011),[6] which increases the potential consumers' expected utility of the product and persuade them to buy. For instance, Centola (2010) finds that the number of recommendations people receive influences their likelihood of adoption. (c) High buzz volume also increases the likelihood and frequency of consumer exposure to the buzz, which enhances normative pressures from social influence, promotes herd behavior (Banerjee 1992), and thus persuades adoption and increases purchase intention (Van den Bulte and Lilien 2001).

Since the evolution path of prerelease buzz differs across products, an important question is, does it matter *how* the buzz volume evolves (e.g., increasing or decreasing) during the prerelease period?[7] All else equal, do different evolution patterns in prerelease buzz predict different postrelease sales?

First, if prerelease buzz volume declines (either absolutely or relatively compared with the market average) over time, it may imply that the market coalesced around the premise that the new product is not as attractive as initially believed. For instance, consumer excitement faded over time before product launch for video games *Daikatana* and *Battlecruiser 3000AD*, both of which had ambitious concepts and early campaigns. Conversely, an increasing trend (especially compared with the average) in prerelease buzz volume is likely to predict greater sales, since the *momentum* in buzz not only boosts awareness but also increases social salience and familiarity enhancing the anticipation of those already aware (Cialdini 2001, Fiske and Taylor 1991), foreshadowing purchase behavior (Houston et al. 2011). In addition, Chintagunta and Lee (2012) find that a growing trend in purchase intentions over time increases purchase likelihood. Since prerelease buzz reflects and influences purchase intention continuously over time before product launch, the trend in prerelease intentions is likely to mirror that in prerelease buzz.

Research in social psychology and political science on the momentum (or bandwagon) effect also provides support for the expectation discussed above. For instance, Bartels (1985) finds that political candidacies in declining trend tend to lose while those in increasing trend are more likely to gain further support and win. As suggested by Bartels (1988) and Kenny and Rice (1994), an increasing trend can (1) generate such contagious excitement that people tend to throw in their support automatically and uncritically as a result of *herd instinct*, (2) make people "jump into the bandwagon" for the emotional pleasure of following a winner, (3) bring in the *cue takers* who simply like the current favorite of the fellow partisans, and (4) convince people that the popularity of the candidate or product is inevitable. Moreover, drawing on the persuasive argumentation and cognitive response theory, Mutz (1997) finds that when a person observes an increasing number of people supporting a political candidate or showing interest in a forthcoming product, he or she mentally rehearses possible arguments that could explain such behaviors. Such arguments would not otherwise have come to his or her mind and are most likely in favor of the candidate or the product, leading to self-persuasion. As commonly seen on the front pages of many social media websites, changes in the daily ranks of "Today's Most Discussed Topics" and "What's Hot" sections make it even easier to spot the topics with largest discussion volumes over time and identify products with growing popularity. For example, observing that the game *Alan Wake* had been "gaining more and more buzz" before its launch, blogger "catherine preth" was convinced and wrote in her November 2009 blog that it must be one of the "most anticipated [forthcoming] Xbox video game" (Articlesbase 2009). Taken together, an upward trend in prerelease buzz evolution pattern can foretell high product sales after launch.[8]

[6] In addition to buzz volume, the sentiment of buzz may also influence sales. We control for buzz sentiment as a robustness check. Prior research finds that the volume of all buzz with or without sentiments can enhance product popularity. Godes and Mayzlin (2004, p. 556) find it "quite common" that "the content of a post was deemed irrelevant," but that post still has an impact on sales due to "the fact that the name of the show (product) was in the subject line may contribute to the overall impression of a large volume of conversations."

[7] Consumers do *not* only collect information about a product at the time of purchase. They read about a forthcoming product over time during a long period before its release. For example, Google Trends, which tracks online search of keywords over time, shows that the earliest search records for the game *Borderlands* can be traced back to five months before its release.

[8] This does *not* indicate that buzz in the early stages of the prerelease period is unimportant or that managers only need to focus on hyping up last-minute buzz right before release. Consumer behavior literature suggests that early buzz can significantly influence final purchase as a result of the novelty effect (Shen and Wyer 2008) and the persistence of prior impressions (Herr et al. 1991, Tetlock 1983). From a managerial perspective, firms can incorporate consumer feedback from early buzz to modify the product before its launch (Fay and Xie 2008). Also, as we discuss in §3.3.1, our results show that high buzz volume *throughout* the prerelease predicts

Moreover, the momentum effect also indicates that an upward trend in *early* buzz (which is not the same as simply high volume of early buzz) can predict further increase in consumer interest closer to product launch. This suggests the possibility of accurate early forecasting using earlier prerelease buzz evolution pattern, which we will illustrate later in §3.3.3.

Note that testing the theories above is not intended to be the primary objective or contribution of this study. The purpose of this theoretical development is to highlight the importance of considering the shape of the prerelease buzz evolution pattern when forecasting new product sales (i.e., by ignoring the dynamics in prerelease buzz, researchers can miss important information for sales forecasting). As demonstrated in §3.3.2, the shape of prerelease buzz evolution pattern, as opposed to the accumulated buzz volume only, results in significantly better sales forecasts.

2.3. Looking Beyond Sales—Prerelease Buzz and Firm Stock Market Value

A survey by the Brunswick Group shows that a large number of stock analysts and investors now consider social media buzz when making investment decisions (Duckworth et al. 2009). Before product launch, little information is available about the product, and investors cannot judge its financial value based on sales (because no actual sales occur before launch). Investors are thus likely to monitor prerelease buzz over time, because it reflects consumer purchase interest before product launch. Hence, firms have started to inform the investment community about the prerelease buzz of their upcoming products, as Activision Blizzard did in a conference call to investors about its game *Call of Duty: World at War*. To the best of our knowledge, no existing research has examined the link between *pre*release buzz and firm stock market value. If prerelease buzz can be related to shareholder value, it can help marketing managers justify the budget they need for social media management before product launch. Recent research finds that stock prices reflect consumer reviews and complaints *after* product adoption (Luo 2007, Tirunillai and Tellis 2012). They argue that *post*release buzz can influence stock returns because it influences cash flows (i.e., through sales). Notably, although product sales are directly observable to investors in the postrelease period and thus could confound the effect of buzz, they are not controlled for in these studies. A unique advantage of studying the stock market effect of prerelease buzz is that, during the period before product launch, no actual product sales occur.[9] This allows us to examine the link between buzz and stock returns without the actual sales being a confounding factor.

higher opening sales. However, although early buzz is important, it does *not* have to be higher than buzz closer to product launch to enhance sales. We thank the associate editor for pointing this out.

Firms' stock prices are determined by expected future cash flows, which can be influenced by the expected performance of their forthcoming products. According to the efficient market hypothesis, as soon as new information about a firm's forthcoming product becomes publicly available, stock market investors quickly adjust their expectations about the product's future performance and thus firm future cash flows, and the stock prices immediately impound the new information[10] (Fama 1991, Sorescu et al. 2007). Imagine a situation in which investors already have perfect information about an upcoming product *prior to* its release and thus can accurately predict the product's future performance—in this situation, stock prices should have already correctly reflected the financial value of this new product *before* its release, and there should *not* be any significant stock price corrections when investors observe actual product performance *after* product release. In contrast, the *less* the market knows about the new product prior to its release, the more likely the investors need to make corrections about its financial value upon product release (Chen et al. 2011, Joshi and Hanssens 2009), and thus the more significant the stock value change could be on the product release day.

Prerelease buzz contains important information not only about the upcoming product itself but also about how consumers may potentially respond to the new product offering. The higher the volume of prerelease buzz, the more likely the market has access to more and richer information before product release to predict new product performance. Consequently, there is likely to be less "surprise" or "new news" to the stock market at the time of new product launch. This in turn reduces the likelihood and magnitude of correction in the firm's stock price upon product release, leading to a lower *absolute amount* of abnormal stock price change on product release day. Note that although stock prices can go either up or down on product release day, in this case, we focus on the *absolute amount* of abnormal stock return, i.e., *how much* the stock price correction will be, because this

[9] Some products have preorders before release. We control for the number of preorders in the stock return model.

[10] For this reason, a forthcoming product can influence a firm's stock returns over a long time period before its release. To demonstrate this phenomenon, we conduct additional analysis on the contemporaneous changes of stock prices *throughout the prerelease period* in response to daily buzz. In contrast, in this section, the theory focuses on how the stock returns *on the day of product launch* (i.e., on day 0) can be explained by prerelease buzz dynamics (i.e., entire history until day -1).

absolute amount of change reflects the level of information asymmetry before product release.

In sum, we expect that the volume of prerelease buzz lowers the level of information asymmetry or imperfectness about the forthcoming product, and therefore it mitigates the size (absolute amount) of abnormal change in firm value on product release day. In the video game industry, game developers are usually called upon by publishers to develop new products and are paid by publishers against recouped costs of development. Publishers market the games, assume most of the risks, and gain most of the profits. We thus focus on the stock price of the publishers in this context.

3. Empirical Analyses and Results

3.1. Functional Data Analysis Method

Social media buzz evolution is analogous to the spread of viruses. An upcoming product's potential customer base develops over time, and the product-related information is disseminated continuously before product launch. It is thus reasonable to expect the existence of a continuous evolution process in prerelease buzz, which can be captured by a mathematical function. To model this evolution process, we employ the FDA method. The key feature of FDA is its ability to examine each curve (function) as the unit of observation (Ramsay and Silverman 2005). In this case, FDA can effectively incorporate the entire prerelease buzz histories (i.e., it can use all the information until product release). FDA has become increasingly popular among statisticians as more automatically collected time-series data become available. Marketing researchers have employed it to examine market penetration (Sood et al. 2009) and movie virtual stock price (Foutz and Jank 2010).

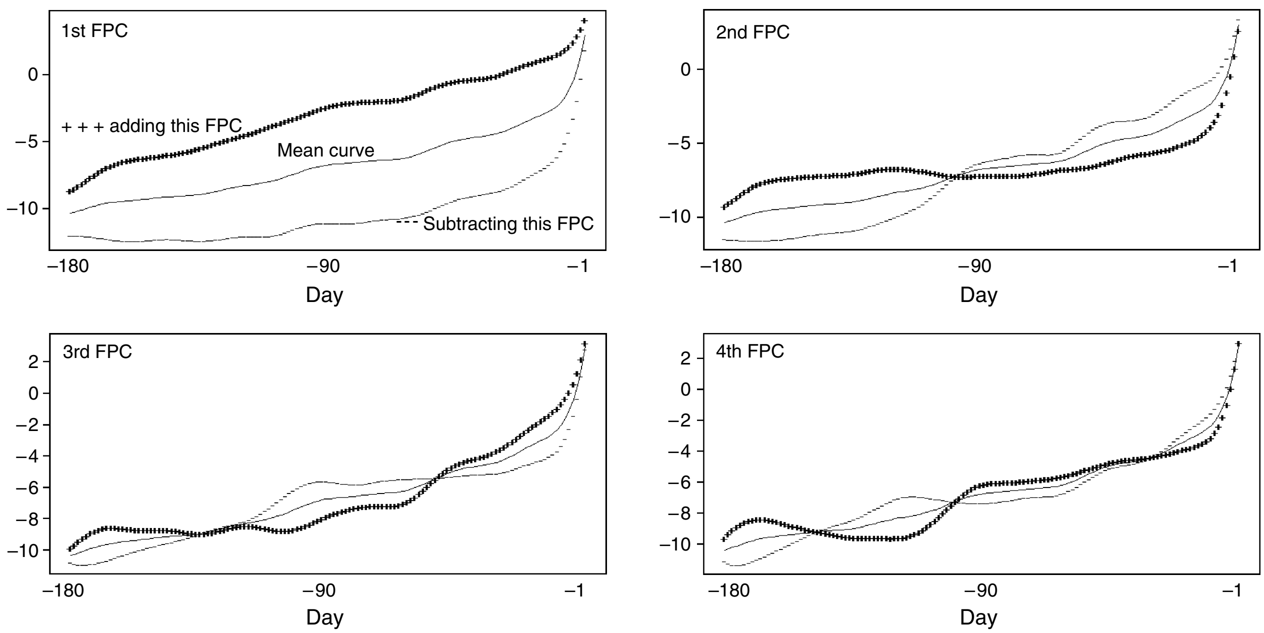
The functional modeling approach, as a nonparametric method, assumes only smoothness and permits as much flexibility as required by the data. It offers several advantages. First, it does not fix the number of parameters (e.g., mean, variance) or parameter distribution specifications in advance (in contrast, parametric models are restricted by a fixed and small number of parameters that follow "textbook density functions") (Ramsay and Silverman 2005). Second, it does *not* require a *stationarity* assumption and is best suited for analysis of nonstationary time-series data (Ramsay and Dalzell 1991). For example, in a classic study by Ramsay et al. (1995), FDA is used to analyze the curves of a group of girls' heights over time (nonstationary data). Recent research in marketing has fit the nonstationary data of virtual Hollywood Stock Exchange stock prices with functional curves (Fan et al. 2013, Foutz and Jank 2010). Third, FDA does not require a covariance assumption, and the covariance structure can be efficiently captured by a small number of functional principal components.

Such flexibility fits our data structure and research purpose. First, the prerelease buzz evolution patterns (see Figures 1 and 2 for examples) and their mean (solid line in Figure 3) do not appear to follow any "textbook" density distribution. Second, for many products, the prerelease buzz volume exhibits a trend (e.g., growing) over time and is thus nonstationary. Third, to explain the link between prerelease buzz dynamics (longitudinal, observed daily for each product for 180 days[11] before its launch) and postrelease opening sales (cross-sectional only, observed for each product at a single point of time), we face the challenge of regressing a 180-dimensional vector on a scalar variable. The FDA approach helps overcome this challenge because it allows us to capture most of the variability in buzz across 180 days with only several functional principal components, and then use the small number of functional principal component scores as independent variables (Ramsay and Silverman 2005, Yao et al. 2005). This reduces dimensionality significantly and avoids the "curse of dimensionality." The enhanced flexibility of this nonparametric method might come at a cost of high variability in the estimates. However, the problem can be mitigated by a large sample size (681 curves in this case) that adds strength to the regression (see Sood et al. 2009).

3.1.1. Revealing the Prerelease Buzz Evolution Curves. We have data of each product's daily prerelease buzz dynamics consisting of 180 daily observations. Random events and recording errors can cause noise in the raw data. Hence, although we expect an underlying continuous buzz evolution curve to exist for each product, its raw data are discrete dots surrounding (above or below) this underlying curve as a result of random influences. Prior literature has demonstrated the effectiveness of functional smoothing in removing such random influences (Fan et al. 2013, Foutz and Jank 2010, Ramsay and Silverman 2005, Reddy and Dass 2006, Sood et al. 2009), and thus we use penalized smoothing *splines* to recover the underlying continuous smooth buzz evolution curve $V_j(t)$ for each new product j ($j = 1, 2, \ldots, J$; $J = 681$). A detailed description of the

[11] The 180-day window covers the entire history of prerelease buzz for a majority of sample products. In line with this, industry reports also find that most online searches for game info start six months before launch (Getomer et al. 2012). We also employ prerelease windows of alternative lengths for early forecasting and as a robustness check.

Figure 3 Functional Principal Components of Prerelease Buzz Evolution Curves



Notes. A principal component represents variation around the mean. The solid line is the mean log buzz evolution curve $\mu(t)$, the $+++$ $(---)$ line represents adding (subtracting) a small amount of the FPC. Numerically, the $+++$ line is $\mu(t) + \xi_p \mathrm{FPC}_p$, and the $---$ line is $\mu(t) - \xi_p \mathrm{FPC}_p$, where ξ_p is a value proportional to the standard deviation of the pth FPC score_p. The FPCs of the subsample of 310 games released by publicly listed publishers are consistent with those of the complete sample reported in the figure. Figure A2 in Online Appendix 2 plots prerelease search FPCs, whose shapes are also consistent with prerelease buzz FPCs shown above.

smoothing approach is in Online Appendix 1 (available as supplemental material at http://dx.doi.org/10.1287/mksc.2013.0828).

Figure 1 plots the curves of prerelease buzz volume (logged) for all the 681 sample products. On the horizontal axis, day −1 is the day before the new product release, and day −180 is the 180th day before release. Significant heterogeneity across products can be observed in the prerelease buzz evolution pattern.

3.1.2. Generating Functional Principal Components. We conduct functional principal component analysis (functional PCA) to reveal the distinguishing shapes characterizing the heterogeneous prerelease buzz evolution curves. Functional PCA is analogous to conventional PCA (see Online Appendix 1). The smooth curve $V_j(t)$ for product j can be decomposed into

$$V_j(t) = \mu(t) + \sum c_{jp} \pi_p(t), \tag{1}$$

subject to the orthogonality constraints $\int \pi_p^2(s)\,\mathrm{d}s = 1$ and $\int \pi_p(s)\pi_q(s)\,\mathrm{d}s = 0$ for $p \neq q$, where $p = 1, 2, 3, \ldots$; $\pi_p(t)$ is the pth functional principal component (FPC); c_{jp} is the pth FPC score for product j; and $\mu(t)$ is the average curve of the sample (Ramsay and Silverman 2005). The first (second) FPC π_1 (π_2) represents the direction of the greatest (second-greatest) variability in the curves relative to their mean. In other words, each FPC is a distinguishing *shape* that characterizes the variations among buzz evolution curves, and the first few FPCs are the most crucial components because they can explain a significant portion of the variability in the sample. The pth FPC *score* c_{jp} describes *to what extent* $V_j(t)$ varies in the direction of the pth FPC $\pi_p(t)$. Hence, if c_{jp} of a product j is positive (negative), the product's prerelease buzz evolution curve tends to deviate from the sample average in the same (opposite) direction as described in π_p. Figure 3 plots the first four FPCs of the prerelease buzz evolution functions. The solid line is the mean curve $\mu(t)$, and the $+++$ $(---)$ line shows the effects of adding (subtracting) an FPC. The plot of the first FPC shows that if product j has positive value in the first FPC score ($c_{j,1}$), it is likely to have higher than average buzz volume throughout the prerelease period. However, as shown in Equation (1), the overall shape of a product's prerelease buzz evolution pattern depends on not only the first FPC score ($c_{j,1}$) but also the other FPC scores ($c_{j,2}, c_{j,3}, \ldots$), or to what extent it deviates from the mean curve in the direction of each of the first few FPCs. The second FPC describes another feature; i.e., the buzz volume is higher than sample average in the beginning but turns lower than average later in the prerelease period. Hence, if a product j's second FPC score $c_{j,2}$ is positive, the shape of its prerelease buzz evolution curve is more likely to have a descending trend relative to the mean curve. The third and fourth FPCs have more complicated shapes and are not directly related to the theory we proposed. For comparison purposes, we also generated the FPCs for the evolution curves of prerelease consumer search volume, the shapes of which are largely consistent with those of prerelease buzz FPCs (see Figure A1.5 in Online Appendix 1).

A most desirable feature of functional PCA is that a significant portion of the total variability can be explained by a small number of FPCs (Foutz and Jank 2010, Ramsay and Silverman 2005, Sood et al. 2009). For example, the first four FPCs together explain 87.3% of the variability in prerelease buzz volume evolution. Hence, $V_j(t)$ approximately equals to $\mu(t)+c_{j1}\pi_1(t)+c_{j2}\pi_2(t)+c_{j3}\pi_3(t)+c_{j4}\pi_4(t)$, or a function of the first four FPC scores. This is important because it reduces the number of observations in each curve from 180 to a small number (e.g., 4). We thus do not have to regress a 180-dimensional vector on a 1-dimensional scalar variable (e.g., opening sales) to examine the effect of prerelease buzz dynamics. Instead, we can run regression with only a few FPC scores as independent variables. Focusing on a small number of most crucial features not only reduces dimensionality and facilitates estimation but also generates important managerial insights: although there is significant variation in the prerelease buzz evolution pattern, managers only need to focus on a few crucial features that have significant coefficients to track and manage prerelease buzz.

3.1.3. Examining the Link Between Prerelease Buzz Evolution Patterns and New Product Outcomes. To examine the relationship between prerelease buzz evolution curve $V_j(t)$ and new product outcomes, we can specify the model as follows with a vector of control variables $Ctrl_j$,

$$y_j = f(V_j(t), Ctrl_j) + \varepsilon_j. \tag{2}$$

Note that the dependent variable y_j is a constant for each product j (e.g., opening sales is *not* observed over time during the prerelease period; instead, it is observed at one point of time after product launch). In contrast, the independent variable of interest $V_j(t)$ is the entire history of buzz dynamics over time throughout the prerelease period. If we were to directly apply the raw time-series data of daily buzz for analysis, the model would have been extremely difficult to estimate because the independent variable is 180-dimensional whereas the dependent variable is 1-dimensional.[12] With the functional approach, because each function has an approximately equivalent function composed of its FPC score c_{jp}'s, we can transform Equation (2) into

$$y_j = \beta_0 + \sum_{p=1}^{P}(\beta_p c_{jp}) + Ctrl_j\gamma + \varepsilon_j, \tag{3}$$

where β_p is the coefficient of the pth FPC score c_{jp}, and γ is the vector of the coefficients of the control variables.

To address the potential endogeneity between buzz and sales, we adopt an instrumental variable (IV) approach similar to that in Gopinath et al. (2010). Following established guidelines for IV selection, we look for variables that are (1) correlated with the potentially endogenous variable (prerelease buzz FPC scores in our case) but (2) uncorrelated with the error term (game-specific unobservable in our case) (Wooldridge 2002). Our instrument $c\_INST\_G_{jp}$ is the average of the pth FPC scores of *all* games under the same genre released before and after game j's release week.[13] First, we can expect a positive correlation between c_{jp} (the FPC score of the focal product j) and $c\_INST\_G_{jp}$ because they belong to the same genre (and we indeed observe such positive correlations in the data). Second, $c\_INST\_G_{jp}$ is not likely to be correlated with the game-specific unobservables of product j at the time of its release because these other games were released at other times than that of the focal game, and we control for all the other game-specific characteristics with $Ctrl_j$ in Equation (3).

3.2. Data and Measures

We conduct the study in the video game industry for two reasons. First, video games are entertainment goods of experiential nature. It is difficult to judge a game's quality before playing it. Comments and opinions from peers are thus very influential, and buzz is considered more trustworthy and informative than advertising for entertainment goods (Liu 2006). Second, using online buzz is not only effective (Godes and Mayzlin 2004) but also appropriate to study word

[12] For the same reason, a traditional time-series model cannot be applied in our case because it requires both the dependent variable and the independent variable to be time series. In our case, although the independent variable *prerelease buzz* is time series, the dependent variable *opening sales* is not. Even if we do employ a time-series model (e.g., with both opening sales and sales in later periods and with both prerelease and postrelease time series of buzz), we can only examine the effects of a very limited number of lags of buzz (X_{t-1}, X_{t-2}, X_{t-3}, etc.) on sales at time $t(Y_t)$.

[13] The first-stage regression of two-stage least squares shows positive correlations between the first four FPC scores and their corresponding instruments. We also employ alternative instruments as a robustness check. First, we instrument c_{jp} with $c\_INST\_GC_{jp}$, the average pth FPC score of all games under the same genre, developed for the same console, and released before and after game j's release. Second, we adopt the latent instrumental variables approach that has recently been used by marketing researchers to study online buzz (Sonnier et al. 2011; see Online Appendix 2 for details). The results remain consistent with alternative IV or without IV (see §3.4).

of mouth in this context, since online communities are the major communication platforms for video game players.

We obtained online buzz data for 681 new video games released in 2009 and 2010 from a market research company that tracks online blog and forum postings (e.g., MySpace, Blogger, Blogspot, Digg, Gforums) on a daily basis. The subsample used to test the buzz-stock value relationship includes 310 products, since not all video games publishers are publicly listed in the U.S. stock market.[14] Using blog and forum postings to measure consumer-generated buzz is consistent with the practice in existing literature (e.g., Gopinath et al. 2010, Dhar and Chang 2009, Onishi and Manchanda 2012). We also use blog and forum data separately for robustness check. In addition to counting buzz volume, the system also conducts sentiment analysis of buzz in 2010 using automated natural language processing algorithms (see Online Appendix 3 for more details). We also collected data on the daily volume of consumer online searches of the product name before launch from Google Trends (e.g., Moe and Schweidel 2012).

We focus on video games for the Xbox 360, Playstation (PS) 3, Playstation 2, Nintendo Wii, Sony PSP, and Nintendo DS consoles. We collected weekly sales data from VGChartz and daily stock market information from the Center for Research in Security Prices and the Kenneth R. French Data Library (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html, last accessed January 6, 2013). We purchased from TNS Media the daily data of TV advertising dollars and number of online advertising occurrences as well as weekly total advertising dollars across all media outlets for each product.[15] Product details such as genre, release date, professional rating, and publisher and developer information were collected and verified across major video game websites, including VGChartz, IGN, and GameSpot.

We measure new product sales with the units of a new product sold in the first week after release, since a large portion of the total product sales is realized soon after product release in the entertainment industry (typically within the first week for both movies and video games), and researchers have been interested in opening sales (e.g., Chintagunta et al. 2010). We also employ sales within two and three weeks after release as a robustness check. The size (absolute amount) of abnormal change in firm value upon product release is calculated as the product of firm market capitalization and the absolute value of abnormal stock returns on the new product release day (Chan et al. 1997). The measurement of abnormal stock return is detailed in Online Appendix 3.

The control variables are as follows. On the product level, we follow the literature and control for product features, advertising, competition, and product release time (e.g., Chintagunta et al. 2010, Zhu and Zhang 2010). Product features include (1) a sequel dummy (indicating whether the game belongs to a sequel) and (2) average expert ratings as a proxy of product quality[16] (measured on a 0–10 scale averaged over press/professional reviews). Since each game targets on different segments because of its genre and console version, we control for the (3) genre dummy (action, adventure, fighter, first-person shooter (FPS), platform, puzzle, role-playing game (RPG), shooter, and sports, with "other" as a base genre) and (4) console version dummy (Xbox, PS3, PS2, PSP, and two Wii dummies for before and after the introduction of Wii MotionPlus, with DS as the base version). In both the sales and stock price model, we include (5) the total amount of advertising spending (using the FPC scores of daily prerelease advertising dynamics function does not significantly alter the results), since the marketing finance literature suggests that advertising influences stock price (e.g., Srinivasan and Hanssens 2009). (6) Competition is measured by the number of games released in the same week as the focal game. (7) Release time dummies represent the months of product release (with January as the base month). At the firm level, we control for (8) publisher experience using the number of games published by a publisher in the past 10 years prior to the current new game

[14] Although we only have data on buzz in English, whereas stock prices can be determined by expected future cash flows from the world markets, using our buzz data does not pose a fundamental threat of "mismatching" the financial dependent variable in this study. Specifically, of the 310 game titles in the stock return model, 83 (27%) games were released in the United States only. Out of the 227 games that were released both in the United States and worldwide, 221 (97%) of them were released worldwide on a different day from the U.S. release day. And 181 (80%) games were released in the United States before their releases worldwide. Therefore, there is no significant "mismatch" between the buzz variable and financial outcome, since our focus was to explain the firm value change on the product's release in the United States.

[15] No *other* daily data are available from TNS Media. Advertising dollars across *all* media outlets are only available weekly. We not only compute total advertising spending with weekly advertising dollars from all media outlets (used in the sales model; when replaced with accumulated daily TV ad dollars or online ad occurrences, the effects of buzz variables remain consistent) but also derive functional curves (and FPC scores) of prerelease advertising dynamics with daily TV and online advertising data (used in explaining the antecedents of the prerelease buzz evolution pattern and for robustness checks in the sales model).

[16] Before product release, consumer ratings and reviews are not available. Expert ratings are often available around product launch time since firms make the product available to some experts before launch. Hence, the expert rating is an appropriate proxy for product quality in our context and can influence opening sales. In addition, we controlled for the sentiment (positive or negative) of prerelease buzz in §3.4.

release. For the stock return model, we also include (9) dummies for publicly listed publishers to control for the firm-specific effects on the stock price, and (10) the median analyst recommendations (reverse rescaled I/B/E/S measure with 5 as a strong buy) (Tirunillai and Tellis 2012).

3.3. Results

3.3.1. Prerelease Buzz Evolution Pattern and Opening Sales. We examine the relationship between the shapes of prerelease buzz evolution curves and new product sales by estimating Equation (3). Table 2 presents the results. Both the first and second FPC scores have significant effects. Recall that the first FPC depicts higher than average buzz volume throughout the prerelease period. Thus, the positive effect of the first FPC score (0.015, $p < 0.01$) suggests that higher than average buzz volume throughout the prerelease period predicts higher sales. The second FPC score has a negative effect (-0.012, $p < 0.01$). Hence, the shape captured by the second FPC (the buzz volume starts higher than average but turns lower than average later, i.e., a descending trend relative to the mean curve) is negatively associated with sales. In other words, the shape with a steeper upward trend than the mean curve (the direction of variation *opposite to* the second FPC) augurs superior sales. Similar results are observed when using data of prerelease search

Table 2 **Effect of Prerelease Buzz or Search Evolution on** ln(*Opening Sales*)

		Buzz models		Search models	
Variables	No buzz or search variables	Total Volume model	Evolution (functional) model	Total Volume model	Evolution (functional) model
Prerelease buzz or search					
First FPC score			0.015***		0.005***
Second FPC score			−0.012***		−0.004**
Third FPC score			−0.004		0.008**
Fourth FPC score			−0.007*		0.004
Cumulative prerelease volume		0.463***		0.052***	
Control variables					
Firm level					
Publisher experience	0.152***	0.116***	0.133***	0.106***	0.099***
Product level					
Advertising spending	0.082***	0.053***	0.045***	0.061***	0.066***
Avg. press rating	0.330***	0.221***	0.194***	0.324***	0.322***
Sequel	0.290***	0.222**	0.167*	0.129	0.125
Competition	−0.245*	−0.027	−0.101	−0.102	−0.110
Genre					
Action	0.716***	0.555***	0.551***	0.449***	0.662***
Adventure	0.803***	0.744***	0.679***	0.527***	0.697***
Fighter	1.343***	1.241***	1.185***	1.020***	1.238***
FPS	1.514***	1.048***	1.044***	1.169***	1.305***
Platform	0.575**	0.426*	0.337	0.112	0.396
Puzzle	0.677***	0.520**	0.465*	0.690***	0.799***
RPG	1.659***	1.167***	0.994***	1.408***	1.629***
Shooter	1.120***	0.725***	0.669**	0.978***	1.120***
Sports	0.453***	0.408***	0.387***	0.336**	0.526***
Console version					
Xbox	1.303***	1.024***	0.937***	1.146***	1.175***
Wii (*pre-MotionPlus*)	1.302***	1.283***	1.030***	1.225***	1.219***
Wii (*post-MotionPlus*)	0.282**	0.161	0.137	0.273**	0.303**
PS3	1.071***	0.779***	0.656***	0.853***	0.908***
PS2	0.275	0.519**	0.494**	0.180	0.257
Release month					
December	0.617***	0.752***	0.707***	0.492**	0.539**
July	−0.400*	−0.014	−0.116	−0.111	−0.180
May	−0.405**	−0.538***	−0.477***	−0.445***	−0.494***
April	−0.532**	−0.542**	−0.433**	−0.542**	−0.487**

Notes. Entries are coefficients. Robust standard errors are estimated by adjusting the standard errors for 61 clusters representing the video game publishers. Dummy variables representing genres racer, sim, and strategy; console version PSP; and release months November, October, September, June, March, and February do not have significant coefficients and are thus removed from the final models. Cumulative prerelease buzz/search volume, advertising spending, and publisher experience are logged.

*, **, and *** indicate the two-tailed significance at the 10%, 5%, and 1% levels, respectively.

Table 3 Comparison of Model Fit and Forecasting Error (Mean Absolute Percent Error)

Using prerelease *buzz* data				Using prerelease *search* data			
		BIC	MAPE (%)			BIC	MAPE (%)
1	No buzz or search variable	2,299.8	13.95				
2	Total buzz volume	2,188.9	11.02	7	Total search volume	2,261.4	11.76
3	Buzz volume the day before launch	2,288.6	11.86	8	Search vol. the day before launch	2,253.1	11.73
4	Linear trend + total buzz volume	2,179.8	10.64	9	Linear trend + Total vol	2,250.2	11.25
5	Late volume − early volume	2,284.9	12.45	10	Late volume − early vol.	2,294.4	12.53
6	FPC scores	2,167.2	8.96	11	FPC scores	2,237.9	10.03

Notes. We hold out one product at a time to estimate MAPE. The "Linear trend + Total" model includes total prerelease buzz/search volume and a linear trend estimated by fitting the demeaned daily buzz/search data (relative to sample average) on a linear model of time with zero intercept; the "Late volume − Early volume" model includes the difference between buzz/search volume in the last 30 days and that in the first 30 days of the prerelease period. Additional FPC scores do not have significant effects, and including them does not enhance model fit or forecasting accuracy. All models include control variables specified in Equation (3).

volume dynamics (the last two columns of Table 2). The findings support our theoretical arguments. However, this does not mean that early buzz is of no value to managers. As shown in §3.3.3, the early buzz evolution pattern is very useful for managers to forecast product sales *well before* product release.

Among the controls, advertising, press ratings, and publisher experience have positive effects. Other variables with significant effects include certain genres, platforms, and seasonality.

3.3.2. Forecasting New Product Sales Using Prerelease Buzz Evolution Pattern. Table 3 compares the model fit and forecasting performance of the proposed model (in bold, including the first four FPC scores as independent variables as specified in Equation (3)) versus alternative models. Similar to Foutz and Jank (2010), we hold out one product at a time to forecast its sales; i.e., holding out the jth product, we estimate the models with all the other products in the sample, and then forecast product j's sales using the estimated coefficients and product j's variable values. The lower the mean absolute percent error (MAPE), the higher the forecasting accuracy. The models with FPC scores, which capture the history of prerelease buzz evolution dynamics, have significantly higher model fit and lower MAPE[17] than the model using accumulated prerelease buzz data (total buzz volume) or using the last period (day) buzz prior to release alone. We also find that the proposed model outperforms simpler models that capture prerelease buzz evolution trend, i.e., the "Linear trend + Total" model (including total prerelease buzz volume and a linear trend estimated by fitting the demeaned 180-day daily buzz data relative to the sample average on a linear model of time with zero intercept) and the "Late volume − Early volume" model (including the difference between buzz volume in the last 30 days and that in the first 30 days of the 180-day prerelease period).

Moreover, we find lower forecasting errors (MAPEs) with prerelease *buzz* dynamics than with prerelease *search* dynamics. Although we acknowledge that search data could be a stronger indicator of product performance in some contexts,[18] in our case, buzz dynamics better predict new product sales for several possible reasons. First, it requires a higher level of engagement for potential consumers to create buzz in blogs or forums than to search online for product information (Gallaugher and Ransbotham 2010). Thus, prerelease buzz can be a stronger indicator of consumer interest than prerelease search. Moreover, a potential consumer can easily observe the buzz generated by others but typically does not know the search volume of other people. Buzz data thus may capture additional information about the social influence compared with search data.

3.3.3. ***Early* Prerelease Forecasting of New Product Sales.** Managers often attempt to predict sales as early as possible before product launch so that they will have sufficient time to adjust marketing strategy or product design. Accurate early forecasting results are thus very important. Suppose firms require forecast of sales at time $-T$, i.e., T days

[17] If early buzz data are not available (e.g., only the buzz evolution pattern within several weeks before launch were recorded), the forecasting accuracy is lower than using buzz curve from longer prerelease period. More important, it is impossible to perform early forecasting (illustrated in the next section) without early buzz dynamics data. Also note that, since we use ln(*sales*) as a dependent variable, the MAPE difference between the proposed model and the alternative model represents a large amount of forecasting error reduction in terms of absolute units of products sold.

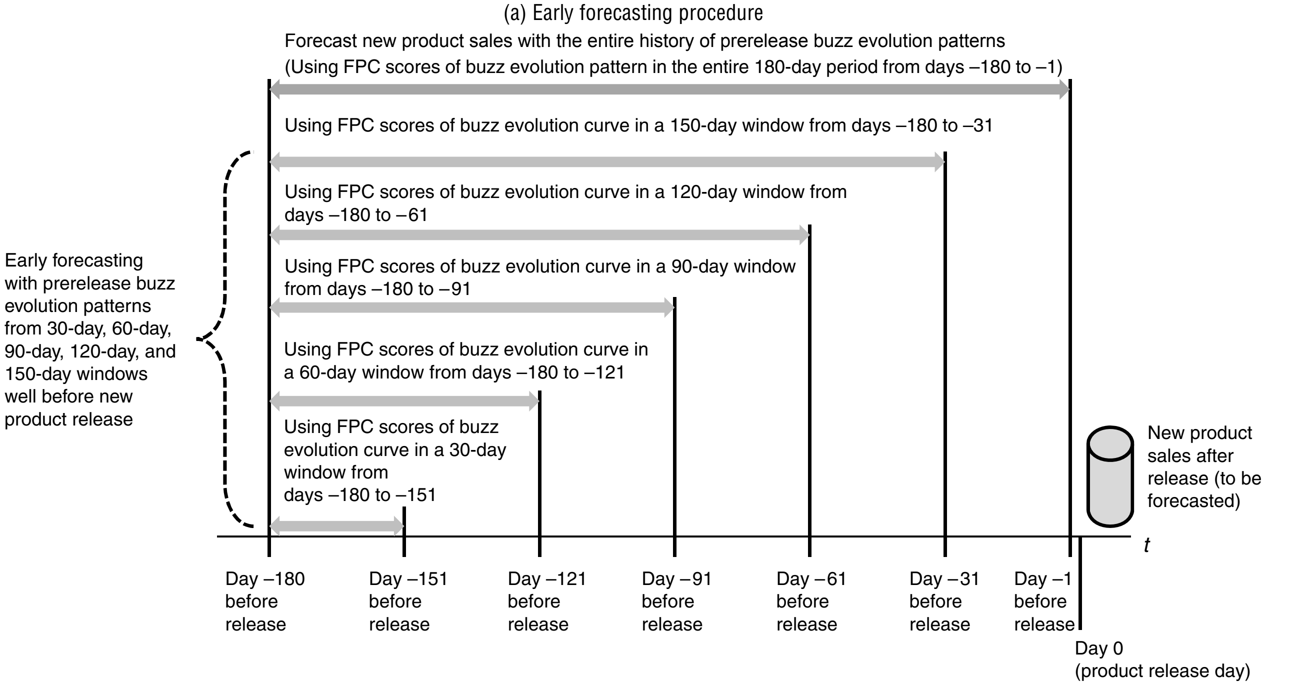
[18] Recent Google white papers using Google search data to explain sales with other samples or types of products find high R^2 after including postproduct launch search volume (e.g., Getomer et al. 2012) or industry-specific product or marketing factors that directly determine sales (e.g., Panaligan and Chen 2013) in the model. In contrast, this study uses prerelease information only and is conducted in a different industry for a different type of product. When these additional variables are excluded, the model fit reported in Panaligan and Chen (2013) is comparable to what we find using buzz or search data alone (without adding product- or firm-level controls).

before product release. Can the partial history of prerelease buzz dynamics up until day $-T$ help enhance forecasting accuracy? To answer this question, we perform early forecasting following the procedure visualized in Table 4, panel (a). Holding out one product at a time, we first derive the smooth curves of daily buzz dynamics ending on day $-T$ ($-T = -151, -121, -91, -61, -31$) for the *other* 680 products in the sample (in practice, managers can use a sample of previous games) and compute their FPC scores. We then estimate coefficients in Equation (3) with these FPC scores. The estimated coefficients are similar to those reported in Table 2. Finally, we smooth the buzz evolution curve ending on day T for the hold-out product j, estimate its FPC scores, and use them together with the game-specific controls to forecast its opening sales.

Models with the FPC scores of early buzz curves provide significantly enhanced forecasting accuracy (lower forecasting error MAPE; see Table 4, panel (b)). For instance, using the daily buzz evolution curve ending on day -61 (the 61st day before release), MAPE is 10.41%. This is significantly lower than the model with cumulative buzz volume until then (MAPE = 12.82%), with product characteristics alone (MAPE = 14.91%), with both product characteristics and the entire prerelease advertising budget (MAPE = 13.95%), or with total preorder (advanced sales) volume included (MAPE = 12.13%). Not surprisingly, the forecasting error continues to decrease as we include buzz dynamics closer to product release. It is important to note that using partial (early) history of prerelease buzz dynamics (e.g., MAPE = 10.41% or 9.83% when using the early buzz evolution pattern

Table 4 Early Forecasting of New Product Sales

(a) Early forecasting procedure



(b) MAPE in early forecasting of ln(*opening sales*)

	With FPC scores of daily buzz evolution curves (%)	With cumulative buzz volume (%)	No buzz variable (%)
Early forecasting			
Using buzz data between day −180 and day −151	12.72	13.63	—
Using buzz data between day −180 and day −121	12.20	13.42	—
Using buzz data between day −180 and day −91	11.05	12.96	—
Using buzz data between day −180 and day −61	10.41	12.82	—
Using buzz data between day −180 and day −31	9.83	12.61	—
Using buzz data between day −180 and day −1	8.96	11.02	—
With product characteristics only	—	—	14.91
With product characteristics + Advertising	—	—	13.95
With product characteristics + Advertising + Total preorder (advance sales) volume	—	—	12.13

Table 5 Effect of Prerelease Buzz Evolution on the Size (Absolute Amount) of Abnormal Firm Value Change upon a New Product Release

Variables	Model without prerelease buzz evolution dynamics	Model with prerelease buzz evolution dynamics
Prerelease buzz evolution pattern		
First FPC score of prerelease buzz curve		−0.005*
Second FPC score of prerelease buzz curve		0.004
Third FPC score of prerelease buzz curve		−0.003
Fourth FPC score of prerelease buzz curve		−0.023*
Buzz on the release day	−0.028	−0.028
Control variables		
Firm level		
Publisher experience	−0.282	−0.335*
Analyst recommendation	0.348	0.448*
Product level		
Prerelease advertising spending	0.012	0.007
Cumulative number of preorders	−0.020*	−0.028*
Average press rating	0.281***	0.275***
Publisher[a]		
COOL	−5.678***	−5.777***
DIS	−0.742	−0.962
ERTS	−1.207**	−1.306**
MSFT	2.216***	2.157***
SNE	−2.019***	−2.075***
THQ	−5.317***	−5.395***
TTWO	−3.949***	−4.023***
TWX	−0.564	−0.610
VIA	−1.048	−1.146

Notes. Entries are coefficients. Dummy variables representing console versions and sequels do not have significant coefficients and are not included in the final model.

[a]COOL, Majesco Entertainment; DIS, Disney Interactive Studios; ERTS, Electronic Arts; MSFT, Microsoft; SNE, Sony; TTWO, Take-Two Interactive; TWX, Time Warner; VIA, Viacom.

*, **, and *** indicate the two-tailed significance at the 10%, 5%, and 1% levels, respectively.

ending on day −61 or day −31) does a better job of forecasting sales than using cumulative or aggregated prerelease buzz data from *all* 180 days (MAPE = 11.02% when using the total volume of *all* buzz throughout the prerelease period).

3.3.4. Prerelease Buzz Evolution Pattern and Stock Price Correction upon Product Release. With the size (*absolute* amount) of abnormal change in firm value upon product release as the dependent variable in Equation (3), the estimation results are presented in Table 5. Both the first and fourth FPC scores have significant effects.[19] The negative coefficient of the first FPC *score* (−0.005, $p < 0.1$) indicates that the *higher* the product's buzz volume throughout the prerelease period, the *lower* the absolute amount of abnormal change in firm value on product release day (since the first FPC depicts higher than average buzz volume throughout the prerelease period). As we expected, consistent with the efficient market theory, because investors already predict the financial value of the forthcoming product based on prerelease buzz and reflect this prediction in stock valuation prior to product release, there is lessened "surprise" to the stock market and thus a lower amount of stock price corrections at the time of new product release.

3.4. Robustness Check

To assess whether adding buzz sentiment variables alters the estimated effect of the buzz volume curve,

[19] Although the fourth FPC score has a significant effect, it is difficult to interpret because of the complexity of the fourth FPC's shape. Hence, we follow Ramsay et al. (2009) and estimate the overall effect of buzz at each time t before product release by combining the effects of the four FPC scores while incorporating the shapes of the FPCs. This overall effect curve is plotted in Figure A4 of Online Appendix 4. The effect is significant during the period marked between the two vertical dashed lines. Consistent with the efficient market hypothesis, the most informative buzz should have the most significant impact on decreasing information asymmetry. Very early buzz may contain less information than later buzz for investors to predict the forthcoming product's value. This may explain the relatively insignificant effect of earlier buzz in the presence of later buzz in the model. The effect is also insignificant very close to product release, for which there are two possible explanations. First, there might be little "new news" in buzz right before product release and the stock price has fully absorbed all the news in prior buzz. Second, as suggested by Chen et al. (2011) and the vector autoregressive results in §4, buzz in the last couple of days right before product release may positively influence firm value (especially when the uncertainty about product success is high and the new buzz reflects incremental consumer interest) and thus stock returns on product release day if there is lagged effect. This effect may attenuate the expected role of prerelease buzz in reducing postrelease stock price correction, if the buzz under consideration occurs right before product launch.

we first reestimate Equation (3) for a subsample of games after controlling for the sentiment effect. Specifically, we obtained data on the daily numbers of blog and forum postings with positive, negative, and neutral sentiments for the sample games released in 2010 (we do not have sentiment data for 2009 games since the Lithium automated sentiment analysis program was not available when we collected data in 2009). We calculated the daily percentage of buzz with positive or negative sentiment during the 180-day period prior to each game's release, derived the smooth curves that capture the dynamics in prerelease sentiment, and added their FPC scores in Equation (3):

$$y_j = \beta_0 + \sum_{p=1}^{P}(\beta_p c_{jp}) + \sum_{p=1}^{P}(\beta_p^{POS} c_{jp}^{POS}) + \sum_{p=1}^{P}(\beta_p^{NEG} c_{jp}^{NEG}) + Ctrl_j\,\gamma + \varepsilon_j, \tag{4}$$

where c_{jp}^{POS} (c_{jp}^{NEG}) is the pth FPC score of daily percentage of buzz with positive (negative) sentiment. The results are reported in Table A5.1 of Online Appendix 5. We also rerun the model controlling for (1) cumulative percentage of buzz with positive or negative sentiment or (2) the FPC scores of the volume of daily buzz with positive or negative sentiment. The effects of buzz volume remain consistent and significant after including these controls.[20] This result is consistent with prior research, which finds that increased awareness through buzz volume, independent of sentiment, leads to increased consideration and purchase (e.g., Berger et al. 2010). Dellarocas et al. (2007) also find that volume has a positive and significant effect on box office revenue, after controlling for valence. Similarly, Gopinath et al. (2010) find that even after accounting for endogeneity, buzz volume still has a significant effect in markets with a great proportion of youth. This may also help explain the significant buzz volume effect on a youth-oriented product, video game sales in this study. Moreover, because games are not sequentially released like movies are, the effect of buzz volume versus sentiment is not subject to the bias described in Chintagunta et al. (2010) due to sequential rollout and spatial aggregation across local markets.

[20] As shown in Table A5.1, dynamics in the percentage of positive prerelease buzz do not have significant effects, whereas the second and third FPC scores of the negative buzz percentage do. Note that negative sentiment is scarce during the prerelease period (see also Liu 2006). Hence, if we remove the negative buzz, the shape of prerelease buzz evolution curves remains largely unchanged, and their FPC scores have consistent effects on sales. If we do not, the results in Table A5.1 show that the effects of buzz volume variables are not affected after controlling for buzz sentiments. In sum, although we acknowledge the impact of negative sentiment, our main purpose is to demonstrate the usefulness of the evolution pattern of prerelease buzz volume in forecasting new product sales.

Then, to test whether the results are robust when the number of FPC scores included in the model is altered, we reestimate Equation (3) including the first two or six FPC scores instead of four. Next, we replace first-week sales with sales from two to three weeks after product release as the dependent variable. We rerun the analysis with buzz from 200 (instead of 180) days prior to new product release for a subsample of games released in 2009, and we also estimate the model with alternative instrumental variables. We then test whether including opening-week advertising and buzz volume in the model influences the estimated effects of prerelease buzz evolution pattern. Results remain robust with these alternative measures or model specifications (see Online Appendix 5). Finally, we are able to separate the blog and forum data for the games released in 2010. For the subsample of 2010 games, we find that the FPCs of both blog and forum data exhibit very similar patterns (Figures A5.1 and A5.2), and their corresponding FPC scores are highly correlated. Moreover, functional regressions with separate data yield results consistent with pooled blog and forum data (see Table A5.5).

4. Additional Analysis

4.1. How to Manage Prerelease Buzz Evolution to Enhance Opening Sales

4.1.1. Antecedents of the Prerelease Buzz Evolution Pattern. Since prerelease buzz dynamics significantly explain new product performance, it is important for managers to understand the factors that drive prerelease buzz over time so that they can use these factors to stimulate or manage buzz before product launch. We expect the prerelease buzz evolution pattern to be influenced by demand-side, supplier-side, and product characteristics. First, because buzz in social media is viral in nature, the amount of future buzz can depend on the amount of previous buzz, and we thus use the cumulative amount of buzz in the past to capture the viral effect (e.g., Onishi and Manchanda 2012). Second, the product diffusion literature points to the network effect, i.e., a product's value increases as the number of existing consumers grows (e.g., Iyengar et al. 2011, Tellis et al. 2009). In the prerelease context, although no "existing consumers" have already purchased the product, some consumers commit to purchasing the product before launch by placing preorders.[21] Such

[21] Preorder data are only available on a weekly basis. We collected weekly preorder data for the sample games from VGChartz and then average the numbers on the daily basis. For verification purposes, we contacted and obtained preorder data from one major video game publisher, and even it did not have daily preorder recorded.

committed consumers are more likely to disseminate information about the product, and the buzz they generate can induce even more buzz from their followers (Nair et al. 2010, Rogers 1983). Thus, we expect that the cumulative number of current and past preorders can influence buzz volume at any time t before product launch. In sum, on the demand side, both viral effect and network effect can explain prerelease buzz dynamics.

In the prerelease period, since consumers have no consumption experience with the product, buzz can be largely driven by supplier-side actions. First, advertising can enhance buzz because it increases consumer awareness and curiosity (Holbrook and Addis 2008) and engages consumers (Kim and Hanssens 2012), leading them to create greater buzz. Second, the more games a publisher has introduced in the past, the more experienced it is in new product marketing, and the stronger the publisher brand becomes. Hence, publisher experience can enhance prerelease buzz volume. Third, new product alliances occur very frequently (Rindfleisch and Moorman 2001), especially between video game publishers and developers.[22] Alliance partners bring together their own customer bases, forming a larger pooled customer base for the new product offering (Bucklin and Sengupta 1993).[23] Such partnerships may connect otherwise unconnected customer communities associated with different firms, engendering additional conversations among customers about the potential output of the partnership (Schlosser 2005). The pooled and enlarged fan base therefore leads to increased buzz volume throughout the prerelease period. Moreover, joint efforts of multiple firms can combine their strengths to create more effective promotions and attract more audience attention, thus increasing buzz volume. Hence, we expect the number of new product alliance partners to enhance prerelease buzz. However, if the alliance partners have cooperated repeatedly in previous product introductions, their customer bases are likely to overlap. Overlapping customer bases reduce the opportunity for a wider interaction and information sharing among more customers (Regans and McEvily 2003). Moreover, the shared product experience among consumers may limit the extent of exposure to multiple thought worlds, novel and unique ideas in debate and conversation (Burt 1997). Hence, repeated partnerships can reduce the positive impact of the number of alliance partners on buzz volume.

Finally, we control for product-specific factors, including product quality, genres, and console versions, as they can also influence prerelease buzz. We specify the model in Equation (A6.1) of Online Appendix 6. Each graph in Figure A6.1 visualizes the effect of a proposed antecedent on prerelease buzz evolution over time. The solid curves are the estimated coefficient across time, and the dashed curves are the upper or lower bounds of the 95% confidence interval. Both the viral effect and network effect are positive and significant (Figures A6.1.1 and A6.1.2; the lower bounds of confidence intervals remain above zero in most part of the 180-day window). As for the supplier-side factors, daily prerelease advertising positively impacts buzz[24] (see Figure A6.1.3). In Figure A6.1.4, strong publisher experience enhances buzz, but the effect vanishes over time as more information becomes available about the upcoming product. Figure A6.1.5 shows the positive effect of the number of alliance partners throughout the prerelease period. The effect is negatively moderated by repeated alliance partnerships (Figure A6.1.6), and the size of the interaction impact increases over time. Plots of some control variables' coefficients can be found in Figure A6.2.

4.1.2. Factors Explaining the Desirable Trend in Prerelease Buzz Evolution. Since an upward trend in the prerelease buzz evolution curve predicts superior sales, we examine what kind of games are (or are not) likely to have such a trend. We expect that the increasing or decreasing patterns can be explained

[22] We interviewed senior managers at a major video game firm for richer insights into the context. Publishers (the marketers of games) often hire software developers on a "work for hire" basis to develop games. Software developers primarily create video games and rely on publishers to brand and market them to consumers. A marketing manager we interviewed pointed out that it could be in the developers' best interests to maintain ongoing relationships with established publisher partners, since "there is inherent cost to beginning a relationship ... shopping around for work for hire projects, proving your studio has the experience to deliver, etc. ... ," making it "mutually beneficial for developers and publishers to continue working with each other over time." Consequently, we test whether repeated partnership is really beneficial in this study.

[23] For example, in his December 5, 2011 presentation to investors at the UBS' 39th Annual Global Media and Communications Conference, Electronic Arts (EA) Chief Financial Officer Eric Brown discussed the planned launch of a new game. He said that the game had a large fan base since both EA and its partner developer BioWare are highly regarded, with fan bases of millions.

[24] We run the model with daily online ad occurrences and TV ad dollars (Figures 6.1.3 and A6.2.4 in Online Appendix 6) separately. Both exhibit a significant effect (lower bound of confidence interval above zero) in the beginning, the end, and in the middle of the 180-day prerelease period. The effect is significant in the beginning since early advertising provides new information about the product for the first time and thus stimulates buzz. Advertising has a significant effect close to product release most likely because consumers pay more attention to ads as the release date approaches. The periods with significant effect in the middle may correspond to the times when new rounds of ad campaigns begin.

by the following factors.[25] First, the trend of prerelease buzz can be influenced by the inherent "interestingness" and quality of the forthcoming product. Berger and Schwartz (2011) argue that people want to talk about interesting things. Similarly, Brown and Reingen (1987) suggest that the social benefit is higher when one talks about a popular subject rather than a less popular one. The blog and forum postings about new games of high quality are likely to be interesting topics and can thus trigger more follow-up postings, leading to an increasing trend in buzz. In contrast, a game that appeared interesting initially (e.g., with an ambitious concept or blueprint) could have decreasing buzz over time, if as time goes by (and more information about the game becomes available) consumers find it not as interesting as initially expected. Hence, product quality can be related to a buzz evolution pattern. It is important to note that, during the prerelease period, consumer ratings and reviews are not available, and expert ratings are also not available until around the product launch time. In a sense, the trend in prerelease buzz reflects consumers' expectation about the product's quality and their excitement about the product. Second, highly expected games (e.g., games based on something that people are already aware of, such as movie-based games or sequels) can have high initial awareness and thus high buzz volume early in the prerelease period, whereas the buzz of less expected games typically starts low and could have more room to grow. Third, the pattern of buzz can also be influenced by the amount of prerelease advertising over time. Fourth, joint efforts in new product alliances can enhance the effectiveness in product development and marketing as a result of the economy of scale and scope (e.g., Rindfleisch and Moorman 2001). As the number of alliance partners increases, the upcoming product is more likely to attract and retain the potential consumers' excitement due to the combined marketing strengths of partner firms, leading to an upward trend in prerelease buzz. Fifth, the nature of the targeted potential consumer base (e.g., involvement in online activities and connectivity among potential consumers, which affect the level and speed of information generation and dissemination) can also play a role. Since direct measures of these variables are difficult to obtain, we control for the genres and console version of the games, which can represent the different nature of the relevant consumer groups. In addition, we control for the prerelease number of news reports about the game and preorders over time.

To test the expectations above, we first regress the first and second FPC scores of prerelease buzz evolution on the proposed variables. Recall that products with *positive* first FPC scores[26] and *negative* second FPC scores tend to have upward trends in prerelease buzz. Hence, if a proposed variable has a positive (negative) coefficient on the first (second) FPC score, it is likely to be associated with increasing prerelease buzz evolution pattern. The regression coefficients and detailed explanations are presented in Online Appendix 7 and Table A7.1. In brief, we find that, as expected, product quality and the number of new product alliance partners are positively related to upward trends in prerelease buzz. Movie-based games (which tend to have high initial awareness and thus high buzz in the beginning of the prerelease period) are not likely to have an increasing trend in prerelease buzz. However, sequel games, which are also highly anticipated, are positively associated with increasing prerelease buzz trend. Hence, it appears that a game that is worth making a sequel engages consumers unlike a movie-based game. Prerelease advertising also influences the trend of prerelease buzz.

We also validate the results by using a simple measure, the linear slope (by fitting a zero-intercept linear model) of a product's daily prerelease buzz volume relative to the sample mean, to capture the trend in prerelease buzz evolution. If the slope is positive (negative) and statistically significant at the 95% confidence level, we classify the trend as "increasing" ("decreasing"). If the slope is not statistically significant, we classify the trend as "flat."[27] We then performed discriminant analysis using the variables proposed above and find consistent results (see Online Appendix 7 and Table A7.2).

[25] We expect the factors proposed below to explain *some, but not all,* variation in the prerelease buzz evolution trend. The trend in prerelease buzz contains additional information about popular taste, market perception or liking of the product, and the nature of the potential consumer base above and beyond the explanatory variables proposed below. For this reason, in the sales model, after controlling all of these antecedent variables, the FPC scores of buzz still have significant effects. Although beyond the main objective of this study, the results presented in this section combined with the findings in the sales model indicate that the trend in prerelease buzz evolution can *mediate* the effects of the proposed explanatory variables on new product sales.

[26] The first FPC depicts a direction of variability with higher than average buzz volume throughout the prerelease period. Since the average prerelease buzz evolution curve of the sample has an increasing trend, products with positive values in the first FPC score are more likely to have an increasing trend as well.

[27] Based on the simple linear slope, 347 sample games (50.96%) have a decreasing trend relative to the mean, 94 (13.80%) have flat trend, and 240 (35.24%) have an increasing trend. Alternatively, we also estimate the "absolute" trend without subtracting the sample mean. Discriminant analysis results based on absolute trend classifications lead to consistent conclusions.

4.2. The Dynamic Relationship Between Prerelease Buzz and Abnormal Stock Returns

In the main analyses presented previously, we used functional regressions to estimate the link between the *prerelease* buzz evolution pattern (the functional curve over time before release) and two *postrelease* outcomes—namely, first-week sales and stock value change upon new product release (both of which are scalar responses observed at a single time point after release). Meanwhile, firm stock returns can be observed prior to product release and move concurrently with prerelease buzz dynamics. Prerelease buzz increases investors' familiarity with the firm and its product, and investors are more likely to invest in better-known stocks (Huberman 2001). Moreover, prerelease buzz can provide new information that influences investors' expectation of new product performance and future cash flows. The efficient market theory suggests that stock prices reflect such new information immediately. Thus, prerelease daily stock returns can respond contemporaneously to changes in prerelease daily buzz. Since firm stock market performance may also influence buzz (Tirunillai and Tellis 2012), we employ a VAR approach to model the dynamic relationship between buzz and stock returns during the prerelease period while accounting for potential endogeneity. In addition to prerelease buzz volume and abnormal stock returns, we control for daily advertising, financial analysts' forecast of the current fiscal year's earnings per share, preorder volumes, the daily number of news articles about the new product, and the daily number of new game releases by the same publisher in the model. We conduct the analyses for five major publishers: Activision, Majesco Entertainment, Electronic Arts, THQ, and Take-Two Interactive (the five publishers together released 73.87% of the 310 sample games released by all publishers publicly listed in the United States).

For each company, the daily prerelease abnormal stock return increases significantly in response to a shock in daily prerelease buzz volume (see the first row of Table A8.1). This shows the impact of prerelease buzz on contemporaneous stock returns: prior to product release, the stock market does reflect prerelease buzz immediately. This finding complements the effect tested by the functional regression—since the stock prices before product release have already reflected the forthcoming product's value based on prerelease buzz (a result of the VAR model), there can be little change in firm value on product release day, especially if there has been a large amount of prerelease buzz, which provides investors with more and richer information before product launch (a result of functional regression). Results of the Granger causality tests (see Table A8.3) indicate that prerelease buzz Granger-causes prerelease abnormal stock returns. Moreover, consistent with our findings with functional regression, the VAR results show that daily prerelease buzz volume increases significantly in response to a shock in daily prerelease advertising, and the Granger causality tests show that prerelease advertising Granger-causes prerelease buzz (significant for three of the five companies).

Interestingly, these results allow us to extend recent work on the impact of prerelease advertising on stock returns (Joshi and Hanssens 2009) and comment on the mixed results in the literature about the relative roles of advertising versus social influence in new product performance (Van den Bulte and Lilien 2001). The results suggest that prerelease buzz has a positive effect in the presence of advertising, whereas advertising has a significant effect only in two instances. Together with the Granger causal impact of advertising on buzz, it appears that buzz or social influence mediates the impact of marketing efforts on stock returns. Clearly, this result needs to be supported by formal mediation tests, but it is the first (to our knowledge), albeit preliminary, finding of the mediating role of social influence.

5. Discussion and Conclusions

Online buzz for a forthcoming product evolves over time before product release. This study examines the relationship between the prerelease buzz evolution pattern and new product performance (sales and stock market value). Using a flexible nonparametric FDA method, we treat the curve of prerelease buzz evolution as the unit of analysis. Our findings (1) provide new managerial insights about how to manage buzz dynamics before product release to enhance product performance, (2) suggest a new way to enhance the accuracy in forecasting new product sales well in advance of product launch, and (3) help marketing managers better justify their budget and resource allocation in social media management. We discuss these contributions in detail below.

We demonstrate how the shape of the prerelease buzz evolution curve helps predict new product sales. The results suggest that firms should not only be interested in monitoring "how much prerelease buzz there has been in total" but also keep tracking the trend in prerelease buzz over time. Although there can be significant variation in the prerelease buzz evolution curve across products, we identify some specific patterns that managers could focus on to monitor and influence buzz dynamics: (1) It is ideal if, throughout the prerelease period, the buzz volume for the focal product is above the average prerelease buzz curve of competing products. (2) If the buzz volume starts higher but turns lower than average closer to product release (i.e., a decreasing trend relative to the mean), it negatively affects opening sales. Such insights cannot be generated by examining accumulated prerelease buzz data (e.g., total volume of prerelease buzz). Moreover, we conduct additional analysis on what factors drive prerelease buzz dynamics and the increasing or decreasing trend in prerelease buzz, providing insights into what firms can do to manage prerelease buzz dynamics to enhance new product performance. In addition, as shown in §3.4, whereas prerelease buzz mostly reflects consumer interest in the product, if any negative buzz emerges before product launch, it can affect opening sales. The effect of prerelease buzz volume dynamics remains consistent when controlling for buzz sentiment.

The functional model based on disaggregated data over time (daily prerelease buzz dynamics) significantly outperforms a model using aggregated data (total prerelease buzz volume) in terms of both model fit and forecasting accuracy, indicating the importance of capturing the history of prerelease buzz evolution. It should be noted that even with only a partial history of disaggregated prerelease buzz dynamics (e.g., daily buzz evolution curve ending two months before product launch), one can obtain a more accurate sales forecast than using the accumulated volume of *all* prerelease buzz up until product release. Early forecasting allows managers to accurately predict postlaunch sales *well before* product release, thus leaving them with sufficient time to change the product (especially for digital or media products such as video games, software, and movies) or other marketing plans. Note that accurate early forecasting is made possible because of the availability of time-series data on online prerelease buzz, which can be conveniently recorded over time by firms. Alternatively, firms may conduct repeated consumer surveys before product launch to collect data on consumer interest over time or use sales dynamics from other markets where the product was launched earlier. However, the former is significantly more expensive, and the latter is not available if the product is launched for the first time or at the same time for all markets (Foutz and Jank 2010). In addition, prerelease buzz dynamics help forecast new product sales better than prerelease advertising after controlling for it. We thus address the mixed results about the relative effects of social contagion and advertising on product performance (Trusov et al. 2009, Van den Bulte and Lilien 2001) in a novel context (i.e., the prerelease context).

Prerelease buzz is also related to firm stock market value. Specifically, stock returns quickly and positively impound prerelease buzz before product release (findings in the VAR model), and prerelease buzz reduces the absolute amount of stock price change on the product release day (findings in the functional regression model). This can be beneficial for firms in two ways. First, the time value of money principle suggests that cash earlier is more valuable than cash later. Because of prerelease buzz, stock prices can better reflect the true financial value of a forthcoming product long before it hits the consumer market; i.e., the shareholders do not have to wait until product launch to start earning financial returns from new product introductions. Second, large fluctuations in stock price can be detrimental because they increase firm risk (Srinivasan and Hanssens 2009), and prerelease buzz can reduce the amount of "shock" to the stock market upon product release. The findings indicate the financial value of investing in prerelease buzz and thus help marketing managers justify the budget they need for social media management. Moreover, given the value relevance of buzz, managers should consider more effective means of communicating buzz information to the investor community.

Although the objective of this study is not to establish the causality between prerelease buzz dynamics and new product outcomes, we provide the following empirical evidence. First, prerelease buzz evolution temporally precedes opening sales and firm value change upon product release. Second, when estimating the effect of prerelease buzz evolution, we eliminate alternative explanations using control variables (see Shadish et al. 2001). Finally, we account for endogeneity and unobserved omitted variables with an instrumental variable approach (see Chintagunta et al. 2010).

This study also provides empirical evidence about the mechanism by which prerelease buzz is linked to stock prices, i.e., daily prerelease buzz dynamics provides additional information to predict postrelease sales (as shown by our sales model after controlling for other variables), and such information is value relevant to investors, thus influencing both prerelease and postrelease stock prices. Moreover, whereas marketing researchers have examined *whether* abnormal stock price changes exist at the time of new product introduction (Pauwels et al 2004, Sood and Tellis 2009), we show that prerelease buzz can explain the *heterogeneity* in abnormal stock returns upon new product release.

The study is not without limitations, which suggest opportunities for future research. First, individual-level characteristics of the customer community are not observable in our data set. More insights into the antecedents and effects of buzz evolution might be generated if future research can access information on the demographics of blog or forum writers or readers, as well as the number of visits to each posting. Second, although existing studies suggest that blog and forum postings serve as an effective proxy for buzz (e.g., Dhar and Chang 2009, Gopinath et al. 2010, Onishi and Manchanda 2012), future research could get a fuller coverage of buzz by including rapidly growing sites such as Twitter and Reddit. Third, using prerelease buzz evolution curves and the method we proposed can be appropriate and effective for new products about which consumer interest and conversations emerge over time before product launch, and future research can compare the effects of buzz curves across industries or different types of products. Finally, although we employ instrumental variables in the main analysis to account for endogeneity and conduct causality tests in the VAR model, our data and analysis do not empirically distinguish whether prerelease buzz predicts new product performance by influencing or reflecting (or both influencing and reflecting) consumer perception.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mksc.2013.0828.

Acknowledgments

The authors thank the associate editor and the anonymous reviewers for their constructive comments. The authors also thank Yehua Li, Adina B. Robinson, Raj Srivastava, Ryan Hamilton, Son K. Lam, Sriram Venkataraman, Steve Carlin, and Kevin Hamilton for discussion on earlier versions of the paper.

References

Ainslie A, Drèze X, Zufryden F (2005) Modeling movie life cycles and market share. *Marketing Sci.* 24:508–517.

Articlesbase (2009) Top 3 most anticipated Xbox 360 video games of 2010. (November 23) http://www.articlesbase.com/art-and-entertainment-articles/top-3-most-anticipated-xbox-360-video-games-of-2010-1495114.html.

Asur S, Huberman BA (2010) Predicting the future with social media. *Proc. IEEE/WIC/ACM Internat. Conf. Web Intelligence Intelligent Agent Tech., Toronto*, 492–499.

Banerjee A (1992) A simple model of herd behavior. *Quart. J. Econom.* 107:797–817.

Bartels L (1985) Expectations and preferences in presidential nominating campaigns. *Amer. Political Sci. Rev.* 79:805–815.

Bartels L (1988) *Presidential Primaries and the Dynamics of Public Choice* (Princeton University Press, Princeton, NJ).

Berger J, Schwartz E (2011) What drives immediate and ongoing word-of-mouth? *J. Marketing Res.* 48:869–880.

Berger J, Sorensen AT, Rasmussen SJ (2010) Positive effects of negative publicity. *Marketing Sci.* 29:815–827.

Brown J, Reingen P (1987) Social ties and word-of-mouth referral behavior. *J. Consumer Res.* 14:350–362.

Bucklin L, Sengupta S (1993) Organizing successful co-marketing alliances. *J. Marketing* 57:32–46.

Burt R (1997) The contingent value of social capital. *Admin. Sci. Quart.* 42:339–365.

Centola D (2010) The spread of behavior in an online social network experiment. *Science* 329:1194–1197.

Chan S, Kensingerc J, Keown A, Martin J (1997) Do strategic alliances create value? *J. Financial Econom.* 46:199–222.

Chen Y, Liu Y, Zhang J (2011) Why do third-party product reviews affect firm value and what can firms do? *J. Marketing* 75: 116–134.

Chevalier J, Mayzlin D (2006) The effect of word of mouth on sales: Online book reviews. *J. Marketing Res.* 43:345–354.

Chintagunta PK, Lee J (2012) A prediffusion growth model of intentions and purchase. *J. Acad. Marketing Sci.* 40:137–154.

Chintagunta PK, Gopinath S, Venkataraman S (2010) The effects of online user reviews on movie box-office performance. *Marketing Sci.* 29:944–957.

Cialdini R (2001) Harnessing the science of persuasion. *Harvard Bus. Rev.* 79:72–79.

Coleman J, Katz E, Menzel H (1966) *Medical Innovation: A Diffusion Study* (Bobbs-Merrill, Indianapolis).

Dellarocas C, Zhang X, Awad N (2007) Exploring the value of online product reviews in forecasting sales. *J. Interact. Marketing* 21:23–45.

Dhar V, Chang E (2009) Does chatter matter? Impact of user-generated content on music sales. *J. Interact. Marketing* 23: 300–307.

Duan W, Gu B, Whinston A (2008) The dynamics of online word-of-mouth and product sales: An empirical investigation of the movie industry. *J. Retailing* 84:233–242.

Duckworth A, Golz J, Trayner G (2009) Are analysts and investors engaging with new media? *Brunswick Rev.* (2). http://www.brunswickgroup.com/insights-analysis/brunswick-review/brunswick-review-issue-2/research/engaging-with-new-media.aspx.

Fama E (1991) Efficient capital markets: II. *J. Finance* 46:1575–1617.

Fan Y, Foutz N, James GM, Jank W (2013) Functional response additive model estimation with online virtual stock markets. Working paper, University of Southern California, Los Angeles.

Fay S, Xie J (2008) Probabilistic goods: A creative way of selling products and services. *Marketing Sci.* 27:674–690.

Fiske S, Taylor S (1991) *Social Cognition*, 2nd ed. (McGraw-Hill, New York).

Foutz NZ, Jank W (2010) Prerelease demand forecasting for motion pictures using functional shape analysis of virtual stock markets. *Marketing Sci.* 29:568–579.

Gallaugher J, Ransbotham S (2010) Social media and customer dialog management at Starbucks. *MIS Quart. Exec.* 9:197–212.

Getomer J, Okimoto M, Cleaver J (2012) Understanding the modern gamer. White paper, Google, Mountain View, CA.

Godes D, Mayzlin D (2004) Using online conversations to study word-of-mouth communication. *Marketing Sci.* 23:545–560.

Godes D, Mayzlin D (2009) Firm-created word-of-mouth communication: Evidence from a field test. *Marketing Sci.* 28:721–739.

Godes D, Silva JC (2012) Sequential and temporal dynamics of online opinion. *Marketing Sci.* 31:448–473.

Gopinath S, Chintagunta PK, Venkataraman S (2010) Measuring local market-level differences in the effects of prerelease blogs on a movie's opening box-office performance. Working paper, Northwestern University, Evanston, IL.

Herr P, Kardes F, Kim J (1991) Effects of word-of-mouth and product-attribute information on persuasion. *J. Consumer Res.* 17:454–462.

Holbrook M, Addis M (2008) Art versus commerce in the movie industry. *J. Cultural Econom.* 32:87–107.

Houston M, Hennig-Thurau T, Spann M, Skiera B (2011) A theory of buzz for new product: How individual-level anticipation leads to intentional social action. Working paper, Texas Christian University, Fort Worth.

Huberman G (2001) Familiarity breeds investment. *Rev. Financial Stud.* 14:659–680.

Iyengar R, Berger J (2011) How the quantity and timing of social influence impact new product sales. Working paper, University of Pennsylvania, Philadelphia.

Iyengar R, Van den Bulte C, Valente TW (2011) Opinion leadership and social contagion in new product diffusion. *Marketing Sci.* 30:195–212.

Janiszewski C (1993) Preattentive mere exposure effects. *J. Consumer Res.* 20:376–392.

Joshi AM, Hanssens DM (2009) Movie advertising and the stock market valuation of studios: A case of "great expectations?" *Marketing Sci.* 28:239–250.

Kenny P, Rice T (1994) The psychology of political momentum. *Political Res. Quart.* 47:923–938.

Kim H, Hanssens D (2012) Pre-launch advertising, online buzz, and new product sales. Working paper, University of California, Los Angeles, Los Angeles.

Kulkarni G, Kannan PK, Moe W (2012) Using online search data to forecast new product sales. *Decision Support Systems* 52: 604–611.

Liu Y (2006) Word of mouth for movies. *J. Marketing* 70:74–89.

Luo X (2007) Consumer negative voice and firm idiosyncratic stock return. *J. Marketing* 71:75–88.

Moe WW, Fader PS (2002) Using advance purchase orders to forecast new product sales. *Marketing Sci.* 21:347–364.

Moe WW, Schweidel DA (2012) Online product opinions: Incidence, evaluation, and evolution. *Marketing Sci.* 31:372–386.

Mutz D (1997) Mechanisms of momentum: Does thinking make it so? *J. Politics* 59:104–125.

Nair H, Manchanda P, Bhatia T (2010) Asymmetric social interaction in physician prescription behavior: The role of opinion leaders. *J. Marketing Res.* 47:883–895.

Onishi H, Manchanda P (2012) Marketing activity, blogging and sales. *Internat. J. Res. Marketing* 29:221–234.

Panaligan R, Chen A (2013) Quantifying movie magic with Google search. White paper, Google, Mountain View, CA.

Pauwels K, Silva-Risso J, Srinivasan S, Hanssens D (2004) New products, sales promotions, and firm value: The case of the automobile industry. *J. Marketing* 68:142–156.

Ramsay JO, Dalzell CJ (1991) Some tools for functional data analysis. *J. Roy. Statist. Soc. Ser. B* 53:539–572.

Ramsay JO, Silverman BW (2005) *Functional Data Analysis* (Springer, New York).

Ramsay JO, Bock RD, Gasser T (1995) Comparison of height acceleration curves in the Fels, Zurich, and Berkeley growth data. *Ann. Human Biol.* 22:413–426.

Ramsay J, Hooker G, Graves S (2009) *Functional Data Analysis with R and MATLAB* (Springer, New York).

Reddy S, Dass M (2006) Modeling online art auction dynamics using FDA. *Statist. Sci.* 21:179–193.

Regans R, McEvily B (2003) Network structure and knowledge transfer. *Admin. Sci. Quart.* 48:240–267.

Rindfleisch A, Moorman C (2001) Acquisition and utilization of information in new product alliances. *J. Marketing* 65:1–18.

Rogers E (1983) *Diffusion of Innovations*, 3rd ed. (Free Press, New York).

Schlosser A (2005) Posting versus lurking: communicating in a multiple audience context. *J. Consumer Res.* 32:260–265.

Shadish W, Cook T, Campbell D (2001) *Experimental and Quasi-Experimental Designs for Generalized Causal Inference* (Houghton-Mifflin, New York).

Shen H, Wyer R (2008) Procedural priming and consumer judgments. *J. Consumer Res.* 34:727–737.

Sonnier GP, McAlister L, Rutz OJ (2011) A dynamic model of the effect of online communications on firm sales. *Marketing Sci.* 30:702–716.

Sood A, Tellis GJ (2009) Do innovations really pay off? Total stock market returns to innovation. *Marketing Sci.* 28:442–456.

Sood A, James GM, Tellis GJ (2009) Functional regression: A new model for predicting market penetration of new products. *Marketing Sci.* 28:36–51.

Sorescu A, Shankar V, Kushwaha T (2007) New product preannouncements and shareholder value. *J. Marketing Res.* 44: 468–489.

Srinivasan S, Hanssens D (2009) Marketing and firm value. *J. Marketing Res.* 46:293–312.

Tellis G, Yin E, Niraj R (2009) Does quality win? Network effects versus quality in high-tech markets. *J. Marketing Res.* 46: 135–149.

Tetlock P (1983) Accountability and the perseverance of first impressions. *Soc. Psych. Quart.* 46:285–292.

Tirunillai S, Tellis GJ (2012) Does chatter really matter? The impact of online consumer generated content on a firm's financial performance. *Marketing Sci.* 31:198–215.

Trusov M, Bucklin R, Pauwels K (2009) Effects of WoM versus traditional marketing. *J. Marketing* 73:90–102.

Van den Bulte C, Lilien GL (2001) Medical innovation revisited: Social contagion versus marketing effort. *Amer. J. Sociol.* 106:1409–1435.

Wooldridge JM (2002) *Econometric Analysis of Cross Section and Panel Data* (MIT Press, Cambridge, MA).

Yao F, Muller H, Wang J (2005) Functional linear regression analysis for longitudinal data. *Ann. Statist.* 33:2873–2903.

Zhu F, Zhang X (2010) Impact of online consumer reviews on sales: The moderating role of product and consumer characteristics. *J. Marketing* 74:133–148.