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# Dynamics of pre-release consumer buzz: Driving communication, search, and participation for market performance

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## Abstract

While pre-release consumer buzz may drive new product market performance, little is known about the importance of its distinct behavioral manifestations: communication, search, and participation. This paper not only studies how these three pre-release buzz behaviors affect market performance but also their dynamic interplay and how firms can drive pre-release buzz. Using movie data, we find self-enhancing and spillover effects of buzz throughout the pre-release period. For driving communication and search behaviors, firm social media posts are most effective, while movie trailers are most effective in evoking participatory behaviors. Furthermore, box office sales benefit the most from pre-release communication, followed by participation and search. These findings extend current knowledge by showing that while all buzz behaviors matter for driving market performance, communication plays a central role due to its powerful spillover effects on search and participation, and firms can effectively stimulate it through social media posts about the new product.

**Keywords** Buzz · Pre-release marketing · New product success · Communication · Search · Participation · Social media · Movies

## Introduction

Consumers are often interested in new products well before these products are released. Their excitement and curiosity about new products become visible in their online behaviors. Collectively, Houston et al. (2018) refer to these “observable expressions of anticipation by consumers for a forthcoming

product” (p. 338) as *pre-release consumer buzz* (hereafter: PRCB). Houston et al. (2018) distinguish between three different types of PRCB: anticipatory communication, search, and participation. Anticipatory communication means that consumers express their views about a forthcoming product (e.g., on X, formerly Twitter); search refers to consumers actively searching for information about the upcoming product (e.g., via Google); and participation involves taking part in certain experiential activities related to the product, such as watching a trailer on YouTube. Pre-release buzz reflects a new product’s shadow diffusion (Peres et al., 2010) and indicates the number of potential adopters of the new product once released (Xiong & Bharadwaj, 2014).

Many companies gear their pre-release marketing activities towards creating buzz. Fueling consumers’ excitement about a new product is particularly crucial for products with short lifecycles, such as entertainment products, e.g., movies, video games, or TV series (Hennig-Thurau & Houston, 2019; Karniouchina, 2011). Marketing such products is notoriously challenging for several reasons. First, their production costs can be enormous, frequently exceeding \$100 million and possibly reaching \$300 million for a single upcoming movie or video game (Bowen, 2022; The Numbers 2024a). Second, their lifecycles decay exponentially,

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with most sales generated within the first weeks after release, which makes the time window to break even markedly short (Luan & Sudhir, 2010). Third, consumer demand for such experiential goods is difficult to predict (Liu, 2006). As a result, marketing entertainment goods entails significant uncertainty, and costly flops are the rule rather than the exception (e.g., seven of ten movies do not break even; Elberse, 2007). In short, the success or failure of an entertainment product typically hinges on its early adoption.

Hence, it is not surprising that entertainment companies pursue front-loaded marketing practices that focus on creating buzz to support the formation of consumers' early adoption intentions (Hennig-Thurau & Houston, 2019). By doing so, companies stimulate shadow diffusion, which materializes in early demand for the new product and minimizes the risk of a flop (Xiong & Bharadwaj, 2014). If buzz persists, it can even affect subsequent distribution channels (e.g., home entertainment), thus enhancing the product's long-term revenue potential (Kübler et al., 2021).

Extant research provides empirical evidence of the positive effects of pre-release buzz on a new product's (post-release) market performance (see Table 1). However, most of these studies treat buzz as a unidimensional construct by focusing on a specific type of buzz behavior, such as communication (e.g., Gelper et al., 2018; Hennig-Thurau et al., 2015). In an important departure from the preceding literature, Houston et al. (2018) argue that pre-release buzz is a multi-behavioral phenomenon. They conceptualize that communication, search, and participatory behaviors may have distinct effects on market performance, and as such, existing studies focusing on a single behavioral manifestation of buzz cannot offer insights into their relative importance. In addition, many studies treat buzz in an aggregated manner by considering its total volume over a specific period (e.g., Chen et al., 2019; Craig et al., 2015; Divakaran et al., 2017; Kulkarni et al., 2012). However, the intensity of buzz varies throughout the pre-release phase (Elberse & Eliashberg, 2003). Therefore, research on pre-release buzz should consider such intertemporal variations to explain how and why buzz evolves over time (Houston et al., 2018). While some recent contributions have shed first light on the dynamic nature of buzz (e.g., Gelper et al., 2018; Xiong & Bharadwaj, 2014), these studies do not account for its multi-behavioral nature.

The lack of research adopting a multi-behavioral, dynamic perspective leaves three essential questions unanswered: (1) What is the relative importance of pre-release communication, search, and participation in driving market performance? (2) How do the buzz behaviors influence each other throughout the pre-release phase? (3) How can firms effectively stimulate communication, search, and participation? This research addresses these questions by studying the antecedents, dynamics, and consequences of pre-release

communication, search, and participation in the context of the movie industry. The global entertainment industry earned \$2.4 trillion in revenue in 2023, and experts forecast further growth (Statista, 2024a). We collect a unique data set that comprises consumers' communication, search, and participatory behaviors, as well as firms' pre-release marketing activities related to 330 movies released in the US.

This research extends current knowledge about pre-release consumer buzz in three major ways. First, building on Houston et al.'s (2018) seminal work, we explicitly consider the multi-behavioral nature of buzz by simultaneously investigating the distinct effects of pre-release communication, search, and participation. This multi-behavioral perspective allows for novel insights into the relative importance of each buzz behavior in driving market performance. The estimated elasticities suggest that new products benefit the most from pre-release communication (.23), followed by participation (.09) and search (.08), and extend prior findings of studies focused on single buzz behaviors (e.g., Gopinath et al., 2013; Karniouchina, 2011; Marchand et al., 2017).

Second, we overlay Houston et al.'s (2018) multi-behavioral conceptualization with a dynamic perspective to answer their call for research on how and why buzz evolves over time. Conceptually, we argue that pre-release consumer buzz is dynamic due to social dynamics that set action-based buzz cascades into motion (Bikhchandani et al., 1992; Hennig-Thurau & Houston, 2019), i.e., bursts in the three buzz behaviors amplify themselves and spill over to other buzz behaviors. We employ panel vector autoregression to empirically account for the dynamics within (self-enhancing effects) and across (spillover effects) communication, search, and participation. This dynamic, multi-behavioral approach offers novel insights into the complex interdependencies among the three buzz behaviors. The findings confirm the existence of cross-behavioral buzz cascades, revealing that the buzz behaviors reinforce each other but to a varying extent. The results also underscore the central role of communication, as both its self-enhancing and spillover effects are consistently stronger than those of search and participation. These findings contribute to the limited literature on intertemporal patterns in buzz (Gelper et al., 2018; Kim & Hanssens, 2017; Xiong & Bharadwaj, 2014).

Finally, this research expands current knowledge about the drivers of buzz. While earlier studies have examined the role of drivers determined months or years before the release (e.g., genre, production budget, cast characteristics; Divakaran et al., 2017; Karniouchina, 2011; Liu, 2006), we focus on key marketing tools (firm social media posts, trailer releases, and mass media advertising) that firms can dynamically deploy during the pre-release phase. Our findings reveal that firm social media posts are most effective in stimulating communication and search behaviors,

**Table 1** Selected studies on pre-release consumer buzz

Study	Pre-Release Buzz Behaviors			Pre-Release Marketing		Pre-Release Dynamic Effects		Key Findings
	Communication	Search	Participation	Firm Social Media Posts	Trailer Releases	Mass Media Advertising	Within and Across Buzz Behaviors	
Liu (2006)	✓							Communication volume (but not valence) helps explain both weekly and total box office sales.
Karniouchina (2011)		✓						Search volume related to a movie and its cast helps explain both box office sales and screen allocation decisions.
Hennig-Thurau et al. (2012)		✓				✓		Search volume weakens the impact of professional reviewer judgments on short-term box office sales.
Kulkarni et al. (2012)		✓				✓	✓	Search volume is an effective measure to forecast new product sales.
Onishi and Manchanda (2012)	✓					✓	✓	Advertising spurs communication, and both have a positive impact on audience size.
Gopinath et al. (2013)	✓					✓		Communication volume (but not valence) and advertising drive opening day box office sales.
Xiong and Bharadwaj (2014)	✓	✓				✓		Considering communication (volume) dynamics improves the accuracy of sales and stock return forecasts.
Divakaran et al. (2017)	✓							Buzz (modeled as a latent construct) is positively associated with post-launch sales.
Kim and Hanssens (2017)	✓	✓				✓	✓	Communication and search are mutually highly responsive. Communication has a stronger effect on search than advertising.
Marchand et al. (2017)	✓					✓		Communication (in terms of consumer reviews and microblogs) volume significantly affects post-release sales.
Houston et al. (2018)	✓	✓	✓		✓	✓		Multi-behavioral specification of buzz outperforms single-behavior specifications.
Gelper et al. (2018)	✓					✓		Communication can occur in (event or rogue) spikes, which increase in frequency towards the release. More spikes are associated with more box office sales.
<b>This research</b>	✓	✓	✓	✓	✓	✓	✓	<b>Box office sales depend mostly on communication, followed by search and participation. Communication and search can be stimulated best through firm social media posts, while participation can be stimulated best through trailer releases.</b>

whereas trailer releases are most effective in evoking participatory behaviors. By contrast, mass media advertising is ineffective in creating buzz. These findings extend those of previous studies that almost exclusively focused on the role of mass media advertising in driving PRCB and/or new product performance (e.g., Kulkarni et al., 2012; Onishi & Manchanda, 2012; Xiong & Bharadwaj, 2014). Overall, the insights highlight the role of pre-release marketing activities with direct implications for marketers of entertainment goods.

## Buzz and market performance

### Pre-release consumer buzz

The concept of *buzz* has received much attention over the past two decades (e.g., Elberse & Eliashberg, 2003; Hewett et al., 2016; Marchand et al., 2017). With the advent of social media platforms that allow consumers to express and exchange their opinions, it became possible to observe and measure buzz in online environments (Hennig-Thurau & Houston, 2019). However, most extant research on buzz uses the term as a synonym for word-of-mouth and other behaviors that may occur before or after a new product's release or consumption (Houston et al., 2018). Post-release buzz, mostly corresponding to word-of-mouth, is well understood, and meta-analytical evidence underscores its critical role in driving a product's market diffusion (e.g., Babić Rosario et al., 2016).

In comparison, research on pre-release buzz is more limited. Houston et al. (2018) clarify the distinctiveness of pre-release consumer buzz and offer a comprehensive conceptualization of the construct.<sup>1</sup> The authors define pre-release consumer buzz as “the aggregation of observable expressions of anticipation by consumers for a forthcoming new product” (p. 338) and argue that it manifests in three distinct behaviors: anticipatory communication, search, and participation (Houston et al., 2018).<sup>2</sup> Figure 1 displays examples of these buzz behaviors.

<sup>1</sup> Table A of Web Appendix A clarifies how pre-release consumer buzz differs from word-of-mouth and other post-consumption behaviors.

<sup>2</sup> Houston et al. (2018) conceptualize an additional dimension of buzz termed *pervasiveness*, which refers to “the degree to which the PRCB behaviors are spread across the population of interest rather than being confined to only a niche of enthusiasts” (p. 339). Our research adopts a mass-market perspective, focusing exclusively on pervasive buzz (i.e., diffused widely across the population) instead of non-pervasive buzz (i.e., confined to a niche market). This approach is consistent with Houston et al.'s (2018) observation that “niche PRCB behaviors (i.e., activities by enthusiasts) provide only incremental information when compared to broad PRCB information (i.e., activities performed across the population)” (p. 354).

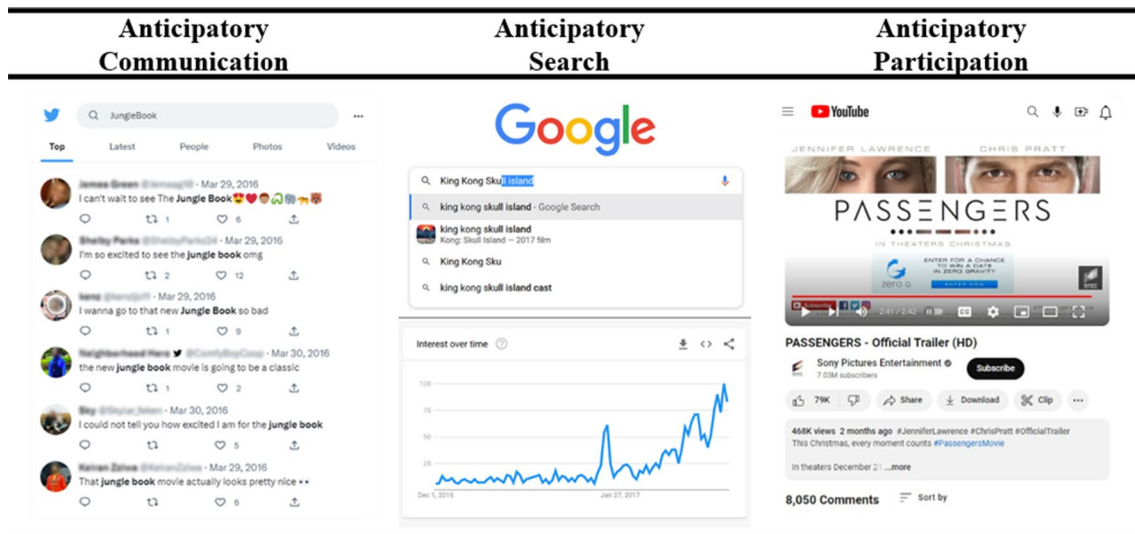
*Communication* refers to user-generated content related to a new product, such as personal opinions and expectations about its features (e.g., the cast and the plot of a movie), expressing the intention to adopt it, and recommending it to others (Hennig-Thurau et al., 2004). It includes conversations or contacts with acquaintances as well as anonymous users (Houston et al., 2018). *Search* refers to consumers actively gathering information concerning a forthcoming product from official websites or using search engines (Ho et al., 2009). It reflects consumers' curiosity regarding the product, such as product attribute levels, release dates, and points of sale. *Participation* refers to diverse activities reflecting consumers' excitement about a new product, such as watching product previews (e.g., movie trailers), participating in prize games (e.g., winning tickets for an upcoming movie), or following the product's official social media (i.e., actively opting in to receive more information; Houston et al., 2018).

### Prior research on pre-release communication, search, and participation

Table 1 provides an overview of this paper's key contributions to the pre-release buzz literature. Most studies have investigated buzz in terms of just one behavior, i.e., *communication*. In one of the earliest works, Liu (2006) applies communication data from the Yahoo Movies message board to operationalize movie buzz and shows that it is associated with increased box office sales. Investigating movie-related communication on Twitter, blogs, and user forums, Gelper et al. (2018) demonstrate that buzz does not evolve smoothly but can contain sudden spikes or bursts, underscoring its dynamic nature. Marchand et al. (2017) study the impact of microblogs (i.e., tweets) and consumer reviews on new product success, both before and after launch. Similarly, Xiong and Bharadwaj (2014) measure the buzz surrounding forthcoming video games in terms of online blog and forum postings (e.g., MySpace and Blogspot). Their results reveal a positive relationship between pre-release communication and new product sales.

Several studies have examined consumers' *search* activities as a manifestation of buzz and established the predictive power of search volume regarding market performance. For example, Karniouchina (2011) shows that consumers' aggregated search behavior (i.e., IMDb MovieMeter)—indicating consumer excitement and interest—has a positive effect on sales. Kulkarni et al. (2012) also show that pre-release search activities (on Google, Yahoo!, and MSN) predict box office sales during the first week after release. Kim and Hanssens (2017) also demonstrate the predictive power of search activities (using Google Trends data) for the initial sales of both movies and video games. They further show that consumer blog posts and search volume





**Fig. 1** Examples of pre-release consumer buzz. Note: Usernames and profile pictures are blurred for privacy reasons

reinforce each other. Hennig-Thurau et al. (2012) reveal that buzz, as reflected in search activity on IMDb, may not only directly affect movies' box office sales but can moderate other effects. They demonstrate that increasing buzz reduces the influence of professional reviews on short-term and long-term market performance.

The literature on consumers' *participation* is limited. Only Craig et al. (2015) employ two participation variables measuring pre-release buzz, i.e., awareness (a combination of the number of times a movie trailer was viewed and the number of comments a particular movie obtained from ComingSoon). They establish a positive correlation between participation and box office sales on a movie's opening weekend. To date, only Houston et al. (2018) consider communication, search, and participation simultaneously. They operationalize buzz as a formative construct and establish a positive link between the composite score (based on aggregated volumes during the pre-release period) and box office sales during the opening weekend. However, no prior paper has studied the separate impact of the three PRCB behaviors.

Many extant studies adopt a static perspective on buzz by considering the total amount of buzz that occurred over a specific period (e.g., Craig et al., 2015; Karniouchina, 2011), disregarding its intertemporal variations. Others have accounted for the dynamic nature of buzz in their analysis. Xiong and Bharadwaj (2014) examine the evolutionary trajectory of pre-release communication about video games and show that it adds explanatory power to forecast post-release market performance. Gelper et al. (2018) study spikes in movie-related word-of-mouth before launch, showing that buzz can emerge spontaneously ("rogue spikes") as well in reaction to firm activities, such as the release of movie

trailers ("event-driven spikes"). The latter two studies exclusively focus on pre-release communication.

Table 1 shows that this study offers significant contributions to the literature by—for the first time—investigating the three behavioral manifestations of consumer buzz (communication, search, and participation) in terms of their relative impact on market performance, how they are driven by three forms of pre-release marketing (social media posts, trailer releases, and mass media advertising), as well as their dynamic interplay throughout the pre-release phase.

## Study framework

Figure 2 displays our study framework, linking the three focal buzz behaviors to relevant antecedents (pre-release marketing activities) and consequences (market performance). Because of the broad scope of our investigation (i.e., antecedents, dynamics, and consequences of PRCB) and the primary interest in uncovering the (relative) magnitude of different effects (whose positive directionality is clear), we follow the Empirics-First (EF) approach (Golder et al., 2023). Theory-guided research tends to be satisfied with establishing the direction of specific effects. However, "theory rarely informs effect sizes" (Golder et al., 2023, p. 329). In contrast, EF research is geared toward estimating the magnitude of specific effects to inform marketing stakeholders about the economic significance of certain actions. In line with the EF paradigm, we do not present hypotheses. Instead, we offer theoretical underpinnings for the dynamic nature of PRCB and discuss our expectations regarding the relationships.

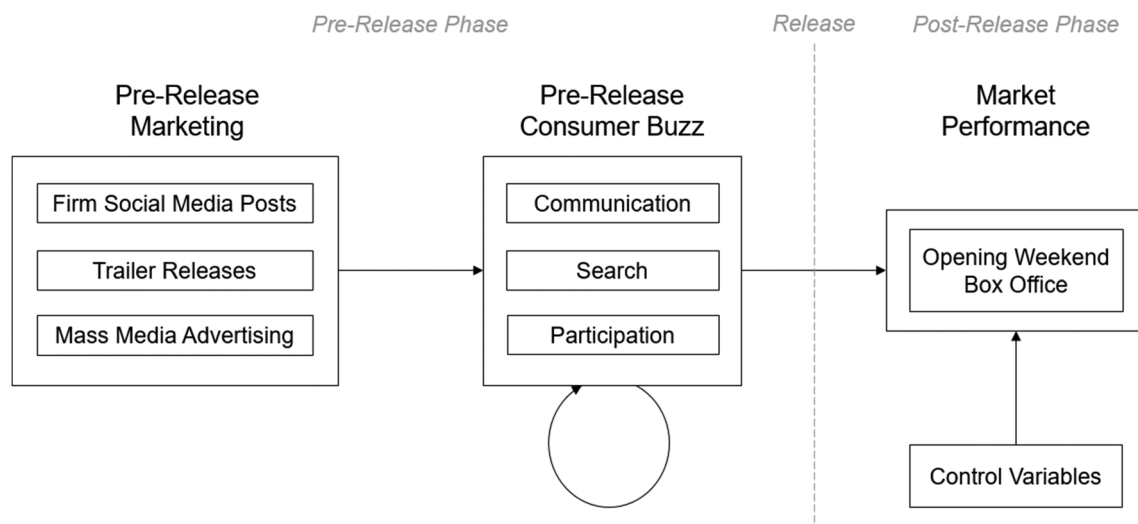


Fig. 2 Study framework

## Buzz dynamics

In general, communication, search, and participation are not static but vary dynamically in the period leading up to a product's release (Houston et al., 2018). The dynamic nature of buzz is rooted in the fact that it is a social, collective phenomenon. It reflects a new product's shadow diffusion, which refers to accumulating latent demand (i.e., adoption intentions) for the product while it is not yet available (Peres et al., 2010). Like every diffusion process, shadow diffusion is at least partly driven by social processes (Rogers, 1983). Before the release of a product, consumers have no information about the actual performance of a product—but consumers can interpret the “buzz” that they observe in the market for a new product as an indicator of the overall anticipation for the product. Thus, the observed anticipation itself serves as a signal of the forthcoming product's attractiveness and quality. Consequently, firms can use the amount of buzz as a lead indicator of the number of potential adopters of the new product (Houston et al., 2018; Xiong & Bharadwaj, 2014). After release, the accrued latent demand can manifest in actual sales, and the product's diffusion becomes observable.

But how does pre-release buzz emerge, and how does it evolve? The dynamics of buzz are rooted in its social observability. Today's digital environment allows consumers to witness other consumers' excitement about a forthcoming product. This observability facilitates the so-called action-based cascade effects. Action-based cascade effects are an extension of Bikhchandani et al.'s (1992) original idea of informational cascades. Informational cascading effects set in when individuals observe the actions of those ahead of them and follow their behavior without regard to their own information. Informational cascades can explain

“rapid and short-lived fluctuations such as fads, fashions, booms” (Bikhchandani et al., 1992, p. 994)—and consumer buzz (De Vany and Lee, 2001).

In the pre-release context, these cascading effects are referred to as action-based (or uninformed) buzz cascades since consumers “infer quality levels from the actions [buzz behaviors], rather than the articulated judgments [experience-based word of mouth] of other consumers” (Hennig-Thurau & Houston, 2019, p. 606) because the product cannot be experienced in the pre-release stage. Buzz cascades are resemblant of bandwagon effects in that other people's preferences can affect the preferences of an individual (e.g., Xiong & Bharadwaj, 2014), and herding behavior, in that individuals may follow other people's actions rather instinctively without much deliberation (Bikhchandani et al., 1998). In other words, consumers who observe other consumers' excitement about a forthcoming product might start engaging in buzz behaviors themselves. Their anticipatory behaviors, in turn, may affect others, which incites further cascading effects, i.e., “buzz breeds buzz” (Bikhchandani et al., 1992; Houston et al., 2018). As a result, “a single voice can escalate into massive [...] buzz cascades” (Hennig-Thurau & Houston, 2019, p. 560).

Importantly, the cascading effects of buzz imply that communication, search, and participation not only reinforce themselves but also each other. For example, intensifying communication about a new product can motivate search behaviors (Kim & Hanssens, 2017), and more search activities may also manifest in more participation in experiential activities. Thus, the focal buzz behaviors evolve dynamically throughout the pre-release phase due to both self-enhancing effects and cross-behavioral spillover effects.

## Buzz dynamics and market performance

**Communication** Communication is often driven by social motivations such as consumers' need for social interaction or the chance to share their opinions, attitudes, or identities with others. Other vital aspects are self-enhancement motives and altruistic concerns for the community (Hennig-Thurau et al., 2004). Importantly, when consumers manage and express behaviors, relationships, and attitudes through social media, their online activities affect other consumers in their network (Wang et al., 2019). Consequently, consumers' communication about a new product likely triggers other consumers' awareness, curiosity, and interest, which could motivate them to enter the conversation (Babić Rosario et al., 2016). Due to social dynamics, consumers' communication activities mutually reinforce and accumulate over time (Houston et al., 2018; Liu, 2006). Continuous and potentially intensifying communication signals broad interest in the forthcoming product. The popularity not only attracts consumers' attention but can also serve as a quality signal. In contrast, if the volume of communication decreases during the pre-release phase, consumers may infer from the fading interest that the new product is no longer considered attractive. Taken together, we expect more communication during the pre-release phase to manifest in higher opening weekend sales.

**Search** Given the lack of experience-based evaluations, such as product reviews during the pre-release phase, product-related information is limited and uncertain (Houston et al., 2018; Liu, 2006). Many consumers turn to the internet to find information, satisfy their curiosity, and assess an upcoming product before its release (Kim & Hanssens, 2017; Liu, 2006). Search engines like Google have become essential for retrieving information about an upcoming product or service (Kulkarni et al., 2012). Search engines usually track and report the number of consumers who searched for the same or similar keywords (Houston et al., 2018). As consumers primarily use search engines as sources of information to satisfy their informational needs, the reported search traffic can serve as a proxy for their collective interest in the product (Kim & Hanssens, 2017). Consumers may search for different types of information throughout the pre-release phase. For example, in the early stages, they might search for product-related information, such as cast members and plot details, when such information is sparse. Towards the release, the search behavior may shift towards purchase-relevant information, such as the exact release date and screenings nearby, as the purchase opportunity is nearing. At this point, the idea of experiencing the movie becomes more concrete, and consumers' involvement with the purchase decision tends to be high (Puccinelli et al., 2009).

Thus, we expect a high search volume to translate into high box office sales upon release.

**Participation** Participatory behaviors include following an official social media account, watching product previews, or sharing product-related content, such as still shots or behind-the-scenes clips (Houston et al., 2018). Similar to communication, consumers' participatory activities are often motivated by social motives. Consumers enjoy opportunities to interact with other like-minded consumers and express their identities through engaging with content related to a specific product of interest (Berger & Schwartz, 2011). The frequent exposure to new product-related information cues cements the prominence of the new product in consumers' minds. Also, it can stimulate consumers' further participation, such as passing on (i.e., sharing) the content they are exposed to (Berger & Schwartz, 2011; Houston et al., 2018). Consumers' engagement with and dissemination of product-related content, as reflected in trailer views on YouTube, signals substantial interest and excitement among consumers. Hence, participation should reflect increased adoption intentions and manifest in sales once the new product becomes available.

## Pre-release marketing and buzz dynamics

Because firms are aware of the positive consequences of buzz, they direct resources to actively stimulating it rather than exclusively relying on social dynamics. This research focuses on three key pre-release marketing tools that managers can deploy during the pre-release phase: (1) firm-generated social media posts, (2) trailer releases, and (3) mass media advertising.

**Firm social media posts** As product-related information is limited before release, firm-generated content on social media platforms, such as X, Facebook, or Instagram, is a valuable source of information to stimulate consumers' interest (Hewett et al., 2016; Houston et al., 2018). Firms, such as film studios and distributors, often use corporate social media accounts (e.g., @disney on X) or product-specific social media accounts (e.g., @disneylionking) to inform consumers about a forthcoming product. Such firm social media posts help increase awareness among consumers, evoke their curiosity, and promote anticipatory activities such as liking and commenting or searching for additional product-related information (Kumar et al., 2016).

**Trailer releases** Trailers (or teasers, which are shorter) are short videos that firms release before a movie release (or other types of products, e.g., TV shows or video games) to create curiosity and excitement (Liu et al., 2018). They typically comprise a series of selected shots from the movie that



provide hints of the story arc, thus providing a “free sample of the finished product” (Archer-Brown et al., 2017, p. 160). Trailers represent a key source of information for consumers when deciding which movie to watch (Boksem & Smidts, 2015). Consumers watch trailers on video platforms, such as YouTube or Vimeo, where most film studios and distributors release official trailers on channels they control. Thus, trailer releases are essential to facilitate and boost anticipatory behaviors, such as viewing, liking, and commenting on the trailer. Video platforms usually allow consumers to share a link to the trailer on other social media platforms, like X or Facebook, which may not only attract more views but can also spark product-related conversations on these platforms (Gelper et al., 2018). Therefore, we expect trailer releases to play an important role in triggering consumers’ pre-release buzz behaviors.

**Mass media advertising** Advertising creates awareness of and interest in a new product before release. Especially for entertainment goods, a significant portion of the total advertising spend is allocated to the pre-release phase (Elberse & Anand, 2007). The positive impact of pre-release advertising on market performance is well-documented (e.g., Hennig-Thurau et al., 2015; Kulkarni et al., 2012). In addition, several studies provide first insights into the relationship between mass media advertising and specific pre-release behaviors, although with mixed findings. For example, Onishi and Manchanda (2012) find that pre-release TV advertising can help to spur online communication on blogs (a relationship that disappears after a product’s release). Similarly, Kulkarni et al. (2012) and Kim and Hanssens (2017) establish that (mass media) advertising leads to greater online search volume. Empirical evidence provided by Xiong and Bharadwaj (2014) corroborates these relationships. In contrast, Gelper et al. (2018) do not find a significant effect of weekly advertising spend on the occurrence of spikes in consumers’ online communication. Hence, we need a better understanding of the role of mass media advertising as a driver of pre-release buzz.

## Data and measures

### Data

We analyze the dynamics of PRCB in the context of movies. The entertainment industry is a suitable setting for our study because it is of great public interest and has high economic value. Furthermore, the entertainment business is risky since the production costs are often very high, while the demand for an upcoming product is difficult to predict due to the experiential nature of entertainment goods (Liu, 2006; Xiong & Bharadwaj, 2014). Since the lifecycles of

entertainment goods are typically very short, firms focus their marketing activities on maximizing demand right at the release. These front-loaded marketing practices aim to create and reinforce consumers’ intentions to adopt the forthcoming product well before its release. Accordingly, prior research has attributed a crucial role to pre-release buzz in the entertainment industry (Houston et al., 2018; Karniouchina, 2011; Xiong & Bharadwaj, 2014).

We compile the dataset from diverse sources. It comprises information on consumers’ buzz behaviors, firms’ pre-release marketing activities, and movie market performance for all movies released in the US between January 2016 and December 2017 that generated at least \$3 million at the domestic box office. The data collection results in 330 movies (see Web Appendix B for details) with average US box office sales of \$20.31 million (opening weekend).<sup>3</sup> To ensure the data reflect the US movie industry, we only consider releases in the US and measure US advertising spend and US box office sales.

Table 2 shows characteristics related to the 330 movies, which include sequels (20.30%, e.g., *Captain America: Civil War*), remakes of existing movies (5.76%, e.g., *The Jungle Book*), or adaptations of books, series, or video games (32.42%, e.g., *Fantastic Beasts and Where to Find Them*). Moreover, the movies vary in genre, age restriction, and seasonality of release.

Because of the dynamic nature of PRCB, we collected daily data for each buzz behavior, i.e., daily communication, search, and participation data. Since the pre-release period is the focus of this study, we measure only activities that emerge *before* the particular release of a movie to ensure that the data consists of pre-release anticipatory behaviors rather than post-release experience-based attitudes. To ensure that we capture most anticipatory behaviors leading up to the release of a movie, data collection starts 56 days (eight weeks) before release (in line with Gelper et al., 2018; Kulkarni et al., 2012).

### Measures for pre-release consumer buzz

Following Houston et al.’s (2018) conceptualization, we measure pre-release buzz in terms of three distinct online behaviors.

**Communication** For communication, we collected the number of tweets about a movie posted on X each day. X represents communication across a broad population, with almost

<sup>3</sup> We use all movies in the observation period for which all variables could be measured. Four movies had to be excluded due to deactivated YouTube comment sections (e.g., *The Divergent Series: Allegiant*), which prevented us from measuring participation levels.

**Table 2** Movie characteristics

Variable		Frequency	Percent
MPAA rating	G & PG	52	15.76%
	PG-13	144	43.64%
	R	134	40.61%
Movie type	Sequel	67	20.30%
	Remake	19	5.76%
	Adaptation	107	32.42%
Season (release)	1st quarter	78	23.64%
	2nd quarter	85	25.76%
	3rd quarter	82	24.85%
	4th quarter	85	25.76%
Genre	Action	15	4.55%
	Adventure	10	3.03%
	Animation	30	9.09%
	Comedy	47	14.24%
	Documentary	6	1.82%
	Drama	65	19.70%
	Fantasy	25	7.58%
	History	13	3.94%
	Horror	33	10.00%
	Music	5	1.52%
	Mystery	5	1.52%
	Romance	20	6.06%
	Sci-Fi	22	6.67%
	Sport	4	1.21%
	Thriller	28	8.48%
	Western	2	.61%

*G* General audiences, *PG* Parental guidance suggested, *PG-13* Parents strongly cautioned, *R* Restricted

100 million users in the United States (Statista, 2023). To select the relevant tweets for a movie, we used the official hashtag published by the production firm on the official website (see Web Appendix B). In line with prior studies, we limited the language of the tweets to English (e.g., Hennig-Thurau et al., 2015).

First, to make sure we capture consumer (rather than other) buzz, we removed tweets posted by firms related to the production or distribution of the movie. Next, to ensure the tweets represent communication but not participation, we removed tweets with participatory elements, such as watching trailers, rentals of previous releases of a sequel, or reading books/comics related to a movie adaptation (Houston et al., 2018). We conducted this task through human coding combined with Machine Learning since there are millions of tweets to classify. We took a random sample of 3,000 tweets and instructed three coders to label 2,000 tweets each as having participatory elements (1) or not (0), such that each tweet was coded exactly two times. The initial intercoder agreement was 92.05%, and the remaining disagreements

were solved by discussion. As a result, we could utilize 3,000 tweets to finetune RoBERTa, a transformer-based pre-trained classifier that has demonstrated outstanding performance across various applications (e.g., Hartmann et al., 2023), to learn the connection between the content of a tweet and its classification as participatory or not. We split the 3,000 tweets randomly into a training (80%) and a test set (20%). RoBERTa achieved a 96.48% accuracy rate on the test set. Next, we used the finetuned RoBERTa model to classify all 3+ million tweets. We find that 14.41% of all tweets have participatory elements, which were removed from the daily user tweets count to obtain a clean count of tweets representing communication.

**Participation** To capture consumers' participatory behaviors, we use data obtained from YouTube, where users can watch trailers of upcoming movies. YouTube is the world's primary platform for sharing video content, with 2.5 billion users worldwide (Mohsin, 2023). Watching movie trailers is a form of anticipatory participation (Houston et al., 2018). As we cannot observe historic daily YouTube views for all movies in the sample, but we can observe daily YouTube comments, we use the latter variable to operationalize participation. This choice is reasonable as more views typically mean more comments, and viewing plus commenting is an even more active form of participation than just viewing.

**Search** We used the product-related daily search volume on Google to capture search behavior for an upcoming movie. Google Trends reflects consumers' search activities well, as Google holds more than 80% of the search engine market share (Statista, 2024b). We used each movie's title to ensure that the search behavior considered was related to the movie in our dataset. Specifically, we capture searches in Google's pre-defined category *Arts & Entertainment*, the subcategory *Movies*, and the region *United States*. Since Google keeps the absolute search volumes confidential, we had to use a benchmark when gathering daily search volumes for all movies in our dataset. We used the letter "c" as a benchmark, as it exhibits a relatively constant search volume throughout the observation period.

### Measures for pre-release marketing

We capture marketing in the pre-release period through three marketing activities typically deployed by movie studios: social media posts, trailer releases, and mass media advertising.

**Firm social media posts** For social media activity, we measure the daily number of tweets about the upcoming movie published via any official X account associated with a firm involved in the production and distribution of

the movie (e.g., the movie *Finding Dory* might be promoted via the official Pixar channel [@Pixar] as well as the official Disney channel [@Disney]), including official movie-specific accounts (e.g., @IndependenceDay). We determined the pertinent studios and distributors based on information provided by IMDb. Consistent with the way we capture user tweets described above, relevant tweets must include the official movie hashtag and be in English (corresponding with the investigated market). For all analyses, we distinguish between movie-related (non-trailer) and trailer-related firm social media posts. We identify trailer-related firm social media posts based on their use of the terms “Trailer,” “trailer,” “Teaser,” “teaser,” “Video,” “video,” “Clip,” “clip,” “Youtube,” “YouTube,” and “youtube.” One in three firm social media posts (32.86%) are related to trailers.

**Trailer releases** For trailer releases, we utilized data from YouTube. Using each movie’s title and official hashtag as search criteria, we identified all trailers (and shorter teasers) published via the official firm channel (e.g., @sonypictures), franchise channel (e.g., @StarWars) or movie channel (e.g., @OfficialMaxSteel) during the movie’s pre-release period. The trailer release variable is the number of newly released movie trailers/teasers on a given day.

**Mass media advertising** For mass media advertising, we use Kantar Media’s AdSpender data (Gelper et al., 2018; Hennig-Thurau et al., 2015). These data capture the advertising support movies received during the pre-release phase across

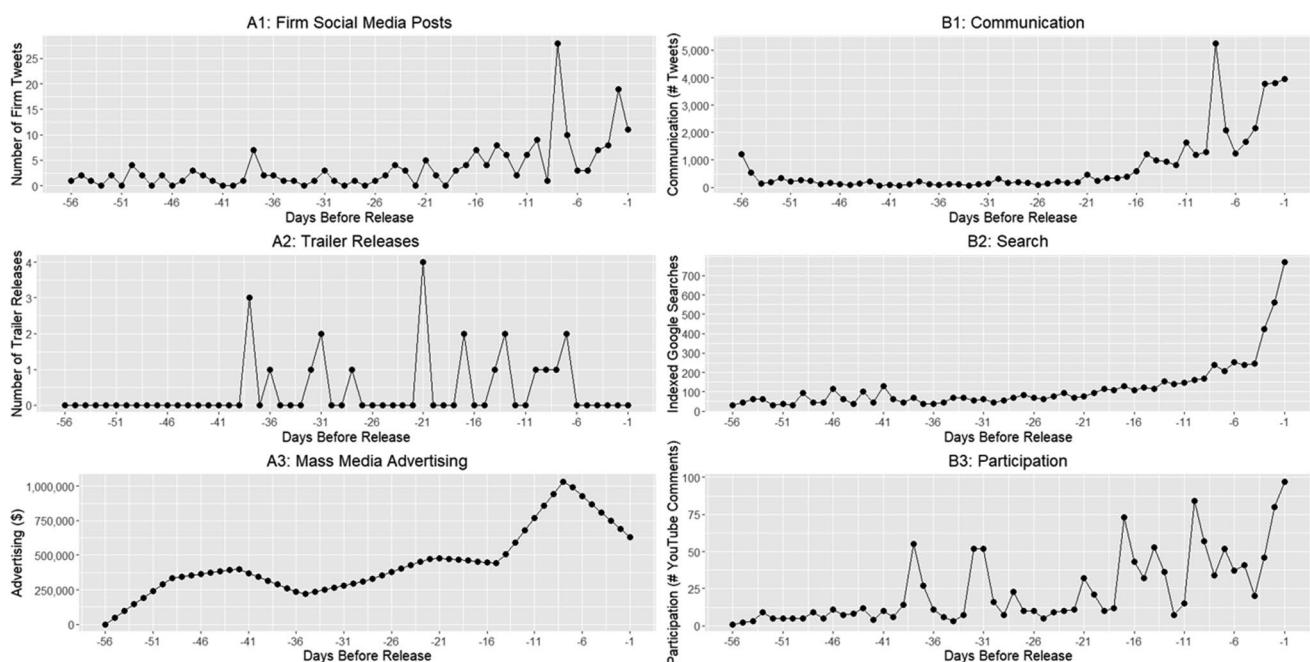
various channels. As these data are at the weekly level, while all other variables are at the daily level, we use linear interpolation to convert the weekly figures to daily figures.

Figure 3 illustrates the three pre-release marketing variables and the three focal buzz variables for the movie *Dunkirk* for the pre-release period from 56 days before release to one day before release (day –1 in Fig. 3). Figure 3 (Panels A1 and A3) shows how the studio ramps up social media posts and mass media advertising in the lead-up and releases several movie trailers as well (Fig. 3, Panel A2). Pre-release buzz is also building up in the lead-up to the movie release, with communication (Fig. 3, Panel B1) and Google searches (Fig. 3, Panel B2) trending up especially rapidly in the last ten days before release. Participation (Fig. 3, Panel B3) shows spikes earlier, following new studio trailer releases.

We note that in our data, the three buzz behaviors are empirically sufficiently distinct. With an average (maximum) correlation of .57 (.61), the buzz behaviors are far from being perfectly correlated and exhibit relatively limited amounts of shared variance.

## Measures for dependent variables and control variables

**Market performance** For the dependent variable market performance, we collected box office sales data from the movie database The Numbers. Since a large percentage of product sales in the entertainment industry occurs within a narrow time frame right after product release, we focused on



**Fig. 3** Trajectories of pre-release marketing and buzz behaviors of the movie *Dunkirk*

the opening weekend box office sales (in USD) in line with prior research (Gopinath et al., 2013; Houston et al., 2018; Liu, 2006). We also use total box office sales as a dependent variable in a robustness check reported below.

**Control variables** Prior research has established several control variables for movie success. We follow this research stream and control for production budget to account for movies' varying blockbuster potential (Liu, 2006), publicly available at The Numbers (2024b). Besides the production budget, we use the overall mass media advertising budget for each movie, using the same Kantar Media AdSpender data discussed before. Moreover, we account for the number of screens that screen the movie at the opening weekend to control for the availability of movies (Liu, 2006), also available at The Numbers. We included star power, i.e., the number of popular actors based on IMDb's STARMeter. Following Karniouchina (2011), we considered an actor/actress popular if s/he is ranked within

the top 1000 before release. We control for critics' ratings from the publicly available website Metacritic. In addition, we use dummy control variables to capture the effects of a sequel, remake, or adaptation received from the official movie websites, genre (Houston et al., 2018), season (Ho et al., 2009), and MPAA rating (Craig et al., 2015), i.e., age-restriction rating available at IMDb, ranging from G (general audiences) to R (restricted). Table 3 presents the variables and data sources.

## Descriptive statistics

Table 4 shows that, on average, a movie's box office sales on the opening weekend exceed 20 million USD. *Star Wars Ep. VIII: The Last Jedi* was the highest-grossing movie within this period, grossing more than \$220 million domestically on its first weekend and more than \$620 million in total. Across our data set of 330 movies, each observed across 56 days, we count 3.03 million tweets and 421,133 YouTube

**Table 3** Variables and data sources

Variable	Description	Source
<b>Buzz behaviors</b>		
Communication	Total number of tweets per day about a movie using the official hashtag, excluding tweets expressing participation and tweets of firms involved in the production or distribution of the movie	X (formerly Twitter)
Search	Volume of Google searches per day for a movie. We used the movie's title in the predefined category <i>Arts &amp; Entertainment</i> , the subcategory <i>Movies</i> , and the region <i>United States</i> . The search volumes are normalized, using the search term "c" as benchmark.	Google
Participation	Total number of comments on YouTube per day related to an official trailer about a movie	YouTube
<b>Pre-release marketing</b>		
Firm social media posts	Total number of tweets per day about a movie (using the official hashtag) published by any firm involved in the production or distribution of the movie	X (formerly Twitter)
Trailer releases	Total number of trailers per day published by any firm involved in the production or distribution of the movie	YouTube
Mass media advertising	Total daily advertising spend 56 days before release to one day before release	Kantar Media
<b>Controls (for post-release model)</b>		
Production budget	Production costs of a movie	The Numbers
Mass media advertising	Total advertising spend within an eight-week period before release	Kantar Media
Critics' ratings	Average quality rating of a movie	Metacritic
Number of screens	Number of screens at the opening weekend	The Numbers
Star power	Number of acting stars that have a StarMeter rank below 1000 before release of the movie	IMDb
Genre	Genre of a movie	IMDb
MPAA rating	Age-restriction rating by the Motion Picture Association of America	IMDb
Sequel	1 if a movie was listed as a sequel	Official movie website
Remake	1 if a movie was listed as a remake	Official movie website
Adaptation	1 if a movie was listed as a book-/series-/video game-adaptation	Official movie website
Season	Season in which a movie was released	IMDb
<b>Market performance</b>		
Opening weekend box office sales	Opening weekend box office revenues of a movie in the US	The Numbers

**Table 4** Descriptive statistics

Variable	Day-Movie Observations					
	5%	25%	Mean	75%	95%	SD
<b>Buzz behaviors</b>						
Communication	.00	5.00	163.81	85.50	639.00	714.28
Search	.00	2.20	37.39	34.00	155.21	99.86
Participation	.00	.00	22.79	10.00	73.00	219.82
<b>Pre-release marketing</b>						
Firm social media posts	.00	.00	6.26	3.00	12.00	93.81
Trailer releases	.00	.00	.18	.00	1.00	.63
Mass media advertising (in \$1,000)	.00	.52	240.99	420.47	876.28	309.28
<b>Movie Observations</b>						
<b>Market performance</b>						
Opening weekend box office sales (in \$1,000)	80.33	1,679.10	20,311.25	22,525.00	96,050.00	32,307.24
<b>Controls</b>						
Production budget (in \$1,000)	1,000.00	10,000.00	50,261.09	60,000.00	180,000.00	59,850.03
Mass media advertising (in \$1,000)	152.22	5,522.50	15,236.85	24,789.62	33,448.53	10,912.19
Critics' ratings	26.00	41.00	56.04	71.00	84.00	18.61
Number of screens	4.00	579.00	2,265.15	3,434.00	4,144.00	1,473.23
Star power	.00	2.00	3.94	5.00	9.00	3.00

The columns 5%, 25%, 75%, and 95% correspond to the 5th, 25th, 75th, and 95th percentiles, respectively  
*SD* Standard deviation

wcomments. These numbers correspond to an average of 164 tweets and 23 YouTube comments per movie per day across the 56-day pre-release period. The averages for search numbers reflect relative data, as Google does not disclose absolute numbers.

## Empirical analysis

### Pre-release stage: Buzz and marketing

The empirical analysis of the pre-release stage faces requirements. In line with Houston et al. (2018), we view PRCB as a multi-behavioral construct. The trajectories of these behavioral dimensions may vary over the pre-release period. In addition, the buzz behaviors may reinforce themselves and spill over to other behaviors. Moreover, pre-release marketing may drive the buzz behaviors over time (and vice versa). To capture these dynamic interdependencies, we need a times series model that (i) can capture dynamic relationships between multiple variables, (ii) treats buzz and pre-release marketing as endogenous variables, (iii) handles panel data (time series for multiple movies), (iv) controls for unobserved movie characteristics (through movie fixed effects) and (v) allows to control for

other aspects such as the day of the week. To address these five requirements, we use a panel data VAR-X model, i.e., Vector Autoregressive Model with exogenous (X) variables. The VAR model has a long history in marketing research and has been successfully used to model, e.g., dynamic sales promotion effects (Nijs et al., 2001) and the dynamic effects between firm communication and user communication (Hewett et al., 2016).

The dependent (or endogenous) variable is vector  $y_{it}$  that captures the three buzz behaviors and the four pre-release marketing variables for a movie  $i$  on day  $t$ . To allow for interpreting the effects as elasticities, we use log variables (+ 1 to avoid taking the log of 0):

$$\begin{aligned}
 y_{it} = & \\
 & (\ln(\text{Communication}_{it} + 1), \ln(\text{Search}_{it} + 1), \ln(\text{Participation}_{it} + 1), \\
 & \ln(\text{FirmSocialMediaMovie}_{it} + 1), \ln(\text{FirmSocialMediaTrailer}_{it} + 1), \\
 & \ln(\text{TrailerReleases}_{it} + 1), \ln(\text{MassMediaAdvertising}_{it} + 1))
 \end{aligned} \quad (1)$$

where  $\text{Communication}_{it}$  is the number of user tweets about movie  $i$  on day  $t$  (after excluding tweets related to participation and firm social media posts),  $\text{Search}_{it}$  is the number of Google searches,  $\text{Participation}_{it}$  is the number of user YouTube comments,  $\text{FirmSocialMediaMovie}_{it}$  is the number



of tweets about the movie published by any firm involved in the movie's production or distribution which are not trailer-related,  $FirmSocialMediaTrailer_{it}$  is the number of tweets about the movie which are trailer-related,  $TrailerReleases_{it}$  is the number of trailer releases for the movie  $i$  on day  $t$ , while  $MassMediaAdvertising_{it}$  is daily advertising spend.

The panel data VAR-X regresses the seven-variate dependent variable  $y_{it}$  on its lags (up to  $s$  days ago) and control variables  $X$ :

$$y_{it} = B_{0i} + B_1 y_{it-1} + \dots + B_s y_{it-s} + CX + e_{it} \quad (2)$$

In (2),  $B_{0i}$  are fixed effects for movie  $i$  (with seven elements, one for each endogenous variable), which capture the effect of any time-invariant movie characteristic (such as genre, budget, cast) on  $y_{it}$ .  $B_1 [B_s]$  is a (7 by 7) matrix with the regression coefficients for the first lag ( $y_{it-1}$ ) [for the  $s^{\text{th}}$  lag ( $y_{it-s}$ )].  $X$  is a vector of control variables (dummies for each day of the week and a time trend),  $C$  is a matrix with the regression coefficients for  $X$ , and  $e_{it}$  is an error term with mean zero and covariance matrix  $V$ . To understand the dynamic relationships between the endogenous variables in VAR models, rather than individual coefficients, researchers use Impulse Response Functions (IRFs) where one component is shocked and its effect is measured using the entire multivariate system (e.g., Dekimpe & Hanssens, 2018).

The VAR model not only sheds light on the dynamic relationships between the endogenous variables, but it can also provide forecasts. We use the forecasted (log) levels of the three buzz behaviors on the movie release date as predictors of opening weekend box office sales.

### Post-release stage: Box office sales

We estimate a linear regression model for opening weekend box office sales. Following Elberse and Eliashberg (2003), we log-transform all non-binary variables, resulting in a log–log model specification. Consequently, we can interpret the estimated coefficients as elasticities and compare them. The focal independent variables are the forecasted (log) levels of pre-release communication, participation, and search.<sup>4</sup> To account for the precision of the forecasted buzz behaviors, we estimate the model for box office sales using Weighted Least Squares, using as weights the inverse of the average standard error of the forecasted buzz behaviors.

<sup>4</sup> We use Dynamic Forecasting in EViews 12, which means a multi-step forecast of the endogenous variables, beginning at the start of the forecast sample. For one period at a time, the endogenous variables are forecasted based on their observed lagged values (when available) and otherwise based on their forecasted lagged values, while the exogenous variables in the “X”-part are used as observed, as these values are predetermined, e.g., star power does not change.

## Results

### Pre-release stage: Buzz and pre-release marketing

A VAR-X model requires endogenous variables without unit roots for consistent estimates (Dekimpe & Hanssens, 2018). Consequently, we test all endogenous variables for unit roots and find that all variables are stationary apart from log mass media advertising. For log mass media advertising, we take the first difference (which is stationary) and use this variable in the model (see Table C1 of Web Appendix C). Because the VAR-X model utilizes only stationary variables, cointegration tests are not required (Dekimpe & Hanssens, 2018). Next, we explore the optimal lag length, i.e., how many lags of the endogenous variables should be included in the model. The Schwarz Information Criterion (SIC) is optimized for four lags (see Table C2 of Web Appendix C); hence, we use this lag length in the VAR-X model. Figures 4 and 5 show IRFs, which are the effects of a generalized shock of one standard deviation in the residual of one variable (e.g., participation) on another variable (e.g., communication). Figure 4 illustrates the dynamic effects between the three buzz behaviors, showing that all buzz behaviors reinforce each other. The effects decline over time but are still significantly different from zero after 14 days (except for the effects of participation on communication and search).

Figure 5 visualizes the dynamic effects of pre-release marketing on the buzz behaviors. Movie-related and trailer-related firm social media posts influence all buzz behaviors positively. The effects of movie-related posts are declining relatively slowly and are still significantly different from zero after two weeks. In contrast, the effects of trailer-related posts are declining faster. Similarly, trailer releases affect buzz positively and decline rapidly. Notably, the IRFs reveal that mass media advertising has no significant effect on any of the buzz behaviors.

Figure 6 visualizes the cumulative dynamic effects among the three endogenous buzz variables and of the four pre-release marketing variables on the buzz behaviors, utilizing arrow sizes proportional to the cumulative effects. A cumulative dynamic effect captures the effect of a generalized one-standard-deviation shock in the error term of a variable on day  $t$  on the sum of the effects on another variable across days  $t, t+1, \dots, t+14$ . Figure 6 shows that communication generates the highest cumulative dynamic effects. Its effects on the other buzz behaviors are consistently stronger than the other way around. For instance, the effect of communication on search ( $\psi = 1.29$ ) is stronger than the effect of search on communication ( $\psi = .89$ ). Overall, communication has the strongest clout, followed by participation and search.

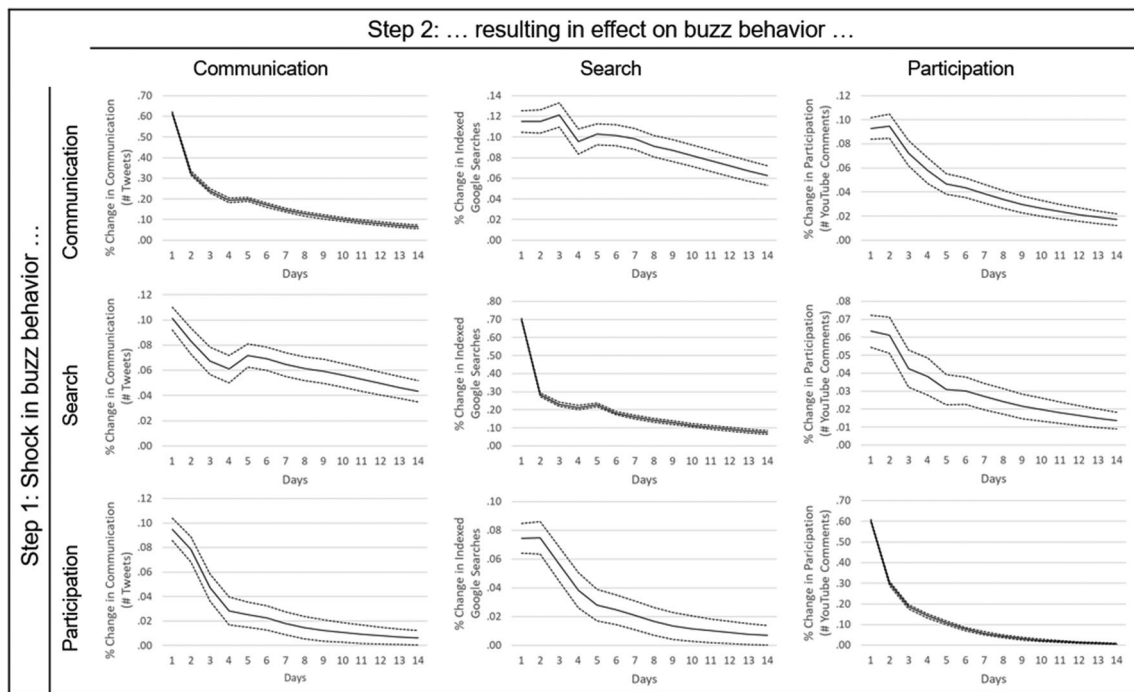


Fig. 4 Impulse response functions for buzz behaviors

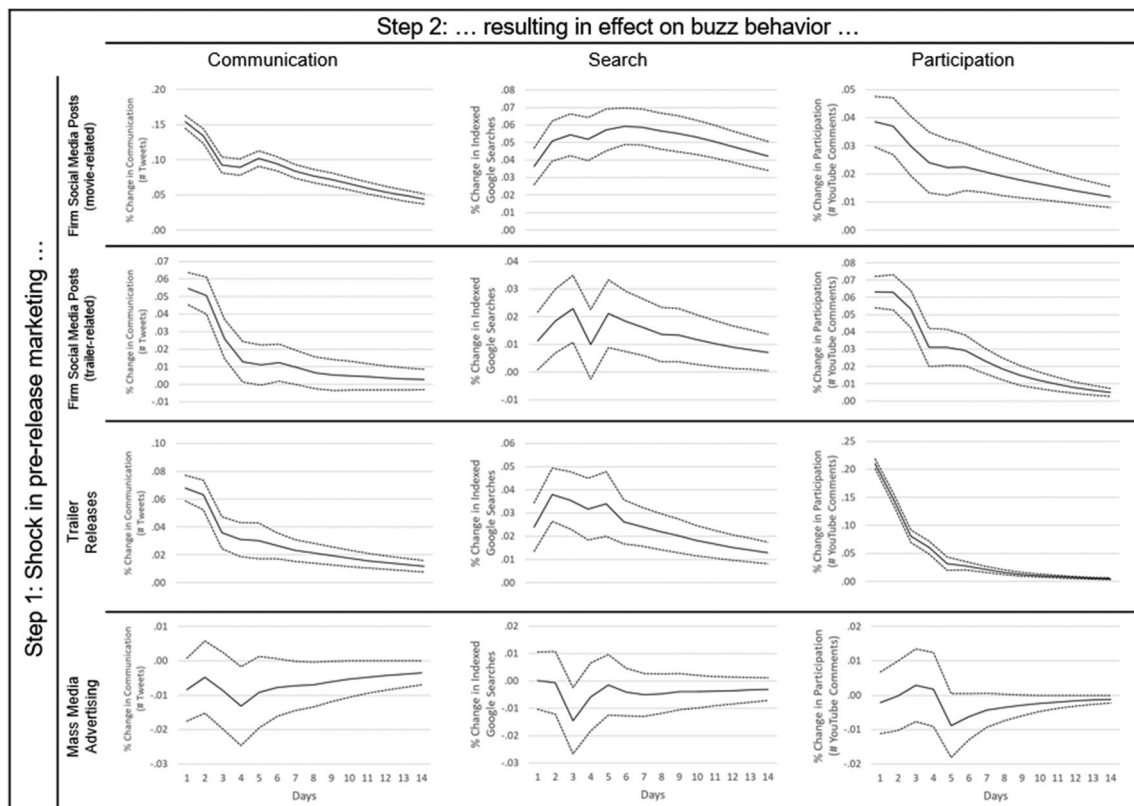
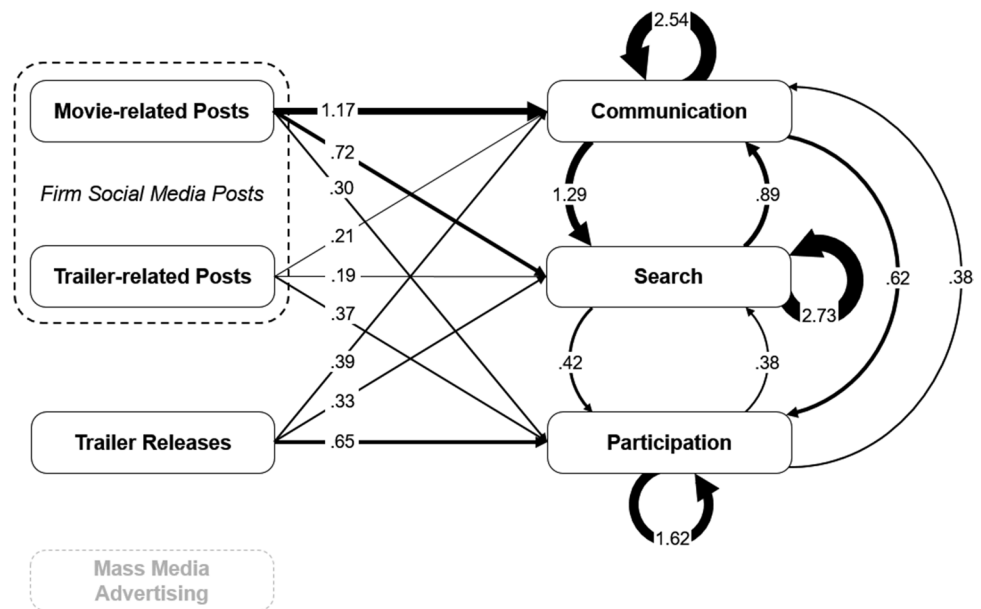


Fig. 5 Impulse response functions for the effects of pre-release marketing on buzz behaviors

**Fig. 6** Cumulative dynamic effects. Notes: A cumulative dynamic effect (labeled  $\psi$  in the text) is the effect of a generalized one-standard-deviation shock in the error term of a variable on day  $t$  on the sum of the effects on another variable across days  $t, t+1, \dots, t+14$ . All shown cumulative dynamic effects are significant ( $p < .05$ ).



We identify a distinct order of clout when investigating the cumulative dynamic effects of pre-release marketing on the three buzz behaviors (see Fig. 6). The weakest element is mass media advertising, as none of its cumulative dynamic effects are significant. The effects of movie-related firm social media posts on communication ( $\psi = 1.17$ ) and search ( $\psi = .72$ ) are at least three times as strong as the effects of trailer-related posts on these variables (communication:  $\psi = .21$ , search:  $\psi = .19$ ) and twice as strong as the effects of trailer releases (communication:  $\psi = .39$ , search:  $\psi = .33$ ). In contrast, trailer-related firm social media posts and trailer releases are particularly effective in driving participation. The effects of trailer-related firm social media posts ( $\psi = .37$ ) and trailer releases on participation ( $\psi = .65$ ) are distinctly stronger than the effect of movie-related firm social media posts on participation ( $\psi = .30$ ).

### Post-release stage: Box office sales

For the post-release stage, we utilize forecasted levels of communication, search, and participation based on the estimates of the VAR-X model as independent variables (see Table C3 of Web Appendix C). Table 5 shows the results of the focal log–log model in the first column, with log opening weekend box office sales as the dependent variable (Model 1). For all models, the variance inflation factor values are below 6; hence, multicollinearity is not a concern (Neter et al., 1996). The three buzz behaviors, in combination with the control variables, explain more than 94% of the variance in the data.

As expected, the control variables number of screens ( $\beta = .61, p < .01$ ), advertising spend ( $\beta = .12, p < .05$ ), and

critics ratings ( $\beta = .46, p < .01$ ) have a positive impact on movies' opening sales. In contrast, we do not detect a positive impact of production budget ( $\beta = .00, p = .85$ ) or star power ( $\beta = -.01, p = .93$ ). These estimates mirror the findings of Elberse and Eliashberg (2003), who report non-significant effects of production budget and star power on box office sales. Importantly, we find that all three PRCB behaviors have significant positive effects on opening sales. As we can directly compare elasticities, we find that communication has the strongest impact on opening weekend box office sales ( $\beta = .23, p < .01$ ), followed by search activities ( $\beta = .08, p < .01$ ) and participatory behaviors ( $\beta = .09, p < .01$ ) whose impact is similar.

### Alternative model specifications

**Estimator** Model 2 (see Table 5) uses the Ordinary Least Squares estimator (instead of the Weighted Least Squares estimator) and leads to nearly identical results.

**Total box office** Model 3 uses a movie's total box office sales as the dependent variable (instead of opening sales) and still explains about 78% of the variance. We observe positive and significant effects of communication, search, and participation; their ordering regarding relative importance persists. This finding is remarkable because, after release, other factors beyond buzz influence a movie's box office sales. Consumers start to experience the product, and consequently, post-release word of mouth takes off. Moreover, firms may adjust their advertising spend according to sales numbers. Although we do not control for these influences, we still observe significant effects of communication, search, and participation on total box office sales.

**Table 5** Impact of PRCB on market performance

	<i>Model 1</i> Focal Model DV: Opening Week- end Box Office Sales			<i>Model 2</i> Focal Model Esti- mated with OLS			<i>Model 3</i> DV: Total Box Office Sales			<i>Model 4</i> Using Averaged 3-Day Buzz Forecast			<i>Model 5</i> Lag Structure Based on AIC		
	$\beta$		<i>p</i>	$\beta$		<i>p</i>	$\beta$		<i>p</i>	$\beta$		<i>p</i>	$\beta$		<i>p</i>
<b>Buzz behaviors</b>															
Communication	.230	***	<.001	.229	***	<.001	.183	***	<.001	.216	***	<.001	.239	***	<.001
Search	.082	***	.002	.083	***	.002	.110	***	<.001	.089	***	.001	.082	***	<.001
Participation	.092	***	.008	.092	***	.008	.120	***	.003	.100	***	.005	.085	**	.012
<b>Controls</b>															
Production budget	.002		.852	.002		.880	.008		.560	.002		.863	.002		.881
Mass media advertising	.119	**	.032	.121	**	.031	.470	***	<.001	.127	**	.020	.101	*	.068
Critics' ratings	.459	***	<.001	.461	***	<.001	.499	***	<.001	.444	***	<.001	.458	***	<.001
No. of screens	.614	***	<.001	.615	***	<.001	-.009		.702	.612	***	<.001	.620	***	<.001
Star power	-.005		.931	-.003		.962	.015		.836	.000		.997	.005		.930
Genre	Included (not shown for parsimony)														
MPAA rating	Included (not shown for parsimony)														
Sequel	Included (not shown for parsimony)														
Remake	Included (not shown for parsimony)														
Adaptation	Included (not shown for parsimony)														
Season	Included (not shown for parsimony)														
<b>R<sup>2</sup></b>	.940			.940			.775			.944			.942		
Estimation method	WLS			OLS			WLS			WLS			WLS		

\* $p < .10$ , \*\* $p < .05$ , \*\*\* $p < .01$  (two-tailed). We also estimated a 2-day forecast model. The results of this model align with the results of the 3-day forecast model in both sign and significance

DV Dependent Variable, WLS Weighted Least Squares, OLS Ordinary Least Squares, AIC Akaike Information Criterion

**Forecast horizon** Model 4 uses averaged three-day forecasts (instead of one-day forecasts) for the three buzz behaviors, in line with a three-day opening weekend (including Friday). The results are similar to those from the focal model.

**Lag structure** Model 5 relies on a lag structure determined based on the AIC (instead of the SIC), i.e., nine lags. Again, the results for the focal buzz behaviors remain the same in terms of sign, significance, and relative order. Moreover, the accumulated effects on buzz behaviors in the corresponding VAR-X model also replicate according to sign and significance, although the effects based on the AIC are slightly smaller (see Table D1 of Web Appendix D).

### Robustness checks

In addition to the alternative model specifications, we conducted several robustness checks involving alternative variable operationalizations and additional explanatory variables (see Web Appendix E). Specifically, we replicated the main results (i) using a different benchmark for our search measure, (ii) splitting mass media advertising into digital and traditional advertising, (iii) aggregating movie-related and

trailer-related firm social media posts to form a unidimensional measure of firm social media posts, (iv) using the tweets that have been classified as participatory as a second measure of participation, and (v) considering the valence of communication and participation in both the VAR-X and box office models.

### Interactions

We explore potential interactions among variables in the box office model. Following the EF approach (Golder et al., 2023), we motivate the interactions we study. The first set of (two-way) interactions is among the three buzz behaviors. We expect positive synergies between these behaviors based on encoding variability theory (Lord & Putrevu, 1993). According to this theory, consumers who encounter information in more than one channel or mode have multiple retrieval cues available, leading to stronger, clearer, and more accessible information (Stammerjohan et al., 2005). The second set of interactions involves two variables that movie studios can control during the planning stage but are no longer actionable after the production stage: the movie's star power and whether the movie is a sequel or

adaptation (from a book, series, or video game). In general, consumer judgments are positively biased towards familiar stimuli, especially when information is limited (Gigerenzer & Goldstein, 1996). Thus, the positive effect of buzz behaviors on market performance should increase for movies with well-known cast members or source material. The results are documented in Web Appendix F. First, we do not find any significant interactions among the three buzz behaviors, suggesting that each PRCB dimension exerts a unique, independent effect. Second, we find that star power strengthens the impact of communication on market performance ( $\beta = .14, p < .01$ ) and that the effect of participation is stronger for movies based on existing source material ( $\beta = .15, p < .05$ ).

## Discussion and conclusions

Consumer buzz in the run-up to a new product's release plays a crucial role in its early adoption and overall success, especially for experiential goods with short lifecycles, such as entertainment goods. This research extends current

knowledge about pre-release consumer buzz by investigating its antecedents, dynamics, and consequences through a multi-behavioral lens inspired by recent conceptual advances (Houston et al., 2018). The adopted multi-behavioral, dynamic perspective not only offers novel insights into the relative impact of anticipatory communication, search, and participation on new products' market performance but also sheds new light on their interplay throughout the pre-release phase.

Table 6 provides a summary of the key findings. First, we find a consistent pattern regarding the three buzz behaviors' relative importance for early market performance, i.e., communication has the strongest effect, followed by participation and search. Specifically, the effect of communication on opening weekend box office is two times stronger than those of participation and search. Second, in line with the notion of action-based buzz cascades (Bikhchandani et al., 1992; Houston et al., 2018), our research establishes that pre-release communication, search, and participation reinforce themselves and each other. The cascading effects emanating from communication are consistently stronger than those of the other buzz behaviors, highlighting its central role in

**Table 6** Summary of key findings

	Antecedents	Consequences
Communication	<ul style="list-style-type: none"> <li>• Movie-related social media posts are the strongest driver of communication (<math>\psi = 1.17</math>), followed by trailer releases (<math>3 \times</math> weaker; <math>\psi = .39</math>) and trailer-related social media posts (<math>5 \times</math> weaker; <math>\psi = .21</math>).</li> <li>• Mass media advertising has no significant effect on communication.</li> <li>• <b>Key takeaway: To drive communication, movie-related social media posts are by far most effective.</b></li> </ul>	<ul style="list-style-type: none"> <li>• Communication has the strongest impact on opening weekend box office sales (<math>\beta = .23</math>), which is roughly <math>2.5 \times</math> stronger than the impact of search (<math>\beta = .09</math>) and participation (<math>\beta = .08</math>).</li> <li>• Communication has strongest spillover effects on search (<math>\psi = 1.29</math>) and participation (<math>\psi = .62</math>), which are <math>1.5 \times</math> stronger than the reverse spillovers (<math>\psi = .89</math> and <math>\psi = .38</math>, respectively).</li> <li>• Strong self-reinforcing effects (<math>\psi = 2.54</math>), suggesting strong stickiness.</li> <li>• <b>Key takeaway: Communication plays a crucial role in propagating pre-release buzz and in driving box office sales.</b></li> </ul>
Search	<ul style="list-style-type: none"> <li>• Movie-related social media posts are the strongest driver of search (<math>\psi = .72</math>), followed by trailer releases (<math>2 \times</math> weaker; <math>\psi = .33</math>) and trailer-related social media posts (<math>3 \times</math> weaker; <math>\psi = .19</math>).</li> <li>• Mass media advertising has no significant effect on search.</li> <li>• <b>Key takeaway: To drive search, movie-related social media posts are by far most effective.</b></li> </ul>	<ul style="list-style-type: none"> <li>• Impact of search on opening weekend box office sales (<math>\beta = .08</math>) is comparable to the impact of participation (<math>\beta = .09</math>).</li> <li>• Spillover effect of search on communication (<math>\psi = .89</math>) is <math>2 \times</math> stronger than on participation (<math>\psi = .42</math>).</li> <li>• Strongest self-reinforcing effects (<math>\psi = 2.73</math>), suggesting strong stickiness.</li> <li>• <b>Key takeaway: Search plays a support act in driving box office sales and reinforces the crucial buzz behavior communication.</b></li> </ul>
Participation	<ul style="list-style-type: none"> <li>• Trailer releases are the strongest driver of participation (<math>\psi = .65</math>), followed by trailer-related social media posts (<math>2 \times</math> weaker; <math>\psi = .37</math>) and movie-related social media posts (<math>2 \times</math> weaker; <math>\psi = .30</math>).</li> <li>• Mass media advertising has no significant effect on participation.</li> <li>• <b>Key takeaway: To drive participation, trailer releases are by far most effective.</b></li> </ul>	<ul style="list-style-type: none"> <li>• Impact of participation on opening weekend box office sales (<math>\beta = .09</math>) is comparable to the impact of search (<math>\beta = .08</math>).</li> <li>• Weakest spillover effects on other buzz behaviors: <math>\psi = .38</math> on search (vs. reverse spillover: <math>\psi = .42</math>) and <math>\psi = .38</math> on communication (vs. reverse spillover: <math>\psi = .62</math>).</li> <li>• Weakest self-reinforcing effect, suggesting relatively weak stickiness (<math>\psi = 1.62</math>).</li> <li>• <b>Key takeaway: Participation also plays a support act in driving box office sales and is more strongly influenced by other buzz behaviors than vice versa.</b></li> </ul>

The reported antecedent and cascading effects (i.e., spillover and self-reinforcing effects) are cumulative dynamic effects (see Fig. 6 and labeled  $\psi$ ) from the pre-release stage (i.e., the effect of a generalized one-standard-deviation shock in the error term of a variable on day  $t$  on the sum of the effects on another variable across days  $t, t+1, \dots, t+14$ ). The reported effects on box office sales are elasticities from the post-release stage (see Table 5 and labeled  $\beta$ )



the dynamic evolution of buzz. In addition to showcasing the dynamic and intertwined nature of buzz, we study the effectiveness of key pre-release marketing tools for stimulating these buzz behaviors. We find that firms' social media activities and trailer releases on video platforms can trigger communication and participatory behaviors, whereas mass media advertising does not have an influence on the dynamics of buzz. Movie-related (i.e., non-trailer-related) social media posts have particularly strong effects on buzz, especially on communication and search, whereas trailer releases are more effective in generating participatory behaviors. Overall, our study answers Houston et al.'s (2018) call for research regarding how and why pre-release consumer buzz develops over time and offers new insights of theoretical and practical value.

## Theoretical implications

This research contributes to the pre-release marketing literature in several ways. First, we extend the limited body of studies focusing on the dynamics of pre-release consumer buzz (Gelper et al., 2018; Kim & Hanssens, 2017; Xiong & Bharadwaj, 2014) by explicitly accounting for the phenomenon's multi-behavioral nature. Building on Houston et al.'s (2018) seminal work, which employs a theory-in-use approach to conceptualize pre-release consumer buzz as a multi-behavioral phenomenon, we explicitly distinguish between consumers' communication, search, and participatory activities leading up to the release of a new product. The simultaneous investigation of these buzz behaviors facilitates novel and managerially relevant insights regarding their relative importance, which unidimensional approaches (e.g., Gopinath et al., 2013; Karniouchina, 2011; Marchand et al., 2017) cannot provide.

Regarding the impact of the three buzz behaviors on early market performance, we identify communication as the strongest driver. Its comparatively strong effect might be due to accessibility-diagnostics reasons (Feldman & Lynch, 1988). As for accessibility, communication can be observed more easily by other consumers compared to the other anticipatory behaviors. Because communication is typically aimed at reaching as many people as possible, consumers' expressions of anticipation are visible to a broader audience, thus increasing the probability of affecting others (i.e., broadcasting function). As for diagnosticity, pre-release communication is a clear and positive signal that other consumers are excited about the new product, requiring little cognitive effort from the user. However, the signals for participation (number of trailer views) and search (trending keywords) may be perceived as more ambiguous in terms of informational value and underlying motivation (e.g., spikes

in search could be caused by scandals rather than genuine anticipation) compared to user-initiated communication. Consequently, consumers might rely more strongly on communication-based signals of anticipation than on search- or participation-based pre-release buzz.

Notably, we also find significant effects, in the same relative order, regarding movies' market performance in the long term (i.e., total box office sales). This finding implies that pre-release buzz echoes beyond a movie's release date and emphasizes its relevance to short-term and long-term market performance. The results further suggest that communication, search, and participation each influence market performance in their own right since we find no significant interaction effect between buzz behaviors.

Regarding the dynamics of buzz during the pre-release phase, our work showcases the complex interdependencies among consumers' anticipatory behaviors. In line with the notion of action-based buzz cascades (Bikhchandani et al., 1992; Hennig-Thurau & Houston, 2019), we find that bursts in a specific buzz behavior will spill over to other anticipatory behaviors. Our findings offer comprehensive insights into these interdependencies, showing that all buzz behaviors reinforce each other but to a varying extent. Communication has the strongest clout in that it has more pronounced effects on search and participation than vice versa. The estimates obtained from the VAR-X model reflect and quantify—for the first time—these complex interdependencies among the three anticipatory behaviors.

In combination, the self-enhancing and cross-behavioral spillover effects of pre-release buzz offer a key explanation for why buzz tends to increase toward the release date. The benefits of setting buzz cascades into motion underscore the importance of generating buzz early in the pre-release phase to benefit from accumulative effects. But how can firms do this? Our findings establish that firms' social media activities are the main driver of pre-release communication, with movie-related posts being particularly useful to elicit communication and search, compared to trailer-related posts. Trailer releases are particularly effective in driving participatory behaviors. However, we find no significant impact of mass media advertising on any of the buzz behaviors, which echoes Gelper et al.'s (2018) null finding regarding the link between advertising spend and pre-release communication. While mass media advertising does not drive buzz, it nonetheless affects box office sales. In terms of attribution modeling, this finding suggests that part of the box office sales is directly attributable to advertising, yet advertising does not have an indirect effect through buzz behaviors. We note that the advertising elasticity (.12) can be used in budget allocation decisions, which is preferable to attribution-based allocation (Danaher & van Heerde, 2018).

## Managerial implications

Our research offers actionable insights for managerial practice. First, we establish that all buzz behaviors have a significant impact on market performance, with communication having a higher elasticity (.23) than participation (.09) and search (.08). Second, we establish the existence of interdependencies among them, with cross-behavioral spillover effects that are particularly pronounced for communication as well. Overall, this highlights the increased importance of anticipatory communication for affecting the trajectory of pre-release buzz relative to search and participation. However, these differences do not justify an exclusive focus on communication. Managers should adopt a holistic perspective and deploy marketing tools to stimulate all forms of pre-release anticipation.

Our findings show that firm social media posts and trailer releases are effective tools to generate pre-release buzz, whereas mass media advertising has no effect. Firm social media posts, especially non-trailer-related ones, are most effective in stimulating anticipatory communication and search. Thus, firms should direct resources to the creation and dissemination of product-related content on social media far before a new product is released. To boost dynamic effects, the content needs to be engaging and easy to share, causing consumers to like it, comment on it, and forward it to their peers (Kumar et al., 2016). As buzz evolves dynamically over time, we recommend that firms prepare social media content for distribution at least two months (i.e., the observation period of this research) before release. Additionally, firms can deploy social media posts in the last days before release to ensure that PRCB reaches top levels right when it matters the most.

Releasing trailers is the second major pre-release marketing tool that has significant effects on all buzz behaviors. Compared to social media posts, trailers and teasers are more vivid and engaging (i.e., consumers get “a real taste” of the product). Our findings underscore their relevance, especially for promoting participatory behaviors. As trailers and teasers can unfold their effects over days, weeks (the IRFs reported in this research are based on a period of two weeks), or even longer periods (some popular trailers may be viewed years after the movie release), we recommend releasing them as early as possible. Recent research (Liu et al., 2018) provides further insights into the design of successful trailers.

Finally, managers should pay attention to a movie’s star power and whether it is a sequel to or adaptation of existing intellectual property. Both movie characteristics can be determined by studios and augment the impact of buzz on market performance. Movies equipped with well-known casts and movies based on existing source material can better transform anticipatory communication and participation, respectively, into actual sales.

## Limitations and directions for future research

This study has several limitations that offer ideas for future research. First, while we find mass media advertising has a significant effect on market performance, its ineffectiveness in stimulating pre-release buzz is surprising. Advertising is often the lion’s share of a movie’s marketing budget, which can account for half of a movie’s total budget (Liu et al., 2018). Although significant amounts of mass media advertising spend are allocated to the pre-release period, as our data suggests, it appears to have no impact on consumers’ expressions of anticipation. This finding raises the question of whether the role of advertising is limited to enhancing awareness or if it might generate buzz only under specific circumstances, such as the presence of explicit call-to-actions that incite buzz behaviors. Future research should address this puzzling finding by not only considering advertising spend but also advertising content.

Second, our study considers key pre-release marketing actions aimed at the mass market. Hence, we focused on leading platforms with broad reach. While the studied platforms continue to play major roles in studios’ pre-release marketing campaigns, the platform economy is evolving. New platforms like TikTok, Snapchat, and Discord have gained significant popularity among younger cohorts like Gen Z consumers. Concurrently, new marketing tactics targeting this specific demographic group have emerged, such as inviting social media influencers to special screenings at visually captivating – or ‘Instagrammable’ – venues (Calnan, 2023) or directly compensating them for posting tailored promotional content about a new movie (Guerasio, 2023). The popularity of platforms like TikTok and Instagram among younger cohorts suggests a preference for shorter and visually engaging content, raising the question of the extent to which the effectiveness of pre-release marketing activities may depend on audience and channel characteristics. Corresponding research insights would be a valuable extension of our work and could help fine-tune pre-release marketing campaigns.

Third, our study is set in the movie industry and exclusively focuses on box office sales as a measure of market performance. As noted earlier, PRCB may even influence subsequent marketing channels, thereby contributing to a new product’s long-term revenue generation (Kübler et al., 2021). Due to macro-level changes, such as the rise of streaming services and changing consumer habits following the COVID-19 pandemic, studio’s release strategies are evolving (Lang & Rubin, 2021). For example, the theatrical release window continues to shrink, with movies becoming available sooner on streaming platforms (Brueggemann, 2023). Studios have even experimented with releasing movies simultaneously in cinemas and on streaming platforms (e.g., *Wonder Woman 1984* and

*The Matrix Resurrections*). These changes highlight the increasing importance of studying the short- and long-term across multiple distribution channels, which will require alternative outcome measures such as hours streamed and subscriber growth.

Finally, our research setting is limited to the entertainment industry. While PRCB plays a vital role in this industry, pre-release marketing campaigns seeking to create PRCB among consumers have become increasingly common in other industries, such as automobiles (e.g., Tesla's Cybertruck reveal show) and fashion (e.g., video trailers for upcoming collections). Therefore, we call for more research that explores the generalizability of our findings to other contexts and identifies potential boundary conditions for the drivers and impact of PRCB.

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**Data availability** Supporting data are not available because some of the variables are based on proprietary data.

## Declarations

**Ethical approval** Not applicable.

**Competing interest** The authors have no competing interests to declare that are relevant to the content of this article.

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