Forget “The Nobody-Knows-Anything” It's Time for Entertainment Science!

Student: Atya Zeb
Degree: Doctor of Philosophy
University of Technology Sydney
Business School, 2021

Certificate of Original Authorship

I, Atya Zeb declare that this thesis is submitted in fulfillment of the requirements for the award of doctor of philosophy, in the Business School at the University of Technology Sydney.

This thesis is wholly my work unless otherwise reference or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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Abstract

My thesis deals with the impact of WOM and brand extension strategy on box-office revenue to provide insights to studios and academics on how to reduce uncertainty in movie performance.

Essay1 examines the impact of WOM experiential content on box-office performance at the micro level beyond the aggregate measures of WOM. Word-of-mouth (WOM) is the most important source of information for consumers while making purchase decisions and its impact has been studied extensively in the movies industry. However, a major limitation of prior online WOM research is that most studies have focused on the quantitative attributes of WOM—volume, valence, and variance— while ignoring the information conveyed by the text of reviews. To overcome this limitation the authors analysed unstructured experiential information in the form of textual reviews and its impact on a movie box-office revenue. Natural Language Processing (NLP) methods were used to extract unstructured experiential information from a total sample of 24368 reviews for 79 movies. Results show that experiential information about actors and the plot influences box-office revenue, above and beyond the quantitative WOM measures found in the literature. Furthermore, the authors find that experiential information about the performance of the actors and the quality of the plot has a stronger positive effect on box-office at the beginning of the movie life cycle before quickly fading away. Hence, as predicted by accessibility and diagnosticity theory, the impact of experiential cues saturates after the initial product launch. Overall, these findings suggest that studios can better predict movie box-office performance by monitoring reviews content and can also better leverage WOM by investing in acting performance and plot quality.

Essay 2 aims to quantify and generalize the impact of sequels on box-office performance through a meta-analysis.

Sequels are brand extensions that are expected to offer higher returns while involving less risk. The movie industry is relying on sequels to generate more revenue as the share of sequels in the top-grossing films is on the rise. The extant movie literature has also found that sequels perform better than non-sequel movies however, the estimates of the effect vary considerably. To quantify the mean effect of sequels and determine their effectiveness, this study integrated a total of 91 studies from 1989 until 2019 reporting 170 effects and found that sequels positively influence movies box-office performance. The sequel's short-term box-office performance is greater than long-term box-office performance due to the familiarity with the parent movie and steady over time. However, too many sequels released in a year negatively affect sequel's box-office performance providing insights for studios managers that too much competition could lead to box office cannibalization of otherwise successful movies.

Introduction

Entertainment products (movies, video games, books, and music) annually generate a revenue of $750 billion globally (Hennig-Thurau and Houston 2019). Movie entertainment accounts for the largest share of this revenue, almost more than $100 billion. The success potential of a single product can be millions of dollars such as “The Force Awakens” in December 2015 generated $248 million in the U.S just in three days and overall a revenue of $1 billion. Entertainment is among the largest industries that require a huge financial investment. However, this industry is characterized by high risk and uncertainty (De Vany 2006; Henning-Thurau and Houston 2019), because of the volatility in demand and large investments, the old mantra of the industry "nobody knows anything" should be replaced with analytical analyses (Hennig –Thurau and Houston 2019).

In recent years, the production and marketing budgets for entertainment products mostly exceed $100 million and sometimes reach $500 million for a single movie or video game, therefore, a single flop can threaten the studio’s future. The traditional approach in the entertainment industry to use instinct or gut feeling is not a viable approach in the competitive digital environment, with so much information being available, managers can no longer justify making important decisions primarily based on their instinct. Marketing scholars consider entertainment science as an alternative that suggests an approach to managing entertainment products through data analytics which have the potential for incredible value and recognize the fundamental role of theory for the foundation (Hennig-Thurau and Houston 2019). The combination of smart analytics and theoretical foundation can provide valuable insights for decision making hence, reducing the risk and uncertainty in the performance of these products. Entertainment science is all about determining the probability of the next product being successful. For example, for the movie “Beasts of No

Nation" Netflix estimated the cost by predicting the number of viewers using viewer's data for similar movies and made a well-informed decision. Disney is also using new technologies to forecast their film success better. However, entertainment products like movies are unique and strategies are effective if carefully adapted to a specific entertainment marketing offering because the main purpose is to provide pleasure. Also, data analytics cannot replace the artistic aspect of entertainment products which being cultural products is necessary for their success (Hennig-Thurau and Houston 2019). Entertainment science can help in reducing the uncertainty and risk of entertainment products related decisions and aid managers to make informed decisions (Liu et al. 2018), however, the hedonic nature of products makes it difficult to fully understand the consequences.

Entertainment products have very unique characteristics, which add to the uncertainty in performance. First, these products are hedonic in nature (experiential), which makes it difficult for consumers to evaluate the quality before consumption (Hennig-Thurau and Houston 2019). Second, they have very short life cycles, and the sales of these products decay exponentially over time (Elberse and Eliashberg 2006). Additionally, technological advancement has changed the characteristics of the markets for such products with information availability just one click away. Furthermore, with hundreds of new products every year and the availability of data, the entertainment industry (especially the movie industry) offers good settings for research of different marketing phenomena.

My thesis looks at the management and marketing of entertainment products and tries to offer some insights on how to reduce the uncertainty in product performance to contribute to entertainment science.

Essay 1 "Putting words back into WOM: The case of motion pictures" examines the informational content of WOM and its impact on movie box-office performance. The primary goal of essay1 is to extend WOM knowledge by examining the rich textual experiential information available in online reviews and determine its impact on movie performance above and beyond the aggregate measures of WOM- *volume, valence, and variance* (*VVV*). The secondary goal of essay 1 is to explore WOM effects over time. The findings of essay 1 based on the insights from the theory of diagnosticity (Feldman and Lynch 1988) and information theory (Shannon 1948) show that the micro-level experiential information influences box-office performance above and beyond the macro VVV measures. Moreover, WOM dynamics change over time such that experiential information has a strong positive impact on box-office revenue at the beginning of the movie life cycle but quickly fades as the diagnosticity of experiential cues saturates after the initial product launch. Furthermore, the results show that negative experiential information is diagnostic throughout the life cycle of movies and has a strong negative influence on box-office performance.

The target journal for the essay1 is JAMS, the paper will be submitted after the friendly reviews.

Essay 2 "From Spiderman to Spiderman2 and 3: a meta-analytic examination of brand extensions impact on movies performance" looks at the entertainment product decisions by examining the effectiveness of brand extension strategy in the movie industry. Sequels are extensions of existing movies that are expected to offer higher returns while involving low risk (Hennig-Thurauet al. 2009; Palia et al. 2008). Extant literature on movie performance has examined sequels impact on movie performance (Ho et al. 2009; Henning-Thurau et al. 2015; Karinouchina 2011; Ravid and Basuroy 2004). Their findings show that sequels perform better than non-sequel movies. However, the estimates of the effect of sequels vary considerably, maybe due to the short time period, sample selection criteria, lack of explanatory variables in early studies, and different estimations approaches. Therefore, this study aims to quantify and generalize the impact of the sequel on movie box-office performance. Moreover, the industry is increasingly relying on sequels, hence this study examines the effectiveness of sequels as a risk-reducing strategy over time. In addition, given the prevalence of sequels in the movie industry, this study aims to determine whether sequels are still effective because studios are releasing too many sequels?

To answer these concerns this study integrated a total of 91 studies from 1989 until 2019 reporting 170 effects and found that sequels positively affect movie box-office performance. The sequels short-term box-office performance is greater than long-term box-office performance due to the familiarity with the parent movie, also the sequels' performance is stable over time. However, too many sequels released in a year negatively affect sequels box-office performance, thus studios need to be cautious.

Essay 2 is still a work in progress and will be submitted in two months to Marketing Letter for review.

Essay 1 and Essay 2 provide Insights for studio managers and contribute to the literature.

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Essay 1: Putting words back into WOM: The case of motion pictures

Introduction

Word-of-mouth (WOM) present in the form of product reviews is regarded as the most important means of informal communication among consumers. WOM information communicated through the Internet in the form of reviews, tweets, blog posts, etc. is called "electronic word of mouth" (eWOM) and generally referred as WOM embodies one of the most significant developments in contemporary consumer behavior (Liu 2006; Rosario et al. 2016). Nearly all consumers (95%) read online reviews before making purchase decisions (Spiegel Research Center, 2017), and almost three-quarters of consumers identify WOM as the main influence in their purchase decisions (Nielson report 2012). Consequently, researchers strive to understand the links among WOM (i.e., in the form of product reviews) pertaining to consumers decision making and product sales (Chevalier and Mayzlin 2006; Chintagunta, Gopinath, and Venkataraman 2010; Dellarocas, Zhang, and Awad 2007; Duan et al, 2008; Floyd et al. 2014; King et al 2014; Lamberton and Stephen 2016; Moe and Trusov, 2011; Rosario et al. 2016; You, Vadakkepatt, and Joshi 2015). The plethora of digital communication technologies have enabled consumers to share their consumption experiences easily, which overall, has increased WOM buying influence. Hence, understanding how social media and digital technologies influence a purchase decision is a key research priority (Marketing Science institute 2018; Srinivasan et al 2016).

Some product or service offerings, such as movies and their associated box office revenue, are even more influenced by WOM because it is not possible to fully ascertain their quality before consumption (Liu 2006; Eliashberg et al. 2006). As such one would expect that movies with a larger number of total reviews, higher average ratings, and little variation among those ratings to align positively with box office revenue but this is not always the case. For instance, *Source Code* and *The Adjustment Bureau* are two similar Hollywood movies in terms of genre, production budget, advertising expenditure, and star power but *Bureau* earned almost 13 percent more in revenue than *Code* during the same time period, despite 33 percent fewer reviews and a lower average rating. In sum, there must be something else underlying the WOM communication that is driving results.

Within the literature, most WOM studies examine one or more of the following metrics; *volume* (number of reviews), *valence* (average review ratings: e.g., between 1 and 5 stars, etc.,) and *variance* (standard deviation among review ratings) - referred to as *VVV* herein after. While exploring *VVV* metrics has produced a rich conversation, these studies largely examine WOM on a macro level only and ignore any micro-level textual data presented in an online review. Although challenging, it is hoped that this investigation will spur more research into understanding the unstructured nature of micro-level textual information (Kim and Hanssen 2013; Rosario et al. 2016; Ullah et al. 2016).

The primary goal of the research presented here is to extend our knowledge of WOM effects by examining the rich textual information available in online reviews and therefore, its impact on revenue. The influence of WOM textual data on product performance has received scarce attention despite calls from meta-analytic studies. Both Rosario et al. (2016) and You et al. (2015) suggested that researchers should consider the informational or textual content of WOM to help explain the contradictory findings present in their research. To be consistent with the literature, this research also examines both macro *VVV* effects and micro textual effects within the same study.

A secondary goal of this study is to explore WOM effects over time. Interestingly, the longitudinal effect of WOM has been largely ignored in the literature (Rosario et al. 2016; You et al. 2015). This exploration is especially important for experiential products with a compressed life cycle. A movie, for instance, earns the majority of its revenue within the first six weeks of theatrical release. While some research examined WOM at pre-release (Hennig-Thurau et al. 2015), post-release (Duan et al. 2008), or both (Liu 2006), no study to date has examined week-by-week WOM during the critical first six weeks of movie exploitation.

Drawing insights from the theory of diagnosticity (Dick et al. 1990; Feldman and Lynch 1988; Lynch et al. 1988), information theory (Shannon 1948), and using U.S. movie reviews with their associated box-office performance as the empirical setting, results show that micro-level experiential information influences box-office performance above and beyond the macro *VVV* measures. Moreover, WOM dynamics change over time such that textual information has a strong positive effect on box-office sales at the beginning of the movie life cycle but quickly fades as the diagnosticity of experiential cues (i.e., movie characteristics) saturates after the initial product launch.

This manuscript is organized as follows. First, the literature pertaining to macro *VVV* variables is presented along with a detailed description of how micro WOM textual variables extend this conversation in the literature. Next, the diagnosticity and information theories are presented with their associated hypotheses. The methodology and a detailed description of the experiential nature of the study's context, are presented along with the study's findings. The manuscript concludes with a discussion of research contributions and notable managerial implications pertaining to which experiential cues should be promoted at different stages of the product life cycle.

Related Literature

Table 1 provides a summary of previous studies results regarding the impact of WOM on consumer's behavior for experience products such as movies. Our research differs from these studies in two important ways. First, existing literature has considered the effect of WOM at a macro level only through *VVV* (i.e., Chintagunta et al 2010; Duan et al. 2008; Liu 2006;

Rosario et al. 2016) while the present research not only examines the impact of *VVV* but also that of experiential information in WOM content. This distinction from prior research is crucial given that macro WOM measures such as *volume* and *valence* cannot substitute for textual information in reviews (Ullah et al. 2016). Therefore, the assumption that *VVV* is representative of all the information contained in product reviews is tenuous.

"Insert Table 1 here"

Research has shown that *valence* is subject to selection bias (Hu, Pavlov, and Zhang 2009) and inflation bias (Chavelier and Mayzlin 2006). Moreover, by reducing a full review to a single number, valence ratings assume that product quality is one-dimensional; however, economic theory states that products have multiple attributes with different levels of importance for consumers (see, for example, Rosen 1974). Furthermore, *variance* is derived from valence measured as dispersion of ratings, because of which its impact on product evaluation shows less consistency (Rosario et al 2016). Whereas, *volume* creates awareness by providing information about how many people have used or experienced a product (Rosario et al. 2016). However, the information of how many people have used or experienced the product alone is not enough and to avoid the risk of watching a poor quality movie consumers have to read detailed content (Mudambi and Schuff 2010). In light of these arguments, it is perhaps not surprising that studies focused on *VVV* have yielded inconsistent results, alternatively showing a positive (i.e., Chintagunta et al. 2010) or a non-significant impact (i.e., Liu 2006) of *valence* on box-office performance. Whereas, a positive (Duan et al 2008; Gopinath, Chintagunta, and Venkataraman 2013) or non-significant relationship (Chintagunta et al 2010; Henning-Thurau et al. 2015) of *volume* with box-office performance. Furthermore, meta-analyses studies of the relationship between *VVV* account for approximately 25 percent of the heterogeneity in findings (i.e., Rosario et al. 2016; You et al.

2015). As a consequence, researchers advocate turning to textual information to better understand product sales beyond the influence of *VVV* (Rosario et al. 2016).

A second differentiating feature of the present research is to examine the temporal unfolding of experiential cues in textual reviews. Despite the recognition that movie dynamic changes (Eliashberg and Shugan 2003) as well as that of WOM changes over time (e.g., Duan et al. 2008), only a handful of studies accounted for such pattern and the few that did examine *VVV* rather than experiential cues from textual reviews. For example, some studies find a decreasing effect of *volume* (e.g., Liu 2006; Cui et al. 2012) or valence (e.g., Hu et al. 2008; Moon, Bergey, and Iacobucci (2010) on sales over time, whereas others find an increasing effect of *volume* (e.g., Bruce et al. 2012) or *valence* (e.g., Gopinath, Thomas, and Krishnamurthi 2014; Marchand et al. 2017).

Conceptual Framework

The research presented here is based on the accessibility-diagnosticity framework of the influence of experiential cues in WOM in the form of product reviews (Feldman and Lynch 1988). Figure 1 represents the framework. Accordingly, the influence of such cues on consumer choice depends on their capacity to lower the uncertainty of experiential product quality, on their *valence* (positive or negative), and when their informative content saturates during the lifecycle of the product. The theory of diagnosticity suggests that negative cues are more diagnostic and use negativity bias as the foundation for this effect however, the main focus this study is on movie experiential cues and their diagnosticity rather than negativity bias as the impact vary based on the characteristic of these attributes.

“Insert Figure 1 here”

Accessibility-diagnosticity of experiential cues in WOM

Experience products quality remain uncertain until consumption therefore individuals rely on relevant cues to evaluate experience products a priori (Jacoby, Olson, and Haddock 1971; Olson and Jacoby 1972; Olson 1977). As such, the theory of accessibility-diagnosticity stipulates that the probability of consumers to rely on a given cue for decision making increases when: (1) the cue is accessible, (2) no alternative cue is accessible, and (3) the cue is diagnostic of product quality (Feldman and Lynch 1988; Lynch et al. 1988). Accordingly, which contend that consumers are likely to rely on the experiential cues conveyed by textual product in their decision making. First, experiential cues are widespread and easy to access in the form of online product reviews.

Second, although *VVV* are also easily accessible, they are not alternative cues (Dick et al. 1990; Basu 2018; Feldman and Lynch 1988; Lynch et al. 1988) because they do not contribute to lowering experiential quality uncertainty as experiential cues do for several reasons. Generally, the text conveys more textured meaning than numbers, which enhances the diagnosticity of information (Andrew and Allen 2016; Kirmani and Rao 2000). Furthermore, experiential cues communicate other consumers' personal consumption experiences (Houston et al. 2018)—e.g., descriptions of product usage scenarios, what the product can and cannot do (Chen and Xie 2004)—information which is not included in *VVV*. Indeed, reviews of the same experiential product may feature different arguments to support similar summary ratings (Tang, Fang, and Wang 2014).

The diagnosticity of experiential actor and plot cues

WOM in the form of movie reviews may contain information about many different attributes—e.g., plot, actor, director, producer, visual effect, music—actor and plot play the most critical roles from the standpoint of both consumers and movie studios. The extent to which consumers discuss certain cues in reviews indicates how important they are for decision making (Peterson and Pitz 1988; Purohit and Srivastava 2001; Qiu et al. 2012). First, typically, more than 60 percent of the review content is devoted to discussion about the actors and the plot. For instance, in our data, actors and plot are the two attributes that are most discussed with 31 percent and 27 percent respectively, whereas other attributes, such as directors (2 percent) or visual effects (5 percent), are rarely discussed for the six weeks theatrical life cycle of movies. Second, studios often consider the actors and the plot of a movie as the most influential factors of movie success (Hadida 2009) because they serve as a key for the green-lighting of movie projects and the start of the production process (Eliashberg, Elberse, and Leenders 2006).

The influence of actors and plot on consumer choice is determined by the capacity of these cues to lower uncertainty about the experiential quality of movies. Crucially, the performance of actors is harder to ascertain before consumption than plot quality due to the notion of the 'singularity' of artistic performances. According to Karpik (2010), such performances are singular because they are incommensurable: the performance of each actor in each movie is unique and cannot be approximated by other performances of the same actor in other movies or by the performances of other actors in the same movie. By contrast, the plot contributes to the overall artistic quality of a movie but it is not an artistic performance by itself. In addition, studio-provided information gives a good sense of the narrative, even if partially disclosed. For instance, movie trailers and synopses are easily accessible before and after release (e.g., IMDB.com, movies' Wikipedia page), which allows moviegoers to assess whether the story appeals to them. Hence, because plot quality is less singular than actor performance, the latter cues should be less diagnostic than the former—i.e., they remove less uncertainty about experiential quality.

The valence of experiential cues

Accessibility-diagnosticity theory states that consumers consider both negative and positive cues to discriminate between high and low quality products (Richardson et al. 1994). In general, negative cues are expected to be more diagnostic of experiential product quality than positive cues (Kanouse 1984; Kanouse and Hanson 1987; Rozin and Royzman 2001; Skowronski and Carlston 1987, 1989). This effect is rooted in the *negativity bias*, according to which negative information carries greater weight than positive information in various judgments and information processing tasks (e.g., Kahneman and Tversky 1979; Fiske 1980).

The negativity bias is driven by several factors. First, the negativity bias is a crucial evolutionary adaptive function that helps individuals to avoid potential danger and harmful situations (Cacioppo et al. 1999; Vaish et al. 2008) as such, the brain shows greater activity to negative stimuli than positive at the neural level (Cunningham et al. 2004). Therefore, negative cues are more salient perceptually than positive cues, which lead consumers to allocate more resources when processing the former than the latter cues (Kanouse 1984; Kanouse and Hanson 1987; Rozin and Royzman 2001; Vaish, Grossmann, and Woodward 2008). Second, consumers trust negative cues more easily as input for judgments because they are less ambiguous than positive cues, which allows categorizing products in low and high quality groups more accurately (Akdeniz et al. 2013; Skowronski and Carlston 1987, 1989). Several studies have documented the negativity bias when evaluating experiential products. For instance, consumers are more adamant about not choosing a low-quality movie (negative cue) than choosing a high-quality movie (positive cue) (Luo and Homburg 2008; Hennig-Thurau et al. 2015). Therefore, negative experiential cues should be more diagnostic of experience products quality than negative experiential cues.

The temporal unfolding of experiential cues

Actor and plot cues are particularly important upon movie release because, up to that point, only studio-provided information is available, which is not effective to remove uncertainty from the market (Akdeniz and Talay 2013). Beyond initial release, however the diagnosticity of the actor and plot cues should vary throughout the movies' theatrical run (Geng et al. 2019). According to information theory, information is considered relevant by decision makers only if it reduces the uncertainty of outcomes (Shannon 1948). However, when the same information is repeated in the market, it becomes redundant and leads to saturation, which decreases the utility consumers derive from it (Stigler 1961), and lowers the probability of using information in the decisions making (Shannon 1948), hence time will moderate the relationship between experiential information cues and box-office performance.

Hypothesis Development

The hypotheses are formulated regarding the impact of actor and plot cues on movie box-office performance based on how much experiential quality uncertainty they remove from the market. Figure 1 illustrates the hypotheses within our conceptual framework. Based on the literature review, the framework reflects actor's cues, which inform highly uncertain attributes, before turning to plot cues, which inform attributes that are easier to assess a priori. Also, it reasons how much uncertainty both negative and positive cues about actors and plot is removed upon release as well as throughout the theatrical run of the movies.

Actor

Negative cues. Negative cues about the performance of actors should remove the most experiential quality uncertainty from the market. Due to the negativity bias, negative cues tend to be seen as more diagnostic than positive cues in general (Kahneman and Tversky 1979; Fiske 1980). In addition, the acting in a movie is an artistic performance, which singularity makes it particularly difficult to assess prior to consumption due to being incommensurable with prior performances from the same actors or with the performance of other actors in the movie (Karpik 2010; Waguespack and Solomon 2016). Altogether, negativity and singularity make negative actor cues particularly effective at lowering quality uncertainty upon release. Furthermore, because negative WOM develops a negative attitude and leads consumers to avoid the product, it should lower box-office performance (Chintagunta et al. 2010; Rosario et al. 2016; You et al. 2015).

In summary, negative actor cues remain diagnostic over the entire theatrical life cycle of movies. Since more processing resources are devoted to negative information, it accumulates supporting evidence over time continuously (Peterson and Pitz 1988), maintaining diagnosticity (Nagpal et al. 2011). As a result, because the lifecycle of movies is unfolding very quickly (Liu 2006), the temporal unfolding of negative actor cues is unlikely to lead to the saturation of market information (Shannon 1948), maintaining the same level of influence on box-office throughout the movies' theatrical runs. Thus:

H_1: Negative experiential information about actors has (a) a negative impact on box-office revenue; that, (b) is constant throughout the theatrical lifecycle of a movie.

Positive cues. The diagnosticity of positive cues in general is weaker than that of negative cues but the uncertainty surrounding actor performance quality being so difficult to ascertain a priori (Karpik 2010), such cues are likely to remove uncertainty upon movie release. This is consistent with the findings that even consumers who have a positive predisposition toward the adoption of a new movie may still rely on diagnostic cues to reduce uncertainty (Feldman and Lynch 1988). However, in comparison with negative cues, the positive actor cues are less likely to keep removing quality uncertainty from the market as the theatrical lives of movies unfold. Since positive actor cues are less diagnostic than negative cues, it is more likely to saturate in the later stages of the lifecycle of movies when much information has already accumulated, as suggested by the theory of information (Shannon 1948). In summary, positive experiential information about actor performance is diagnostic mostly at the beginning of the life cycle while it removes very little uncertainty as time unfolds. Thus:

H_2: Positive experiential information about actors has (a) a positive impact on box-office revenue; that, (b) weakens over time.

Plot

Negative cues. Negative cues about this attribute should be diagnostic of quality upon movie release when uncertainty is at its highest (Akdeniz and Talay 2013; Kanouse 1984). Studio-provided information about the plot in the trailer and synopsis summaries are already available when movies are released in theatres that highlight to audiences what is appealing about the plot. Hence, negative cues provide new information about the plot quality that further removes uncertainty upon release. However, negative plot cues should be saturated during the movies' theatrical lives at later stages (Shannon 1948). The movie plot is less singular than actors' performance and pre-release information is made available by studios whereas detailed information is revealed about the plot in WOM upon release. This increases the likelihood that, as negative cues from WOM accumulate, information about plot quality becomes redundant in the market, hampering diagnosticity. In summary, we expect negative experiential information about plot quality to be more diagnostic of movie quality at the beginning than at the end of the movie's lifecycles. Thus:

H_3: Negative experiential information about the plot has (a) a negative impact on box-office revenue; that, (b) weakens over time.

Positive cues. Positive experiential cues about the plot quality should remove the least uncertainty from the market about experiential quality. The negativity bias is not at play (Kanouse 1984)—consistently, research shows that positive cues have a lower likelihood to impact decision making than negative cues (Herr et al. 1991)—and the plot is less singular than actor performance (Karpik 2010). A single weak element of the story can have a massive negative impact on the quality of the movie (Hennig-Thurau and Houston 2019) and the presence of a clear premise is of great importance for a story to influence a film's commercial performance (Eliashberg et al. 2007). The influence of diagnostic cues on consumer choice depends on their capacity to lower the uncertainty of experiential product quality and the positive plot cue is the least diagnostic cue (Feldman and Lynch 1988). Moreover, high diagnostic cues can attenuate the effect of a low diagnostic cue and consumers do not consider a low diagnostic cue such as positive plot quality information in decision making (Purohit and Srivastava 2001). In summary, positive cues about the plot are unlikely to remove uncertainty from the market, as studios made accessible positive information prior to release, such cues are redundant with existing information even upon release. Thus:

H_4: Positive experiential cues about plot do not impact box-office revenue.

Method

Data and Variables

The data is collected from three publicly available sources: the Internet Movie Database[1] (IMDb), Box Office Mojo[2] (Mojo) and The Numbers[3]. This research focused on movies that were widely released in the United States from its opening day. The movies for which there is no reliable information available about all control variables and those run in theatre for less than six months are omitted from the sample. The final sample consists of 79 movies that were released in theatres between January 2011 and December 2011.

From IMDb, the following information is scrapped for each movie: textual reviews, reviewer ID (to make sure that reviewers are included only once and they belong to U.S.), posting date, each review ratings, and movie release date. We obtained the information for weekly box-office revenue, the weekly number of screens and production budget for all the movies from Mojo. Movie characteristics information, such as MPAA ratings, genre and sequel information were collected from IMDb and The Numbers. The sample data covers the first 6 weeks of the theatrical release, which is the most critical time frame of a movie life; (Duan et al. 2008; Elberse and Eliashberg 2003). Also, the early release weeks account for more than 90 percent of the total box-office revenue in the sample data.

Table 2 provides the description and measurement of the key explanatory variables. The main variables; the experiential information in WOM about actors' performance and plot quality are determined using content analysis such as Natural language processing (NLP) techniques. Positive (negative) information about the actor performance is measured as the percentage of positive (negative) words in WOM about actors' performance relative to total

[1] http://www.imdb.com
[2] http://www.boxofficemojo.com
[3] http://www.the-numbers.com

number of words, whereas the positive (negative) information about plot quality is measured as the percentage of positive (negative) words in WOM about the plot quality relative to the total number of words. The details of content analysis are provided in the content analysis section.

"Insert Table 2 about here"

The dependent variable is the weekly box-office revenue for each movie released in the United States, whereas time is measured as the numbers of weeks since the movie release. Moreover, previous research has extensively studied the determinant of movie box-office revenue. This study controls for the aggregate measures of WOM to identify the effect on box-office above and beyond these measures (Rosario et al. 2016). Hence, classified each movie reviews on weekly basis from its posting date to obtain the aggregate measures of WOM: *volume, valence, and variance*. For WOM *volume*, the number of reviews was added up on weekly basis. The weekly average rating is calculated by taking the average of weekly ratings from individual reviews as a measure of *valence* (Chintagunta, Gopinath, and Venkataraman, 2010). While, WOM variance is measured as the standard deviation of the weekly WOM valence, which shows the inconsistency in WOM (Moe and Trusov 2011; Sun 2012).

Drawing on the previous literature the following movie characteristics are included as control variables in the estimation: the weekly number of screens (Elberse and Eliashberg 2003); whether the movie is a sequel (Hennig-Thurau, Houston, and Hetjans 2009); production budget (Basuroy et al. 2003); stars-power, which is obtained from bankability index on the Numbers, measured as the mean of previous 3-year box- office revenue of movies in which an actor has appeared prior to the respective movie and then ranked from highest to lowest (Hennig-Thurau et al. 2006; Hofmann et al. 2017); movie genre as dummy variables (Liu et al. 2015); and the strength of movie competitive environment which is measured by the competition for screens space and the competition for revenue (Elberse and Eliashberg 2003; Clement et al. 2014). The competition for screens space is measured as the competition from new releases and ongoing movies, whereas the competition for revenue is measured as the focal movie competition from similar movies over the run time.

Model

WOM content analysis

There is no standardized method for mining information from WOM content, therefore prior studies have used a variety of methods, including lexicon-based sentiment analysis (Bae and Lee 2012), product-specific dictionaries (Gopinath, Thomas and Krishnamurthi 2014), and semantic analysis using naïve Bayes (Chern et al. 2015). This study used different techniques of natural language processing (NLP) suitable for the sentiment analysis (positive and negative performance on attributes) of the experiential information related to plot quality and actor performance in WOM. The sentiment analysis is performed through the following steps.

In the first step, crawled reviews from IMDb for all movies in the sample. IMDb is a leader among movie portals with 250 million visitors each month. Moreover, to write a review individuals need to create a profile with IMDb website which upon approval give access to users. Although, the “quality” of online reviews in terms of trustworthiness or source credibility of data (e.g.,Reimer and Benkenstein 2016) is becoming an issue however, most of the research on movie industry considers IMDb reviews as trustworthy and a major source of information than other social media platforms (Mass et al. 2015; Moon et al. 2014). The final data set consists of 24,368 total number of reviews. Movie reviews are accompanied by a star rating from 1 to 10 stars on IMDb. We Split reviews of each movie by week. Week0 is numbered as reviews before the release date and week #N as reviews that are from #Nth week from the release date. For example, week 1 reviews contain reviews written from release date to release date + 6.

In the second step[4], eliminated the special characters, non-English characters and words (e.g., URLs, HTML tags, numbers and Punctuation etc.), that do not typically have any informational content about the movie. Next anaphoric resolution methods are used to replace the pronoun with their corresponding nouns. For example, if a sentence talks about the actor and then mentions “he or she” it is replaced with the name to better extract information. The reviews are broken-down into individual sentences by identifying characters at the end of a sentence (e.g. “.” “!”, “?”). We remove all stop words (e.g., “the”, “and”, “is”, “at”, “on”, “in”) that are not required for understanding the meaning of content and have no informational value. The resulting set becomes the corpus (document) “structured set of texts” which is used for further analysis (Manning et al., 2008). Moreover, we stemmed the words for example like for likable, like and liked using a stemming algorithm[5] (Kennedy and Diana 2005). The procedures mentioned in step two are performed on each movie reviews.

In the third step, Stanford parser (POS tagger) assigned part of speech (such as noun, verb, and adjective, adverb) or other marks for each word in the sentence to obtain the opinion words and phrases that express sentiments tag as opinion or feature. These words usually express a positive or negative opinion (such as-very, hate, like, etc.). This method converts sentences into individual words or phrases and is tagged for processing. The sentiment position is also considered by taking negation and polarity (sentiment) shifter words by prefixing them to the word that they follow (Mass et al. 2015; Taboada et al., 2011). For example, “*nobody performed well in this movie*”, here nobody negates “well” and changed it to negative, whereas “not” in “not only” does not change the sentiment.

[4] All the steps done at the second stage are implemented using the modules in Natural Language Toolkit(ww.nltk.org)
[5] http://www.tartarus.org/˜martin/PorterStemmer/

Sentiwordnet[6] is used for sentiment classification. Moreover, considered contextual sentiment for example "I cry at the ends" mean crying here is stating that the end was good, expressing a positive opinion with the negative word (Andrew et al. 2015).

In the fourth step, the method combined machine learning and manually tag learning by developing a bag of words (words dictionary) for positive and negative sentiments classification. First, we manually selected the movie features such as actor, actress, story/plot, visual effects, music, producers, and studio and manually tag the opinion or sentiment related to them for each movie weekly by selecting the top 20 reviews. Then build a bag of words (BoWs) for each movie and update it weekly. These words are used to train the machine learning algorithm until the entire vocabulary of words is classified based on the valence (Lin and He 2009; Turney and Litman 2003). The approach estimates the probability of the valence of newly occurred word based on their co-occurrence with the initial word. These new words are then added to the BoWs.

In the fifth step, the coefficient correlation is used to determine whether a word is negative or positive. This features selection method is appropriate since the aim is to find out meaningful words for the content analysis of movie reviews in which the positive and negative features are separately selected and explicitly combined. Finally, we did words classification and selection based on the criteria explained in appendix 1. After selection manually classified words into their respective categories such as acting (actors' names or acting-related words count), plot (plot related words count), director, visual effect, and sound/music. This process is done for both the negative and the positive information.

[6] http://sentiwordnet. isti.cnr.it/

Empirical model

The empirical model is based on the assumptions from previous studies (e.g., Elberse and Eliashberg 2003; Duan et.al. 2008; Clement et al. 2014). Movies usually collect revenue over weeks and the role of determinants can vary throughout a movie theatrical run. Therefore, we model the dynamics of box-office weekly revenue and the impact of experiential content in WOM, in a system of dynamic equations.

WOM has a very strong influence on box-office revenue whereas, WOM is also influenced by the box-office performance thus, considered endogenous in the literature (Duan et al. 2008; Moe and Trusov 2011). Furthermore, exhibitors can increase or decrease the number of theatres on which movies are shown according to the demand for movies. The more screens the movie is shown on, the more revenue it generates; slowing down the decay in revenue, in turn keeping the movie playing on a larger number of screens, thus making it endogenous (Eliashberg et al. 2001). However, the main variables, the positive and negative experiential information in WOM about actors' performance and the plot quality itself cannot be influenced by movie sales. Sales may have an impact on the number of reviews, however, causing WOM on specific attributes or topics seems very unlikely (Sanchez et al. 2019). Therefore, to address the endogeneity and interdependencies among the WOM, revenue and screens developed a system a dynamic simultaneous equations. Specifically, constructed a system of three interdependent equations: one equation with weekly box-office revenue as the dependent variable (the revenue equation), second with WOM *volume* as the dependent variable (the WOM-*volume* equation), and the last one with screens allocation of movies as the dependent variable (the screen equation) (Duan et al. 2008; Elberse and Eliashberg 2003; Clement et al. 2014). To account for the dynamic interrelationship among the box-office revenues, the WOM-volume and the screens, these are considered endogenous variables in the empirical model.

The analysis used a multiplicative or more specifically a log-linear formulation (Basuroy, Desai, and Talukdar 2006). The estimated coefficient of the log-linear form directly represents the elasticity of the dependent variable concerning the change in the independent variables. Also, this log formulation smoothes the distribution. The errors in the equations are allowed to correlate in each time period (i.e., weeks) to account for the possibility that factors exogenous to the models specification could simultaneously influence the box-office revenue, WOM, and screens. The empirical model is based on the log-linear transformation of all the continuous variables except the main variables, which represent the positive and the negative experiential information about actors' performance and plot quality content relative to the total words in reviews and the dummy coded variables.

The equations below describe each of the three equations in the model.

Revenue equation

$$REVENUE_{it} = e^{\beta_0} . e^{\beta_1 ACTOR\_NEG_{it}} . e^{\beta_2 ACTOR\_POS_{it}} . e^{\beta_3 PLOT\_NEG_{it}} . e^{\beta_4 PLOT\_POS_{it}} \; e^{\beta_5 \, TIME_t}$$

$$e^{\beta_6 ACTOR\_NEG_{it} * TIME_t} . e^{\beta_7 ACTOR\_POS_{it} * TIME_t} . e^{\beta_8 PLOT\_NEG_{it} * TIME_t} . e^{\beta_9 PLOT\_POS_{it} * TIME_t}$$

$$\mathrm{W}_{it}^{\beta_{10}} . \mathrm{T}_{it}^{\beta_{11}} . \mathrm{Z}_i^{\beta_{12}} . e^{\beta_{13} D_i} . \prod_{k=1}^{K} \mathrm{VOLUME}_{i,t-k}^{\;\beta_k} . e^{\varepsilon_{Rit}}$$

Here, i indexes movies (*i=1, 2, ..., 79*) and t represents the time periods in weeks(*t=1,2,…,6*).

The revenue equation includes the key variables and the control variables based on extant movie research. The Revenue equation, $REVENUE_{it}$ denotes the box-office weekly revenue for movie *i* at time *t* which is the dependent variable. The main variables consist of, *ACTOR_POS, ACTOR_NEG, PLOT_POS, PLOT NEG* which denote the positive and negative experiential information about actors' performance and plot quality of a movie *i* at *t* and their interaction terms with time. The $TIME_t$ denotes the number of weeks from 0 to 5 (week 1 is coded as zero). The vectors of WOM, W_{it}, consists of the usual metrics of WOM such as *Volume, Average Ratings, Variance,* and *Volume*Time* denoting the interaction between volume and time for movie *i* at time *t*. Vectors of time-variant control variables, T_{it}, consist of $Screen_{it}$ (denotes the number of screens allocated to movie *i* at time *t*), $Competition\_Rev_{it}$ of the movie *i* at *t*. Vectors of time-invariant variables, *Zi*, consist of $Budget_i$ and $Starpower_i$ for movie *i* and D_i includes dummy variables such as *Genre* and *Sequel*. Moreover, a multi-lag term of volume, $\prod_{K=1}^{K} VOLUME_{i,t-k}^{\beta_k}$, (where $K = 2$), is included in the model to identify the equation since lagged term are exogenous (Arellano and Bover 1995; Duan et al. 2008) in the Revenue equation and ε_{Rit} are error terms.

WOM equation

$$WOM - Volume_{it} = e^{\alpha_0} . Revenue_{it}^{\alpha_1} . e^{\alpha_2 ACTOR\_POS_{it}} . e^{\alpha_3 ACTOR\_NEG_{it}} . e^{\alpha_4 PLOT\_POS_{it}}$$

$$. e^{\alpha_5 PLOT\_NEG_{it}} . \mathrm{W}_{it}^{\alpha_6} . \mathrm{T}_{it}^{\alpha_7} . \mathrm{Z}_{i}^{\alpha_8} . e^{\alpha_9 D_i} . \prod_{j=1}^{J} \mathrm{Revenue}_{i,t-j}^{\alpha_j} . e^{\varepsilon_{vit}}$$

WOM-volume is a function of the weekly revenue of a movie *i* at time *t*. The WOM equation consists of WOM content variables such as *ACTOR_POS*, *ACTOR_NEG*, *PLOT_POS* and *PLOT_ NEG*, the positive and negative experiential information about actors and plot for a movie *i* at time *t*. Vectors of WOM variables, W_{it}, consist of *Average Ratings* and *Variance* for movie *i* at time *t*. Vectors of time-variant control variables, T_{it}, consist of $Competition\_Rev_{it}$, and $Time_t$, of the movie *i* at *t*. Whereas, Z_i is a vector of time-invariant variable, $Starpower_i$ for movie *i*. The budget was not included in the equation as moviegoers may not know about the budget of the movie which will therefore not have an impact on WOM posting. D_i, includes dummy variables such as *Genre* and *Sequel*. Moreover, a multi-lag term of revenue, $\prod_{j=1}^{J} Revenue_{i,t-j}^{\alpha_j}$ $(where\ J = 2)$, is included as exogenous variables in the WOM equation and ε_{vit} are error terms.

Screen equation

$$Screen_{it} = \mathrm{e}^{\gamma_0} \,.\, \mathrm{Revenue}_{i,t-1}^{\gamma_1} \,.\, T_{it}^{\gamma_2} \,.\, \mathrm{Z}_i^{\gamma_3} \,.\, \mathrm{e}^{\gamma_4 D_i} \,.\, \mathrm{e}^{\varepsilon_{sit}}$$

The weekly number of screens is a function of the revenues in previous weeks, which captures the exhibitor's decision to allocate screens based on the exponential revenue decay overtime (Clement et al. 2014). The vectors of time-variant variables, T_{it}, consist of variables *Competition_New* and *Competition_Ongoing* of a movie *i* at time *t*. These two variables control the competition for screen space from new and ongoing releases. Vectors of the time-invariant variable, Z_i, consist of $Starpower_i$ and $Budget_i$, whereas, *Di* includes dummy variables such as *Sequel*, *Genre* and *Maj_Distributor* and ε_{sit} are error terms. The WOM metrics and the experiential textual informational content in the WOM about the actors and the plot are not included in the screen equation, as these variables affect the decision of a consumer to watch the movie, which is captured by the lagged revenue and might not have a direct effect on exhibitors screen allocation decision.

Estimation

The three-stage least square (3SLS) procedure is used to estimate the equations, since the presence of endogeneity makes OLS estimates inconsistent. Also, correlated error structure across the equations makes the 3SLS procedure more efficient than 2SLS procedure. The Hausman–Wu specification test (*Chi2=1152.6, p<.01*) confirms the simultaneous and endogenous relationship between equations (Wu 1973). The lag terms are considered exogenous for the revenue and WOM equations (Duan et al. 2008), while for screen equation the instruments, *Budget*, *Distr_Major*, *Competition_New,* and

Competition_Ongoing are used (Elberse and Eliashberg 2003). Moreover, to address the potential heteroscedasticity the estimations are bootstrapped (Ando and Hodoshima, 2007).

The VIF values for all the equations are below the critical value of 10. For the revenue equation, the highest VIF value is for *volume* (2.77) and the lowest for positive_ plot (1.12). For the WOM-Volume equation the highest VIF value is for revenue (1.30), whereas, the lowest VIF is for variable competition for revenue (1.05). The VIF for the weekly number of screens equation is below 10 with a maximum value of 1.81 for action and a minimum value of 1.06 for competition by new movies. Moreover, the correlation matrix does not show a severe problem of multicollinearity.

In addition to show that the experiential information explains variation in box-office performance above and beyond the *VVV,* we performed an OLS regression as the bootstrap 3SLS cannot provides this comparison. First, we run the regression only with the *VVV* and all control variables, and then included the experiential information in the same model to compare the model fit. The regression without experiential information resulted in a lower model fit (Adjusted R^2 = .85, RMSE = .23) than the model with experiential information (Adjusted R^2 = .88, RMSE = .21). This comparison show that the inclusion of experiential information to the prediction model improves the prediction of box-office revenue above and beyond the *VVV*.

Results

Revenue equation

Experiential actor and plot cues impact on revenue

Table 4, shows how the positive and the negative experiential information about the actors performance and plot quality affect the movie weekly box-office performance. As it indicates, the coefficient for negative experiential information about actors is negative and statistically significant (β_1 = -.438, p < .05). In support of H_{1a}, this shows that negative experiential information about actors in WOM decreases movies box-office revenue. The coefficient for negative experiential information about the plot is also negative and statistically significant (β_3 = -.834, p < .05). This Supports H_{3a}, which suggests that negative experiential information about the plot in WOM have a negative effect on the weekly box-office revenue. Moreover, the coefficient for positive experiential information about the actor is positive and significant (β_2 = .275, p < .05). This provides support for the positive effect of actor cue that has been hypothesized in H_{2a} —the positive experiential information about actor performance as a diagnostic cue in WOM increases movie box-office revenue.

"Insert Table 4 about here"

H_4 predicts that the positive experiential cues about the plot quality do not effect movie box-office revenue. This is supported: the coefficient of the positive experiential cues about plot quality is statistically insignificant (β_4 = .334, p > .10). Thus, consumers will not consider low diagnostic cues to judge the movie quality hence, it does not impact movie box-office performance. These results support the expectation that experiential content about actors' performance and plot quality in WOM should affect movie-goers and predict box-office revenue above and beyond the usual WOM measures such as *volume, valence,* and *variance*. Importantly, the coefficient of negative diagnostic cue is significantly higher than positive cue as determined by the Wald test that shows the relative strength of negative and positive experiential information about actor and plot. The test is statistically significant at p < .05 for both negative cues, which imply that the negative content about actors' performance and plot quality hurt the box-office revenue more than the gain from positive experiential informational content about plot and actors, confirming the negativity bias in WOM context.

The temporal unfolding of the experiential informational content about plot and actors in WOM

In terms of temporal dynamics of the effects, the coefficient of the interaction between the number of weeks since release (time) and negative experiential information about actor is statistically insignificant ($\beta_6 = .063$, $p > .10$). Thus, the negative experiential information about the actor as a highly diagnostic cue impact box-office performance throughout the theatrical lifecycle of a movie. This provides strong support for H_{1b}, which states that that the negative experiential information about the actor has a negative impact on box-office performance which does not change temporally. Conversely, the coefficient of the interaction term between the negative experiential information about the plot and the number of weeks is positive and statistically significant ($\beta_7 = .219$, $p < .05$). This provides support for H_{3b}, which suggests that the negative experiential information about plot effect box-office revenue when the movie is released, however, the effect weaken overtime after the release.

The estimation results also support H_{2b}. The interaction between time and the positive experiential information about the actor has a negative and statistically significant impact on box-office revenue ($\beta_8 = -.100$, $p < .05$). This shows that the impact of positive actor information as a less diagnostic cue fades over time. Interestingly, the coefficient of the interaction term between time and the positive experiential information about the plot is negative and statistically significant ($\beta_8 = -.167$, $p = .05$). Although, did not expect the interaction to be significant as the main effect is not significant for H_4 because this is the least diagnostic cue. To further investigate these findings, we examine the graphs of interaction terms over time to determine the temporal unfolding of these cues in detail.

Using the estimated revenue equation with mean-centered data, figures 2 to 4 depict the temporal unfolding of the experimental informational content about plot and actors in WOM. The floodlight analysis (Spiller et al. 2013) is performed by showing box-office revenue deviation above (high) and below (low) the mean of positive and negative experiential information about the actors and plot across weeks. The graphs (2-4) show that there is a stronger effect of the experiential cues about the quality of actors and plot at the beginning of the movie theatrical life cycle. Figures (2-3) depict that high positivity about the plot and actor cues weaken faster over time than low positivity. Whereas, figure (4) depicts that the low negativity about the plot weakens faster over time than the high negativity. These trends suggest that the effect of the experiential informational cue saturate in the later weeks and the effect on box-office performance fade over time. However, to examine whether the low positivity (high negativity) is better than high positivity (low negativity) in the later weeks, the statistical significance of each cue is determined at each week using floodlight analysis. The Johnson_Neyman point determines the significant and insignificant region of the floodlight analysis (Spiller et al. 2013).

"Insert Figure 2 about here"

"Insert Figure 3 about here"

"Insert Figure 4 about here"

Figure 2, shows that there are significant differences between high and low positivity about the actor cue at the beginning of the movie's life cycle. Similarly, Figure 4 provides the same results, that there are significant differences between the low and high negativity about plot quality in the early weeks, the negative content on average is higher in the beginning, but in the later run, the differences become insignificant. Interestingly, Figure 3 shows the opposite trend. There are statistically no significant differences between the low positivity and high positivity about the plot in the early release period of movies. However, after week 4, the low and high positivity about the plot shows significant differences. This graph shows, why the coefficient of the interaction term between time and positive experiential information about plot quality is statistically significant because, the low and high positivity differ at later stages. The positive plot cue becomes significant when other low diagnostic cues (positivity about actors and negativity about plot) saturates and when their effect fades away. Surprisingly, the low positivity shows a greater impact on box-office revenue than the high positivity about the plot. This might be because at a later stage in the movie theatrical life cycle movie-goers are mostly the late adopters who know about the plot. Therefore, decent positive information about it may impact their decision-making. However, if it is too positive, the credibility of information may decrease and consumers become skeptical about such information (O'Reilly and Marx 2011). In addition, moderate reviews are better than extreme reviews for experience products as shown by Mudambi and Schuff (2010).

Control variables

Although the control variables are not the focus of this research, their estimated coefficients are in the expected direction. Similar to findings in other studies (Rosario et al. 2016), WOM *volume* has a positive impact on box-office revenue ($\beta = .508$, $p < .05$), which means an increase in the number of reviews will lead to an increase in the box-office revenue. However, this positive effect of the *volume* on weekly box-office revenue is moderated by time. The coefficient of the interaction of time and volume is negative and statistically significant ($\beta = -0.064$, $p < .05$). However, contrary to the findings of Duan et al. (2008), the lag effect of *volume* is not significant. Furthermore, the weekly box-office revenue is not influenced by the average weekly ratings (Liu 2006; Dellarocas et al. 2007, Duan et al. 2008). The estimated coefficient of average ratings is statistically insignificant ($\beta = .122$, $p > .10$). In addition, the parameter estimates for *variance* is also statistically not significant ($\beta = -.002$, $p > .10$).

Similar to the previous findings, the weekly box-office revenue is higher when a movie is shown on large number of screens ($\beta = 1.576$, $p < .05$) and when the movie is a sequel. There is no significant effect of star power ($\beta = .006$, $p > .10$) and the competition for audience attention ($\beta = .005$, $p > .10$) on movie box-office revenue. Whereas, comedy and drama revenue is significantly higher than other categories ($\beta = .231$, $p < .05$).

WOM_Volume equation

In Table 5, the results show that the coefficients for the positive experiential information about the actors and the plot are both positive and statistically significant ($\beta_2 = .252$, $p < .05$; $\beta_4 = .590$, $p < .01$). These results indicate that positive experiential information about actors and plot lead to an increase in the number of reviews. However, the coefficient of negative experiential information about the actor is not significant ($\beta_3 = -.027$, $p > .10$). Whereas, the negative plot information has a marginally negative significant effect on volume ($\beta_5 = -.335$, $p < .10$).). This suggests that the negative information about the plot will lead people to post less about the movie.

"Insert Table 5 about here"

Furthermore, the coefficient *valence* is not significant ($\beta = .042$, $p > .10$), which shows that users do not blindly follow the ratings and pay attention to the content rather than the ratings themselves. The coefficient of *variance* is positive and statistically significant ($\beta = .046$, $p < .01$), which means that greater disagreement results in higher WOM-volume. Whereas, the WOM-volume is higher when the genre is "comedy and drama", and lower when it is action compare to "other" categories. Interestingly, the coefficient of star-power has a positive and statistically significant effect on WOM-volume ($\beta = .003$, $p < .01$).

Screen equation

The results for the screen equation in Table 6 indicate that the previous week box-office revenue does not have a significant effect on the number of screens. The results are different from the previous studies (Clement et al. 2014; Elberse and Eliashberg 2003). This may be because the sample includes the nationwide releases and most of them are the productions of major studios, therefore they may have more power over exhibitors and push them to keep the movie playing on a larger number of screens rather than to rapidly cut back the screens allocation. Moreover, a higher production budget, star-power, and major distributor lead to a higher number of screens. Sequels have less influence on number screens than non-sequel movies. In addition, the competition from ongoing and new movies for screens lead to a decrease in number of screens.

"Insert Table 5 about here"

Robustness checks
Regression with Gaussian copula

To check the robustness of results, this research used the instruments-free method to check and correct for endogeneity bias using Gaussian copulas, introduced by Park and Gupta (2012). Copula builds a joint distribution of the endogenous part of the regressor and error term of the main equation. The analysis used multiple regression and a control function approach to include the explanatory variables based on the Gaussian copulas (Park and Gupta 2012). The new control variables account for the endogeneity of WOM, screen, revenue, and budget. Following Park and Gupta (2012); Burmester et al. (2015) regressors are used to control for endogeneity. The following equations represents the endogenous variables included in the model.

$Cop\_log(Revenue_{it}) = \varphi^{-1}(H(log(Revenue_{it})))$

$Cop\_log(WOM\_Volume_{it}) = \varphi^{-1}(H(log(WOM\_Volume_{it})))$

$Cop\_log(Screens_{it}) = \varphi^{-1}(H(log(Screens_{it})))$

$Cop\_log(Budget_{it}) = \varphi^{-1}(H(log(budget_{it})))$

Where φ^{-1} is the inverse of the normal distribution function and H(.) is the empirical distribution of each variable. All the variables are non-normally distributed (Park and Gupta, 2012). The log-log formulation is used to get the elasticities and the regression is estimated using bootstrap standard error with 500 repetitions. The multicollinearity is also checked and indicated no issue for this analysis.

"Insert Table 7 about here"

The results in Table 7 are similar to the revenue equation results in the3SLS analysis. The positive and negative experimental information about the actors and the negative experiential information about the plot in WOM are statistically significant predictors of box-office weekly revenue. The positive actor and the negative plot cues affect the weekly box-office revenue at the early stage of the movie life cycle; however, this effect weakens over time. Whereas, the negative actor cue impact on weekly box-office revenue does not change over time. The other control variables also have similar results except for the *valence* which show a positive and statistically significant relationship with the movie box-office performance whereas, the coefficient of the interaction term between *volume* and time becomes statistically insignificant. Also, the budget is statistically insignificant, which shows that it has an indirect effect on revenue through the allocation of screens.

3SLS with WOM and revenue equations

The experiential information about actor performance and plot quality may not effect the exhibitor's decision but have a direct effect on users. Therefore, we run the 3SLS with revenue and WOM equations, with the same variables just included budget in the revenue equation. The results in Table 8 are similar to the main findings of the previous analysis.

"Insert Table 8 about here"

To examine the robustness of the results, also run the analysis with absolute values, with time fixed effect, and dummy time variables. All of the robustness checks show that the results remain highly consistent with those reported previously.

Discussion

WOM in the form of product reviews provides information to consumers and influences their purchase decisions. For an experiential product such as movies, consumers cannot evaluate the quality before consumption therefore they look for information or cues to reduce quality uncertainty. Although, the impact of WOM on product sales has been extensively examined in the literature, studies about information embedded in the textual reviews are scarce. To the best of our knowledge, this is the first study that examines the unstructured experiential information about movies in reviews and its impact on box-office revenue.

Research contribution

This research contributes to the extant WOM and entertainment marketing literature. First, this study contributes to the existing WOM literature by examining the unstructured experiential information content in user reviews, which is not captured by the frequently used measures of WOM such as *volume, valence, and variance* (Rosario et al. 2016; Kim and Hanssen 2013). Drawing insights from the theory of diagnosticity, the findings of this study suggest that unstructured experiential information about the actor's performance and plot quality influence box-office revenue, above and beyond the *VVV*. Moreover, previous studies on the impact of WOM *valence* on product performance are inconclusive (Rosario et al., 2016). The findings of this study indicates that negative experiential information about the performance of actors hurts box-office revenue more than positive experiential information about actors' benefits box-office revenue. Hence, consumers find negative experiential information more diagnostic than the positive information, in accordance with the theory of diagnosticity (Fiske 1980; Lynch et al 1988). The coefficient of negative experiential information about the plot quality is significantly different from positive and has a negative effect on box-office revenue (Wald test, $p<.05$), whereas positive experiential information about the plot has no effect. These findings of the negative experiential information effect on box-office revenue are similar to the studies that have shown that negative WOM *valence* is detrimental and decreases sales more than positive WOM *valence* increases sales (Chevalier and Mayzline, 2006; Sun 2012). Therefore, to better understand the effect of negative information on product sales companies need to consider the negative textual information, otherwise considering only WOM *valence* may provide misleading results.

Second, the results indicate that the impact of experiential information in WOM on box-office revenue changes temporally. Although, previous studies have either focused on pre-release or post-release or have compared the pre-release and post-release, none has considered the temporal effect of WOM post-release (Chintagunta et al. 2010, Gopinath, Chintagunta, and Venkataraman, 2013; Henning et al. 2015), with exception of Marchand et al. (2017). Marchand et al. (2017) found that the aggregate measure of WOM-volume and valence influence new product (video games) success and grows over time. However, this study's findings show a stronger effect of experiential information about the actors' performance and plot quality at the beginning of the product life cycle. Marchand et al. (2017) argue that the effect of WOM becomes stronger at the later stages because of the availability of functional information in reviews, without considering the functional information. Our study takes into consideration the experiential information in reviews and interestingly, as predicted by the theory of information (Shannon 1948), the effect of these types of cues saturates after the product launch. Importantly, the findings indicate that the effect for the *volume* of WOM fades away whereas, the *valence* effect is insignificant throughout the movie life cycle when experiential information content in WOM is included in the analysis.

Third, this study contributes to the entertainment marketing literature by providing consumers experiential perspective about the quality of a movie. Movie production factors such as story line, genre, producer, director, leading actors, and production cost directly influence movie performance (Hadida, 2009; Eliashberg, Elberse, and Leenders 2006). Most of the research on movies have looked at these factors from the studios or production perspective. These findings provide insight from the consumers' perspective and show the importance of the film factors such as actors, plot, visual effects, and director. Moreover, researchers and managers recognize the importance of plot, however no one has empirically tested the importance of a plot (Hennig-Thurau and Houston 2019). This research finds that the performance of actors and the quality of plot are the most important quality dimensions for consumers and the experiential information about the actors and the plot serves as quality cues for movie-goers and have significant impact on movies financial performance.

Fourth, this study contributes to the prior research about the role of the human brands (actors) on box-office performance (The Economist 2016; Mathy et al. 2016; Hofmann et al. 2017; Carrillat et al. 2018). Previous research has considered the impact of actors through the star power. Whereas, this research examines the actual acting performance beyond the star's power, by controlling for the star's power. The descriptive statistics show that content about the actual performance of the actors is the most important dimension in WOM with the highest percentage content which, indicates consumer's interest in the actor's performance.

Moreover, the findings indicate that both positive and negative experiential information about the actor performance matter at the early release period and have a significant effect on box-office performance. Furthermore, the analysis with a different types of measures of star power; media, commercial, and artistic star power (Carrillat et al., 2018), does not change the influence of actor's performance cue in WOM on movie performance. Additionally, we studied the star power interaction with positive and negative experiential information about the performance of actors. However, this study does not find any significant effect of star power on the positive and the negative experiential information, which supports the notion that after the release of a movie the actual performance is more important. These findings provide support for the importance of actors as human brands for evaluating the quality of the movie but suggest it matter more in the early release period of the movie theatrical life cycle.

Managerial contribution

Worldwide box-office revenue is growing steadily, movie-goers spent almost $20 billion on cinema tickets for the first six months of 2018. The movie industry is characterized by high risk because of the large investments, volatile demand, and heterogeneous consumers' preferences. While some movies dominate the box-office, most movies fail to even reach breakeven. For example, in 2015, big movies such as "Terminator: Genisys" with $158 million in the budget only earn $89 million at the domestic box-office. The Paramount President Megan Collagen said about the year 2015 that "it was completely designed by reviews and word-of-mouth" (THR 2015). This study provides insights for studios on how to reduce the uncertainty surrounding the movie box-office performance.

The findings suggest that unstructured experiential information about plot and actors in reviews explains the variations in box-office performance above and beyond the aggregate quantitative measures of WOM, the *VVV*. Therefore, studios should monitor experiential information in WOM to anticipate movie box-office performance and need to put back words in WOM by considering the experiential informational content of WOM. If studios only consider the *VVV* for the prediction of movies box-office performance, their prediction will lack accuracy. A simulation analysis based on our model estimated coefficients shows that 20 percent increase in the proportion of positive content about the actors will increase the box-office revenue by $1.5 million Whereas, a 15 percent increase in the proportion of the negative content about the quality of plot and actors performance decrease box-office revenue by $2.05 million and $1.2 million respectively.

The results also provide insights into the management of WOM. Despite extensive research on the impact of WOM on product sales (Rosario et al. 2016), the management of WOM communication is challenging, since managers do not have direct control over WOM communication. Movie studios acknowledge this, as stated by Disney Distribution Chief Dave Hollis “You don't have the luxury anymore of bad buzz not being immediately known". In this regard, this study’s findings suggest that positive experiential information about actors has a positive significant effect on box-office performance, whereas negative experiential information of actor performance and plot quality have a negative significant impact on box-office. Therefore, studios should invest in acting performance and plot quality to better leverage WOM.

Moreover, positive experiential information about actors and the plot has a positive significant effect on the WOM-*volume*, leading to increase in the posting of reviews. This implies that studios should use these two attributes to increase WOM activity about the movies, which will lead to high box-office revenue. Also, these findings suggest that actors should take part in the promotional campaigns and studios should create buzz around actors and the plot immediately after the launch, since post-release WOM is the only vehicle that can have impact on consumer’s decision making. For instance, studios should promote discussions on actors' performance and the plot quality on social media and movies reviews websites. Actors should play an active role in creating buzz about movies through many shows. There should be an update of their activities about movies promotion on movies websites, reviews sites like IMDb and online communities, this will give hype to WOM.

This study also finds that plot positive information has a positive impact on the box-office revenue at later stages after week 4. When other cues (negativity about the plot and positivity about the actor performance) become non-diagnostic the positive experiential information about the plot become diagnostic. This suggests that studios need to change their advertising strategy dynamically. They should consider actors at the beginning of the movie life cycle to advertise the movie and focus on their performance in the later stages for promotion. Furthermore, at the later stage they should highlight more about the plot in advertisement. Studios' can use the reviews that give positive information about the plot to promote movies.

Moreover, the star-power does not have a significant effect on box-office performance, contrary to the experiential information about the actor's performance. Therefore, studios should be careful when estimating the impact of star-power on box-office performance directly. Although, star power has positive significant impact on the number of screens allocated to movies, after the release the actual acting performance matters.

The results suggest that consumers find experiential information in WOM diagnostic and it influences box-office performance. Therefore, review website should provide multi-dimensional attributes evaluation for a product quality because product is composed of multiple attributes and evaluating the quality of the product needs a comprehensive evaluation of these attributes (Nelson 1970; Garvin 1974). For example, movie-goers take into account the actor performance and the plot quality in evaluation as suggested by this research findings, hence along with single ratings system they should be provide multi attribute ratings, so they can evaluate a movie on these experiential attributes.

Finally, this study also examines the experiential information about directors, visual effects, music, and producers and its impact on box-office revenue, however we do not find any significant effect of such information on box-office revenue as well as on WOM volume. Only information about the quality of actors and plot has a significant effect on box-office performance.

Limitation and future research

Reviews are usually rich but unstructured set of consumers' data with noise and to overcome these issues, NLP methods can be used as valuable tools for analysing large numbers of customers reviews for mining important marketing insights. In addition to the techniques outlined in our study, there are also more advanced NLP techniques that can be used for more complex semantic analyses, including word sense disambiguation and discourse analysis. By applying those techniques to user-generated-content including customers reviews, managers can understand customers' needs and wants more deeply. This study only considers movie industry which make the application of more detail findings specific to this industry.

In addition, the sample of this study consists of widely released movie in the U.S domestic box-office which are supported by high production budget and mass media campaign. Although WOM is critical for the formation of demand (Chevalier and Mayzlin 2003), it is considered more important for limited released movies. Limited released movies success solely depend on WOM (Hadida 2009). For example the success of the movie "*The Blair Witch Project*" was driven solely by WOM and usually takes time to spread after the release in comparison to wide released movies. Hence, we expect that WOM content might play more important and different role over the entire run of limited released movies than wide released movies.

Furthermore, this study examines the effect of WOM information on weekly basis. Research on individual review posted daily and throughout the theatrical run can provide more insights about the dynamic of information and its temporal effect. Therefore, future studies can extend the findings to daily and individual review level over the whole theatrical life cycle of the product to see the impact over the whole life cycle. Future studies can also extend to other product types to generalize the findings and investigate the effect of information on different product types, as based on product types importance of textual information may be different (Mudambi and Schuff 2010).

Conclusion

The results of this study show that experiential information content in WOM effect box-office revenue above and beyond the aggregate measures of WOM, the *VVV*. The negative experiential information about actor performance and plot quality decreases box-office revenue, whereas positive experiential information positively influences box-office performance. Therefore, to better understand the impact of WOM on product performance, words needed to be put back in WOM. Companies should consider the experiential information about the product along with VVV. The findings also show that the effect of these experiential information fades away over time and have a stronger impact on the product performance at the beginning of the product life cycle. Most of the entertainment products such music, movies, and video games follow exponential decay. Hence, the experiential information about these products provides diagnostic cues at the beginning which is the most important time as substantial amount of revenue is generated in early weeks. In addition, the negative experiential information about actors remains diagnostic throughout the lifecycle of the movie, which indicates that the negative experiential information is more diagnostic and discourages potential consumers from purchase.

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Figure 1: Conceptual framework

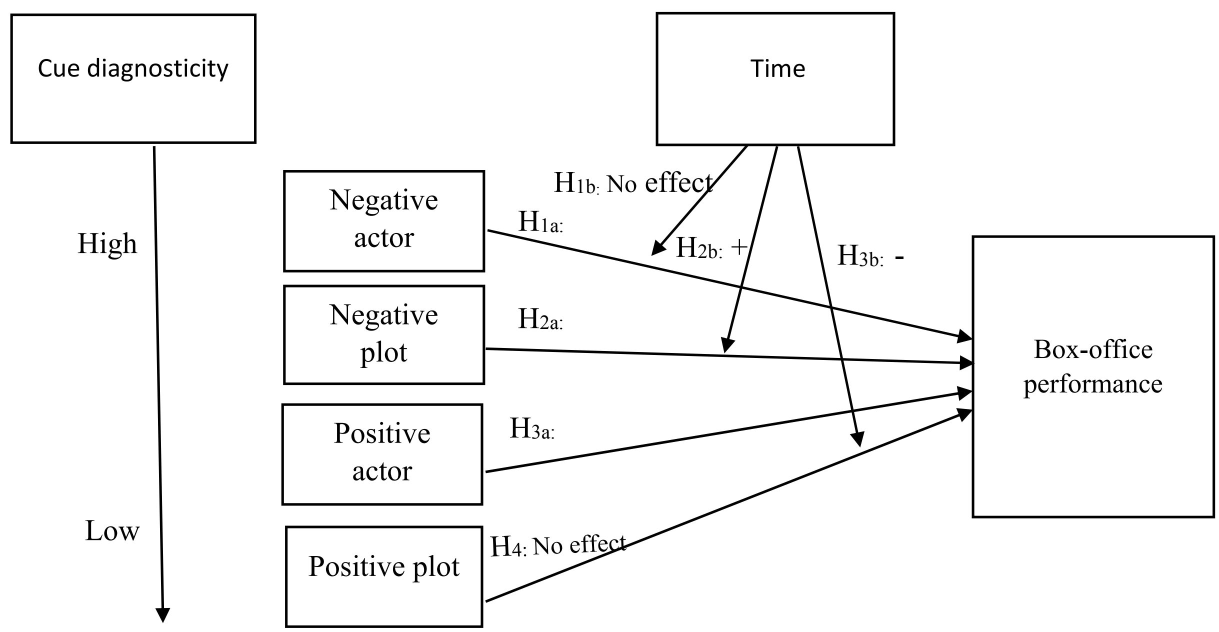

Figure 2: Positivity about the Actors

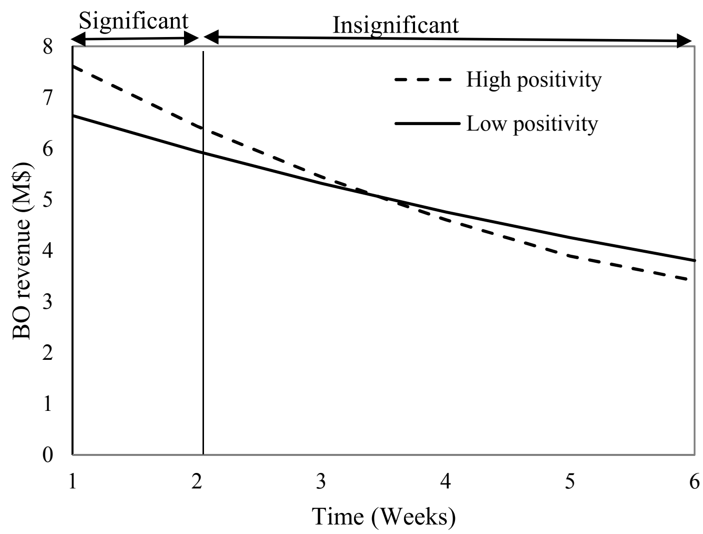

Figure 3. Positivity about the Plot

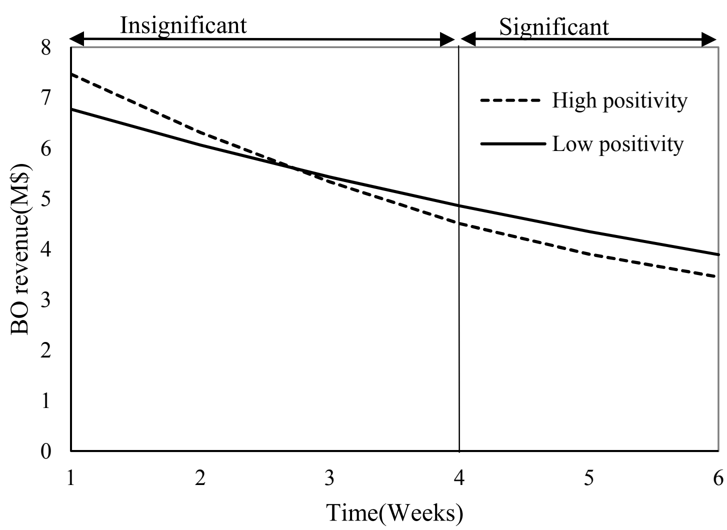

Figure 4. Negativity about the Plot

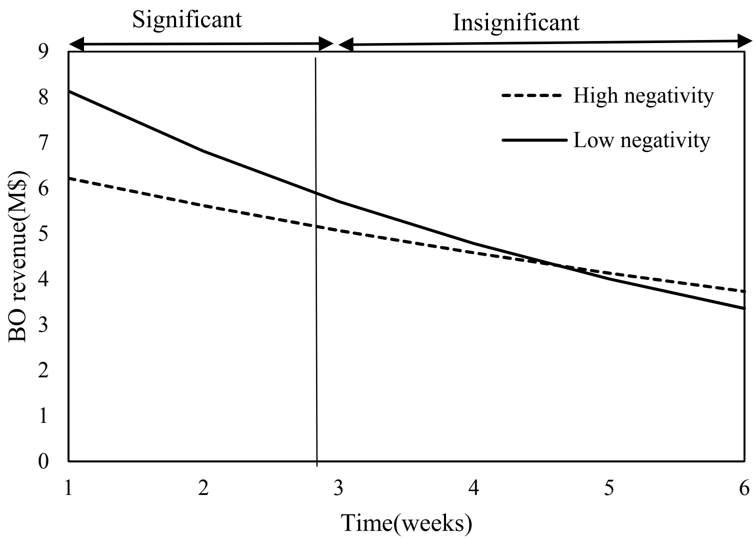

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Table 1. Previous research on WOM and movies performance

Study	Volume	Valence	Variance	Textual content	Temporal unfolding post release
Liu (2006)	Yes	Yes	—	—	—
Duan et al. (2008)	Yes	Yes	—	—	—
Chintagunta et al. (2010)	Yes	Yes	Yes	—	—
Gopinath, Chintagunta and Venkataraman (2013)	Yes	Yes	—	—	—
Rui, Lui and Whinston (2013)	Yes	Yes	—	Intention to watch	—
Hennig-Thurau et al. (2015)	Yes	Yes	—	—	—
You, Vadakkepatt and Joshi (2015)	Yes	Yes		—	—
Rosario et al. (2016)	Yes	Yes	Yes	—	—
This study	Yes	Yes	Yes	Yes	Yes

Table 2. List of variables, measures and descriptions

Variables	Description	Measures
Revenue	Weekly revenue	Weekly box-office revenue in US$
Actor_Positive	The percentage of Weekly Positive sentiments about the actors	The frequency of the positive sentiments about actors in reviews divided by total words in reviews
Actor_Negative	The percentage of Weekly Negative sentiments about the actors	The frequency of the Negative sentiments about actors in reviews divided by total words in reviews
Plot_Positive	The percentage of Weekly Positive sentiments about the plot	The frequency of the positive sentiments about plot in reviews divided by total words in reviews
Plot_Negative	The percentage of Weekly Negative sentiments about plot	The frequency of the negative sentiments about plot in reviews divided by total words in reviews
Volume	Weekly number of user reviews	The total number of reviews posted for each movie weekly
log(Ratings)	Weekly average user ratings	weekly average of each movie user ratings/valence
Std_Deviation	The variance in user reviews	Standard deviation of weekly user ratings of each movie
Screen	Weekly number of screens	Weekly number of screens
Time	The number of weeks	The number of weeks from 1-6, week1 is coded as 0
Budget	Production Budget	Production Budget in US$
Starpower	Star power	Based on the ranking from the Numbers. Calculated as average of each star previous 3 years box-office revenue of movies
Sequel	Sequel	1= sequel; 0= no sequel
Action	Genre action	1= action; 0= others
Comedy/Drama	Genre comedy and drama	1=Comedy and drama; 0= others
Others	Other genre	1= other; 0= any of the genre given above

Comp_Rev	Competition for the attention of audience	Number of similar movies (same genre, same MPAA), weighted by the run time of the movie
Comps_Scr_New	competition for "screen space" from new movies	New releases, weighted by production budget, for each calendar week
Comp_Scrn_Ong	competition for "screen space" from ongoing movies	Average age of the ongoing top 20 movies in the previous weeks(excluding the movie under consideration)
Maj_Distr	Major distributor	1= Paramount, Sony Pictures(Columbia, Tristar), Disney(Buena Vista, Touchstone, Hollywood pictures), 2oth Century Fox, Universal, Warner; other

Table 3. Summary statistics

Descriptive				
Variables	Mean	SD	Min	Max
Actor_Positive	0.1792	0.1268	0.1268	0.656
Actor_Negative	0.095	0.0854	0.0854	0.495
Plot_Positive	0.1293	0.0636	0.064	0.398
Plot_Negative	0.1043	0.0697	0.069	0.538
Total number of words	2719.937	5799.74	26	59539
Budget(millions)	68.700	53.30	22.00	250.00
screens	2365.907	1060.141	2200	4375
Weekly average ratings	6.273	1.571	0	9.666
Weekly box-office revenue(millions)	15.1	22	21049	226

Table 4. 3SLS results for revenue

Log(Revenue) as Dependent Variable		Coeff.	Boot_SE	p
Variables	Constant	1.653	0.249	0.002
	Actor_Positive	0.275**	0.133	0.039
	Actor_Negative	-0.438***	0.186	0.019
	Plot_Positive	0.334	0.314	0.447
	Plot_Negative	-0.834**	0.347	0.016
	Time	-0.058	0.039	0.139
	Actor_Positive*Time	-0.100**	0.043	0.025
	Actor_Negative*Time	0.063	0.060	0.298
	Plot_Positive*Time	-0.167**	0.087	0.050
	Plot_Negative*Time	0.219**	0.095	0.022
	Starpower	0.000	0.000	0.714
	Sequel	0.091**	0.029	0.002
	Action	0.021	0.034	0.534
	Comedy/Drama	0.231**	0.033	0.000
	Log(Comp_Rev)	0.005	0.009	0.597
	log(Screen)	1.576**	0.171	0.000
	log(Volume)	0.508***	0.106	0.000
	log(Valence)	0.122	0.071	0.086
	Log(Variance)	-0.002	0.013	0.878
	log(Volume)*Time	-0.064**	0.027	0.017
	log(Volume-1)	0.030	0.024	0.225
	log(Volume-2)	-0.035	0.024	0.142
Note: ***p<.01, **p<.05, *p<.10 (two sided)				

Table 5. 3SLS results for WOM

Log(WOM) as Dependent Variable		Coeff.	Boot_SE	p
Variables	Constant	3.484	0.256	0.000
	log(Revenues)	0.430***	0.031	0.000
	Actor_Positive	0.252**	0.116	0.029
	Actor_Negative	-0.027	0.164	0.869
	Plot_Positive	0.590***	0.218	0.007
	Plot_Negative	-0.335*	0.202	0.097
	log(Age)	0.055	0.255	0.830
	Starpower	0.003***	0.001	0.006
	Sequel	-0.030	0.036	0.408
	Action	-0.248***	0.039	0.000
	Comedy/Drama	0.143***	0.037	0.000
	log(Valence)	0.042	0.098	0.665
	Std_Deviation	0.046***	0.014	0.001
	log(Revenue-1)	-0.031***	0.006	0.000
	log(Revenue-2)	-0.024***	0.005	0.000
Note: ***p<.01, **p<.05,*p<.10 (two sided)				

Table 6. 3SLS results for revenue

Log(Screen) as Dependent Variable		Coeff.		Boot_se	p
Variables	Constant	3.045	***	0.358	0.000
	log(Revenues-1)	-0.006		0.005	0.311
	log(Comp_Scrn_Ong)	-1.038	***	0.240	0.000
	log(Comps_Scr_New)	-0.020	*	0.012	0.083
	Maj_Distr	0.140	***	0.033	0.000
	log(Avg_Critic_Ratings)	0.367		0.095	0.000
	Sequel	-0.080	***	0.040	0.044
	log(budget)	0.155	***	0.037	0.000
	Starpower	0.000	**	0.000	0.036
	Action	-0.004		0.037	0.922
	Comedy/Drama	-0.068		0.037	0.064
Note: ***p<.01, **p<.05,*p<.10 (two sided)					

Table 7. Regression with copula as control function

Log(Revenue) as Dependent Variable		Coeff.	Boot_SE	p
Variables	Constant	6.799***	0.064	0.000
	Actor_Positive	0.426**	0.151	0.005
	Actor_Negative	-0.345**	0.179	0.054
	Plot_Positive	0.519	0.346	0.134
	Plot_Negative	-0.762**	0.329	0.020
	Time	-0.028	0.029	0.336
	Actor_Positive*Time	-0.114***	0.047	0.016
	Actor_Negative*Time	0.054	0.062	0.388
	Plot_Positive*Time	-0.216**	0.101	0.032
	Plot_Negative*Time	0.185**	0.093	0.047
	log(Budget)	0.004	0.089	0.965
	Starpower	0.000	0.000	0.723
	Sequel	0.074**	0.029	0.011
	Action	0.012	0.027	0.663
	Comedy/Drama	0.227***	0.029	0.000
	log(Age)	-0.055	0.166	0.742
	log(Screen)	1.081***	0.073	0.000
	log(Volume)	0.107	0.272	0.693
	log(Ratings)	0.183***	0.070	0.009
	Std_Deviation	0.009	0.012	0.443
	log(Volume)*Time	-0.035	0.037	0.347
	Screen_Copula	0.069***	0.026	0.007
	Volume_Coplula	0.128	0.124	0.300
	Volume*time_Copula	-0.041	0.043	0.339
	Budget_Copula	0.036	0.040	0.375
Note: ***p<.01, **p<.05,*p<.10 (two sided)				

Table 8. 3SLS for revenue equation

Log(Revenue) as Dependent Variable		Coeff.	SE	p
Variables	Constant	1.787	0.314	0.000
	Actor_Positive	0.202	0.149	0.173
	Actor_Negative	-0.431**	0.214	0.044
	Plot_Positive	0.336	0.331	0.309
	Plot_Negative	-0.880***	0.335	0.009
	Time	-0.012**	0.041	0.776
	Actor_Positive*Time	-0.091**	0.047	0.050
	Actor_Negative*Time	0.079	0.067	0.237
	Plot_Positive*Time	-0.196**	0.097	0.043
	Plot_Negative*Time	0.238***	0.089	0.008
	log(Budget)	0.112***	0.028	0.000
	Starpower	0.000	0.000	0.180
	Sequel	0.102	0.025	0.000
	Action	-0.006	0.028	0.825
	Comedy/Drama	0.243***	0.027	0.000
	Log(Age)	-0.029	0.187	0.875
	log(Screen)	1.139***	0.044	0.000
	log(Volume)	0.417***	0.094	0.000
	log(Ratings)	0.129**	0.069	0.059
	Std_Deviation	0.000	0.010	0.969
	log(Volume)*Time	-0.030	0.028	0.277
	log(Volume-1)	0.025	0.023	0.261
	log(Volume-2)	-0.028	0.023	0.214
	R^2	.892		
Note: ***p<.01, **p<.05, *p<.10 (two sided)				

3SLS for WOM Equation

Log(WOM) as Dependent Variable		Coeff.	SE	p
Variables	Constant	-2.001***	0.344	0.000
	log(Revenues)	0.430***	0.031	0.000
	Actor_Positive	0.252**	0.116	0.029
	Actor_Negative	-0.027	0.160	0.863
	Plot_Positive	0.601***	0.212	0.004
	Plot_Negative	-0.480***	0.196	0.014

	log(Age)	0.055	0.255	0.830
	Starpower	0.003**	0.005	0.019
	Sequel	0.017	0.034	0.627
	Action	0.173***	0.034	0.000
	Comedy/Drama	-0.179***	0.037	0.000
	log(Ratings)	0.161*	0.094	0.088
	Std_Deviation	0.063***	0.013	0.000
	Log(Revenues-1)	-0.031***	0.006	0.000
	Log(Revenues-2)	-0.024***	0.005	0.000
	R^2	.685		
Note: ***p<.01, **p<.05, *p<.10 (two sided)				

Appendix

Appendix 1: Content sentiment analysis

As we are making BoWs overtime by weeks, therefore we used coefficient correlation (CC) to measure the dependency between a word t and a polarity category c. If CC value of a word with positive category is greater than zero, we tagged the word as positive and if a word with negative category is greater than zero, we tagged the word as negative.

CC is defined in figure 1 and can be viewed as a "one-sided" chi-square metric. In figure 1, N is the total number of documents that are used to calculate CC. In here, N is the number of documents of a movie in a week. P (t, c) means the probability of a word t occurred in class c. $\bar{\boldsymbol{t}}$ means words that are not t in a BOW and $\bar{\boldsymbol{c}}$ means categories that are not c. Therefore, CC measures the lack of independence between a word t and a category c.

$$\mathrm{CC}(\mathrm{t}, \mathrm{c_i}) = \frac{\sqrt{\mathrm{N}}[\mathrm{P}(\mathrm{t}, \mathrm{c_i})\mathrm{P}(\bar{\mathbf{t}}\,\overline{\mathbf{c_i}}) - \mathrm{P}(\mathrm{t}, \overline{\mathbf{c_i}})\mathrm{P}(\mathrm{t}, \overline{\mathbf{c_i}})]}{\sqrt{\mathrm{P}(\mathrm{t})\mathrm{P}(\bar{\mathrm{t}})\mathrm{P}(\mathrm{c_i})\mathrm{P}(\overline{\mathrm{c_i}})}}$$

Figure 1. Correlation Coefficient

As some words are ambiguous because they have numerous possible meanings. To take account of this issue, for each word, we picked out the five most frequently appeared adjacent words right next to it and called the five-word pairs as "two-word phrases". Based on the "two-word phrases" analysis and words, we identified movie features related to actor, director, plot, visual etc. To extract co-occurred words of a word t, we collected left 5 words and right 5 words of t. we use semantic similarity to handle context incongruity, to consider similarity between two pair of words. We use similarity scores[7] between words embedding in sentence.

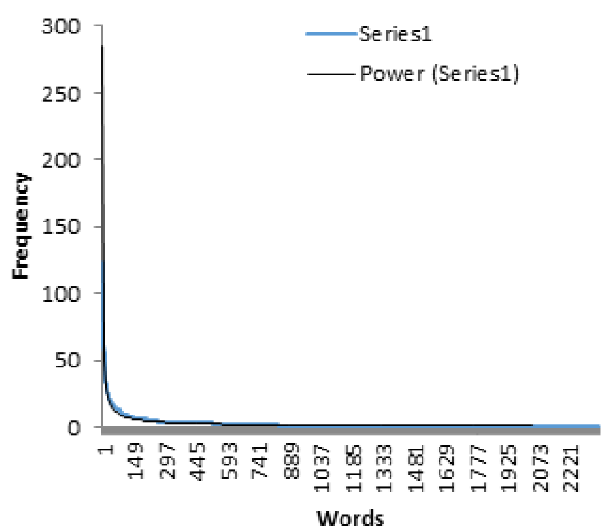
[7] Similarity scores (as given by Word2Vec[7] or Glove[7]), https://code.google.com/archive/p/Word2Vec/,

Selection Criteria words frequency

To select the words frequency cut-off point we sort words data of each week of every movie from highest frequency word to lowest and then determined the best curve fit.

General model Power2: f(x) = a*x^b+c fits well with the curve. As shown in figure A below. We determine the inflection point of the curve by taking derivative of the power equation and calculated the point where the power fit slope is of 45 degree (-1). This way we removed the long tail and determine the inflection point.

Inflection point, Derivative= $f'^{(x)} = -1$



Appendix 2. Table provide a comparison with other methods.

Key: (✔ Means: Similar/close technique is used: **✕ Means**: Not considered or in a different way)

Green ones are to some extent closer to our analysis technique

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http://nlp.stanford.edu/projects/glove/

Authors	Valence Condition	Illocutionary force features	Implicit Sentiments	Speech Act Patterns	Time series-based BOWs or analysis	Specific feature content
This study Method	Negative, positive words	Polarity modifiers (e.g., not) and shifters (e.g., very, lack of)	Context words are used	Not Considered (✕)	Weekly	✓
Pang and Lee 2005	✕	✕	✕	✕	✕	✕
Das and Chen 2007	✓	✕	✕	✕	✓	✕
Wilson,Wiebe, and Hoffman (2009)	✓	✓	✓	✕	✕	✕
Khan, Baharudin and Khan (2011)	✕	✓	✕	✓	✕	✕
Maas et al. (2011)	✕	✕	✕	✕	✕	✕
Taboada et al. (2011)	✓	✓	✕	✕	✕	✕

Berger and Milkman (2012)	✓	✕	✕	✕	✓	✕
Tirunillai and Tellis (2012)	✓	✕	✕	✕	✓	✕
Ghose, Ipeirotis, and Beibel (2012)	✕	✕	✕	✕	✓	✕
Marks and Vossen (2012)	✓	✕	✓	✕	✕	✕
Schumaker et al (2012)	✕	✕	✕	✕	✕	✕
Xiong et. al(2013)	✓	✓	✕	✕	✕	✕
Schweidel (2014)	✓	✕	✕	✕	✕	✕
Homburg et al.(2015)	✓	✕	✕	✕	✕	✕
Cambria et al(2015)	✓	✕	✕	✕	✕	✕
Poria et al.(2016)	✕	✓	✕	✕	✕	✕
Ordenes et al.(2017)	✓	✓	✓	✓	✕	✕

Essay 2: From Spiderman to Spiderman 2 and 3: meta-analytic examination of brand extensions impact on movies performance

"Everyone in Hollywood knows how important it is that a film is a brand before it hit theaters. If a brand has been around, Harry Potter for example, or Spider-Man, you are light years ahead."
— Director and producer James Cameron (quoted in Oehmke and Beier 2011)

Introduction

Brand extension is an important strategy for a new product introduction. For example, in 2014, 85 percent of the top 200 new products introduced in the U.S. were brand extensions (IRI report 2015). The advantage of brand extension is that consumers evaluate the performance of the new products based on the knowledge of the parent brand itself, which reduces the performance risk (Aaker and Keller 1990). This is particularly important for experiential products like movies because theatrical performance is highly uncertain and difficult to forecast. Moreover, movies have a short lifecycles with just a few movies dominating the box-office or even reaching the breakeven point (De Vany 2004). Studio managers pursue sequels as a brand extension[8] strategy of hedonic products to deal with uncertainty and risk, because the existence of a parent movie provides a guaranteed audience for sequels (Eliashberg et al. 2006, Hennig-Thurau et al. 2009).

The study of sequel movies is important from both managerial and academic perspectives. Industry players believe that sequels are brand extensions of experiential products that are expected to offer higher returns while involving less risk (Basuroy and Chatterjee 2008). This reliance on sequels is supported by the observations that, in 2016,

[8] Brand extension can be extensions in similar categories (e.g., line extensions) and extensions in dissimilar categories (e.g., category extensions). Sequels can be defined as line extension because they are based on similar characteristic of parent movie. However, we used the term brand extension since this term is used in prior movie literature such as Basuroy and Chatterjee 2008; Hennig et al. 2008; Sood and Dreze 2006 etc.

seven of the top ten grossing movies were sequels, eight in 2017, nine in 2018 while, in 2019 eight out of the top ten grossing movies were sequels (The Numbers 2020). The highest-grossing film in the history of the movie industry is the sequel "Avengers: Endgame" (Variety 2019). Furthermore, Figure 2 shows that the popularity of sequels have been growing for the last 15 years as the industry is relying more extensively on brand extensions to reduce the risk of movies performance.

From an academic perspective, in the marketing literature, very few studies have primarily focused on sequels as brand extensions (Basuroy and Chatterjee 2008; Hennig-Thurau et al. 2009); rather most of the studies have used sequels as a control variable when determining movies performance (Ho et al. 2009, Henning-Thurau et al. 2015; Karinouchina 2011; Ravid and Basuroy 2004). Their findings show that sequels perform better than non-sequel movies. However, the estimates of the effect of sequels vary considerably, maybe due to the short time period, sample selection criteria's, lack of explanatory variables in early studies, and different estimations approaches. Moreover, the meta-analysis by Hoffman et al. (2017) has considered the power of stars (e.g., actors, directors) as a risk-reducing strategy, while Carrillat et al. (2018) have looked at both the star power and reviews as factors that can reduce uncertainty in box-office performance. Neither of these meta-analyses have considered the effect of sequels which generates greater box-office revenue than non-sequel movies and is a popular strategy for a new movie release in the industry. Therefore, the first objective of this meta-analysis is to quantify and generalize the mean effect of sequels on movies box-office performance.

Second, sequels effects vary considerably across studies, therefore this study also aims to determine whether the effectiveness of sequels as a strategy to reduce uncertainty in box-office performance is conditional on different box-office measures, and whether it has waned over time or still is the reliable source of movies box-office performance. Marketing strategy effectiveness can change over time (Dhar et al. 2012), hence it is important for Hollywood managers that frequently produce sequel movies because of the assumption of high return and low risk to examine their effectiveness.

Third, the movies industry is facing large investments and needs short-run production and marketing (Vogel 2015), the risk reduction is very valuable given the uncertainties and the intense competition. As Fritz (2018) states, the movie industry is in “the franchise film era.” The success of sequels at the box-office have caused an increase in the number of sequels movies released each year as shown in Figure 4. This increase in the number of sequel movies leads to increase in the competition from similar movies that aim to reduce risk for studios. Marketing strategy effectiveness might decrease in a competitive environment which could lead to box-office cannibalization of otherwise successful movies (Slater and Nater 1994). Therefore, this study considers whether too many sequels release can have an impact on sequels effectiveness at the box-office.

The movie industry has realised the profitability of brand extensions and it is necessary to formally examine the success of this strategy due to the staggering number of sequels and whether it makes sense to milk it financially for as long as possible. Answering this question is important for studio managers who count on sequels as a risk reducing strategy in a highly competitive environment (Ravid and Basuroy 2004).

To quantify the sequel’s mean effect across the entire empirical literature and answer the questions above, we conducted a meta-analysis of 170 correlation effect sizes that have appeared in 91 published and unpublished manuscripts consisting of studies from marketing, economics, management, and strategy. The meta-analysis framework is based on the built-in familiarity of sequels as brand extensions. Sequels rely on the familiarity of the parent movie due to which consumer transfer positive attitude and quality to sequels.

The results indicate that sequels positively affect movie performance with a mean effect of $\bar{r}$ = 0.14, supporting the effectiveness of sequels as risk reducing strategy. In addition, the results show that due to the familiarity of sequel movies as brand extensions, the short-term box-office performance is greater than the long-term performance, nonetheless managers can leverage on sequels as brand extension to increase long-term box-office performance. Furthermore, the findings indicate that sequels overall performance is stable over time, however the increase in sequels concentration has a negative impact on the effectiveness of sequels as a risk-mitigating strategy.

The meta-analysis answers important question for studios managers who count on sequels as a risk-reducing strategy in a highly competitive industry where hundreds of new products are released each year (Ravid and Basuroy 2004). Our results provide managerial insights and research contributions by examining the effectiveness of sequels as brand extension strategy.

Literature background

Movies are experiential products, which makes it difficult for consumers to ascertain the quality in advance leading to uncertainty and risk in decision making (Basuroy et al. 2006). Connecting a new product such as movie to a previously known brand through band extension reduces the risk of new product trial (Aaker and Keller 1999; Claycamp and Liddy 1969; Keller and Aaker 1992). Studio managers frequently produce sequels as a risk-reduction strategy in the movie industry (Hennig-Thurau et al. 2009; Knapp et al. 2014). In the entertainment industry sequel measures the brand extension value of experiential products (Basuroy and Chatterjee 2008; Hennig-Thurau et al. 2009; Sood and Dreze 2006), and reduces the uncertainty and risk as consumers transfer positive attitude and quality from the parent movie to the new movie (Erdems and Swait 1998; Erdem 1998; Hennig-Thurau et al. 2009).

In the literature, an early example of the inclusion of sequels as a characteristic of interest is Litman (1989), who found a positive impact of sequels as a binary variable on movie performance. Since then, studies have focused on the conceptualization of sequels (e.g., Sood and Dreze 2006), or on comparing various performance metrics for sequels and non-sequel (e.g., Basuroy et al. 2006, Henning-Thurau et al. 2009). Most studies have considered sequels as a control variable and found a significant positive effect of sequels on movies performance (Basuroy and Chatterjee 2008; Chang and Ki 2005; Devany and Walls 1999; Dhar et al. 2012; Joshi and Mao 2012; Ravid, 1999; Ravid and Basuroy 2004), very few studies in recent time have found a non-significant impact (Bae and Kim 2019; Liu 2006; Henning et al 2006; Yoon et al. 2017). However, the estimates of the effect of sequels vary considerably as shown by Figure 1, because of differences in time period, sample selection criterias, explanatory variables, and estimation approaches.

"Insert Figure 1 about here"

Moreover, to reduce risk and uncertainty, Hoffman et al. (2017) meta-analysis focused on human brands, the stars actors involved in the making of movies. They generalized the findings of 61 studies and found a significant mean effect ($\bar{r} = .10$) of star power on movie success. Also, the meta-analysis of Carrillat et al. (2018), quantify several factors such as the presence of movie stars, critics, and consumers reviews that can reduce consumers' uncertainty by providing diagnostic information. However, neither of these meta-analyses examined the mean effect of sequels despite its importance in the movie literature and its prevalence in the industry. Therefore, this study aims to quantify and generalize the mean effect of sequel on the movie box-office performance.

Meta-analysis framework

Figure 2 represents the meta-analysis framework. The sequel as a brand extension capitalizes on the familiarity of the existing parent brand (Bohenkamp et al. 2015). Hence, the meta-analytic framework is based on the concept of familiarity of the brand extensions. From a branding perspective, familiarity is considered as the product brand knowledge, which everything else being equal, transforms into brand-related behaviours and favour the success of familiar films over other Films (Aaker and Keller 1990; Volckner and Sattler 2006).

"Insert Figure 2 about here"

Marketing studies that have examined the effect of brand familiarity on brand extension evaluation suggest that consumers evaluate familiar brands or products such as sequels more favourably over unfamiliar ones in decision making (Klink and Smith 2001). The positive impact of familiarity can be summarized as; first, familiarity increases consumers' confidence, which increases the likelihood of purchase (Laroche et al. 1996). Second, it creates a better knowledge structure in individuals' memory (Huang et al 2014; Wang et al. 2018). Third, consumers recall familiar brands better than unfamiliar and with less efforts required in processing information (Kent and Allen 1994). Fourth, familiarity accumulated by previous experiences reduces the level of uncertainty or risk in purchase decisions by providing information about product quality (Chang and Ki 2005; Keller 1993). This role is particularly important for movies because consumers value familiarity in sequels as a way to reduce uncertainty and risk (Chang and Ki 2005), and receive enjoyment by connecting with familiar characters (Green et al. 2004).

The meta-analysis framework considers the following moderators, short versus long-term box-office performance, median release year, and sequels concentration. Short versus (vs.) long-term box-office determines whether the sequels are effective in the short-term because of brand extension familiarity or whether they perform better in the long-term. The release year concludes whether the effectiveness of the sequel as a mean to increases box-office revenue by reducing uncertainty and risk in movie quality is changing over time. Sequels concentration determines whether sequels effectiveness as a risk-mitigating strategy has been affected by the increase in the number of sequel movies, leading to competition from other familiar ones. In addition, the control variables account for sampling bias, publication bias, and country of release (Hoffman et al. 2017).

Short-term vs. long-term performance

Previous movie research has frequently considered the short-term box-office in comparison with the long-term box-office performance to predict movie revenue, because early and later performance is driven by different factors (Basuroy et al. 2006; Elberse and Eliashberg 2003; Liu 2006). In the opening weekend or week (short-term box-office performance), which accounts for a substantial amount of total revenue, potential moviegoers have limited information to infer a movie quality. Consequently, sequels offer a familiarity through the earlier experiences with the parent movie and consumers already possess relevant information and knowledge stored in memory, whereas these memories would not exist for a new movie. Movie-goers transfer these positive evaluations to sequels before their release by assuming that they will meet the standard of the parent movies, thus reducing uncertainty and risk in the movies quality evaluation (Aaker and Keller 1990; Basuroy and Chatterjee 2008; Hennig-Thurau, Houston, and Heiljans 2009).

In addition, before release consumers' interest in the sequel is much higher than non-sequel because sequels are based on successful parent movies (Kim and Bruce 2018) which helps sequels to generate more buzz because they are increasingly anticipated by the audience

(Karniouchina 2011). Sequel movies are mostly released on a higher number of theatres in the first week (Dhar et al. 2012). The paradox, as Derek Thompson (2017) puts it, is that "people crave new products, ideas, and stories, provided they are just like the products, ideas, and stories they already know". The reduction in the consumption risk associated with the greater familiarity is likely to drive a higher short-term box office revenue. Consequently, studies found a positive effect of sequels in the first week (Ho et al. 2009; Ravid and Basuroy 2004).

However, after the opening weekend, experiential information about the movie quality becomes more accessible in the form of word of mouth (WOM) from consumers that begin to circulate more widely, which is not available before the release of a movie (Elberse and Eliashberg 2003). Consumers rely more on WOM information to infer movie true quality (Liu 2006). In addition, consumers with a high familiarity are more likely to purchase and spread positive WOM (Hoyer and Brown 1990), as brand familiarity is associated with greater WOM (Amblee and Bui 2008). Furthermore, positive WOM leads to a favourable evaluation of brand extensions (Liu, Hu, and Xu 2017). Whereas, negative WOM has a detrimental effect on unfamiliar brands (Sundaram and Webster 1999). Consumers are more positively predisposed to the effects of WOM on the adoption of brand extensions (Aksoy et al. 2011). In the literature, WOM is an important indicator of a movie long-term performance (Eliashberg and Shugan 1997). Therefore, based on the discussion above we posit to study the research question that:

Is it the familiarity of the sequel movies or the quality of the sequel movies that effect box –office performance?

If sequels enjoy the familiarity effect of brand extension then the mean effect of short-term box office will be greater than the long-term box-office performance, however if it is the quality of brand extension which is translated through the effect of WOM on box-office performance then this difference in performance should not exist as WOM as an indicator of anticipated quality from consumers perspective.

Sequel effectiveness overtime

Marketing researchers have examined both the short-term and long-term effects of marketing strategies (Dekimpe and Hanssen 1995; Wilikinson et al. 1982), therefore the meta-analysis framework considers whether the effectiveness of sequels as a brand extension strategy changes overtime. In the case of sequels, some studies have examined the positive effect of sequels over a short period of time (Basuroy et al. 2006; Ravid and Basuroy 2004), while other studies such as Hennig-Thurau et al. (2009) have looked at the longer time periods (1996-2006), and implicitly assumed that sequels performances remain the same over time. The sequels meta-analysis covers a much longer time period, as the sequels released from 1938 to 2016 based on the primary studies are included, whereas the data used in all the previous studies is limited to the short-time. Therefore, the results cannot be generalized to box-office performance over time. In addition, the accessibility and availability of a movie-related information have changed in the last decades. Older studies typically consider few predictors and the estimates vary overtime.

The descriptive statistics from figure 3 show that sequels represent a larger share of box-office performance over time. As the average movie production and marketing cost continues to increases (MPAA 2019), the sequel's average annual box-office revenue has more than doubled from 1990 making sequels an increasingly important new product introduction strategy for the studios (Sood and Dreze 2006). Although, the percentage of the production budget of a sequel movie has increased sequels still contribute a higher proportion to the profit than the budget and have generated higher rates of return each year than the rates of return of all other movies (Pokorny et al. 2019). Sequels are brand extensions and reduce the uncertainty in box-office performance by providing familiarity with new products. Therefore, in line with the effect of brand extensions familiarity discussed above, it is expected that sequels box-office performance will increase overtime

Sequels concentration

Launching sequel movies is a popular strategy because it is believed to be a reliable source of guaranteed box-office in the movie industry. Studios are producing a large number of sequels (McNary 2006), and there is an upward trend in the sequels movies over time as shown in figure 4. When such benefits become common knowledge, the advantages of the strategy might be competed away. The growing prominence of sequels has been an ongoing source of discussions in the trade press with the agreements pointing in the direction that pursuing endless sequels is leading franchises downhill (Dawson 2016). The sequel concentration moderator in the meta- analysis framework examines this issue formally by testing whether the increase in the number of sequels is profitable to the total number of movies released.

"Insert Figure 4 about here"

The movie industry is characterized by fierce competition, and every week multiple new movies are released. The competition is for the screens from ongoing movies and audience attention from new movies (Elbers and Elaishberg 2003). An increase in the number of movies is associated with more intense competition which is negatively related to within industry share (Einav 2007). Moreover, sequels are mostly released in a high-demand seasons, usually during the summer (Basuroy and Chatterjee 2008). A strong competitive environment leads to a decrease in movie revenue through cannibalization (Litman and Ahn 1998). In addition, fierce competition erodes the effectiveness of competitive strategy (Christensen 1997). Since, the success of a new product is partly determined by the strategy of competitors (Chen 1996), it is expected that an increase in the share of sequels by studios increases the competition which will negatively impact the relationship between sequel and box office performance. Although, sequels will still do better than non-sequels because of quality certainty due to brand extension familiarity. However, the concentration of sequels look at the performance of sequel from a managerial perspective to determine whether producing too many sequels reduce the risk of performance for studios in the competitive movie industry.

Method

We focused on studies of sequel and box office performance to quantify the effect of sequel as a brand extension. Following the approach of Carrillat et al. (2018), we retrieved papers from multiple sources. First, we performed extensive online search in Google Scholar, ProQuest, Scopus, EBSCOhost, JSTOR, EBSCO Open Dissertation, VERM, using key words such as “sequel” “movie brand extension,” “movie,” “cinema,” “film,” “motion picture,” “box-office,” and “cultural product”. Second, we manually reviewed the articles and identified the references and citations of the articles. Third, we conducted a manual search of the leading journals that regularly publish papers on motion picture performance, Marketing Science, Journal of Marketing, Journal of the Academy of Marketing science, International Journal of Research in Marketing, Journal of Retailing, Management Science, Journal of Cultural Economics, Journal of Media Economics, Management information System Quarterly, Electronic Commerce, Technological Forecasting and Social change, Journal of Product Innovation Management and Psychology & Marketing.

Inclusion criteria

To determine the final sample, we applied several criteria. First, the study was considered if movies were the unit of analysis. Second, the study should include sequel vs. non-sequel as a unit of analysis, coded as binary variable. Third, included studies needed to estimate the relationship between sequel and short term box-office (opening weekend or opening week), and long-term box-office performance. Hence, studies like Sood and Dreze (2006), which focus on consumer response rather than box-office are not included in the sample. Fourth, only studies in English were considered. In total, 91 papers met the inclusion criteria (86 published and 5 unpublished), amounting to 170 effect sizes, appendix 1 represents the studies included. We removed six cases identified as outliers, by inspecting individual effect size based on either a standardized residual greater than 2.57 or parameter change index above 1 (Carrillat, Legoux, and Hadida 2018). This led to 170 effect sizes from papers appeared from 1989 to 2019 with sampling year ranging from 1938 to 2018.

Effect size and moderators

The main moderator *type of sequel performance* is coded based on two dimensions, short-term box-office and long-term box-office. We also calculated the *median* and the *range* of *movies release years* from the sampling observation window to examine whether the effectiveness of sequel has changed overtime. To determine the sequel strategy effectiveness in competitive market, we collected secondary data for this moderator and calculated *sequel concentration,* which is the total number of sequels released in sampling year divided by the total number of movies released in the U.S. In addition, we coded for the *U.S. vs. non- U.S.* to control for different markets. Furthermore, we coded for *sampling method* to control for sampling bias as whether the primary studies have used random sampling or non-random sampling. Calculated *Sample sequel ratio* a control variable, is an indicator of the proportion of movies that are sequels to account for the fact that studies with larger samples tend to include more sequels. To control for potential publication bias, we calculated the *precision of the effect size* as the inverse of its standard error (Stanely and Doucouliags 2012), and we added a dummy that indicate whether the *article is published or not*. Table 1 shows the coding for the main and control variables included in the meta-analysis.

"Insert Table 1 about here"

This study uses correlation coefficients as the effect size for meta-analysis (Rosenthal 1994). The correlation coefficient is extracted directly from the studies or is converted from beta coefficients (Peterson and Brown 2005), and t or F statistics (Rosenthal and Rubin 2003). We transformed the correlations to the Fisher's z-score to perform all the analyses because the variance of effect sizes as r is less stable, however we transformed the results m back to r to indicate the summary effect sizes, confidence and prediction interval in order to ease interpretation (Borenstein et al. 2009).

Moreover, when the same dependent variable is measured in different ways (Sequel based on similar title and genre) or sequel box office performance is measured at different point in time (e.g., the sequel box office numbers reported weekly), we combined the effect sizes based on Borenstein et al.' (2009) formulas. This approach leads to a proper estimate of the precision of mean effect because it satisfies the assumption of effect size independence by providing independent outcomes. The following formulas are used:

(1) $Y_i = 1/m(Y_1+Y_2+\ldots+Y_m)$

(2) $\text{var}\ (\frac{1}{m}\sum_{i=1}^{m} Y_i = \left(\frac{1}{m}\right)^2 * (\sum_{j\neq i} \text{Vi} + \sum_{j\neq i}(r_{ij} \quad * \sqrt{V_i} * \sqrt{V_j}))$

Where, $Y_{1\ldots m}$ are individual effect sizes, V_j and V_i are individual effect sizes' variances and m is the number of variables. The r_{ij} is the correlation between variables, because they tend to capture the same effect and, likely to be correlated. The correlation of r=.5 is assumed in all cases (Borenstein et al. 2009); further analyses indicate the similar results when a correlation of .3 and .6 were assumed.

Model development

The final sample consists of 170 effect sizes from 91 papers. The analysis used a multilevel modelling technique to account for the nested structure of the data (Vanden Noortgate et al. 2015). The model accounts for the interdependence among effect sizes. In addition, we fit the random effect model rather than a fixed effect model in order to generalize the results to the population of movies (Fergurson and Brannick 2012), with two random effects, at the effect size, and article level to decompose the total heterogeneity according to the nesting of the data. The analysis is performed with metaphor package for R. The following model is used to estimate to quantify the summary effect size presented in table 3:

(3) $ES_{ij} = \beta_0 + \upsilon_{ij} + \psi_j + e_{ij}$,

Where ES_{ij} reflects the effect size measure i from sample, and paper j, β_0 stands for the overall effect size value, υ_{ij} indicates the variance between effect sizes within papers, ψ_j represents variance between papers and e_{ij} stands for sampling error. In order to examine the sequel performance based on short vs long and competition, while controlling for other sources of heterogeneity, we added the following moderators to obtain the mixed effects model:

(4) $ES_{ij} = \beta_0 + \beta_1$ random sampling + β_2 short-term + β_3 USA market + β_4 median release year + β_5 range of release years + β_6 sequel concentration + β_7 precision + β_8 sample sequel ratio + β_9 short-term* median release year + β_{10} short-term* sequel concentration + β_{11} median release year* sequel concentration + β_{12} range of release years*sequel concentration + $\upsilon_{ij} + \psi_j + e_{ij}$.

We also estimated the following models for the sub-sample tests on short-term box-office performance and long-term box-office performance:

(5) $ES_{ij} = \beta_0 + \beta_1$ random sampling + β_2 USA market + β_3 median release year + β_4 range of release years + β_5 sequel concentration + β_6 precision + $\upsilon_{0j} + \psi_{ij} + e_{ij}$.

Results

Overview

Table 2 provides the descriptive statistics of the overall and subsample. The overall sample consists of 170 effect sizes. Effect sizes r ranges = -0.309 to r = 0.55 (mean = 0.140; median = 0.122; SD = 0.123. Although, there are some negative effect sizes (8), majority such as 95% of the effect size are positive, which mean that sequel movie performance is positive. In addition, the range and heterogeneity of effect sizes show that the effectiveness of sequel is contingent on moderators. Table 2 provides descriptive statistics for the subsample effect sizes of moderators and variables (median and range of the release years based on sample observations and sequel concentration).

"Insert Table 2 about here"

Effect size heterogeneity

We tested the heterogeneity of effect sizes to check if there is variance across observation, reported in table 3. The tau^2, which estimates the amount of heterogeneity among effect sizes due to moderator rather than sampling error; I^2, which reflects the between effect size variance as a proportion relative to total effect size variance (Borenstein et al. 2009); and, the Q-statistic that indicates the weighted sum of squared differences between each effect size and the pooled, measuring the effect size dispersion. The Q-statistic is significant which suggests that the effect sizes are heterogeneous. The I^2 is 89.01 percent, also suggesting high heterogeneity (Huedo-Medina et al 2006). These heterogeneity estimates indicates that the random effect model is appropriate and warrants a test of moderators (Borenstein et al. 2009).

"Insert Table 3 about here"

Publication bias

To address the issue of publication bias when estimating the summary meta-analysis, we used several procedures. We used Egger's regression, which is the ratio of the effect size by its standard error. Significant values suggest asymmetry in the funnel plot formally due to publication bias (Sterne and Eggers 2005). We used the trim and fill procedure, which trim any effect size that creates the asymmetry and simulate (fill) the effect sizes that would make the funnel plot symmetric. This approach also estimates the adjusted mean effect size for a symmetric funnel plot along with its distribution and heterogeneity estimates. These indicators of publication bias are prone to type1 error; therefore, we used a tandem approach, such that publication bias is likely if at least two indicators suggest it (Ferguson and Brannick 2012). In addition, the meta-regression model accounts for the publication bias in two ways. It controls for the effect size precision (the inverse of the standard errors by Stanley and Doucouliagos 2012) and the publication status (whether a study is published or unpublished).

Univariate Meta-Analysis

The univariate meta-analysis quantifies the mean effect size for sequel box office performance, as well as mean effect sizes for the following moderators- short term box-office and long term box-office. Table 3 displays the mean effect size along with confidence interval, prediction interval, heterogeneity, and publication bias indicators. The overall effect of sequel on box-office performance is $\overline{r}$=.13 with a 95% confidence interval ($CI_{95\%}$) ranging from .109 to .146, which reveals a highly significant (p < .01) relationship between sequel and movie success. The mean effect of sequel is higher than reported for star power and movies success ($\bar{r}$= .10) by Hoffmann et al. (2017).

The mean effect of sequel short-term box-office performance is $\bar{r}$=.175 with a 95% confidence interval ($CI_{95\%}$) ranging from .132 to .218 for total of 75 effect size (k=75), while for long term it is $\bar{r}$=.115 ($CI_{95\%}$ from .096 to .134). The effect size is significantly greater than zero ($p < .01$), which shows that sequel as brand extension has positive effect on movies box office performance regardless of the measure used. However, the Wald test shows that sequel short-term box-office yields larger effect sizes than long-term box-office performance, as the difference is statistically significant ($\bar{r}$=.175 and $\bar{r}$=.115, respectively; Wald-type z, p < .05).

Meta regression

Short term box-office vs long-term box-office

Table 4 main model shows that the coefficient of short-term box-office performance of sequel is positive and significant (β = .029, p < .05), which suggests that the impact of sequel short-term box-office performance is greater than long-term box office performance. This support the notion that it is the familiarity effect of brand extension and not the quality of the movie that drive the greater mean effect of short-term box office than long-term box-office.

"Insert Table 4 about here"

The coefficient of long-term box-office is positive and highly significant (β = .112, p < .01), which shows that sequels lead to long-term movie success. Although, the results show stronger effect of short-term on sequel success when long-term is defined as a base. However, the intercept suggests that brand extension effect long-term box-office performance indirectly through the brand extension familiarity which may lead to more positive WOM and long-term movie success, however the short-term effect is greater due to familiarity suggesting that the driving force of the effect is risk reduction.

Sequel effectiveness overtime

The estimate for the median release year while controlling for the years spanned by the sample is not significant ($\beta = -0.0003$, $p > .10$) thus, the movie release year does not influence the relationship between the sequel and the movie box-office performance. This indicates that the effectiveness of sequel as a brand extension strategy has not changed over time and this may be the reason that we see an increase in the number of sequel movies released each year, as most of the top ten grossing movies are sequels.

We also estimated the same model after adding the interaction parameters between the short-term and the median-year of movie release to examine whether the effect is contingent on different box-office performance measures using long-term as a reference category. The interaction between the median year of movie release and the short-term box-office is not significant, which suggests that sequel short-term and long-term box-office performance is not temporal due to the familiarity effect of brand extensions. The subsample analysis in Table 5 with only short-term and long-term box-office also supports this non-temporal notion.

"Insert Table 5 about here"

Sequels concentration

The coefficient of sequels concentration which is an indication of the sequels competition is negative and significant ($\beta = -1.456$, $p < .05$) Thus, increase in the number of sequels in proportion to the total number of movies negatively affects the relationship between sequels and box-office performance. This suggests that the increase in the number of sequel movies lead to an increase in the competition, resulting a decrease in the effectiveness of sequel as a risk-mitigating strategy for studios due to too much competition. To see the effect of sequels concentration on short-term versus long-term box-office performance, the interaction model includes the interaction term of short-term with sequels concentration. The coefficient of this interaction is not significant ($\beta = .8426$, $p > .10$). This suggests that the familiarity effect of the sequel as a brand extension is there, since there is no difference between the short-term and long-term box-office performance for the increase in number of sequels. The main negative effect is because of the increase in the competition from other sequel movies.

The interaction of sequels concentration with median year of movie release is also not significant, suggesting that sequels concentration effect on the relationship between sequel and box-office performance is not temporal. This again supports the expectation that the main negative effect is due to increase in the competition.

Control variables

The coefficient of U.S. does not significantly affect the sequel and box-office performance relationship ($\beta = .016$, $p > .10$), which reflects that sequels affect movie performance in both U.S. and non U.S. countries. The variables for sampling bias control—random sampling and sample sequel ratio—are not significant, suggesting that sampling bias does not affect the relationship between sequel and box-office performance. The variable for effect size precision is negative and significant, suggesting that smaller effect sizes tend to be found in larger samples, which could suggest publication bias. Estimating the effect size precision effectively controls for the systematic relationship between effect size strength and sampling size assuaging any impact the publication bias may have on the results. In addition, the other control for publication bias, the moderator that indicates whether a particular effect size come from a published or unpublished paper, is not significant. Model 1, 2 and 3 show the results with different time variables and model 4 without sequels concentration. Although, the VIF of main model is below 10, however these models show that the results are similar and collinearity between time variables do not effect the results.

Discussion

Sequels are brand extensions of the existing movies that are expected to offer a higher return and low risk (Basuroy and Chatterjee 2008; Hennig-Thurau et al. 2009; Knapp et al 2014), hence considered a popular strategy by Hollywood managers for the introduction of a new movie. A rich body of research has examined sequels impact on movies performance. However, studies present heterogeneous findings with varying degrees of effect on movie performance (for example; Basuroy and Chatterjee 2008; Liu 2006). This meta-analysis has focused on the relationship between sequels and movie box-office performance in the motion picture industry based on the concept of familiarity of brand extensions. Integrating a total of 91 studies from 1989 until 2019 reporting 170 effects, the results provide insights for industries that market experiential products, as well as make several contributions to entertainment marketing and brand extension literature.

First, this study quantifies the mean effect of the relationship between sequels and box-office performance, adding to the research that generalizes and quantify the uncertainty-reducing factors impact on box–office performance (Carrillat et al. 2018; Hoffmann et al. 2017). Our findings suggest that sequel offers more diagnostic information (same actors, formula, aesthetics, characters, etc), therefor it reduces the risk associated with the decision to consume the product to a greater extent than the stars. We found a mean effect size of $\bar{r}$ = .14, which is greater than reported by Hoffmann et al. for the relationship between stars power and product success ($\bar{r}$ = .10). Whereas, Carrillat et al. (2018), found the effect of stars power identified by media and market dimension to be null whereas, the artistic recognition effect on box-office performance was $\bar{r}$ = .07 based on the diagnosticity of this cue. The findings of the effect of sequels on box-office performance add to the literature that examines sequels as a mean that generates more revenue than non-sequel movies by reducing uncertainty and risk in consumption (Hennig-Thurau et al. 2009; Palia et al. 2008; Ravid 1999; Dhar et al 2012). Moreover, the release time results provide insights into the effectiveness of sequels' box-office performance and suggest that sequels box-office performance is steady over time. Thus, extending the findings of Dhar et al. (2012) that have looked at sequels effectiveness over time and found that sequels have affected the supply side over time through a significantly large number of theatres showing sequel movies. Our meta-analysis shows this effect directly by showing that over time the box-office performance of sequels is steady.

Second, this meta-analysis contributes to the brand extensions research as sequels are brand extensions of hedonic products (Sood and Dreze 2006). Our findings that sequels positively affect the box-office performance support the widely believed notion that brand extensions leverage the quality of the previous brand and perform better (Aaker and Keller 1990; Volckner and Sattler 2006). Moreover, previous research is mostly survey-based conducted in a laboratory setting, focuses on the forward effects of brands on brand extensions (Aaker and Keller 1990; Dacin and Smith 1994; Park, Millberg, and Lawson 1991). Relatively little research in the marketing features observational data (Balachander and Ghose 2003; Erdem and Sun 2002; Hennig-Thurau et al. 2009). This meta-analysis provides empirical findings of brand extensions based on 170 effect sizes for experiential brand extensions.

In addition, based on the concept of familiarity of the brand extensions, the findings show that sequels short term box-office performance is greater than long-term box-office, manifesting that familiarity of sequels reduces the uncertainty and risk and consumers prefer familiar product over unfamiliar. Hence, extending the brand extensions literature that brand extensions have a different effect on short vs. long-term performance, confirming the role of familiarity in the motion picture industry that it is the familiarity of sequels that effect box-office performance of movies (Aaker and Keller 1990; Chang and Ki 2005). Moreover, our findings show that brand extensions familiarity not only effect short-term performance but also long-term box-office performance.

Third, the movie industry is characterized by high competition. Our results for sequels concentration indicate that sequels concentration negatively moderates the relationship between sequels and box-office performance. This contributes to studies that look at the effectiveness of marketing strategy in a competitive environment (Einav 2007; Slater and Nerver 1994; Varadarajan and Pride 1989), also to those studies that examine the success of new product based on the reaction and moves of competitors (Chen 1996). The findings show that the strategy effectiveness decreases due to an increase in the competition from other sequel movies. Our findings also apply to other experiential products, such as books, music, and video games, etc. (e.g., Joshi and Mao 2012).

This meta-analysis also provides insights to studio managers. One way that studios are managing risk is by pursuing a brand extension strategy (Eliashberg et al. 2006). This study supports Hollywood reliance on sequels as a risk-reducing strategy since our findings show a positive significant effect of sequels on box-office performance, which is stable over time. Hence, as compared to other movies, sequels will reduce uncertainty in box-office performance for studios. Furthermore, the findings suggest that sequels short-term box-office is greater than long-term box-office due to familiarity of brand extensions, studios can leverage familiarity of sequels to impact its long-term performance. In addition, the result show no difference between the U.S and non-U.S released movies, which provides insights into the effectiveness of sequels movies that it's a global phenomenon and the findings are relevant for non-U.S movies as well.

The investment in sequels seems to be on the rise which has resulted in a comparatively higher initial budget or investment (Basuroy et al. 2006). Our findings suggest that sequels have higher short-term box-office due to high familiarity with brand extensions. Hence, studios should not invest too much in its promotion before the release as the familiarity is built in due to brand extensions. This will help studios to generate more revenue by reducing expenditure.

In recent times, Hollywood has grown increasingly reliant on sequels as a risk mitigating strategy. In the press, the movie industry is considered to be in "the franchise film era" (Fitz 2018). The movie industry has realized the profitability of brand extensions and studios are releasing an increasing number of sequels. If a theme is discovered that audiences enjoy and will pay to see, then it makes sense to exploit it, thus we see the prevalence of sequels in the movie industry. However, our findings show that this prevalence has resulted to negatively effect the sequels box-office performance. Although making sequel is a risk mitigating strategy, studios need to be careful with too many sequel movies in their portfolio because our findings show that sequels concentration negatively impacts its box-office performance. Our results provide insights into the ongoing discussion in the press that pursuing endless sequel is leading franchises downhill (Dawson 2016). In conclusion, sequels reduce the risk and uncertainty in box-office performance, however studios need to be careful and build a portfolio on sequels and non-sequel movies to manage risk and uncertainty in the movie performance.

Conclusion

A movie theatrical performance is highly uncertain and difficult to forecast because of its experiential nature. Sequels are extensions of existing movies that are expected to offer higher returns while involving low risk (Hennig-Thurau et al. 1999; Palia et al. 2008). This study integrated a total of 91 studies from 1989 until 2019 reporting 170 effects, found that sequels positively affect movie box-office performance, however the finding cannot be generalized to other product categories as sequels are brand extensions of hedonic products. The sequels short-term box-office performance is greater than the long-term box-office performance due to the familiarity with the parent movie, also sequels performance is stable over time. Furthermore, too many sequels released in a year negatively affect sequels box-office performance.

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Figure. 1. Effect size over median year

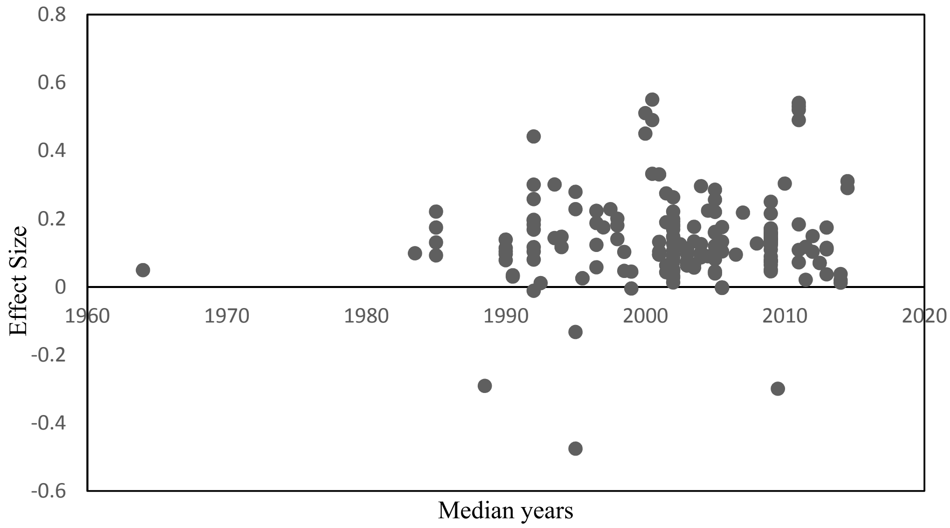


Figure. 2. The meta-analysis framework

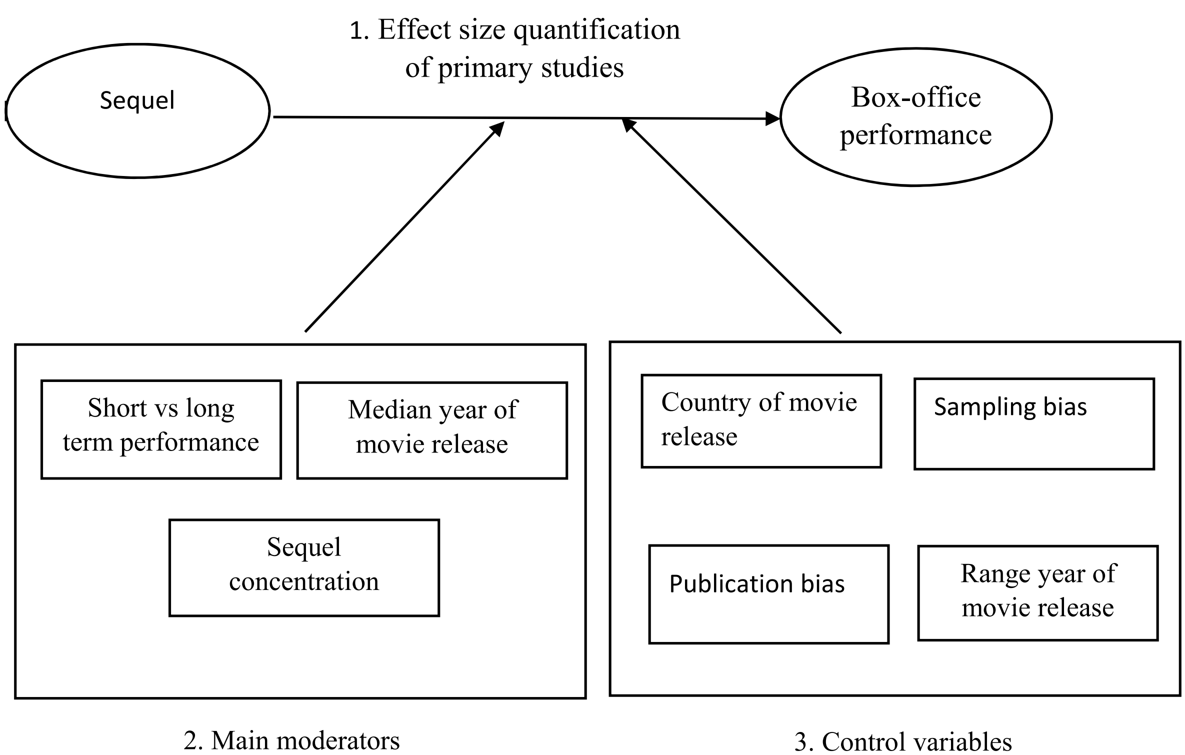
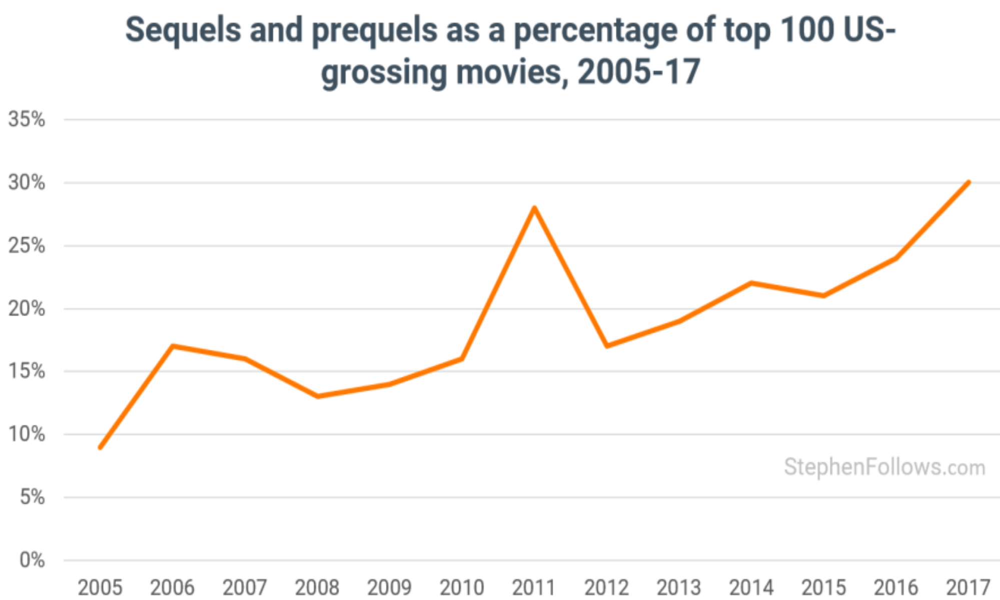


Figure. 3. Sequels as a percentage of top grossing movies release in the U.S



Source: https://stephenfollows.com/the-prevalence-of-sequels-remakes-and-original-movies/

Figure. 4. Number of sequels over year

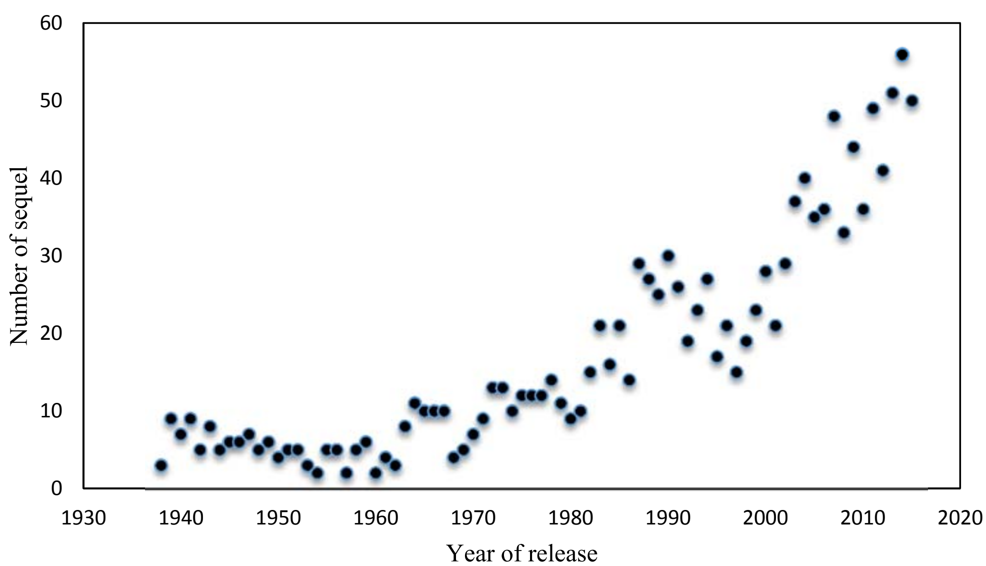


Table 1. Variables and coding

Variables Name	Description
Sequel-theatrical performance	Dummy variable: "1," indicate the effect size is based on short-term domestic box-office (opening weekend or opening week box-office) otherwise 0. The reference is long-term (box- office performance over the entire theatrical run) Short-term refer to weekend or release week box-office performance whereas, long-term box-office is the total box office perfromance.
Country	Dummy variable: "1," indicate whether the box-office data is collected in the USA and 0 otherwise.
Sampling	Dummy variable: 1, indicates when movies were sampled randomly and 0 otherwise.
Median year of movies release	Continuous variable (mean centered): The median year of the of the sampling observation window of the study (for instance 2002 is the median year of the effect size from a primary study sampling movies from 2001 to 2003).
Range of movies release year	Continuous (mean-centered): difference between the earliest and latest sampling years of the observation window.
Effect size precision	Continuous (mean-centered): the inverse of the standard error of the fisher's z transformed correlation.
Concentration of sequel	Continuous (mean-centered): Number of total sequel movies released based on the year of the of the sampling observation window of the study divided by the total movies released in the U.S in English language and produced by US.
Average sequel per total world-wide movies	Continuous: Number of sequel movies based on the sample of study included divided by the total movies release in the U.S
Sample sequel ratio	Continuous: Number of sequel in the study divided by the sample size of it.

Table 2. Descriptive statistics

	Sample size	Mean	Median	SD	Min	Max
Overall	176	0.140	0.122	0.123	-0.309	0.55
Short-term	76	0.149	0.135	0.113	-0.30	0.53
Long-term	100	0.132	0.104	0.129	-0.291	0.55

Table 3. Results for summary meta-analysis

			95% confidence intervals		95% credibility intervals		Effect size distribution heterogeneity			Publication bias analysis		
	Effect sizes(k)	Mean effect size (ES)	Lower-Bound	Upper-Bound	Lower-Bound	Upper-Bound	Q-statistic	Tau^2	I^2	Eggers' regression	Trim & fill	Trim & fill Adjusted ES
Overall	170	0.138***	0.109	0.146	-0.036	0.284	1402.296***	0.0063	89.01%	z= 6.261***	missing studies: 0	0.127***
Short	75	0.175***	0.132	0.218	-0.055	0.405	345.026***	0.0061	81.10%	z = 4.5810***	missing studies: 0	0.148***
Long	95	0.115***	0.096	0.134	-0.034	0.265	819.624***	0.0059	91.10%	z = 4.0362***	missing studies: 0	0.1110***
Significance levels: p < .1, *: p < .05, **: p < .01, ***												

Table 4. Results for meta-regression

	Meta-Regression Model 1	Meta-Regression Model 2	Meta-Regression Model 3	Meta-Regression Model 4	Meta-Regression Main Model	Interaction Meta-Regression
Predictor						
Intercept	0.112***	0.112***	0.112***	.113***	0.112***	0.1054***
Random sampling	0.0127	0.0131	0.0125	0.0038	0.0129	0.0101
Short-term box-office	0.0293**	0.0293**	0.0294**	0.0315**	0.0294**	0.0284*
U.S market	0.0169	0.0163	0.017	0.0195	0.0162	0.019
Median year of movie release		-0.0002		0.0023	-0.0003	-0.0007
Range of movie release years			0	0.0001	-0.0001	0.0004
Sequels concentration	-1.386***	-1.4452*	-1.3784**		-1.456**	-2.8473**
Effect size precision	-0.0016**	-0.0016**	-0.0016**	-0.0016**	-0.0016**	-0.0017
Sample_sequel_ratio	-0.0089	-0.0089	-0.0087	0.0059	-0.0073	-0.0143
Short* Median year of movie release						0
Short* Sequel concentration						0.8426
Median year of movie release average sequel median* Sequel concentration						-0.1124
Range Year of movie release average sequel median* Sequel concentration						-0.0792
	Significance levels: $p < .1$, *: $p < .05$, **: $p < .01$, ***					
	For the meta regression, the reference category is long term box-office performance, non-random sampling, and non-U.S. The reference year is 2002. The continuous variables are mean centered.					

Table 5. Results for meta-regression sub-sample

	Meta-Regression Short	Meta-Regression Long
Predictor		
Intercept	0.2381***	0.0986***
Random sampling	-0.0551	0.0289
U.S market	-0.0606*	0.0282
Median year of movie release	-0.006	0.0009
Range of movie release years	-0.0035	0.0008
Sequel concentration	-0.2521	-1.7421**
Effect size precision	-0.0011	-0.0016**
Sample_sequel_ratio	0.1713	-0.1056
Significance levels: $p < .1$, *: $p < .05$, **: $p < .01$, ***		
For the sub-sample meta regression, the reference category is non-random sampling, and non-U.S. The reference year is 2002. The continuous variables are mean centered.		

Table 6. Correlation

	ES	Median year of movie release	Range of movie release years	Sequels concentration
ES	1			
Median year of movie release	0.0387	1		
Range of movie release years	-0.0774	-0.6143	1	
Sequels concentration	-0.0735	-0.7084	0.2786	1

Appendix 1

Primary studies included in the meta-analysis on the effects of sequels on movie performance

Authors	Publication Outlet	Year	Number of Effect Sizes
Ainslie, Dreze, and Zufryden	Marketing Science	2005	1
Bae and Kim	Journal of Business Research	2019	2
Basuroy and Chatterjee	journal of Business Research	2008	3
Basuroy, Desai, and Talukdar	Journal of Marketing Research	2006	1
Basuroy, Chaterjee, and Ravid	Journal of Marketing	2003	2
Bharadwaj, Noble, Tower, Smith, and Dong	journal of Product Innovation and Management	2017	1
Billur and Talay	Journal of the Academy of Marketing Science	2013	27
Bohenkamp, Knapp, Hennig-Thurau, and Schauerte	Journal of Cultural Economics	2015	2
Brewer, Kelley, and James	Applied Economics	2009	2
Cattani, Ferriani, Mariani, and Mengoli	Industrial and Corporate Change	2013	2
Chang and Ki	Journal of Media Economics	2005	2
Chang, Nam, Chan-Olmsted, and Kim	Journal of Media Economics	2017	1
Clement, Wu, and Fischer	International Journal of Research in Marketing	2014	2
Collins, Hand, and Snell	Managerial and Decision Economics	2002	1
Dastidar and Elliot	Journal of Cultural Economics	2019	2
David Polido	Thesis	2015	7
De Vany and Walls	Journal of Cultural Economics	1999	1
Dhar, Sun, and Wienberg	Marketing Letters	2012	2
Durand and Hadida	Journal of Business Research	2016	1
Elliott and Simmons	Applied Economics	2011	1
Elliott, Caroline, and Rob Simmons	Review of Industrial Organization	2008	1
Fee	Journal of Business Research	2002	1
Filson and Havlicek	Journal of Cultural Economics	2018	1
Gao, Ji,Liu, and Sun	Journal of Marketing	2020	2
Gemser,Van Oostrum, and Leenders	Journal of Cultural Economics	2007	2
Gong, Van Der Stede, and Young	Contemporary Accounting Research	2011	2
Hababou, Amrouche, and Jedidi	Customer Need and Solution	2016	1
Hee Kim	International Journal of Media Management	2019	1

Hennig-Thurau, Marchand, and Hiller	Journal of Cultural Economics	2012	2
Hennig-Thurau, Wiertz, and Feldhaus	Journal of the Academy of Marketing Science	2015	1
Hennig-Thurau, Houston, and Walsh	Journal of the Academy of Marketing Science	2006	2
Hennig-Thurau, Houston, and Heitjans	Journal of Marketing	2009	1
Ho, Dhar, and Weinberg	International Journal of Research in Marketing	2009	1
Hofmann-Stölting, Clement, Wu, and Albers	Journal of Media Economics	2017	1
Hsu	Administrative Science Quarterly	2006	1
Ishihara and Moorthy	Working paper	2018	2
Jeesha,Sumod, Premkumar, and Chowdhury	Working paper	2018	1
Joshi	Journal of Media Economics	2015	1
Joshi and Hanssens	Marketing Science	2010	1
Joshi and Mao	Journal of Academy of Marketing Science	2012	4
Karniouchina	Journal of Product Innovation Management	2011	1
Kim and Kim	Journal of Media Economics	2018	1
Kim, Park, and Park	Journal of Media Economics	2013	1
Knapp, Hennig-Thurau, and Mathys	Journal of the Academy of Marketing Science	2014	2
Kupfer, Holte, Kubler, and Hennig-Thurau	Journal of Marketing	2018	1
Liran Einav	The RAND Journal of Economics		1
Litman and Kohl	Journal of Media Economics	1989	1
Liu, Mazmudar, and Li	Management Science	2015	6
Ma, Huang, Kumar, and Strijnev	Journal of Cultural Economics	2015	2
Mathys, Burmester, and Clement	International Journal of Research in Marketing	2016	6
McKenzie	Journal of Cultural Economics	2010	2
McKenzie and Walls	Journal of Cultural Economics	2013	3
McMullen and Varma	International Review of Business Research Papers	2010	1
Moon and Song	Journal of Retailing	2015	1
Moon, Bergey, and Iacobucci	Journal of Marketing	2010	1
Moon, Park, and Kim	European Journal of Marketing	2014	1
Moon,Mishra,Mishra, and Kang	Journal of International Marketing	2016	1
Narayan and Kadiyali	Management Science	2016	1

Natalia Gmerek	Journal of Marketing and Consumer Behaviour in Emerging Market	2015	1
Nelson and Glotfelty	Journal of Cultural Economics	2012	9
Orlov and Ozhegov	Working paper	2016	1
Packard, Airbarg,Eliashberg, and Foutz	International Journal of Research in Marketing	2016	1
Palia, Ravid, and Reisel	The Review of Financial Studies	2007	1
Peng, Kang, Anwar, and Li	Journal of Cultural Economics	2019	2
Prag and Casavant	Journal of Cultural Economics	1994	1
Prieto-Rodriguez, Gutierrez-Navratil, and Ateca-Emestoy	Journal of Cultural Economics	2015	2
Rao, Ravid, Gretz, Chen, and Basuroy	Marketing Letters	2017	4
Ravid	Journal of Business	1999	2
Ravid and Basuroy	Journal of Business	2004	1
Ravid, Wald, and Basuroy	Journal of Cultural Economics	2006	2
Rodriguez,Gutierrez-Navratil and Ateca-Amestoy	Journal of Cultural Economics	2015	2
Simonton	Empirical Studies of the Arts	2005	5
Sinha, Gu, Kim and Emile	European Journal of Marketing	2019	2
Stimpert, Laux, Marino and Gleason	Journal of Business & Economics Research	2008	1
Terry, Cooley, and Zachary	Journal of International Business and Cultural Studies	2010	1
Terry, king, and JJ walker	Journal of Global Business Management	2010	1
Terry, Neil, king, and Ptterson	Journal of Business and Economic Research	2011	1
Terry, Neil, Lisa, Ashley, and James	Journal of the Southwestern Society of Economists	2016	3
Terry,Neil,Michael and De'Arno De'Armond	Southwestern Economic Review	2011	2
Terry,Neil,Michael, and De'Arno De'Armond	Academy of Marketing Studies Journal	2004	1
Walls	Journal of Media Economics	2009	1
Yi Chen	Working paper	2018	1
Yoon, Charin, and Park	Journal of Advertising Research	2017	1

Conclusion

Entertainment products such as movies are hedonic in nature with short life cycles. These products are surrounded by greater uncertainty and risk of performance. This thesis provides insights in to the management of the movies success in the entertainment industry. Essay 1 shows the impact of WOM communication on movie box-office performance, whereas essay 2 examines the impact of sequels on box-office performance.

The results of essay 1 show that the micro-level experiential information influences box-office performance above and beyond the macro *VVV* measures. Moreover, WOM dynamics change over time such that the experiential information has a stronger positive impact on box-office revenue at the beginning of the movie life cycle but quickly fades as the diagnosticity of experiential cues saturates after the initial product launch.

Essay 2 shows that sequels positively affect movie box-office performance. The sequels short-term box-office performance is greater than long-term box-office performance due to the familiarity with the parent movie, also sequels box-office performance is stable over time. However, too many sequels released in a year negatively affect the sequels box-office performance.

In summary, we hope that this thesis will be insightful for both managers and scholars because it provides empirical insights contrary the mantra of “Nobody knows anything” in the entertainment industry and adds to the entertainment science phenomena introduced by Hennig-Thurau and Houston (2019).