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Screening for the Success Potential of New Products: The Case of the Movie Industry

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SCREENING FOR THE SUCCESS POTENTIAL OF NEW PRODUCTS:

THE CASE OF THE MOVIE INDUSTRY

BY

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ACCEPTANCE

This dissertation was prepared under the direction of the *JEE WON CHOI's* Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration in the J. Mack Robinson College of Business of Georgia State University.

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ABSTRACT

SCREENING FOR THE SUCCESS POTENTIAL OF NEW PRODUCTS:
THE CASE OF THE MOVIE INDUSTRY

BY

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To minimize costs and risks, it is critical for firms to identify the success potential of new products early in the new product development (NPD) process. Despite the benefits of early assessment, however, current NPD processes rarely determine product launch decisions at the idea/concept stage. To provide novel insights about ways to predict market outcomes at an early stage, this paper explores the contributions of key elements of new product ideas/concepts (categorized as product features and emotional features) to financial outcomes. Using the motion picture industry of the United States as the study context, this paper assesses films' return on investments (ROI), by using information available at the idea screening (i.e., greenlighting) stage. A text analysis reveals that product and emotional features of screenplays influence of box office ROI, validating that these proposed features of new product ideas can successfully explain market outcomes. Accordingly, this paper highlights the importance of linking new ideas to market outcomes if the goal is to improve the NPD decision-making process and create a better greenlighting process for movie studios.

Keywords: new product development, idea screening, text analysis, greenlighting, box office, screenplay, movies.

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INTRODUCTION

To remain competitive, firms must create new products and services. Managing new product development (NPD) is challenging, because it is an integrated process consisting of idea generation and screening, concept development, marketing strategy, business analysis, product development, market testing, and product launch (Urban and Hauser 1993). Traditional NPD procedures use sequential stage-gate systems in which each stage leads to the next stage without overlap (Cooper 2011).

Despite the advantages of sequential product development, this method has its drawbacks that lead to product failure: lack of flexibility in the development process, associated with modifying products after launch, lack of end-user collaboration, and increasing product development costs (Goldenberg, Lehmann, and Mazursky 2001; Kornish and Ulrich 2014; Urban and Hauser 1993). Considering the downsides, firms should adapt a non-sequential product development model that is more responsive and flexible. To do so, there is a persistent need to assess the success potential of new products at earlier stages of NPD (Goldenberg, Lehmann, and Mazursky 2001; Kornish and Ulrich 2014). Especially with increased competition and decreased length of product lifecycles, the pressure to make product launch decisions at early stages of NPD, rather than going through an entire sequential NPD process, also has increased.

However, it is difficult to understand the new product success potential at early stages of product development, because of the high uncertainty and limited information about market environment and consumer acceptance (Souder and Moenaert 1992). In the beginning, firms usually only have knowledge about the new product idea itself. These challenges raise important questions. Can firms better access the success potential of their new product idea when they screen ideas? Specifically, we try to answer the following research questions by building up on the consumption values theory:

- What are the features of ideas to be evaluated to identify the likelihood of their financial success?
- What is the role of product categories in influencing the effects of new product idea?

Our proposed framework focuses on the ideas[1] and concepts because great ideas are at the heart of successful new products. Good product ideas create customer value and satisfy their existing or unidentified needs, which are important determinants of commercial success (Goldenberg, Lehmann, and Mazursky 2001). An effective screening and selection of good ideas both lead to more efficient product management (Rochford 1991). Robust idea-screening procedures designed to approve (reject) good (poor) ideas can benefit firms to (1) avoid investments in unsuccessful ideas, (2) allocate resources to more successful product ideas, and (3) achieve better market performance for their new products (Rochford 1991; Von Hippel 1986).

To understand the key components that influence consumer behavior, we rely on the theory of consumption value (Sheth, Newman, and Gross 1991). We propose and define the product and emotional features of ideas for better idea screening. We further improve the evaluation process in evaluating the aforementioned features by adapting text-analysis technique. Digital assessments, such as text mining and neuromarketing, can better assess ideas using systematic idea evaluation and better explain new product/market outcomes (Boksem and Smidts 2015; Toubia and Netzer 2017). Therefore, our proposed conceptual framework applies advances in digital technology, in an effort to minimize the risks posed by subjective evaluation and limit the costs of testing.

[1] Hereafter, we use the term “idea” to refer to both new product ideas and concepts.

Next, we consider the importance of product categorization in influencing consumer purchases. Consumers consider product types when evaluating alternatives and determine the risk involved during product usage (Goldenberg, Mazursky, and Solomon 1999; Rao and Winter 1978; Tzokas, Hultink, and Hart 2004). Our proposed framework finds the interplay between product category and the components of idea (i.e., product and emotional features).

The empirical setting of this study is in the movie industry. The motion pictures industry is an optimal testing ground because it does not follow the traditional sequential product development and it is essential to make production and launch decisions at the early stages of production. This decision-making process, called *greenlighting*, is similar to the idea-screening stage of NPD. Given that this industry is substantial in size, is competitive, features high production costs, have relatively low profitability, and offers publicly available information, the need for better decision making at the greenlighting stage is clear (e.g., Eliashberg, Hui, and Zhang 2007; Luan and Sudhir 2010; Neelamegham and Chintagunta 1999). We collect movie screenplays as raw form of ideas along with their respective movie characteristics, from various websites. We rely on screenplay features extracted by text mining, define the product categories as movie genres, and use with movie studios' strategic actions, to predict screenplays' box office performance.

In the following section, we discuss relevant prior literature on the early stages of new product evaluation. Next, we present the conceptual framework, develop propositions about the effects of new product ideas and firms' strategic actions on market outcomes, and present the data and methodology used to test the conceptual framework. Finally, we present the results and conclude by discussing the implications and limitations of this research.

REVIEW OF LITERATURE

Several studies have explored the use of idea-based information to evaluate new products at the early stages of NPD (e.g., Chandy et al. 2006; Goldenberg, Lehmann, and Mazursky 2001; Kornish and Ulrich 2014). Table 1 provides a summary of select studies from NPD literature.

Insert Table 1

There are, however, several research opportunities. First, to evaluate new product ideas, most papers use simple metrics (e.g., number of patents and citations, collector value) or rely on human judgments (e.g., user purchase intent, expert ratings) (Chandy et al. 2006; Kornish and Ulrich 2014; Singh and Fleming 2010; Taylor and Greve 2006). These subjective evaluations by humans, which rely on expert intuition or user purchase intentions, are valuable. However, high rates of product failure suggest rooms for improvement in the realm of idea evaluation. Such evaluations of the unique product configurations implied by ideas rely on individual judgment, which is prone to errors (either Type 1 errors of accepting unsuccessful ideas or Type 2 errors of rejecting successful ideas). For example, human evaluators are sensitive to external factors such as group structures, cultures, or purchase occasions (Abratt and Goodey 1990; Girotra, Terwiesch, and Ulrich 2010; Iuso 1975), so they may provide biased results by inflating or deflating their actual purchase intention ratings. Moreover, it is costly to hire human evaluators. Rather than relying on simple count metrics or potentially biased individual evaluations, firms can use more objective analytical methods to overcome the shortcomings of idea screening. For instance, by applying text-mining techniques to evaluate new product ideas, they can obtain unbiased analyses and gain new perspectives. Notably, Toubia and Netzer (2017) have adapted big data tools and text-mining technology to review idea descriptions and identify creative ideas. They find that semantic subnetworks in idea descriptions can determine the creativeness of ideas.

Given the abundance of textual information in idea descriptions, these advanced text analysis techniques can be applied to improve the process of idea evaluation. Accordingly, we adapt Toubia and Netzer's definition (2017, pg 2) of an idea "as a document made of words that attempt to add value given a particular idea generation topic."

Second, current studies rarely investigate the financial outcomes of new product ideas. Prior NPD literature uses human subjects' ratings of product concepts (e.g., ratings by senior marketers or research assistants, purchase intentions of consumer panels) or dichotomous dependent variables (e.g., idea conversion and product success/failure) to measure new product success (Chandy et al. 2006; Goldenberg, Lehmann, and Mazursky 2001; Toubia and Netzer 2017). Rather than relying on convenient subjective evaluations or simple binary outcomes as proxies of new product success, firms can use financial performance (e.g., sales, profit, return on investment [ROI]) as a dependent variable to make financially attractive decisions (Kornish and Ulrich 2014). The lack of financial assessment at the idea-screening stage often implies that selected new product ideas are not financially viable. However, minimal work has been done to address this problem.

Finally, research in this area does not account for the interactions of new product idea with product category on market outcome. It is likely that the market outcome of new products can change across product types. Both Chandy et al. (2006) and Kornish and Ulrich (2014) included product categories as control variables to account for this conceivable variation. However, when consumers use the new product, they rely on their prior experience or expectations of the product category to reduce uncertainty. The value of available information on the type of the product can augment or decrease the impact of the true quality of the product (i.e., product and emotional features of new product idea) on market outcome (Bone 1995).

Nevertheless, little research describes the moderating role of the product types in new product development context.

CONCEPTUAL FRAMEWORK

Marketers seek to better understand how consumers evaluate products and make purchase decisions. To effectively screen new product ideas, it is important to understand the key evaluation criteria of products and the drivers of their success. The conceptual framework (see Figure 1) proposed herein integrates the consumption value theory to predict the success potential of new products. We offer an illustration of the early stage NPD evaluation in detail. As depicted in the figure, we leverage the key findings of people's purchasing decisions and capture the impact of new product ideas (measured as *product* and *emotional features*) on firm performance. We measure firm performance as a market outcome, specifically return on investment (ROI), which captures the profits generated from the investment. The effects of these idea elements can be enhanced or decreased depending on product categorization. Since type of product can influence consumers' evaluation of the new product idea we also consider the impact of *product categories* on the relationship between idea and the firm performance.

Insert Figure 1

New Product Ideas and Market Outcomes

Consumers' purchase decisions are heavily influenced by personal and social motives and various consumption values. According to Tauber (1972), people purchase new products to satisfy personal motives such as learning about new trends, stimulating their senses, and trying new things. They also seek to fulfill social motives, including social experiences outside their homes and connecting with peers. These two motives reflect the practical features offered by products and the emotional pleasures and connections that products bring to the usage experience.

Similarly, the theory of consumption value (Sheth, Newman, and Gross 1991) suggests that consumer behavior is shaped by the following consumption values: functional, social, emotional, epistemic, and conditional. Although not all of these dimensions are equally important, a deeper understanding of the relative importance of each can help managers better predict product purchase motivations and expected market outcomes. In particular, functional and emotional values are highly related to consumption experiences and less subject to the heterogeneous nature of the consumers (Bagozzi and Dholakia 1999; Weiner 1985); hence, they are especially important to evaluate in NPD context to select appealing ideas that improve the consumption experience.

Similar to the theory of consumption value, studies on idea screening suggest that managers should consider both product-based and market-based evaluations (Goldenberg, Mazursky, and Solomon 1999; Hart et al. 2003). Product-based information, such as product uniqueness and technical feasibility, is effective in making NPD decisions (Srinivasan, Lovejoy and Beach 1997; Ulrich 1995). When screening new ideas, it is important to understand both the technical features of new products and the emotions that consumers will experience when using them (Iuso 1975) to account for the product- and market-based perspectives. These findings are consistent with theories of consumer purchase. Hence, in this paper, we consider two aspects of new product idea evaluation: product features and emotional features.

Product Features

The product features of an idea include product-based information that pertains to its key components and attributes. They are tangible and/or intangible characteristics that consumers consider when evaluating alternatives and that they experience during product usage (Goldenberg, Mazursky, and Solomon 1999; Rao and Winter 1978; Tzokas, Hultink, and Hart

2004). It is important to identify the key features of ideas, because products with distinct product features perform well in the market. For instance, consumers are drawn to products that have attractive product features of design, structure, or functionality, and are likely to purchase and recommend such products (Kumar 2013). Every product serves a purpose and should have distinct features and benefits. Because ideas are context-specific, product features differ across industries and product categories. For example, the product features of a wearable device are the biometric features, additional technical features such as exercise tracker and compatibility with other devices, the design and color of its band.

We can expect both product and emotional features of ideas contribute to market demand. The more level of product and emotional features that the new product idea has, the more customers will find the features appealing and make purchases. For instance, more number of band colors (i.e., product features) for a fitness wearable device may attract customers away from the competitors and encourage purchases. However, too much of a good thing is often not the best. Too many options available in product features (e.g., too many band colors or too many biometric technologies in wearable devices) can result in information and choice overload, and then reduce choice confidence and satisfaction (Broniarczyk, Hoyer, and McAlister 1998; Malhotra, Jain, and Lagakos 1982). Therefore, we expect that the level of product features reach a saturation point when customers become overwhelmed, and their positive effects on financial outcomes will diminish. Thus, we propose:

> *Proposition 1a: The product features of new product ideas have an inverted U-shaped relationship with market outcomes.*

Emotional Features

Next, the emotional features are also important to understand. Consumers are interested in the emotional experience aroused from product usage, and they discuss their sentiment with others (Berger and Milkman 2012; Iuso 1975). Although studies show that emotions are central to consumption experiences (Holbrook et al. 1984; Oliver, Rust, and Varki 1997), NPD literature and studies of product-based information rarely consider emotions as a determinant of product consumption or market performance. For example, cultural products (e.g., movies and songs) that have more emotionality tend to receive higher ratings (Berger, Meyer, and Kim 2018). Although emotions are difficult to measure, the emotion theory identifies emotionality and positivity as good metrics for understanding consumer emotions (Richins 1997; Yin, Bond, and Zhang 2013). Consumers tend to talk about experiences for which they have strong emotional connections (Berger and Milkman 2012). For example, wearable devices can evoke hedonic arousal by allowing users to feel positive emotions, such as a sense of accomplishment when they reach their fitness goals or a sense of belonging when they see others using the same device. Users of these devices are more likely than non-users to share their experiences with others. Therefore, products that arouse emotions through consumption experience have an impact on market performance because consumers not only repeatedly purchase such products but also recommend them to others (Pansari and Kumar 2017).

Similar to inverted-U effects of product features, more emotional features of new products can improve the market outcome up to a certain point. For example, more emotions aroused from using the wearable device can make users like the product more and encourage indirect purchases through word of mouth (WOM) (Liu 2006). However, too much emotions aroused in product usage can make customers less confident and satisfied (Broniarczyk, Hoyer, and McAlister 1998; Malhotra, Jain, and Lagakos 1982). Therefore, we expect that the positive financial outcomes of emotional features will diminish after reaching a saturation point. We propose:

Proposition 1b: The emotional features of new product ideas have an inverted U-shaped relationship with market outcomes.

Product Category

To enrich understanding of the effects of new product ideas on market outcomes, this paper also considers the role of product category. Companies commonly use product categorization for new product introduction and brand extension strategies (Loken and John 1993). The categorization theory suggests that consumers evaluate new products using the category memories they gain from prior knowledge and experience (Park, Milberg, and Lawson 1991; Sheinin and Schmitt 1994). Thus, consumers adopt different levels of brand associations, variety seeking behaviors, and involvement with the product or service, depending on the product category (Aaker 1997; Hans, Hoyer, and Inman 1996).

The inherent risks that are associated with product categories can influence consumers to be more/less attentive of the product features and affect their final purchase decision (Tauber 1972). For example, a product category that consumers associate with higher prior emotional experience due to a positive brand association will make the consumers more attentive to the emotional features of the new product idea. This product category will ultimately enhance the impact of emotional features on the market outcome. In contrast, consumers have less risk associated with emotionality for a functional product category (e.g., office supplies). In such case, we expect this product category to enhance the impact of product features on the market outcome, while do not influence the effects of emotional features. Depending on consumers' perception and behavior, different product categories will have differential effects on the relationship between the idea elements and the market outcomes. Hence, monotonic effects may not exist and we expect a significant influence of the categorization on the main relationships:

Proposition 2: The product categories of ideas have differential effects on the relationship between the (a) product features, and (b) emotional features of ideas, and market outcomes.

METHOD

This paper answers the research questions using data from the motion picture industry. This section begins by describing the empirical research context and outlining several studies that focus on this topic. Next, we describe the operationalization of the key variables.

Empirical Research Context

The motion picture industry is a suitable context to test the proposed framework, because the sequential NPD process does not apply in movie production. The uncertainty in the link of screenplay-to-film success in Hollywood is high; the vast majority of films fail to break even after their release (Davidson 2012). Although more than 700 movies are released annually in the United States, with box office sales of $11.1 billion (MPAA 2018), approximately 75% fail to make a profit; this rate suggests that film success is fickle (Davidson 2012; Hennig-Thurau, Houston, and Walsh 2007). Because of the high risk of box office failure and the financial burden of film production costs, there are high demands for more reliable greenlighting processes.

Movie studio managers consider countless ideas (i.e., screenplays) annually; they must determine which screenplays to develop and how best to transform the scripts into films. Given that the majority of films have low or negative profitability, movie studios need better decision making techniques at the greenlighting stage. Screenplays are blueprints of final film products that should be thoroughly investigated at an early stage of movie production. Scriptwriters study the key elements of screenplays and seek to unite all elements to make the plays compelling (McKee 1997). They send their finished screenplays to production houses in hopes that they will be converted to films. Typically, the greenlighting process relies on the subjective opinions of script analysts, who are costly to production houses and take a long time to complete their reviews. Production houses receive such numerous screenplays that they need to hire script readers and experts to review the screenplays and make greenlighting decisions on the basis of their elements. Rather than having readers manually review screenplays in such a laborious, costly manner, production houses can use text analysis to capture key screenplay information. The motion picture industry fits the empirical context of this study and provides a unique source of publicly available and reliable data.

Related Studies in the Study Context

It is challenging to predict box office success, because each movie is unique, and numerous factors influence its financial performance. Prior research identifies several determinants of box office performance, including genre, sequel, release date, Motion Picture Association of America (MPAA) rating, director and cast, awards received, performance of competing movies, and online reviews (e.g., Elberse 2007; Eliashberg and Shugan 1997; Litman 1983; Liu 2006). Although these predictors are critical to explaining a movie's performance, many are determined at the later stages of movie production (e.g., post-production or after movie release). Therefore, it is critical for film studios to predict the likelihood of film success *before* they enter production (i.e., in the pre-production stage), to avoid investing in unprofitable movies (Eliashberg, Elberse, and Leenders 2006).

However, given the limited information available at the early stages of production, it is challenging to examine the quality of movies. Several studies measure the success potential of films using pre-production determinants. For example, Gemser, Leenders, and Weinberg (2012) compares demand uncertainty between early and later stages of the NPD process. The authors use film production budget and cast power as early-stage indicators of film performance and minimum guarantee (i.e., price of nearly completed or not-yet-launched film paid by film distributors to producers) as a later-stage indicator. They find the later-stage indicator is a stronger predictor of success than early-stage indicators, underscoring the challenge of forecasting the performance of films at the beginning of the NPD process. Instead of budget and starpower, Geoetzmann, Ravid, and Sverdlove (2013) use screenplay price (paid by film studios) as an early-stage indicator of movie quality. They find that high-priced screenplays are more likely to become profitable films. Because high-quality screenplays are likely to be expensive, this finding suggests that information from ideas themselves (i.e., screenplays) is a good predictor of market success. Although early-stage indicators are reasonable determinants of film success, close examination of raw information in screenplays can provide an even better explanatory measure of market success (Kornish and Ulrich 2014).

Movie ideas can be either short plots or completed screenplays (Eliashberg, Elberse, and Leenders 2006). The importance of evaluating the film idea itself is empirically validated suggesting that films receiving many screenplay awards are more likely to win best picture honors (Simonton, 2002, 2004). Movie ideas can be evaluated with movie spoilers or screenplays (Eliashberg, Hui, and Zhang 2007, 2014; Hunter, Smith, and Singh 2016). Movie spoilers are summaries of movies written by movie viewers after watching the film, while screenplays are blueprints of movies (e.g., storylines, which include scenes, dialogue between characters, and camera or character movements) in a textual format. Prior to discussing these papers, we will explain how the screenplay selection process works.

Greenlighting—that is, deciding which scripts to turn into movies—is one of the most important financial decisions that movie studios make. However, the current greenlighting process relies on subjective human intuition rather than logic and science. For example, script analysts review submitted screenplays and make suggestions for future film productions (Eliashberg, Hui, and Zhang 2007; McKee 1997). Despite the expensive and labor-intensive nature of script analyses, the use of scientific analytics to write and evaluate screenplays continues to be taboo in Hollywood and is often viewed as a tool that stifles creativity. Although film experts, such as script readers and producers, offer valuable insights derived from their industry knowledge, low levels of box office success suggest an opportunity for improving the greenlighting decision process. Considering the high cost and large scale of investments needed in film production, even marginal improvements at the greenlighting stage could benefit film studios and other stakeholders involved in production (Eliashberg, Elberse, and Leenders 2006). Most importantly, products like movies that do not follow the sequential NPD stage-gate system because it is very difficult to test films until finally produced.

Next few studies use the raw information of movie idea to determine the financial success prior to production rather than following the traditional NPD process. Eliashberg, Hui, and Zhang (2007) use movie spoilers to predict box office ROI. The spoilers are detailed descriptions of movies so Eliashberg, Hui, and Zhang (2007) view them as proxies for actual screenplays. They subjectively evaluate movie spoilers by assigning human coders to determine the content and genre of the screenplays and objectively extract the product features of screenplays (e.g., total number of scenes, volume of dialogues, average length of dialogue). The authors use bootstrap aggregated classification and regression tree (Bag-CART) methodology and find that certain elements from movie spoilers predict box office ROI. In their follow up paper, Eliashberg, Hui, and Zhang (2014) use actual screenplays instead of movie spoilers to find the relationship between the textual information from scripts and box office ROI. Their finding that the proposed kernel-based preproduction approach outperforms benchmark models highlights the predictive value of textual information in screenplays. Similarly, Hunter, Smith, and Singh (2016) apply network text analysis (NTA) to derive the sizes of text networks from 170 U.S.-produced scripts. Text network size uses a word-frequency approach to represent cognitive complexity in the communication skills of script dialog. The authors find that a screenplay's text network size strongly predicts box office revenue. These studies (see Table 2) empirically show that objective textual information extracted from films' concepts contributes to subsequent film performance.

Insert Table 2

However, these papers have several limitations. First, the existing studies capture only the product features of screenplays and neglect emotion, which is another critical aspect of ideas. Every product idea has an emotional element, and this is especially true for hedonic products such as movies. Movie consumption is a hedonic experience in which people watch movies not only to pass time but also to feel emotions; they seek laughter from comedies, sympathy or tears from dramas, and adrenaline rushes from action films (Austin 1986; Hirschman and Holbrook 1982). Such experiential consumption arouses movie audiences to have strong emotional connections with storylines, characters, and other external factors (Holbrook and Hirschman 1982; Smith 2003). For movies to evoke emotions in audiences, they must have strong screenplays. Great screenplays connect with audiences through their emotional undercurrents as well as their sequences of events. Screenplays arouse audiences' emotions through narratives, character development, and dialogue (Field 2007; Selbo 2015; Tan 2013). Movies that evoke strong emotions are likely to perform well at the box office because audiences prefer films that they feel connected to, and thus they are more likely to recommend such movies to others (Boksem and Smidts 2015; Liu 2006; Zacks 2014). Therefore, it is essential to understand the emotionality of screenplays to determine whether movies will be successful in capturing audience attention. However, despite the importance of emotion in films, prior studies have not used objective tools to capture screenplay emotionality. We maintain that advance greenlighting processes should use such tools.

Second, prior studies account for movie genre as a control variable but do not consider the interplay between the screenplay features and genre (Litman 1983). As previously discussed, the effects of idea elements on market outcomes theoretically should be distinct, depending on the product category. For example, the effects of screenplay emotionality on box office performance may more positive and significant for dramas than for thriller movies. Thus, it is important to understand the interaction effects of the genre on the relationship between screenplay elements and theatrical outcomes.

Data

We obtain data from various publicly available sources. We procure screenplays of U.S.-produced movies from the following websites: Internet Movie Script Data Base (IMSDb), Daily Scripts, Simply Scripts, and Write to Reel. We also gather movie characteristics from the following major movie websites: Internet Movie Database (IMDb.com), Box Office Mojo (boxofficemojo.com), Rotten Tomatoes (rottentomatotes.com), and The Numbers (the-numbers.com). Consistent with prior studies, we focus on movies written and produced in the United States (e.g., Eliashberg, Hui, and Zhang 2014; Hunter, Smith, and Singh 2015). Consistent with prior studies, we eliminate the following screenplays -- screenplays of foreign and independent films, documentaries, short films, incomplete films, and films without financial information-- to focus on U.S. based and commercial driven movies. The final data set consist of 425 domestic movies released between 1990 and 2016. We test the framework by compiling data from various databases and text-parsing the relevant information. Table 3 describes the data sources and variable operationalization. Table 4 provides the descriptive statistics for key variables.

Insert Table 3 and Table 4

Dependent Variable: Market Outcome

As for the market outcomes of films, this study uses the box office Return on Investment (ROI), operationalized as U.S. box office sales relative to the total expenses in production and marketing (Heath et al. 2015). Although prior studies have used domestic opening weekends' gross revenues or domestic gross revenues to examine the outcomes of films (Hennig-Thurau, Houston, and Walsh 2007; Hunter, Smith, and Singh 2016; Sawhney and Eliashberg 1996). However, record-breaking blockbusters usually require high production and marketing budgets. Production houses are interested in high profits and often allocate resources to large-budget, tent-pole movies in the hopes of generating high surpluses (Elberse 2013); therefore, focusing solely on gross revenue does not necessarily explain a film's profitability. To have a clear understanding of films' financial returns, it is important to account for the total investment cost.

We adjust all revenue, production, and advertising expenses by the consumer price index (CPI) factor, relative to 2016 dollars, which is the last year in the data set (Heath et al. 2015). Similar to prior studies, we use domestic box office sales to calculate the box office ROI (Eliashberg, Hui, and Zhang 2014; Heath et al. 2015; Hunter, Smith, and Singh 2016). Film studios can generate revenue from domestic and worldwide box office sales, and from ancillary markets such as DVD, Blu-ray, Internet streaming, and licensing (Ahmed and Sinha 2016). However, in this data set, the correlation between domestic gross revenue and worldwide gross revenue is 0.95. Therefore, domestic films that perform well in the U.S. market tend to perform well worldwide, and using domestic gross revenue is a good measure to understand the market outcome of for U.S.-produced screenplays. According to Eliashberg, Hui, and Zhang (2007), the distribution of ROI is highly skewed to the right, so we use the log transformation of ROI, which follows a more normal distribution.[2]

Independent Variables

Screenplays are documents that portray the ideas of new films. Scriptwriters study the key elements of screenplays and attempt to unite each element to make them compelling (McKee 1997). They then send the finished screenplays to production houses wishing to be selected. Production houses receive numerous screenplays and hire script readers and experts to review them, to make greenlighting decisions according to screenplay elements. The product and emotional features of screenplays may be captured through objective text analysis, rather than through the laborious and costly process of script review.[3]

Information from Screenplays: Product Features

Screenplays are semi-structured and subdivided into multiple scenes (indoor and outdoor), with each scene containing dialogue and/or descriptions of settings and actions. The "who," "what," "how," and "where" aspects of the context are key product features that describe the structural elements of films and make each film unique (Field 2007). In addition, screenplay information, such as whether it is a sequel, novel-based, or child-friendly, is critical to understanding the product features of a script.

Characters drive stories and make connections with movie viewers (Selbo 2015). Screenplay stories revolve around the actions taken by each character. Interactions among characters and the sequence and logic of their interactions affect narrative development (Nelmes

[2] We add a constant of 1 before taking the log transformation to prevent taking the log of 0.
[3] Although the interaction effects between product and emotion features are not the focus of the study, we estimate the model with a two-way interaction between product and emotion features.

2007). An increase in the number of characters can increase the chances that viewers will find relevance and connection with a film; more viewership can lead to better box office performance. Therefore, we capture the relative number of characters per screenplay (CHARACTERS), operationalized as the total number of characters divided by the total number of screenplay pages.

Dialogue develops characters' voices and builds a narrative (Selbo 2015); it helps audiences relate to characters and become immersed (McKee 1997). Changes in the number of dialogue can also influence a movie's performance; too little may not provide a deep enough explanation of the narrative, and too much may overwhelm the audience with information. Hence, we measure the relative frequency of dialogues in each screenplay (DIALOGS), operationalizing it as the total number of dialogue interactions between characters divided by the total number of screenplay pages. Screenplay stories develop not only from interactions of main characters but also from interactions of minor characters. Main characters are the top four characters with the most dialogue interactions in a script, and minor characters are any characters that are not main characters but are involved in dialogue. Minor characters can create tension and build-up the story. For example, they can provide important information related to main characters and reveal more narrative (Batty 2014). Thus, we operationalize the percentage of minor character dialogue interactions (MINORDI%) as the number of dialogue interactions between minor characters divided by the total number of dialogic interactions. The change in number of dialogic interactions among minor characters can affect movie performance by making stories richer and allowing audiences to connect better with characters.

Film pace builds tension and grabs audience attention (Murtagh, Ganz, and McKie 2009). The pace of a film's score is defined as the number of changing scenes. Less variation in pace can make a film seem less dynamic (McKee 1997). For example, in character interactions, slower-paced scene changes or monotonous dialogue seem mundane; audiences can easily get distracted and bored. However, modulating the action by changing the speed of scenes and dialogue can be eye-catching; faster-paced scene changes signal an impending climax or tension and reveal more information. Consequently, we measure scene pace (SCENES) as the total number of scenes divided by the total number of screenplay pages. Furthermore, because the proportion of indoor and outdoor scenes in a screenplay can create differing senses of ambiance for viewers, we operationalize the percentage of outdoor scenes (OUTDOOR%), as the ratio of the total number of outdoor scenes and the sum of indoor and outdoor scenes.

Information from Screenplays: Emotional Features

We capture the emotional elements of screenplays by using the Linguistic Inquiry of Word Count (LIWC) (Pennebaker, Booth, and Francis 2007), which is an automated sentiment analysis that counts the number of words related to emotions in an article (e.g., happy, cried). The LIWC tool has been used in marketing literature for sentiment analysis (e.g., Berger and Milkman 2012; Yin, Bond, and Zhang 2013). Similar to Berger and Milkman (2012), we obtain both emotionality and positivity in screenplay text: EMOTIONALITY is the percentage of words that are classified as either positive or negative, and POSITIVITY is the difference between the percentage of positive and negative words.

Moderating Variables: Product Category

In the context of this study, we use film genre to represent product category. Genres are one of the key movie characteristics that influence the moviegoers whether to watch movies and share the experience with peers depending (Delre, Broekhuizen, and Bijmolt 2016). In this study, we focus on the following genres: action, comedy, drama, thriller, or other.

Control Variables

In this study context, it is important to control for the determinants of box office success to identify the true impact of new product idea (screenplay) elements. To measure the impact on box office performance, we use control variables that are supported by the literature.

The quality of films is highly dependent on their directors and casts (Elberse 2007; Litman 1983). Upon greenlighting screenplays, film studios hire the most suitable directors and actors to produce good quality films. According to the "auteur" theory, films are characterized by their directors (Albert 1998), because directors are the "authors" who manage the projects and transfer screenplay texts into final cinematic products. These directors, accomplish this by overseeing every aspect of production from visual to audio, casts, scenes, and special effects. According to management literature, strong project leaders have good internal management skills; they are able to increase concept/product effectiveness and induce team members' creativity (Srivastava, Bartol, and Locke 2006; Verona 1999). Leaders with good executive skills tend to lead their projects to success and improve firm performance. However, directors alone may be insufficient to create good movies; strong casts with previous notable performances can also help to transfer the key elements of screenplays through their acting. Therefore, film studios continue to pay more to cast big-name actors hoping for successful box office outcomes (*Economist* 2016).

Prior studies emphasize the importance of directors and actors to box office performance (e.g., Elberse 2007; Hennig-Thurau, Houston, and Sridhar 2006; Litman 1983; Neelamegham and Chintagunta 1999). However, the use of both the direct and combined effects of directors and star power may provide a better measure of the resources allocated to production. Prior studies use the average box office revenue of the star director's latest movies to measure director and star power (Elberse 2007; Hennig-Thurau, Houston, and Walsh 2007). Consistent with the prior studies, we collect data from IMDB and calculated the average box office receipt of each director's five most recent movies to measure the director power.[4] For star power, we used the first-, second-, and third-credited casts of each film and calculate the average box office receipts of the star's five most recent movies. Using director and star power values, we operationalize resources in production (PR) as the sum of individual director and star power, and the product of the two. We also account for synergy effects, because films produced by directors and casts that are both successful may require higher investments in production. We take the logarithm form of production resources to capture the diminishing (but positive) effects.

Firms with strong strategic emphasis on value appropriation allocate more resources to marketing activities. On average, marketing can easily represent 50% of production budgets (Vogel 2014). Often consumers find difficulty in determining the product quality and performance that they rely on firm communications that highlight the competitive advantage of their products. Hence, despite these high costs, production houses can benefit from an increase in awareness and initial perceived quality of their films (Hennig-Thurau, Houston, and Sridhar 2006). For the marketing resource variable (MR), we collect films' domestic print and advertising expenditures from S&P Global Market Intelligence. As with production resources, the logarithm of marketing resources captures the diminishing (but positive) returns. We also include the product of production resources and marketing resources as a control variable, as there can be synergistic effects on a movie's box office that have a high production cost and high marketing cost. We take the natural logarithm of production and marketing resources for diminishing but positive returns.

[4] We tested the use of both three and five previous films and do not find any difference in the results.

Familiarity with new product ideas can improve profitability by leveraging the brand equity of original ideas and consumers' acceptance of the ideas. Consumers who enjoyed an original product may be comfortable enough to try its next generation because they reduce perception of risk; and firms can benefit from the related reduction in marketing expenses (Chandy and Tellis 1998; Heath et al. 2015). In the movie context, familiarity with a screenplay can be captured by whether it is a sequel (SEQUEL) or a novel-based script (NOVEL-BASED). Both sequels and films based on popular books appear to be correlated to movie success (Heath et al. 2015; Hennig-Thurau, Houston, and Walsh 2007). In addition, the certification of scripts can impact the number of consumers who attend movie theaters and watch films. For example, scripts that are not child-friendly have more restrictive certifications (e.g., R-ratings), which can impact their box office performance because of the limited number of viewable audience (Litman 1983; Sawhney and Eliashberg 1996).

The time of year of movie release (SEASONALITY) can highly influence box office performance. For instance, movies released around the peak seasons of holidays tend to have greater viewership (Mukherjee and Kadiyali 2011). Similarly, the greater the number of theaters that feature a movie (SCREENS), the greater the chance of reaching large audiences and the greater the positive impact on box office performance (Elberse and Eliashberg 2003). The greater the number of movies playing in theaters on the same weekend of a movie release, the greater the competition and splitting of viewership; more competition (COMPETITION) has a negative impact on the box office performance (Krider and Weinberg 1998).

In addition, non-studio factors such as reviews and awards are correlated with box office performance. Word of mouth is especially critical for experiential products such as movies. Positive reviews by both professional critics (CRITIC REVIEWS) and audiences (AUDIENCE

REVIEWS) have positive impacts on box office performance (Basuroy, Chatterjee, and Ravid 2003; Liu 2006). Finally, movies that receive notable awards (AWARDS) from prestigious institutions such as the Academy of Motion Picture Arts and Sciences perform well; receiving such awards signals a movie’s quality, and results in better WOM that can influences movie viewers’ decisions to watch the movie (Hennig-Thurau, Houston, and Walsh 2007).

DEMONSTRATING THE IMPORTANCE OF NEW PRODUCT IDEAS

Before developing the model specifications, we highlight the value of including new product idea elements from screenplays to explain box office performance. As an illustration, we measured the mean absolute percentage error (MAPE) of the predicted box office ROI from the actual value. In each step, we include additional information from the new product idea (i.e., product and emotional features, and genre) and measured the change in MAPE.

We find that the use of control variables results in a MAPE of 47.93% in sample. This means that on average our predicted values of box office ROI using just the control variables deviate from the actual value by 47.93%. Instead, when we include additional information from screenplays measured as product and emotional (idea) features, we find the in-sample MAPE reduces to 27.54%. Moreover, including the interplay of genre and idea features further decreases the average deviation of the predictive values to 15.34%. Thus, this simple illustration highlights the importance of evaluating a new product idea to improve the accuracy of the green lighting process.

We also test the out-of-sample MAPE for the holdout sample of films produced after 2013. Out-of-sample results indicate that the predicted value of box office ROI using the screenplay elements, genre, and the control variables deviate from the actual performance by 20.50%. This result further supports the value of considering product category and product and emotional features of new product ideas. Table 5 summarizes both in-sample and out-of-sample mean absolute percentage error.

Insert Table 5

MODEL SPECIFICATION AND ESTIMATION

The main objective of this study is to understand the contributions of new product ideas (screenplay elements) and firms' strategic actions (production and marketing resources) on box office ROI. We use text analysis to extract the key screenplay elements (product features are CHARACTERS, DIALOGS, MINORDI%, SCENES, and OUTDOOR%; emotional features are EMOTIONALITY and POSITIVITY), then estimate the value of firms' strategic actions for each movie. To test for possible non-linear effects of new product ideas, we include quadratic terms for both product and emotional features of each screenplay.

There are modeling challenges that are caused by endogeneity in testing the conceptual framework. Concerning selection bias, there is a chance that the greenlighted (produced) screenplays are systematically different from the unproduced plays (Eliashberg, Hui, and Zhang 2014). Furthermore, there can be an omitted variable bias because production houses may make decisions strategically in evaluating screenplay elements.

Model-Free Evidence

Prior to accounting for the selection bias, we conduct a simple model-free evidence to determine whether there are differences between screenplays that are produced into a movie and those that do not. First, we procured screenplays that were not greenlighted movies and compare the mean differences of the new product idea features between produced and unproduced screenplays (see Table 6).

Insert Table 6

From this model-free evidence, we find statistical difference between the two groups (produced vs. unproduced screenplays). Compared with unproduced screenplays, produced screenplays have higher levels of emotionality (produced = 7.603, unproduced = 5.883, $p < 0.01$), more characters (produced = 0.402, unproduced = 0.367, $p < 0.05$), a higher percentage of outdoor scenes (produced = 0.359, unproduced = 0.237, $p < 0.01$), and more dialogic interaction between characters (produced = 4.758, unproduced = 4.585, $p < 0.05$). However, produced screenplays have fewer scenes per page (produced = 1.348, unproduced = 1.418, $p < 0.05$). We find no statistical difference between produced and unproduced screenplays in regard to the mean differences of positivity in a screenplay and minor character dialogue interactions. Compared with writers of unproduced screenplays, writers of produced screenplays have more screenplay writing awards (produced = 6.348, unproduced = 0.007, $p < 0.01$) and more produced screenplays (produced = 8.595, unproduced = 0.457, $p < 0.01$).

The statistical differences between the produced and unproduced screenplays emphasize the importance of considering selection bias challenges. In the following section, we describe how we account for selection bias.

Endogeneity-Selection Bias

The analysis focuses on screenplays that have been produced as films. As illustrated in the model-free evidence, greenlighted screenplays are statistically different in some key product and emotional features, compared with unproduced scripts. To avoid the potential problem of selection bias, we use the Heckman two-step method (Heckman 1979). First, we collect 420 screenplays that were not produced into movies. The first stage of Heckman approach involves a probit model on the probability of a screenplay being greenlighted.

(1) $Greenlight_i^* = \omega_i^{Greenlight} \xi + u_i$.

(2) $Greenlight_i = \begin{Bmatrix} 1 & \text{, where } Greenlight_i^* > 0 \\ 0 & \text{otherwise} \end{Bmatrix}.$

$Greenlight_i^*$ is the latent variable measuring the underlying propensity for a screenplay to be greenlighted and turned into a film; $\omega_i^{Greenlight}$ represents a vector of exogenous variables that influence the choice of a screenplay being greenlighted. By including both the product and emotional features of each screenplay, as well as exclusion restriction variables, we obtain unbiased estimates. Specifically, we include the product features (CHARACTERS, SCENES, OUTDOOR%, DIALOGS, and MINORDI%) and emotional features (EMOTIONALITY and POSITIVITY), along with two exclusion restriction variables that affect the selection process but not the final equation (Bushway, Johnson, and Slocum 2007). Two variables related to screenplay writers' prior experience in writing movie scripts. As instruments, we use an indicator of whether the writer had received screenwriting awards prior to writing the screenplay (PRIORSPAWARD) and the number of produced screenplays written by that writer (PRIORSP). Both instruments increase the chances of a screenplay being greenlighted. However, a writer's prior experience in writing screenplays (measured with PRIORSPAWARD and PRIOR SP) does not influence box office ROI for a movie, because movie box office performance is influenced by not only screenplays but also other elements, such as firms' strategic actions and external factors such as competition and reviews. This assumption is empirically validated by the low correlation between these variables and box office performance ($\rho = 0.006$, $p > 0.10$ and $\rho = 0.010$, $p > 0.10$, respectively). Finally, we assume that the error term (u_i) is normally distributed.

After estimating the selection probit equation to obtain estimates of the unknown parameter λ, we computed the inverse mills ratio (IMR) of the selected sample.

(3) $IMR_i = \widehat{\lambda_i} = \frac{\phi(\omega_i\hat{\xi})}{\Phi(\omega_i\hat{\xi})}$, if $Greenlight_i=1$

$$\text{IMR}_i = \widehat{\lambda_i} = \frac{-\phi(\omega_i\hat{\xi})}{[1-\Phi(\omega_i\hat{\xi})]}, \qquad \text{if Greenlight}_i\text{=0}$$

The probability density function (ϕ) and the cumulative density function (Φ) from the correction term IMR are the standard normal distribution, respectively. Then we include this correction factor (IMR) as additional variables in the final model (Equation 4) (Germann, Ebbes, and Grewal 2015; Wooldridge 2002). This approach assumes normality for the model error terms.

Endogeneity- Omitted Variable

Both screenplay elements and firms' strategic actions can be endogenous because of unobserved factors that may affect the respective dependent variable. Omitted variables can create endogeneity with the covariates of the model specification. For example, omitted variables, such as soundtrack, that are correlated with emotionality may contribute to box office outcomes (e.g., Elberse and Eliashberg 2003; Liu, Mazumdar, and Li 2014). Endogeneity also may occur if the selected new product ideas and firms' strategic actions are non-random decisions of the firm. As managers make resource allocation decisions, they tend to consider the investments and product decisions made by competing companies (Peteraf and Shanley 1997). Therefore, managerial decisions are influenced not only by their reference groups but also by their industries as a whole. Failure to address this endogeneity issue could bias the effect size of the model estimation.

To avoid these biases, we need to select exogenous instrumental variables that are correlated with the variables of interest but not with the respective error term. We selected instrument variables (IV) according to institutional isomorphism (DiMaggio and Powell 1983). Isomorphism is a condition that makes one unit in a population similar to other units that are in the same competitive environment (Peteraf and Shanley 1997). Film production houses' decisions for movies in the same genre and with the same MPAA rating are likely to have similar magnitudes, because production houses learn appropriate responses and reflect other's investments in film creation. Moreover, previous authors in the motion picture context have used similar IVs to account for endogeneity (Chintagunta, Gopinath, and Venkataraman 2010; Liu, Mazumdar, and Li 2014). Accordingly, for the potentially endogenous variables (i.e., product and emotional features of screenplays and firms' strategic actions), we use the average of the production resources of the movies in the same genre, and with the same MPAA rating for the focal movie.[5] This selected IV should be highly correlated with the focal endogenous variable but not the error term, which met the relevance criterion and exclusion criterion, given the industry (Germann, Ebbes, and Grewal 2015). We test for the validity of the instruments using the Sargan-Hansen test (Kennedy 2003). The null hypothesis of Sargan-Hansen test is that the instruments are exogenous and uncorrelated with the error term. We failed to reject the null, which indicates that the instruments in the estimation are valid.

Using these IVs, we follow a control function approach to account for potential endogeneity (Petrin and Train 2010) and add the endogeneity-correction residuals ($\hat{\eta}_i^{EMOTIONALITY}$, $\hat{\eta}_i^{POSITIVITY}$, $\hat{\eta}_i^{CHARACTERS}$, $\hat{\eta}_i^{SCENES}$, $\hat{\eta}_i^{OUTDOOR\%}$, $\hat{\eta}_i^{DIALOGS}$, and $\hat{\eta}_i^{MINORDI\%}$) as additional explanatory variables in the model estimation.

Final Model Specification

The final model specification after accounting for selection bias and endogeneity is:

[5] As a robustness check, we tried using the average values of the movies in the same genre, MPAA rating, and release month as instrument variables. However, the parameter estimates were not different.

$$
\begin{aligned}
&(\mathbf{4})\\
&\boldsymbol{log}(\boldsymbol{BOX\ OFFICE\ ROI})_{i}\\
&\qquad = \beta_0 + \beta_1\, EMOTIONALITY_i + \beta_2\, EMOTIONALITYSQ_i\\
&\qquad + \beta_3\, POSITIVITY_i + \beta_4\, POSITIVITYSQ_i + \beta_5 CHARACTERS_i\\
&\qquad + \beta_6 CHARACTERSSQ_i + \beta_7 SCENES_i + \beta_8 SCENESSQ_i + \beta_9 OUTDOOR\%_i\\
&\qquad + \beta_{10} OUTDOOR\%SQ_i + \beta_{11} DIALOGS_i + \beta_{12} DIALOGSSQ_i + \beta_{13} MINORDI\%_i\\
&\qquad + \beta_{14} MINORDI\%SQ_i + \Sigma_{j=1}^{J}\gamma_{1j} GENRE_i\\
&\qquad + \Sigma_{j=1}^{J}\gamma_{2j}(GENRE_i \times EMOTIONALITY_i) + \Sigma_{j=1}^{J}\gamma_{3j}(GENRE_i \times POSITIVITY_i)\\
&\qquad + \Sigma_{j=1}^{J}\gamma_{4j}(GENRE_i \times CHARACTERS_i) + \Sigma_{j=1}^{J}\gamma_{5j}(GENRE_i \times SCENES_i)\\
&\qquad + \Sigma_{j=1}^{J}\gamma_{6j}(GENRE_i \times OUTDOOR\%_i) + \Sigma_{j=1}^{J}\gamma_{7j}(GENRE_i \times DIALOGS_i)\\
&\qquad + \Sigma_{j=1}^{J}\gamma_{8j}(GENRE_i \times MINORDI\%_i)\\
&\qquad + \beta_{15}(EMOTIONALITY \times CHARACTERS)\\
&\qquad + \beta_{16}(EMOTIONALITY \times SCENES) + \beta_{17}(EMOTIONALITY \times OUTDOOR\%)\\
&\qquad + \beta_{18}(EMOTIONALITY \times DIALOGS) + \beta_{19}(EMOTIONALITY \times MINORDI\%)\\
&\qquad + \beta_{20}(POSITIVITY \times CHARACTERS) + \beta_{21}(POSITIVITY \times SCENES)\\
&\qquad + \beta_{22}(POSITIVITY \times OUTDOOR\%) + \beta_{23}(POSITIVITY \times DIALOGS)\\
&\qquad + \beta_{24}(POSITIVITY \times MINORDI\%) + \Sigma_{k=1}^{K}\gamma_{9k}X_i + \gamma_{10}\hat{\eta}_i^{EMOTIONALITY}\\
&\qquad + \gamma_{11}\hat{\eta}_i^{POSITIVITY} + \gamma_{12}\hat{\eta}_i^{CHARACTERS} + \gamma_{13}\hat{\eta}_i^{SCENES} + \gamma_{14}\hat{\eta}_i^{OUTDOOR\%}\\
&\qquad + \gamma_{15}\hat{\eta}_i^{DIALOGS} + \gamma_{16}\hat{\eta}_i^{MINORDI\%} + \gamma_{17} IMR_i + \varepsilon_i,
\end{aligned}
$$

where:
i = each screenplay,
j = genre of screenplay i (i.e., action, comedy, drama, and thriller),
X_i= movie characteristics control variables,
γ_{10} = parameter estimate for endogeneity correction residual of EMOTIONALITY,
γ_{11} = parameter estimate for endogeneity correction residual of POSITIVITY,
γ_{12} = parameter estimate for endogeneity correction residual of CHARACTERS,
γ_{13} = parameter estimate for endogeneity correction residual of DIALOGS,
γ_{14} = parameter estimate for endogeneity correction residual of MINORDI%,
γ_{15} = parameter estimate for endogeneity correction residual of SCENES,
γ_{16} = parameter estimate for endogeneity correction residual of OUTDOOR%,
and
ε_i= random error.

RESULTS & DISCUSSION

Sample Selection

Table 7 shows the first-stage probit model as detailed in Equation 1. The results provide insights into production houses' decisions to greenlight screenplays. The quadratic forms of the screenplay features capture the possible nonlinear relationships. The likelihood of screenplays getting produced follows inverted U-shaped curves for emotionality, number of characters, scene pace, and percentage of outdoor scenes. The likelihood of screenplays being produced gradually grows as their overall emotions and key product features increase; however, there is a point beyond which the likelihood of greenlighting starts to decrease.

This finding is not surprising; an increase in the relative number of characters (normalized by number of pages) can create more tension and depth in stories and, accordingly, increase the chances of scripts being greenlighted. However, too many characters can overly complicate narratives and divert attention from key plots, which makes screenplays less likely to be produced. Similarly, excessively fast pace in changing scenes can create information overload for the audience and decrease the attention and satisfaction of the movie (Malhotra, Jain, and Lagakos 1982). These results are consistent with findings in the screenplay-writing domain and the opinions of screenplay experts (e.g., Batty 2014; McKee 1997; Murtagh and Ganz 2014; Smith 2003).

In contrast, positivity and several product features in screenplays (e.g., the number of dialogs, and the percentage of dialogs by the minor characters) do not contribute to separating the produced and unproduced screenplays. This finding is similar to the model-free evidence illustrated in Table 6 as well.

Insert Table 7

Finally, the exclusion variables (PRIORSP and PRIORSPAWARDS) have significant and non-zero coefficients. The chances of screenplays being greenlighted and produced increase if the screenplays are written by writers who have more produced works ($\xi = 0.432$, $p < 0.01$) and have received many screenplay writing awards already ($\xi = 1.611$, $p < 0.01$).

Final Model Estimation

The results for the model corresponding to box office performance are in Table 8; they indicate that both the product and emotional features of screenplays have significant effects on box office ROI.

Importance of emotional features is highlighted in the results. Screenplays that are higher in emotionality have a significantly positive effect on ROI; however, an increase in the level of positivity in screenplays does not have statistically significant influence movie performance. As discussed in studies of emotional arc, our results also seem to suggest the importance of the magnitude of emotions throughout the screenplay rather than the positive or negative direction of the words (Reagan et al. 2016).

Insert Table 8

With regard to product features, screenplays with more characters, higher percentages of outdoor scenes, and more dialogic interactions have a significant impact on box office ROI. In contrast, the effect of faster scene pace is negative, and dialogic interaction between minor characters does not contribute to films' performance. Unlike the results of the selection model, the quadratic terms of the product and emotional features are not significant in the main model. It is possible that there is no tipping point observed in our data set of greenlighted screenplays, however, that does not mean that inverted-U relationships do not exist. It is also possible that the screenplay experts may intuitively know how to select scripts without too many key features. We account for the potential expert intuition by handling the endogeneity issues.

The effects of product features and emotional features of an idea on market outcome are influenced by the product category of the idea. As expected (Proposition 2), screenplay elements have differential effects depending on genre. Regarding emotional elements, all genres enhance or diminish the effect of emotionality on market outcome. Action movies, comedy, and dramas augment the effect of emotionality on ROI, but thrillers diminish the effects of both emotionality and positivity on ROI. With regard to the effects of product features on box office ROI, action movies and thrillers significantly negatively moderate the effect of the number of characters. This result indicates that more characters hurts the box office ROI of action movies and thrillers more than other genres. Meanwhile, having more numbers of characters actually enhances box office ROI for dramas. Concerning scene pace, comedy screenplays with faster-paced scene changes perform better at the box office. The effects of increased percentage of outdoor scenes on ROI are less for both dramas and thrillers. Finally, an increase in the number of dialogic interactions has a significant and positive moderating effect on ROI for comedies but a diminished effect on dramas and thrillers. Specifically, there is a diminished effect on ROI of increased dialogic interactions among minor characters for dramas and thrillers. Although these results are specific to the film context, they validate the expectation that the main effects between ideas and final market outcomes are heavily influenced by product category.

The control variable results are consistent with the findings of previous papers (Heath et al. 2015; Litman 1983; Liu, Mazumdar, and Li 2014). With respect to firms' strategic actions, the logarithmic forms of production resources and marketing resources both have significant and positive effects on ROI. These results suggest that the effects on box office ROI are positive but diminishing with regard to increases in the allocation of resources to production and marketing. Moreover, the interaction of production and marketing resources is positive and significant indicating the synergy between the firms' strategic actions. Finally, IMR is statistically different from zero, suggesting some selection bias issue (which has been accounted for in our model). The endogeneity correction residuals are also significant.

Robustness Analysis

As previously discussed, the correlation between domestic and worldwide gross revenues is very high, so we focus on screenplays produced in the United States. To address the importance of new product ideas for market outcomes, we test the relationships between key focal variables and various measures of market outcome. We also perform a robustness check to evaluate the appropriateness of the variable operationalization, in which we test the effect of product and emotional features of ideas using three movie performance measures: domestic gross revenue, worldwide gross revenue, and worldwide ROI. The domestic and worldwide gross revenues are from IMDb.

With regard to worldwide ROI, we were unable to collect individual movie-level global marketing expenses due to data limitations. Instead, we resort to the next best option, which is using the average ratio of global versus U.S. movie advertising expenditure, and calculate the worldwide marketing cost. We find that the global marketing expenditure is on average 2.3 times greater than the domestic advertising cost (Statista 2016; Statista 2014). The correlation between the computed worldwide box office ROI and domestic box office ROI is 0. 7933 ($p < 0.001$). Using the estimated worldwide ROI, we could determine whether the relationship between new product idea elements and market performance held at the global level.

Table 9 shows that the relationships between product and emotional features of ideas and firms' strategic actions are consistent across differing market-outcome operationalizations. Therefore, the statistical significance and direction of the relationships across the variables are consistent and robust.

Insert Table 9

Testing for Unobserved Heterogeneity

In the main study, we account for observed heterogeneity using the product category of movie genre. In this section, we employ a latent class regression model to account for unobserved heterogeneity, as well as to uncover any homogeneous segments in the data set that might explain the market outcomes. We test for meaningful segments of new product ideas (i.e., screenplays) that differ with regard to box office ROI. To determine whether these segments existed, we use the FlexMix function in R (Leisch 2004). The latent class analysis varies the number of segments and determines the segment number that provides the lowest Bayesian information criterion (BIC) values. Table 10 shows the results.

Insert Table 10

The BIC value is smallest for the one-segment solution, so one segment represents the optimal number of segments; no unobserved heterogeneity exists, and it is not necessary to segment into multiple latent segments. This finding suggests that the variables of new product idea, product category, and firms' strategic actions, as used in the box office ROI model, are sufficient to explain heterogeneity across screenplays. Since the key components of new product ideas (i.e., product and emotional features) are highly dependent on the product category (i.e., genre), heterogeneity can be captured based on the observed information, which in this case the movie genre.

GENERAL DISCUSSION

This study aims to improve the idea screening process of NPD by identifying new product ideas that are more likely to lead better market outcome. The findings of the study make the following contributions:

- Proposes two key features of new product ideas
- Objectively evaluates idea features using text analysis

- Determines whether these features explain market outcomes
- Details the influence of the product category in the relationship between new product ideas and their market outcomes

The results of this study have several implications for academia and companies that are pressured to create new products and services. We have shown that new product ideas can be evaluated at the early stage of NPD with text analysis by measuring the product and emotional features of in the ideas.

Theoretical Implications

Theoretically, this paper contributes to NPD literature on early assessments of new product ideas that do not follow sequential stage-gate systems. This study is one of the few to consider the contributions of new product ideas and firms' strategic actions to the financial outcomes of ideas rather than relying on indirect purchase intentions.

In contrast to other work focusing mainly on the product specific features in the new product ideas, our research explores and highlights the importance of emotional features. Utilizing text-analysis and sentiment analysis, we demonstrate both product and emotional features to explain the market outcome. Our research supplements the growing interest of understanding emotions in marketing. We believe understanding emotionality brings exciting research opportunities in the new product development and innovation domain.

Managerial Implications

Firms are challenged to create successful new products to stay competitive and be profitable. However, it should not be assumed that all new products will become financially successful. This study proposes using a cost-and time-efficient text analysis to improve idea-screening process and increase the chance of product success. Integrating objective idea evaluation methods such as text-driven analyses not only improves the idea-screening/decision-making process but also reduces the costs of an idea evaluation.

According to the current study findings, managers should ensure that their new products have product features that improve the product consumption experiences of consumers but also ensure the magnitude of emotions experienced by the consumers during consumption. Moreover, our findings can be leveraged to help idea generators propose ideas that have the traits of key idea elements (Toubia and Netzer 2017). For example, automakers like Tesla not only make cars with innovative product features but also allow consumers experience emotions while driving their cars. Taking our findings further, companies can adapt appropriate product features based on real-time emotionality, with the advancement of artificial intelligence (AI). For instance, automakers can apply "Emotion AI" that can understand the emotional and cognitive states of the drivers and initiate safety features to improve the overall transportation experience (Crowe 2018).

By integrating the aforementioned findings, our study can be extended to brand marketing strategy. The marketing strategy that utilizes emotions and build connection with the customers can lead to better customer loyalty and financial returns. For example, Coke's recent "Taste the Feeling" marketing campaign is its successful attempt to highlight emotionality (e.g., feeling good and connected with others) while signaling its competitive product features (e.g., taste) (Schultz 2016).

Moreover, we believe our findings can be extended to other tangible goods and experiential products (e.g., books, music, games, shows), for which both product features and emotional features can be identified and analyzed through textual analysis. For example, developers can predict the market performance of mobile fitness applications by identifying both initial ideas' product features (e.g., biometric systems and data analytic components) and emotional features (e.g., feelings of accomplishment in achieving goals or having a sense of community with other users).

Movie-Industry Implications

In the context of the movie industry, this study improves understanding of studios' greenlighting process by suggesting a better tool for assessing the monetization potential of screenplays and avoiding investment in non-hit movies. The model provides a cost-efficient process that avoids expensive and subjective human evaluations of ideas by applying more reliable objective evaluations of screenplays during initial screening. Screenplay writers can use this approach as a tool for screenplay analysis by incorporating successful key screenplay elements prior to submitting their work to production houses.

LIMITATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

There are several limitations of the study that can be addressed in future research. One limitation of this study is that for the analyses, we used final-version shooting scripts, that is, the final versions of screenplays used in producing the films. Although changes in scripts beyond this final-version state are rare, future research should address this limitation in their studies.

A second limitation relates to screenplay content. Content (i.e., storylines) of screenplays is important to consider because the settings, characters, ideas, selection, and arrangement of events of screenplays require, inspire, and mutually influence one another (McKee 1997). Presently, only human experts can evaluate the intricacies of storyline meanings. For example, content elements such as character development are important to strong screenplays; weak character growth can inhibit audiences in emotionally connecting with films (Selbo 2015). Previous studies have shown empirically that content matters to box office performance

(Eliashberg, Hui, and Zhang 2014; Hunter, Smith, and Singh 2016). We concur with these findings and acknowledge the importance of content evaluation. However, content evaluation is time-consuming, costly, and subject to human judgment errors (e.g., rejecting quality screenplays or accepting poor screenplays). Therefore, unlike Eliashberg, Hui, and Zhang (2014), who hired script readers to evaluate the content of every screenplay in their sample, we do not include content analysis in this study, because it is not in line with conducting objective, cost-effective evaluations. However, future studies can incorporate the proposed conceptual framework as a first-stage analysis and use content analyses for second-stage validation. For example, rather than analyzing the content of all screenplays, the proposed method can be applied to pre-screen screenplays with higher chances of box office success. Subsequent researchers can prioritize expert content evaluation for a short list of screenplays.

Finally, future research can support the suggested framework with a grounded theory approach. In this paper, we rely on the support of the literature to find the relevance of new product idea the final outcome based on the support of the literature. Future studies can further augment the proposed framework by conducting managerial interviews across industries and product categories, and finding support for the importance of the suggested drivers of market outcome. Furthermore, the elements of a new product idea can be better highlighted depending on firms' resource allocation efforts on production or marketing. Future studies can explore the interplay between the firms' strategic actions and the new product idea.

TABLES & FIGURES

Figure 1: Conceptual Framework

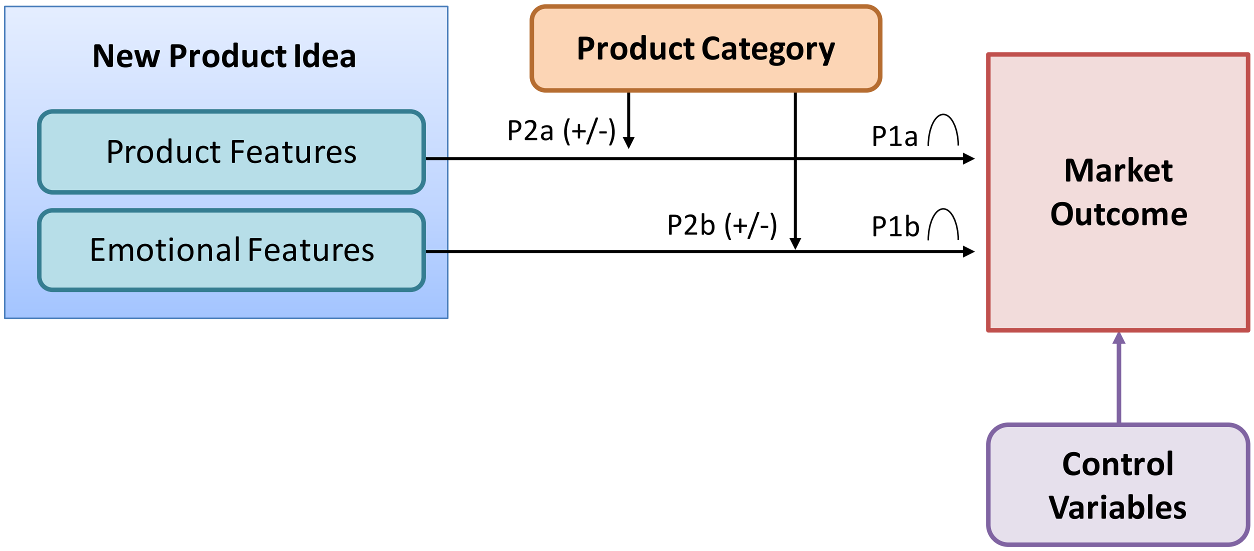

Table 1: Select Studies of Early-Stage New Product Evaluation

Select Studies	Idea-based Evaluation	Dependent Variable	Moderation of Product Category	Proposed Method
Goldenberg, Lehmann, and Mazursky (2001)	-Templates of product change -Source of idea -Project determinants	Product success	No	Logistic regression
Chandy et al. (2006)	-Speed of product launch -Number of ideas -Expertise -Idea importance	Product conversion ability	No (used as control variables)	Logistic regression
Kornish & Ulrich (2014)	-Purchase intention -Expert evaluation	Sales	No (used as control variables)	2SLS
Toubia and Netzer (2017)	Each idea's prototypicality of its edge weight distribution	Average creativity rating; proportion of positive votes	No	Regression; binomial regression
This Study	**New product idea**	**Market outcome (Return on Investment)**	**Yes**	**System of equations**

Table 2: Select Studies in a Movie Context

Select Studies	Pre-Production Predictor(s)	Screenplay Features		Dependent Variable	Account for:			Proposed Method
		Product	Emotional		Moderation of Product Category	Selection -Bias	Endogeneity	
Gemser, Leenders, and Weinberg (2012)	Production budget and star power	No	No	Box office revenue	No	No	No	Regression
Geoetzmann, Ravid, and Sverdlove (2013)	Price of screenplay	No	No	Box office revenue	No	No	No	Regression
Eliashberg, Hui, and Zhang (2007)	Text elements from movie spoiler	Script-specific variables and bag-of-words	No	Box office ROI	No	No	No	Bag-CART
Eliashberg, Hui, and Zhang (2014)	Text elements from movie screenplay	Script-specific variables and bag-of-words	No	Box office ROI	No	No	No	Kernel-based approach
Hunter, Smith, and Singh (2016)	Text elements from movie screenplay	Text network size	No	Box office revenue	No	No	No	Regression
This Study	**Text elements from movie screenplay**	**Script-specific variables**	**Yes**	**Box office ROI**	**Yes**	**Yes**	**Yes**	**Systems of equations**

Table 3: Variables and Data Sources

Variable	Description (Operationalization)	Data Source
Market Outcome		
Box office ROI	Domestic box-office ROI measured as $\frac{\text{Domestic box−office revenue}}{\text{Total Cost}}$. Total cost is the sum of advertising expenditure and production cost.	Computed
New Product Idea Components		
Product Features		Text analysis of screenplays
SCENES	Average pace of the scenes (number of scenes/ total number of screenplay pages)	
OURDOOR%	Percentage of outdoor scenes (outdoor scenes/total number of scenes)	
DIALOGS	Relative frequency of dialogic interaction (Absolute frequency of dialogic interaction/pages)	
MINORDI%	Dialogic interaction between minor characters (number of dialogic interactions between minor characters/ total number of dialogic interactions)	
CHARACTERS	Relative number of characters (total number of characters/total number of screenplay pages)	
Emotional Features		
EMOTIONALITY	Percentage of words that are classified as either positive or negative	LIWC
POSITIVITY	Difference between the percentage of positive and negative words	
Product Classification		
ACTION	genre dummy variable for action movies (1 if action, 0 otherwise)	boxofficemojo
COMEDY	genre dummy variable for comedies (1 if comedy, 0 otherwise)	boxofficemojo
DRAMA	genre dummy variable for dramas (1 if drama, 0 otherwise)	boxofficemojo
THRILLER	genre dummy variable for thrillers (1 if thriller, 0 otherwise)	boxofficemojo
Movie Characteristics (Control Variables)		
PRODUCTION RESOURCES (PR)	Direct and combined effects of director and star power • Director power measured as the average box office receipt of the director's five most recent films • Star power (focus on first three stars posted on the movie poster) measured as the average box office receipt of the three stars' five most recent films	IMDb

MARKETING RESOURCES (MR)	Domestic marketing expenditure ($ millions)	S&P Global Market Intelligence
PR*MR	The product of production resources and marketing resources	Computed
SEQUEL	Sequel dummy variable (1 if sequel, 0 otherwise)	IMDb
NOVEL BASED	Novel-based dummy variable (1 if novel-based, 0 otherwise)	IMDb
MPAA-R	MPAA Film Rating dummy variable (1 if R-rated, 0 otherwise)	IMDb
SEASONALITY	Dummy variables for seven major holidays (New Year's Day, Presidents' Day, Memorial Day, Independence Day, Labor Day, Thanksgiving, Christmas)	IMDb
COMPETITION	Total number of films (including new releases) running in theaters during the week of release	The-Numbers
CRITIC REVIEWS	Ratings given by critics on a 1-5 scale	Rotten Tomato
AUDIENCE REVIEWS	Ratings given by audience on a 1-5 scale	Rotten Tomato
AWARDS	Total number of Academy Awards won	IMDb
SCREENS	Number of screens on opening weekend	boxofficemojo
MAJOR STUDIO	Dummy variable for major studios. Major studios: Walt Disney, Warner Brothers, Fox, Universal, Sony, Paramount Pictures	IMDb

Table 4: Descriptive Statistics

Variable	Mean	SD	Min	Max
Market Outcome				
Box office ROI	0.577	0.336	0.006	1.827
New Product Idea Components				
Product Features				
SCENES	1.349	0.473	0.235	3.302
OURDOOR%	0.359	0.141	0.036	0.916
DIALOGS	4.203	1.476	1.444	10.989
MINORDI%	0.120	0.094	0.000	0.476
CHARACTERS	0.402	0.230	0.085	1.730
Emotional Features				
EMOTIONALITY	7.603	1.394	4.220	13.490
POSITIVITY	0.310	1.516	-3.480	7.490
Product Classification				
ACTION	0.202	0.402	0	1
COMEDY	0.158	0.365	0	1
DRAMA	0.273	0.446	0	1
THRILLER	0.115	0.320	0	1
Movie Characteristics (Control Variables)				
PRODUCTION RESOURCES (PR)	7.096	1.963	1.941	10.933
MARKETING RESOURCES (MR)	3.329	0.891	0.140	4.471
SEQUEL	0.111	0.314	0	1
NOVEL BASED	0.216	0.412	0	1
MPAA-R	0.588	0.493	0	1
SEASONALITY	0.038	0.191	0	1
COMPETITION	91.042	34.164	6	155
CRITIC REVIEWS	0.605	0.141	0.170	0.920
AUDIENCE REVIEWS	0.656	0.189	0.100	0.980
AWARDS	12.301	24.264	0	171
SCREENS	7.437	0.959	2.398	8.731
MAJOR STUDIO	0.638	0.481	0	1

Table 5: In-Sample and Out-of-Sample Mean Absolute Percentage Error (MAPE)

	MAPE	
Variables	**In-Sample**	**Out-of-Sample**
Control Variables	47.93%	57.04%
Control + Screenplay Elements*	27.54%	34.15%
Control + Screenplay Elements + Genre	15.34%	20.50%

* Screenplay Elements are both product features and emotional features.

Table 6: Mean Differences between Produced and Unproduced Screenplays

	Produced Screenplays	**Unproduced Screenplays**	**Difference**	
EMOTIONALITY	7.603	5.883	1.719	***
POSITIVITY	0.361	0.310	0.051	
CHARACTERS	0.402	0.367	0.035	**
SCENES	1.348	1.418	-0.070	**
OUTDOOR%	0.359	0.237	0.122	***
DIALOG	4.758	4.585	0.173	**
MINOR%	0.119	0.118	0.001	
PRIORSP	8.595	0.457	8.138	***
PRIORSPAWARDS	6.348	0.007	6.348	***
Number of observations	425	420		

Note: *$p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Table 7: First-Stage Probit Model to Correct for Sample Selection

Variables	Coefficient		Standard Error
Intercept	-29.512	***	7.200
EMOTIONALITY	4.460	***	1.618
EMOTIONALITY SQ	-0.116	***	-0.009
POSITIVITY	-1.233		0.391
POSITIVITY SQ	-0.110		0.089
CHARACTERS	1.946	***	0.556
CHARACTERS SQ	-1.543	***	0.422
SCENES	6.194	***	1.581
SCENES SQ	-1.066	***	0.379
OUTDOOR%	7.796	***	0.899
OUTDOOR% SQ	-6.960	***	1.206
DIALOGS	0.224		0.637
DIALOGS SQ	-0.005		0.064
MINORDI%	2.062		4.762
MINORDI% SQ	-8.076		9.179
PRIORSP	0.432	***	0.105
PRIORSPAWARDS	1.161	***	0.325

Note: *$p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Table 8: Final Model Estimation

Variables	Coefficient	Standard Error	
Intercept	-1.900	0.727	***
EMOTIONALITY	0.140	0.046	***
EMOTIONALITY SQ	0.011	0.113	
POSITIVITY	0.010	0.009	
POSITIVITY SQ	0.002	0.003	
CHARACTERS	0.134	0.056	**
CHARACTERS SQ	-0.028	0.043	
SCENES	-0.064	0.029	**
SCENES SQ	0.001	0.009	
OUTDOOR%	0.223	0.092	**
OUTDOOR% SQ	-0.043	0.106	
DIALOGS	0.022	0.009	**
DIALOGS SQ	-0.002	0.004	
MINORDI%	0.016	0.156	
MINORDI% SQ	-0.172	0.378	
ACTION	-0.046	0.041	
COMEDY	0.001	0.022	
DRAMA	-0.025	0.008	***
THRILLER	-0.049	0.024	**
EMOTIONALITY*ACTION	0.009	0.004	**
EMOTIONALITY*COMEDY	0.012	-0.006	**
EMOTIONALITY*DRAMA	0.024	0.007	***
EMOTIONALITY*THRILLER	-0.012	0.003	***
POSITIVITY*ACTION	-0.013	0.015	
POSITIVITY*COMEDY	0.011	0.014	
POSITIVITY*DRAMA	0.003	0.011	
POSITIVITY*THRILLER	-0.037	0.019	**
CHARACTERS*ACTION	-0.153	0.092	*
CHARACTERS*COMEDY	0.014	0.082	
CHARACTERS*DRAMA	0.148	0.084	*
CHARACTERS*THRILLER	-0.138	0.043	***
SCENES*ACTION	0.032	0.029	
SCENES*COMEDY	0.044	0.015	***
SCENES*DRAMA	-0.004	0.029	
SCENES*THRILLER	-0.011	0.015	
OUTDOOR%*ACTION	-0.094	0.100	
OUTDOOR%*COMEDY	0.033	0.053	
OUTDOOR%*DRAMA	-0.089	0.049	*
OUTDOOR%*THRILLER	-0.223	0.057	***
DIALOGS*ACTION	-0.189	0.116	
DIALOGS*COMEDY	0.014	0.007	*

DIALOGS*DRAMA	-0.218	0.101	**
DIALOGS*THRILLER	-0.033	0.012	***
MINORDI%*ACTION	-0.109	0.204	
MINORDI%*COMEDY	0.130	0.237	
MINORDI%*DRAMA	-0.232	0.102	**
MINORDI%*THRILLER	-0.219	0.126	*
EMOTIONALITY*CHARACTERS	0.011	0.022	
EMOTIONALITY*SCENES	0.007	0.009	
EMOTIONALITY*OUTDOOR%	0.002	0.003	
EMOTIONALITY*DIALOGS	0.029	0.012	**
EMOTIONALITY*MINORDI%	-0.036	0.064	
POSITIVITY*CHARACTERS	-0.065	0.049	
POSITIVITY*SCENES	0.015	0.020	
POSITIVITY*OUTDOOR%	-0.002	0.005	
POSITIVITY*DIALOGS	0.056	0.063	
POSITIVITY*MINORDI%	-0.006	0.125	
logPR	0.017	0.007	**
logMR	0.075	0.015	***
logPRMR	0.019	0.005	***
SEQUEL	0.115	0.034	***
NOVEL BASED	-0.020	0.025	
MPAA-R	-0.036	0.018	**
SEASONALITY	-0.020	0.056	
COMPETITION	-0.001	0.000	*
CRITIC REVIEWS	0.129	0.072	*
AUDIENCE REVIEWS	0.355	0.080	***
AWARDS	0.003	0.001	***
SCREENS	0.045	0.015	***
MAJOR STUDIO	0.018	0.023	
ENDOGENEITY RESIDUAL-EMOTIONALITY	0.030	0.011	***
ENDOGENEITY RESIDUAL-POSITIVITY	-0.017	0.009	**
ENDOGENEITY RESIDUAL-CHARACTERS	0.005	-0.003	**
ENDOGENEITY RESIDUAL-SCENES	-0.062	0.029	**
ENDOGENEITY RESIDUAL-OUTDOOR%	-0.054	0.027	**
ENDOGENEITY RESIDUAL-DIALOGS	-0.002	0.001	**
ENDOGENEITY RESIDUAL-MINORDI%	-0.037	0.012	***
IMR	-0.103	0.040	**
R-Square (Adj R-Square)	0.5465 (0.4538)		

Table 9: Robustness Check Results for Different Market Outcomes

	Domestic						World-wide					
	DV=log(ROI)			DV=log(Rev)			DV=log(ROI)			DV=log(Rev)		
Variables	Coef	SE		Coef	SE		Coef	SE		Coef	SE	
EMOTIONALITY	0.140	(0.047)	***	0.873	(0.327)	***	0.214	(0.099)	**	1.124	(0.372)	***
EMOTIONALITY SQ	0.011	(0.114)		0.013	(0.013)		0.014	(0.010)		0.028	(0.016)	
POSITIVITY	0.010	(0.010)		0.026	(0.029)		0.022	(0.015)		0.026	(0.055)	
POSITIVITY SQ	0.002	(0.004)		0.007	(0.010)		-0.007	(0.006)		-0.023	(0.02)	
CHARACTERS	0.104	(0.062)	*	1.231	(0.598)	**	0.373	(0.211)	*	2.562	(1.522)	*
CHARACTERS SQ	-0.028	(0.043)		-0.326	(0.322)		-0.244	(0.165)		-0.651	(0.413)	
SCENES	-0.064	(0.029)	**	-1.752	(0.585)	***	-0.853	(0.306)	***	-2.324	(0.769)	***
SCENES SQ	0.001	(0.009)		0.248	(0.202)		0.077	(0.204)		0.187	(0.112)	*
OUTDOOR%	0.173	(0.094)	*	1.505	(0.614)	**	0.377	(0.217)	*	2.907	-1.633	*
OUTDOOR% SQ	-0.043	(0.107)		-0.254	(1.848)		-0.201	(0.471)		-1.390	(1.183)	
DIALOGS	0.022	(0.009)	**	0.291	(0.165)	*	0.032	(0.014)	**	0.199	0.085	**
DIALOGS SQ	-0.002	(0.004)		-0.029	(0.019)		-0.005	(0.006)		-0.024	(0.019)	
MINORDI%	0.016	(0.156)		1.263	(2.530)		0.508	(0.602)		1.578	(1.514)	
MINORDI% SQ	-0.172	(0.379)		-3.894	(2.523)		-0.124	(1.318)		-1.922	(3.792)	

*In this table, we report the results of the main variables to illustrate the consistency in the direction and significance across different market outcome measures.

Table 10: Latent Class Analysis to Understand Unobserved Heterogeneity

Number of Segments	Log-Likelihood	AIC	BIC
1	103.17	-86.34	156.78
2	175.64	-109.28	381.02
3	342.40	-320.81	416.67

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