International Journal of Application or Innovation in Engineering & Management (IJAIEM)
Web Site: www.ijaiem.org Email: editor@ijaiem.org
Volume 11, Issue 11, November 2022 ISSN 2319 – 4847

Valuing sequel right via brand extension spillover effect

Zheng Ren [1], Zihui Zhuo [2] and Zhiwen Zhu [3*]

[1]Business School, Huaiyin Institute of Technology, Huaian 223001, China

[2]Business School, Huaiyin Institute of Technology, Huaian 223001, China

[3]Business School, Huaiyin Institute of Technology, Huaian 223001, China
**Correspondence*

Abstract

Brand extension right is a part of brand value, which reflects a brand's sustainability to launch new products with the existing brand name. Conceptualizing movie sequels as brand extensions of their parent movies, we propose a novel approach to evaluate the financial value of the right to make a sequel (referred to in this article as the "sequel right") from the perspective of brand extension spillover effect and analyze the impacts of core attributes in brand extension (e.g., whether the sequel is produced by the original team) on the value. This valuation approach can be used to explain the revenue and risk differences between the sequel and non-sequel movies, thus providing investors with a novel approach to evaluate the risks of the two investment alternatives. We conducted regression analyses for 96 sequel subsamples and the matched 223 non-sequel subsamples screened in mainland China theaters during 2010-2017 and estimated the risk-adjusted value of sequel right by comparing the predicted box revenues between the sequel and the matched non-sequel subsamples.

Keywords: brand extension, movie sequel, sequel right, spillover effect

1. INTRODUCTION

Brand extension strategy refers to the use of an extant brand name on a new product, which helps to improve consumers' interest in the new product while it is introduced [1]. This strategy is particularly important for new products that reach peak income immediately after being introduced and then diffuse in the market following an exponential-decay pattern. These products usually include high input media products such as movies, television, books, music, and games [2,3].

Brand extension right is a very important but difficult-to-measure intangible asset [4]. We examine an important issue of brand extension in this paper: How to measure the financial value of this right? We conceptualize sequel films as brand extensions of their parent films. Through the analysis of the Chinese film market data, a novel approach is proposed to enable movie investors to estimate a movie's sustainability in producing sequels and calculate the financial value of the sequel right. For example, the Bona Pictures Group owns the right to produce a sequel to the action movie *Action Red Sea*, and its corporate value should reflect the value of that right. But any firm with a well-known brand may ask: What is the financial value of this right?

In addition to the impact on the balance sheet, the valuation of brand extension rights is also important for the transactions of these rights. Such transactions are ubiquitous in the film, television, and other media industries. For example, in February 2017, Goldlok Toys, a listed company of China, signed a license agreement with Disney, and Disney allowed Goldlok Toys to use Disney related prototypes and trademarks on specific toy products at a specific time limit, and authorize Goldlok Toys to sell licensed products through a specific channel. The battle for "dormant or interrupted" sequels has also been fierce among major movie studios. In 2001, Intermedia Films spent $14.5 million to get the sequel right of *The Terminator*. So, is this price overvalued or underestimated the value of *The Terminator* brand?

Brand extension products usually have a variety of attributes, but when a firm has just acquired an extension right, these attributes are often not finally formed, so it is also important to understand how changes in these attributes affect the value of the extension right. For example, if the star in the parent film (Arnold Schwarzenegger) does not participate in the sequel, how will the value of the sequel to *The Terminator* change?

Most extant researches focus on the determinants of consumer evaluations of brand extensions. The research on the valuation of brand extensions can be first traced back to 28 years ago [5]. However, little research has assessed the revenues generated by individual brand extensions. Because this information is crucial for accurately assessing firm value and negotiating between trading parties of extension right, its lack has become a “significant gap in existing approaches” [6].

We aim to develop a valuation approach of brand extension rights, which can be used to evaluate an individual brand’s extension right (specifically in this paper, the sequel right of a parent movie). Using the Chinese film market data from 2010 to 2017, we establish a valuation model of movie sequel right based on brand extension theory. This model can well explain the income- and risk-related effects of brand extensions. We illustrate the applicability of the model through a valuation example for an actual movie brand.

2. LITERATURE REVIEW

2.1 Valuation of brand extension right

Brand extension strategy is an important brand strategy. Although it has been extensively discussed by both academia and industry [7], little is known about the valuation of the right that a firm owns to extend a brand. According to Simon and Sullivan's [8] brand valuation framework, valuing a brand’s extension right requires comparing the market performance of brand extension products with that of similar products without brand identification. Although some literature has used stock prices [9] and market share [5] to measure market performance, little has directly used product income to measure the financial value of a brand’s extension right.

Some researchers believe that the real options theory should be used to estimate the value of a film’s sequel right [10]. As information increases over time, options theory requires a multi-period, multi-product perspective [11], which means that multiple options are valued before the parent brand (i.e., the existing parent film) is released. However, we focus on how to evaluate the financial value of a brand’s extension right given that the brand (parent film) has been successful.

2.2 Movie brand extension

Brand extension theory holds that consumers’ attitudes toward a brand will shift to other products of the brand because they usually memorize a product by a certain brand name [1]. Similarly, audiences remember a film by its title (i.e. the brand of the film), so the title is an important part of the film’s copyright. A sequel film inherits the name of its parent film, so the parent film and the sequel film can be deemed as two products of the same movie brand according to brand extension theory. Therefore, a sequel movie can be conceptualized as an extension of its parent movie, through which studios try to produce the new movie with the same roles and backgrounds to maximize their benefits from the parent movie [12]. Films’ production and publicity costs have soared in recent years, and sequels have helped studios take advantage of successful parent movies for high profits [13]. Although sequels have these advantages, they are not necessarily guaranteed to be a success at the box office. Box office failures are frequent in sequels. One of the key issues in the success of sequels is the criteria by which a film company chooses among movie brands when making a sequel [14].

Several studies have conceptualized sequels as the brand extensions of parent movies. Sood and Dreze [12] analyze consumers' psychological responses to the changes of a sequel’s title but do not measure the sequel’s financial success. Basuroy and Chatterjee [15] examine the effects of sequel characteristics on box office and find that, box office revenues and profits of sequels are lower than those of parent movies, and that the smaller the interval between the release of sequels and parent movies, the more successful the box office is. Yalcinkaya and Aktekin [16] investigate the relative performance of the parent product and its extended products of an experiential product series with the same core attributes. Using franchise data and Bayesian models, they find that the core attributes of a movie series, such as continuity, release time selection, and consumer perception, are the key antecedents of the success of the series. Deeming adaptations (i.e., adaptations from video games, TV series, toy lines, comic books, and books) and sequels as brand extensions, Kim [17] formulates brand extension strategies for the film industry by examining movies screened during 2010-2013 in the U.S. He finds that adaptations from comic books and toy lines are successful, and those made as sequels are much more successful in terms of box office revenue and profit.

Some other movie studies have found that sequels are associated with high returns, by adding a sequel dummy variable to regression equations [e.g. 18,19,20], or a sequel predictor to box office prediction models [e.g. 21]. However, these estimates may be seriously distorted because sequels usually have higher budgets and are shown in more cinemas [15,22-24]. Besides, the single sequel parameter makes it impossible for researchers to evaluate a particular film’s sequel right, especially while not considering the characteristics of the parent film and the fit between the sequel and the parent film.

3. A CONCEPTUAL MODEL OF BRAND EXTENSION RIGHT

We define the spillover effect as the risk-adjusted revenue difference between a new brand extension and similar unbranded new products [8] (see Figure 1). We also examine some key determinants of brand extension success (e.g., whether the production team of a parent film participates in the sequel), to be able to evaluate a brand's extension right under different conditions. To estimate the value of a potential brand extension, only factors that the brand's owner can control and that are known before the product is produced are considered.

According to the literature on brand extension [7,25,26], we divide the determinants of brand extension success into four categories: 1) parent brand characteristics; 2) the fit between a brand extension and its parent brand; 3) the interaction between parent brand characteristics and fit; 4) extended product characteristics. Table 1 lists these determinants and their corresponding factors and operationalizations in this research context.

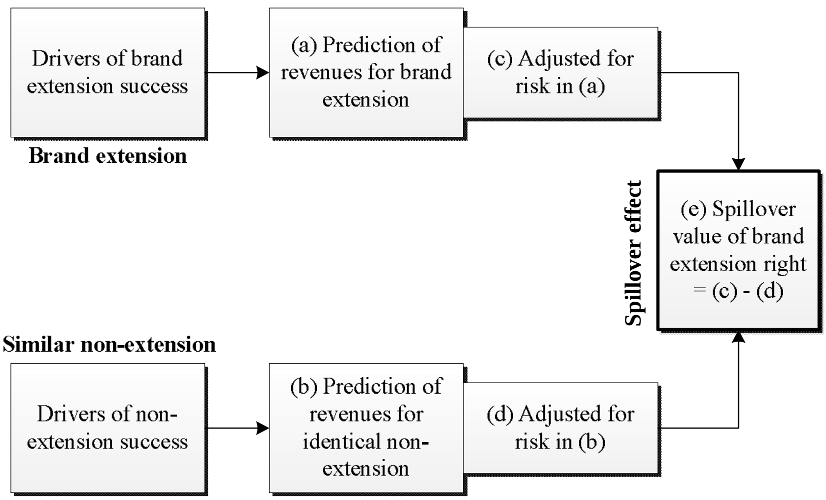


Figure 1 The valuation model of brand extension right

First of all, in terms of parent brand characteristics, a parent brand's image (PBI) and brand awareness (PBA), as well as their interaction, would affect consumer evaluations of the brand extension [25,27]. According to the characteristics of the film industry, the production area of the parent film (i.e. the parent film is domestic, foreign, or Sino-foreign coproduced) is included as a proxy variable to the cultural familiarity of the parent brand [20]. Secondly, according to the brand extension literature, the fit between the extension and its parent brand has a significant impact on consumer evaluations of the brand extension [28]. Because of this, 10 fit variables are used to measure the continuities/similarities of the production team, genre, poster, title, budget, and release season between the sequel and its parent film respectively. This multi-dimensional measurement is more conducive to revealing the practical implications of the research than the general fit measurement. Thirdly, considering that the interaction between parent brand characteristics and fit also affects brand extension evaluation [7], cross-product terms (CPTs) of parent brand characteristics and fit variables are constructed to form 10 $PBI \times fit$ and 10 $PBA \times fit$ interactions. Finally, in terms of the characteristics of the extended product, the sequel's budget and distribution intensity are included as proxy variables to marketing support and retailer acceptance respectively [7,28], and some of the unique features of the film industry (i.e., star power, genres, and audience scorings of the sequels) are also included [29,30].

The extended product characteristics (i.e., budget, distribution intensity, star power, genres, and audience scorings of the sequel in this research context) and cultural familiarity variables in the brand extension (i.e., sequel) model are also applied to the non-extension (i.e., non-sequel) model because such information is available for both non-sequel films and sequels.

4. METHOD

4.1 Samples and matching procedure

First, data on 96 first sequels (only the first in a series of sequels) were collected from movies screened in cinemas in mainland China from 2010 to 2017. Then, 223 non-sequel matching samples were extracted from the 892 non-sequel movies which were released in the same period by using a multi-variable matching procedure. The matching samples and the sequel samples are matched by film characteristics such as budget and star power. By this matching procedure, sequels and non-sequels with similar characteristics can be identified, thus eliminating potential sample bias, which is mostly due to the difference in the processing of the two by studios [31]. Specifically, using four key box office predictors as the matching variables (i.e. budget, distribution intensity, star power, and audience scorings), we calculated squared Euclidian distances between each sequel and all 892 non-sequel movies and selected 2-3 nearest non-sequel movies for each sequel as its matching samples [31]. The data were drawn from well-known Chinese movie websites such as the China Film Database, maoyan.com, and 1905 Films. All variables were standardized before the matching.

4.2 Operationalization

The dependent variable is the sample's box office revenues in mainland China. Box office data were adjusted for inflation and the natural logarithmic transformation was carried out for the total revenue variable. The data were drawn from the Movie Box Office Network and the Chinese Film Database. PBI and PBA adopt multi-item measures to reflect the multiple facets of these two variables respectively and take the arithmetic average value of standardized scores of each item as variable values (see Table 1). PBI takes the arithmetic average value of audience scorings on three video websites: Douban.com, Mtime, and maoyan.com (alpha = 0.89). PBA is measured by two formative indicators – the total audience and the cinema screening total. The samples with a long-time span require considering the audience's forgetting of movies over time. Therefore, a forgetting curve function was used to discount the PBA scores of each movie [32].

Table 1: General and film industry-specific determinants of brand extension success

General determinants	Corresponding industry-specific determinants	Variable names [1]	Operationalizations
1) Parent brand characteristics			
parent brand image (PBI)	PBI of the parent film	*PBI*	Mean of parent film's audience scorings on Douban.com, Mtime, and maoyan.com
parent brand awareness (PBA)	PBA of the parent film	*PBA*	Mean of two formative indicators – the total audience and the cinema screening total of the parent film
PBI-PBA interaction	PBI-PBA interaction	*PBI×PBA*	CPR of regression of the CPT of PBI and PBA to the two variables [2, 3]
N.A.	the cultural familiarity of the parent film	*country_(types)*	Dummy variables indicating parent film's making countries (i.e., made in China or foreign countries, or Sino-foreign coproduced)
2) Fit characteristics			
fit	star-continuity	*fit_star*	1 if main stars of the parent film appear in the sequel and 0 if otherwise
	director-continuity	*fit_director*	1 if directors of the parent film direct the sequel and 0 if otherwise
	scriptwriter-continuity	*fit_writer*	1 if scriptwriters of the parent film and the sequel are the same and 0 if otherwise
	producer-continuity	*fit_producer*	1 if producers of the parent film and the sequel are the same and 0 if otherwise
	distributor-continuity	*fit_distributor*	1 if distributors of the parent film and the sequel are the same and 0 if otherwise
	genre-continuity	*fit_genre*	1 if genres of the parent film and the sequel are the same and 0 if otherwise
	poster-similarity	*fit_poster*	The similarity between posters of parent film and sequel from 1 = "very dissimilar" to 5 = "very similar", as coded by three independent researchers
	title-continuity	*fit_title*	1 If sequel's title simply adds a serial number to the title of its parent film and 0 if otherwise, as coded by three independent researchers
	budget-continuity	*fit_budget*	Sequel's budget divided by its parent film's budget
	season-continuity	*fit_season*	The difference in the month between the month of release of the parent film and the sequel
3) Interaction effects			
PBI-Fit interaction	interaction of PBI of parent film and each fit variable	*PBI×fit*	CPR of regression of the CPT of PBI and each fit variable to the two variables [2, 3]
PBA-Fit interaction	interaction of PBA of parent film and each fit variable	*PBA×fit*	CPR of regression of the CPT of PBA and each fit variable to the two variables [2, 3]
4) Extended product characteristics			

marketing support	budget of sequel	*budget*	Residual term of regression of inflation-adjusted budget to PBA
retailer acceptance	distribution intensity of sequel	*first_day*	Residual term of regression of percentage of first-day screenings to PBA
N.A.	the star power of the sequel	*star_power*	Residual term of regression of star power, as coded by three independent researchers from 1 = "no star" to 10 = "more than two A-listers", to PBA
N.A.	the genre of the sequel	*genre_(types)*	Dummy variables for major genres (i.e., comedy, animation, drama, etc.)
N.A.	audience scorings of sequel	*scorings*	Mean of sequel's audience scorings on Douban.com, Mtime, and maoyan.com

[1] Original data were retrieved from MBON (Movie Box Office Network), CFD (Chinese Film Database), IMDb (Internet Movie Database), Douban.com, Mtime, and maoyan.com; [2] CPR = cross-product residuals; [3] CPT = cross-product term.

Using the residual centering regression approach, the cross-product term (CPT) of PBI and PBA is regressed on these two variables to obtain the cross-product residuals (CPRs) as the *PBI* × *PBA* interaction variable (Table 1). Previous studies on brand extension have used the residual centering regression approach to minimize the multicollinearity between regression variables [33]. Generally speaking, there exist high correlations between a regression variable and its product terms, and the residual centering regression approach can reduce the multicollinearity between the regression variable and its product terms.

The fit variables are directly calculated based on second-hand data (Table 1). Among them, poster-similarity and title-continuity were coded manually by three researchers. Poster-similarity takes 1 when a sequel's poster is not similar to its parent movie's poster, 3 when neutral, 5 when very similar. If a sequel's title simply adds a serial number to the title of its parent movie (e.g., *Zhan lang 2*, also known as *Wolf War 2*), the title-continuity takes 1, otherwise 0 (e.g., *King Kong: Skull Island*). The residual centering regression approach was also used to obtain 10 *PBI* × *fit* and 10 *PBA* × *fit* interaction variables (Table 1).

In terms of extended product characteristics, we regress film characteristic variables - budget, distribution intensity, and star power of the sequels - on PBA respectively and use the residuals of these regressions rather than the original data of these variables as the product characteristic variables, so these product characteristic variables contain only the information that is not explained by PBA. Star power was manually coded by three researchers (1 = no star; 10 = more than two A-listers). By establishing the structural relationship between these variables and PBA, the endogeneity problem is controlled and the multicollinearity is reduced [29].

4.3 Parameter estimation

Firstly, we pool the sequel samples with the non-sequel samples to replicate previous researches, using a dummy variable to indicate sequels. The sample matching procedure enables us to estimate treatment effects for the sequel dummy unbiasedly [31]. An OLS regression model is used to estimate the effects of the sequel dummy, film characteristics (i.e., budget, distribution intensity, star power, genres, and cultural familiarity), and the CPTs (obtained by the residual centering approach) between the sequel dummy and the film characteristics on box office revenues. Unobserved heterogeneity is controlled by the film's release year.

Although the pooling sample model can show the general differences between the sequel and non-sequel samples in box office revenues, it cannot reveal some of the key issues in evaluating the sequel right. Specifically, the fit variables that measure the continuity/similarity between sequels and their parent films do not apply to non-sequel samples, so these variables cannot be included in the pooling sample model. For example, if a star in a parent movie does not participate in its sequel (e.g. Andy Lau starred in *Di Renjie's Empire of Heaven*, but not in *Di Renjie's Dragon King*), the variable star-continuity (and the CPT star-continuity × sequel dummy) takes 0. But in the pooling sample model, the star-continuity of non-sequel movies should also be 0. In other words, the pooling sample model with the sequel dummy cannot capture the conceptual difference between non-sequel films and sequel films with zero star-continuity. However, star-continuity may be an important variable affecting the box office of sequels, because audiences would miss the stars in parent films and may even regard it as a signal of the sequel's quality. Thus, it is expected that low star-continuity is unfavorable for the box office of sequels. Given this, confusing these two fundamentally different concepts can lead to erroneous estimates and ambiguity in the meaning of the coefficient of star-continuity.

Also, the lack of these key variables makes it difficult for the pooling sample model to explain the box office differences among different sequels. Therefore, the pooling sample model does not allow marketers to understand what is a more favorable brand extension context. Moreover, sequels and non-sequels are two different investment alternatives for film investors, so the potential differences in project-specific risk must be considered. However, the pooling sample model cannot allow investors to evaluate and compare the risk levels between the two investment alternatives.

Therefore, we further use the matched subsamples to have a comparison analysis, conducting two groups of OLS stepwise regression for the sequel and non-sequel subsamples respectively, with the independent variables and dependent variables of the two models being the same as the previous (Table 1). Stepwise regression is used to observe the existence of multicollinearity on the one hand, and to achieve an acceptable level of freedom in the case of a limited number of samples on the other hand. Given the limited number of samples, Critical F-values are set at 0.15 for entry and 0.25 for removal of variables respectively. In the two groups of regression models, the release year is included as a separate regression variable. Finally, the two groups of regression models are used to predict the box office of the sequel and non-sequel films respectively.

5. RESULTS

5.1 T-tests

The means of most of the box office predictor variables of the non-sequel subsamples are similar to those of the sequel subsamples, in other words, consistent with our expectations, the matching procedure has successfully eliminated potential sample bias. Specifically, the two subsamples' budget (M_{sequel} = ￥120.67 million, $M_{non\text{-}sequel}$ = ￥99.16 million; $F(1, 317) = 1.53$, $P > 0.20$), audience scoring ($M_{sequel} = 6.98$, $M_{non\text{-}sequel} = 6.91$; $F(1, 317) = 0.26$, $P > 0.60$) and star power ($M_{sequel} = 5.73$, $M_{non\text{-}sequel} = 6.19$; $F(1, 317) = 2.02$, $P > 0.10$) have no significant difference. Nevertheless, on average, the box office revenues of the sequels are higher than those of the non-sequels (M_{sequel} = ￥353.67 million, $M_{non\text{-}sequel}$ = ￥197.18 million; $F(1, 317) = 9.55$, $P < 0.01$), and the cinema screening total of the sequels are also more than those of the non-sequels (M_{sequel} = 360.90 thousand, $M_{non\text{-}sequel}$ = 256.00 thousand; $F(1, 317) = 8.10$, $P < 0.01$).

5.2 Pooling sample regression

The pooling sample model explains box office revenues well ($R^2 = 0.68$) (see Table 2). The sequel dummy variable has a moderately significant, positive effect ($\beta = 0.07$, $P = 0.07$), which further shows that, on average, sequels outperform non-sequels in terms of box office revenue generation. Consistent with previous film studies, the distribution intensity (i.e., the percentage of first-day screenings; $\beta = 0.60$, $P < 0.001$), audience scoring ($\beta = 0.21$, $P < 0.001$), release year ($\beta = 0.22$, $P < 0.001$), cultural familiarity (i.e., the production area of films; $\beta = 0.14$, $P < 0.01$) and star power ($\beta = 0.10$, $P < 0.05$) also significantly affect box office. But counterintuitively, the effect of budget is only marginally significant ($\beta = 0.06$, $P = 0.136$). In addition, genres (comedy, action, fantasy and war dummy), season (summer dummy), and interactions between the sequel dummy and some variables also significantly influence box office.

5.3 Matched subsamples regressions

The brand extension model (sequel model) explains the box office revenues of sequel samples very well ($R^2 = 0.81$). The fourteen variables representing the four categories of drivers for brand extension success (i.e., parent brand characteristics, fit characteristics, parent brand characteristics - fit characteristics interactions, extended product characteristics) are significant or marginally significant (see Table 3). Specifically, the distribution intensity (i.e., the percentage of first-day screenings) and PBA are the strongest ($t = 7.14$, $P < 0.001$) and the second strongest ($t = 5.49$, $P < 0.001$) predictors of box office, respectively. Besides, the main effect of cultural familiarity (i.e. the *country_China* dummy) is significant ($P < 0.001$). In terms of fit characteristics, poster-similarity and scriptwriter-continuity are significant ($p < 0.05$), but the sign of the latter is negative, which indicates that it is more advantageous to adopt new scriptwriters in sequels. Budget-continuity ($p = 0.095$) and title-continuity ($p = 0.114$) are marginally significant, and the sign of the latter is negative, indicating that simply adding a numeral serial number to the title of the parent film is not conducive to the box office of sequels. It is noteworthy that the main effect of PBI is not significant, but its interaction terms *PBI* × *PBA* ($p < 0.05$) and *PBI* × *fit_producer* ($p < 0.001$) are significant, which is different from some findings in prior studies. Moreover, the interaction terms *PBA* × *fit_poster* ($p < 0.001$), *PBA* × *fit_producer* ($p < 0.001$) and *PBA* × *fit_budget* ($p < 0.05$) are significant. Among the extended product characteristics, the main effects of the distribution intensity ($p < 0.001$), animation-genre dummy ($p < 0.05$) and audience scorings ($p < 0.001$) are significant.

Table 2: Pooling sample regression

Regressor [1]	b	β [6]	t	p	VIF [7]	Regressor [1]	b	β [6]	t	p	VIF [7]
constant	5.16		9.94	0.000		*sequel×budget* [4]	-0.01	-0.00	-0.05	0.959	1.40
sequel [2]	0.22	0.07	1.78	0.076	1.17	*sequel×country_China* [4]	0.93	0.15	3.20	0.002	1.97
budget	0.02	0.06	1.50	0.136	1.25	*sequel×star_power* [4]	-0.04	-0.04	-0.85	0.394	1.53

country_China	0.43	0.14	2.61	0.010	2.56	*sequel×scorings* [4]	0.18	0.06	1.41	0.161	1.77
country_coproduce	-0.37	-0.04	-0.92	0.357	1.29	*sequel×comedy* [4]	0.19	0.03	0.66	0.511	1.35
star_power	0.06	0.10	2.35	0.019	1.59	*sequel×animation* [4]	-0.70	-0.08	-1.70	0.091	1.86
scorings	0.28	0.21	4.32	0.000	1.99	*sequel×drama* [4]	0.33	0.04	1.01	0.315	1.49
genre_comedy [3]	0.39	0.11	2.89	0.004	1.32	*sequel×action* [4]	0.25	0.04	0.78	0.438	2.03
genre_animation [3]	-0.17	-0.04	-0.83	0.407	1.97	*sequel×adventure* [4]	0.09	0.01	0.28	0.777	1.47
genre_drama [3]	0.17	0.05	1.26	0.210	1.44	*sequel×horror* [4]	-0.72	-0.03	-0.88	0.380	1.33
genre_action [3]	0.24	0.08	1.74	0.082	1.73	*sequel×science_fiction* [4]	0.23	0.03	0.67	0.503	1.58
genre_adventure [3]	0.19	0.06	1.36	0.175	1.46	*sequel×thriller* [4]	0.16	0.02	0.38	0.704	1.39
genre_horror [3]	-0.54	-0.05	-1.38	0.168	1.27	*sequel×romance* [4]	-0.19	-0.02	-0.45	0.655	1.32
genre_science_fiction [3]	0.09	0.02	0.57	0.572	1.60	*sequel×fantasy* [4]	-0.06	-0.01	-0.15	0.879	1.16
genre_thriller [3]	0.26	0.05	1.32	0.187	1.33	*sequel×crime* [4]	-0.11	-0.01	-0.19	0.852	1.44
genre_romance [3]	0.14	0.04	0.90	0.370	1.33	*sequel×history* [4]	-2.46	-0.09	-1.71	0.088	2.16
genre_fantasy [3]	0.41	0.09	2.44	0.015	1.12	*sequel×war* [4]	2.81	0.13	2.58	0.011	2.17
genre_crime [3]	-0.31	-0.05	-1.22	0.224	1.33	*sequel×suspense* [4]	0.53	0.04	1.03	0.304	1.24
genre_history [3]	-0.05	-0.01	-0.12	0.908	1.69	*sequel×family* [4]	1.43	0.12	3.01	0.003	1.35
genre_war [3]	0.73	0.08	1.78	0.076	1.73	*release_year* [5]	-0.13	-0.22	-5.73	0.000	1.28
genre_documentary [3]	0.93	0.05	1.29	0.198	1.24	*season_new_year*	0.19	0.06	1.37	0.171	1.77
genre_suspense [3]	-0.10	-0.02	-0.42	0.677	1.25	*season_summer*	0.26	0.09	1.88	0.062	1.76
genre_family [3]	-0.21	-0.04	-0.92	0.358	1.30	*season_national_day*	0.54	0.03	0.75	0.452	1.21
first_day	0.07	0.60	12.72	0.000	1.90	R^2	0.68	adj-R^2	0.63		

[1] The dependent variable is natural log-transformed inflation-adjusted box office revenues; [2] Dummy variable: non-sequel = 0, and sequel = 1; [3] Dummy variable: not in this genre = 0, and in this genre = 1; [4] The residual term was used for this variable; [5] The release year was operationalized as the difference in years from 2018, so 2017 = 1， 2016 = 2， 2015 = 3, and so on; [6] Standardized coefficient; [7] Variance inflation factors.

The estimation results of the non-sequel model are consistent with those of prior box office prediction studies, but the goodness of fit (Adj-R^2_{sequel} = 0.77, Adj-$R^2_{non\text{-}sequel}$ = 0.62) and prediction accuracy ($WMAPE_{sequel}$ = 9.60, $WMAPE_{non\text{-}sequel}$ = 12.74; $RMSE_{sequel}$ = 82.01, $RMSE_{non\text{-}sequel}$ = 85.57) are lower than those of the sequel model. The standard error of the estimation (a parameter similar to RMSE) is also higher ($\sigma_{sequel} = 0.17$, $\sigma_{non\text{-}sequel} = 0.32$). Six predictors are significant: the distribution intensity (i.e., the percentage of first-day screenings) is the strongest predictor of box office ($t = 13.59$, $p < 0.001$), followed by audience scorings ($t = 3.36$, $p < 0.001$), family-genre dummy ($t = -3.33$, $p < 0.001$), star power ($t = 3.22$, $p < 0.001$), comedy-genre dummy ($t = 2.61$, $p < 0.01$) and fantasy-genre dummy ($t = 2.52$, $p < 0.05$). Budget and crime-genre dummy are marginally significant ($P < 0.15$).

Table 3: Matched subsample regressions

Regressor [1]	**Revenue prediction of sequels (RPS)**				**Revenue prediction of non-sequels (RPN)**			
	b	**t**	**p**	**VIF** [4]	**b**	**t**	**p**	**VIF** [4]
constant	6.02	6.50	0.000		6.15	14.50	0.000	
PBA	0.00	5.49	0.000	1.41				
budget [2]					0.01	1.47	0.143	1.07
genre_war [2]	1.060	1.29	0.201	1.97				
genre_family [2]					-0.87	-3.33	0.001	1,07
genre_fantasy [2]					0.44	2.52	0.012	1.02
star_power					0.08	3.22	0.001	1.23
genre_comedy [2]					0.36	2.61	0.010	1.09
genre_crime [2]					-0.38	-1.50	0.135	1.08
first_day [2]	0.07	7.14	0.000	2.25	0.07	13.59	0.000	1.32
PBA×fit_poster	-0.00	-4.06	0.000	1.44				
PBA×fit_budget	0.00	2.01	0.048	1.80				
PBI×PBA	-0.00	-2.39	0.019	1.25				
PBA×fit_producer	-0.00	-3.36	0.001	1.23				
fit_poster	0.25	2.32	0.023	1.16				
fit_title	-0.33	-1.60	0.114	1.22				
PBI×fit_producer	0.68	3.68	0.000	1.32				
country_China [2]	0.83	3.56	0.001	1.89				

genre_animation [2]	-0.56	-2.23	0.029	1.62				
fit_writer	-0.37	-1.96	0.054	1.25				
fit_budget	0.01	1.69	0.095	1.18				
scorings [2]	0.46	4.05	0.000	2.61	0.19	3.36	0.001	1.15
release_year [3]	-0.21	-5.44	0.000	1.20	-0.11	-4.87	0.000	1.08
R^2	0.81				0.63			
Adj-R^2	0.77				0.62			

[1] The dependent variable is natural log-transformed inflation-adjusted box office revenues; [2] The residual term was used for this variable in the sequel subsample regression; [3] The release year was operationalized as the difference in years from 2018, so 2017 = 1，2016 = 2，2015 = 3, and so on; [4] Variance inflation factors.

The preceding analyses imply that sequels (i.e., brand extensions) have two major advantages over identical non-sequel movies (i.e., original new products). Firstly, the t-tests and pooling sample regression analysis demonstrate that, on average, sequels generate higher box office revenues than non-sequels. As a post hoc test, we apply the non-sequel model to the sequel subsamples to illustrate what box office results will be achieved if these sequels are presented in the form of non-sequels. The results show that the average box office of the sequel subsamples predicted by the non-sequel model is ￥122.10 million, which is lower than the actual box office average of the sequels, but close to that of the matched non-sequels.

Secondly, and as important as the valuation of brand extension right, the prediction accuracy indicators show that the risk of investing in sequels is lower than that in non-sequels. Although we haven't conducted any empirical statistical tests to compare the prediction accuracy between the two models, the difference in prediction accuracy indicators can explain the problem to a certain extent (WMAPE and RMSE decreased by 24.65% and 4.16% respectively), with the reduction pattern being consistent across the sub-samples and post hoc analyses. Comparing the WMAPE of the sequel model with the nested model composed of independent variables from the non-sequel model (i.e., excluding independent variables unincluded in the non-sequel model), the WMAPE of the nested sequel model is 13.32, which is 38.75% higher than the prediction error of the sequel model. These results illustrate the value of additional information provided by sequel-specific variables in reducing risk.

6. Valuation of Sequel Right

Through the matched subsample regressions, the value of the sequel right can be calculated according to the spillover effect. We take the Chinese sequel movie *Lost on Journey: Lost in Thailand* as an example to demonstrate the calculation process. Assuming that the sequel has not been filmed yet, the financial value of the potential sequel can be estimated in advance by this approach. Because box office revenues need to be shared with studios, cinemas, and distributors, we only consider the revenues earned by movie investors. In China's film market, the percentage of box office share earned by film investors is generally around 43%.

6.1 In the case of risk neutrality

Firstly, from the perspective of risk-neutral investors, we examine how to calculate the value of the sequel right when the risk needs to be accepted. For risk-neutral investors, their investment decisions are based on the expected return, μ, of different investment alternatives (e.g., sequels vs. non-sequels), and investors will choose the alternative with the highest expected return (expected value criteria). Risk neutrality means that the risk of investment opportunities is not considered. We calculate the spillover value (SV) of the sequel right for the Chinese movie brand *Lost on Journey* as the expected revenue difference between investing in sequels and investing in non-sequels. Inputting the movie characteristic data into the RPS and RPN models (Table 3) respectively, we subtract the investors share of revenues predicted by the RPN model from that predicted by the RPS model:

$$SV_{\text{Lost on Journey: Lost in Thailand}} = (RPS_{\text{Lost on Journey: Lost in Thailand}} - RPN_{\text{Lost on Journey: Lost in Thailand}}) \times 0.43 = (797.93 - 469.14) \times 0.43 = ￥141.38 \text{ million} \quad (1)$$

Equation (1) implies that investing in the sequel, *Lost on Journey: Lost in Thailand*, could generate about ￥140 million more in returns than investing in a similar movie (i.e. a movie with the identical budget, distribution intensity, audience scorings, star power, and genre) without *Lost on Journey* brand, which indicates the spillover effect of the parent movie. The extra returns can be attributed entirely to the use of the *Lost on Journey* brand, so investors can expect that the SV of the sequel right of *Lost on Journey* is approximately ￥140 million.

This approach also enables investors to predict how box office would change if some of the brand extension predictors were changed during the production of *Lost in Thailand* (see Table 4). For example, other things being equal, increasing the title-continuity (e.g., changing the title from *Lost on Journey: Lost in Thailand* to *Lost on Journey 2*) will reduce box office revenues by ￥223.20 million, resulting in a decrement of ￥95.98 million in the value of sequel right. But if the poster-similarity is increased, for example, the poster-similarity between *Lost on Journey: Lost in Thailand* and *Lost on Journey* is increased from 4 (similar) to 5 (very similar), the box office revenues will be increased by ￥86.80 million, thus generating an extra value of ￥37.32 million for investors. Similarly, increasing the scriptwriter-continuity (i.e., the scriptwriters of *Lost on Journey* and *Lost on Journey: Lost in Thailand* are the same) would reduce box office revenues by ￥244.71 million, resulting in a decrement of ￥105.22 million in the value of sequel right.

Table 4: Sequel right value of the Chinese movie Lost on Journey (million Yuan)

Variable	Sequel as filmed	The sequel with the title *Lost on Journey 2* instead of *Lost on Journey: Lost in Thailand*	Sequel's poster is very similar instead of similar to its parent's	The sequel with the original scriptwriter of its parent
Revenues: sequel [1]	797.93	574.73	884.73	553.22
Revenues: non-sequel [2]	469.14	469.14	469.14	469.14
Investor revenues: sequel [3]	343.11	247.13	380.43	237.88
Investor revenues: non-sequel [3]	201.73	201.73	201.73	201.73
Sequel right value [4]	141.37	45.40	178.70	36.15
Risk-adjusted investor revenue/value				
60% Risk Averse				
Investor revenue: sequel [3]	325.95	234.78	362.81	225.99
Investor revenues: non-sequel [3]	182.77	182.77	182.77	182.77
Sequel right value [4]	143.18	52.01	180.04	43.22
75% Risk Averse				
Investor revenues: sequel [3]	300.56	216.49	333.26	208.39
Investor revenues: non-sequel [3]	150.69	150.69	150.69	150.69
Sequel right value [4]	149.87	65.79	182.57	57.69
90% Risk Averse				
Investor revenues: sequel [3]	261.79	188.56	290.27	181.51
Investor revenues: non-sequel [3]	104.30	104.30	104.30	104.30
Sequel right value [4]	157.50	84.27	185.97	77.21

[1] Box office revenue prediction based on the RPS model; [2] Box office revenue prediction based on the RPN model; [3] Investor's share of box office revenues; [4] Investor revenues for the sequel minus investor revenues for the identical non-sequel.

Investors face two kinds of payoff risk while making investment decisions. On the one hand, project-specific risk refers to the level of uncertainty in project returns, which can be well measured by the standard error of predictions according to a sample of similar projects. On the other hand, market risk has nothing to do with specific projects and is usually indicated in terms of the discount rate that investors choose by normal capital budgeting and investment planning. Being affected by investor's and firm's characteristics, the firm's capital cost, etc., risk preferences differ across investors, so we are unable to determine an investor's acceptable level of market risk objectively. Nevertheless, we illustrate how to determine project-specific risk and integrate it with an investor's individual risk preferences to value sequel right.

6.2 In the case of risk aversion

To determine the right owner's preference for a risky investment, we adopt the Value at Risk (VaR) approach of risk management in finance theory to calculate the risk-adjusted value of the sequel right. The VaR approach measures the potential losses of risky assets or portfolios over a period of time, enabling investors to value these assets with a confidence level approximating their risk preferences [34]. The standard approach for calculating VaR for specific assets is the variance-covariance analysis, which assumes that returns on risky assets follow a specific probability distribution (usually a normal distribution). Integrating the expected return on assets with their standard deviation and distribution assumptions, the lower limit of a confidence interval (e.g., 90%) under a given risk level is determined by the variance-covariance method. Generally speaking, suppose investors are risk-averse.

We define the risk-adjusted spillover value of sequel right for a movie brand i ($raSV_i$) as the difference between the VaR_i^{sequel} estimated from the sequel subsample (i.e., the risk-adjusted expected return of the investment in a sequel) and the $VaR_i^{non-sequel}$ estimated from the non-sequel subsample (i.e., the risk-adjusted expected return of the investment in a similar non-sequel film):

$$raSV_i = VaR_i^{sequel} - VaR_i^{non-sequel} \quad (2)$$

$$VaR_i^{sequel} = e^{\hat{X}_i^{sequel}} * [1 - t_{1-\alpha} * (e^{\sigma_{sequel}} - 1)] \quad (3)$$

$$VaR_i^{non-sequel} = e^{\hat{X}_i^{non-sequel}} * [1 - t_{1-\alpha} * (e^{\sigma_{non-sequel}} - 1)] \quad (4)$$

where $\hat{X}_i^{sequel}$ and $\hat{X}_i^{non-sequel}$ are the expected natural logarithmic revenues of investment alternative i estimated from the sequel and non-sequel subsample respectively, $t_{1-\alpha}$ represents the Student's t distribution parameter corresponding to a given confidence level 1 – α (e.g., 90%), σ_{sequel} and $\sigma_{non-sequel}$ represent the standard error of the expected natural logarithmic revenues of the sequel and non-sequel subsample, as predicted through the RPS and RPN models respectively.

To summarize, to integrate risk into the valuation of sequel right, we use the project-specific risk parameters of the sequel and non-sequel investment alternatives, which are estimated with the matched sub-sample approach. Take *Lost on Journey: Lost in Thailand* as an example, we divide the risk preference of investors into three levels: 1) 60% certainty (t = 0.25); 2) 75% certainty (t = 0.67); 3) 90% certainty (highly risk-aversion, t = 1.28). We apply equations (2)-(4) to the *Lost on Journey* sequel and a similar non-sequel and calculate the risk-adjusted value of the sequel right at these risk-aversion levels. The results in table 4 show that the lower investors' acceptable level of risk is (i.e., investors are more risk-averse), the higher the value of *Lost on Journey*'s sequel right is. These results also imply that the sequel model RPS has higher prediction accuracy (i.e., lower prediction error) than the non-sequel model RPN. Specifically, if investors demand 90% certainty (i.e., accept a 10% risk), the sequel right of *Lost on Journey*, based on brand extension spillover effect, is worth about ￥160 million.

7. DISCUSSION AND CONCLUSIONS

7.1 Findings

We calibrated both a pooling sample regression model and the matched subsample regression model for sequels and the matched non-sequel films released in mainland China from 2010 to 2017 in this article. The regression results show that for film investors, launching a brand extension (i.e., making a sequel) has two advantages in 1) generating higher expected box office revenues (as indicated by the parameters of the pooling regression and t-statistic), and 2) reducing project-specific risk (as evidenced by higher prediction accuracy and a lower standard error for sequels than for non-sequels).

Although this article supports many conclusions of existing brand extension researches, there are also some differences. Existing studies have shown that fit and marketing support are the most important factors driving brand extension success [7,35], nevertheless, we find that retailer acceptance (using percentage of first-day screenings as the proxy) and parent brand awareness (PBA) are the strongest drivers of brand extension success. The reason may lie in the unique research context of this article: Most of the existing brand extension literature focuses on fast-moving consumer goods (FMCG), where a major challenge for these new products is how to rapidly increase their visibility in a wide range of markets, and marketing support is the key to letting consumers understand the new products. In contrast, for hedonic media products, marketing support plays a relatively minor role in educating and attracting consumers because the media will actively focus on sequels from popular parent films and consumers are intrinsically interested in hedonic categories.

7.2 Implications

The prediction model established in this paper enables managers to effectively evaluate the brand extension right, an important intangible asset. This approach is more objective than the intuitive decision-making approach commonly used in the film industry. It increases transparency among stakeholders and can be applied to negotiations and transactions between them over the right to make sequels. Besides, the model can also be applied to evaluate alternative combinations of strategic brand elements. The model contains parameters that managers can control while planning an extension, allowing them to predict the impacts of similarity or difference between the sequel and parent films in specific features (e.g., title, poster, and genre). Because some variables (e.g., distribution intensity) have not been available while valuing a sequel right, managers can apply our approach to conduct sensitivity analyses of outcomes to different levels of these variables.

Although the operationalizations and empirical evidence in this article are limited to the film industry, the overall conceptual framework (adapted from brand value literature) and valuation approach (adapted from finance literature) can be extended to brand extensions in other industries. Managers in other industries can also calculate the SV by comparing the predicted revenues of the brand extension model (i.e., RPS model) and non-extension model (i.e., RPN model). To estimate the revenue prediction models for the two investment alternatives, managers need to acquire historical (or experimental) data for both brand extensions and similar non-extension products. However, when applying the general categories of brand extension drivers (i.e., parent brand characteristics, extended product characteristics, fit, and the interaction of fit and parent brand characteristics) used in this article, managers should adjust these abstract categories according to the characteristics of their respective industries. Moreover, industry-specific variables are required to replace the film industry-specific variables used in this article.

Because the variables used in this article are easy to quantify and have nothing to do with the aesthetic dimensions of films, our approach has a wide range of applicability. Besides, we create fit measures from several aspects rather than an overall measure, which is conducive to encouraging other scholars to carry out more diversified researches on the dimensions of fit in different contexts in the future.

7.3 Limitations and further research

This article examines only the first sequel without considering the impacts of more sequels (e.g., *Fast & Furious 3*, *Fast & Furious 4*, etc.). The success of the first sequel has a great impact on the subsequent production of additional sequels. For example, *Speed* initially aimed to become a *007*-like series, but the idea was abandoned after *Speed 2* failed at the box office. Therefore, when extending our approach to additional sequels, we need to consider the relationship between the additional sequel and the first sequel. But it is difficult to model the complex relationship between them because of the limited number of movie series. However, it should be recognized that this is interesting and worthy of in-depth study direction, investigators may apply real options theory to a sequential, multi-stage decision-making process.

Brand extension theory holds that the fit between a brand extension and its parent brand is a key driver of the brand extension's success. However, among the 10 fit measures in this article, budget-continuity affects box office positively, title-continuity and scriptwriter-continuity affect box office negatively, while the direction of the effects of poster-similarity and producer-continuity on box office depends on PBA or/and PBI, and other fit variables are not significant. Maybe we can explain these results by the "moderate schema incongruity" [36], which holds that when there is a moderate level of incongruity between a product and its associations with consumers, consumers have the best evaluation of the product. Nevertheless, these results may also come from the research method we used.

Given the limited sample size, to reduce multicollinearity and achieve an acceptable level of degrees of freedom, we used stepwise regression analysis. However, when the number of variables is large, especially when there are many binary variables, the search bias may affect the results of stepwise regression [37]. Most of the fit variables used in this article are dichotomic variables, which may have caused the inconsistencies of our findings and other findings in the film research literature regarding the influence of fit variables (such as star-continuity and director-continuity) on sequels' box office [e.g., 19]. Therefore, further research should obtain more sample data for fitting models over a longer time span, and consider adopting new measures to quantify the fit variables. For example, for star-continuity, we can quantify the proportion of the top five actors in the parent film to participate in the sequel, so that the variable is changed from dichotomic to continuous.

In conclusion, we propose an approach to determine the financial value of the brand extension right. Using the data of films screened in mainland China from 2010 to 2017, we provide film copyright owners and potential buyers with an approach to estimate a movie's sustainability in producing sequels and calculate the financial value of movie sequel right, and demonstrate that the value of sequel right can be attributed to the brand extension spillover effect.

Funding

This work was supported by the National Undergraduate Innovation and Entrepreneurship Training Program, grant number 202211049036Z.

References

[1] D.A. Aaker, K.L. Keller, "Consumer Evaluations of Brand Extensions," Journal of Marketing, 54(1), pp.27-41, 1990.
[2] A. Ainslie, X. Drèze, F. Zufryden, "Modeling Movie Life Cycles and Market Share," Marketing Science, 24(3), pp.508-517, 2005.
[3] B.I.S. Frederik, A.A.M.L. Mark, M.W. Nachoem, "The Good, the Bad and the Variable: How Evaluations of Past Editions Influence the Success of Sequels," European Journal of Marketing, 48(7/8), pp.1466-1486, 2014.
[4] R.K. Srivastava, T.A. Shervani, L. Fahey, "Market-based Assets and Shareholder Value: A Framework for Analysis," Journal of Marketing, 62(1), pp.2-18, 1998.
[5] D.C. Smith, C.W. Park, "The Effects of Brand Extensions on Market Share and Advertising Efficiency," Journal of Marketing Research, 29(3), pp.296-313, 1992.

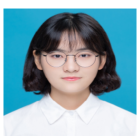
[6] V. Srinivasan, C.S. Park, D.R. Chang, "An Approach to the Measurement, Analysis, and Prediction of Brand Equity and its Sources," Management Science, 51(9), pp.1433-1448, 2005.
[7] F. Volckner, H. Sattler, "Drivers of Brand Extension Success," Journal of Marketing, 70(2), pp.18-34, 2006.
[8] C.J. Simon, M.W. Sullivan, "The Measurement and Determinants of Brand Equity: A Financial Approach," Marketing Science, 12(1), pp.28-52, 1993.
[9] V. Lane, R. Jacobson, "Stock-market Reactions to Brand Extension Announcements - The Effects of Brand Attitude and Familiarity," Journal of Marketing, 59(1), pp.63-77, 1995.
[10] S.M. Young, J.J. Gong, W.A. Van der Stede, "Using Real Options to Make Decisions in the Motion Picture Industry," Strategic Finance, 93(11), pp.55-59, 2012.
[11] M. Haenlein, A.M. Kaplan, D. Schoder, "Valuing the Real Option of Abandoning Unprofitable Customers when Calculating Customer Lifetime Value," Journal of Marketing, 70(3), pp.5-20, 2006.
[12] S. Sood, X. Dreze, "Brand Extensions of Experiential Goods: Movie Sequel Evaluations," Journal of Consumer Research, 33(3), pp.352-360, 2006.
[13] B. Gunter, "Why are sequels and remakes so popular with movie studios?" in Predicting Movie Success at the Box Office, B. Gunter (eds.), Springer International Publishing, Cham, 2018.
[14] K. Loock, "The Sequel Paradox: Repetition, Innovation, and Hollywood's Hit Film Formula," Film Studies, 17(1), pp.92-110, 2017.
[15] S. Basuroy, S. Chatterjee, "Fast and Frequent: Investigating Box Office Revenues of Motion Picture Sequels," Journal of Business Research, 61(7), pp.798-803, 2008.
[16] G. Yalcinkaya, T. Aktekin, "Brand Extension Effects and Core Attributes of Experience Product Franchises: A Bayesian Approach," Journal of Product Innovation Management, 32(5), pp.731-746, 2014.
[17] D.H. Kim, "Brand Extension Strategies in the Film Industry: Factors behind Financial Performance of Adaptations and Sequels," International Journal on Media Management, 21(3-4), pp.161-176, 2019.
[18] D.A. Griffith, G. Yalcinkaya, G. Rubera, V. Giannetti, "Understanding the Importance of the Length of Global Product Rollout: An Examination in the Motion Picture Industry," Journal of International Marketing, 25(4), pp.50-69, 2017.
[19] T. Hennig-Thurau, M.B. Houston, T. Heitjans, "Conceptualizing and Measuring the Monetary Value of Brand Extensions: The Case of Motion Pictures," Journal of Marketing, 73(6), pp.167-183, 2009.
[20] T. Hennig-Thurau, M.B. Houston, G. Walsh, "The Differing Roles of Success Drivers across Sequential Channels: An Application to the Motion Picture Industry," Journal of the Academy of Marketing Science, 34(4), pp.559-575, 2006.
[21] M. Ghiassi, D. Lio, B. Moon, "Pre-production Forecasting of Movie Revenues with a Dynamic Artificial Neural Network," Expert Systems with Applications, 42(6), pp.3176-3193, 2015.
[22] D. Orlov, E. Ozhegov, "Do sequel movies really earn more than non-sequels? Evidence from the US box office," No AWP-03-2016, ACEI Working Paper Series, Association for Cultural Economics International, https://EconPapers.repec.org/RePEc:cue:wpaper:awp-03-2016.
[23] T. Dhar, G. Sun, C.B. Weinberg, "The Long-term Box Office Performance of Sequel Movies," Marketing Letters, 23(1), pp.13-29, 2012.
[24] K. Kposowa, The Financial Success of Franchise Film Sequels: An Exploration of the Relationship of Budget, Personnel Factors, and Reviews with Sequel Return on Investment, Thesis or Dissertation, Ohio University, 2015.
[25] K.L. Keller, "Conceptualizing, Measuring, and Managing Customer-based Brand Equity," Journal of Marketing, 57(1), pp.1-22, 1993.
[26] K. Zhong, Y. Wang, H. Wang, "Sense hardness: Effect of haptic perception on consumer attitudes towards brand extension," Journal of Consumer Behaviour, 20(3), pp.535-549, 2021.
[27] S. Balachander, S. Ghose, "Reciprocal Spillover Effects: A Strategic Benefit of Brand Extensions," Journal of Marketing, 67(1), pp.4-13, 2003.
[28] R.R. Klink, D.C. Smith, "Threats to the External Validity of Brand Extension Research," Journal of Marketing Research, 38(3), pp.326-335, 2001.
[29] A. Elberse, J. Eliashberg, "Demand and Supply Dynamics for Sequentially Released Products in International Markets: The Case of Motion Pictures," Marketing Science, 22(3), pp.329-354, 2003.
[30] H. Hwangbo, J. Kim, "A Text Mining Approach for Sustainable Performance in the Film Industry," Sustainability, 11(11), 3207, 2019.
[31] H.L. Smith, "Matching with Multiple Controls to Estimate Treatment Effects in Observational Studies," Sociological Methodology, 27(1), pp.325-353, 1997.

[32] J.T. Wixted, S.K. Carpenter, "The Wickelgren Power Law and the Ebbinghaus Savings Function," Psychological Science, 18(2), pp.133–134, 2007.
[33] P.A. Bottomley, S.J.S. Holden, "Do We Really Know How Consumers Evaluate Brand Extensions? Empirical Generalizations based on Secondary Analysis of Eight Studies," Journal of Marketing Research, 38(4), pp.494-500, 2001.
[34] T.J. Linsmeier, N.D. Pearson, "Value at Risk," Financial Analysts Journal, 56(2), pp.47-67, 2000.
[35] F. Volckner, H. Sattler, "Empirical Generalizability of Consumer Evaluations of Brand Extensions," International Journal of Research in Marketing, 24(2), pp.149-162, 2007.
[36] G. Mandler, Mind and Emotion, Krieger Publishing Company, Melbourne, Florida, 1982.
[37] W.T. Wallace, A. Seigerman, M.B. Holbrook, "The Role of Actors and Actresses in the Success of Films: How Much is a Movie Star Worth?" Journal of Cultural Economics, 17(1), pp.1-27, 1993.

AUTHOR

Zheng Ren is an undergraduate student in the Business School at Huaiyin Institute of Technology, majoring in Financial Management. He has participated in three National Undergraduate Innovation and Entrepreneurship Training Program and won the National Scholarship of the Ministry of Education of the People's Republic of China, the bronze prize of the 8th "Internet plus" Undergraduate Innovation and Entrepreneurship Competition.

Zihui Zhuo is an undergraduate student in the Business School at Huaiyin Institute of Technology, majoring in Business Administration. She has participated in two National Undergraduate Innovation and Entrepreneurship Training Program and won the National Scholarship of the Ministry of Education of the People's Republic of China, the third prize of the 8th "Oriental Fortune Cup" National Undergraduate Financial Challenge, the bronze prize of the 8th "Internet plus" Undergraduate Innovation and Entrepreneurship Competition, the 5th President Medal of Huaiyin Institute of Technology.



Zhiwen Zhureceived the PhD degree in Management from Peking University in 2010. He is now a full professor of the Business School at Huaiyin Institute of Technology. His current research interests include branding, consumer behavior and business valuation.