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ORIGINAL ARTICLE

When does it make sense to do it again? An empirical investigation of contingency factors of movie remakes

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Abstract A substantial number of current Hollywood productions are remakes of earlier motion pictures. This research investigates the economic implications of this strategy. It develops a conceptual framework of brand extension success in the movie industry that builds upon the sensations and familiarity that a movie offers and uses this framework to illustrate how remakes differ from other movie brand extensions (e.g., sequels). The sensations-familiarity framework is complemented by a contingency model that identifies factors which influence revenues and risk of movie remakes. Using a dataset of 207 remakes released in North American theaters between 1999 and 2011 and a matched sample of other movies, the authors find that, on average, remakes do not increase revenues but do reduce financial risk. The authors also provide evidence of the contingency role of several factors, including the original movie's awareness and image and the relationship between the original movie and the remake. These insights should be valuable for the movie industry, as they can guide movie producers in their selection of movie brands that, if remade, should be more successful at the box office than the "average" movie remake.

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1 Introduction

> Hollywood seems obsessed with remaking extremely well-known properties that are well-known purely because of how near-perfect they were the first time.
>
> (Mendelson 2013)

When searching for the next blockbuster, Hollywood managers frequently produce remakes of previous movies (e.g., Mendelson 2013). The underlying rationale is that remakes, just like sequels and bestseller adaptations for which high returns and low risk have been demonstrated (Hennig-Thurau et al. 2009; Joshi and Mao 2012; Knapp et al. 2014), are extensions of existing brands that can be expected to offer higher return rates than other movies while involving less risk (Palia et al. 2008; Ravid 1999).

This research, however, argues that remakes differ fundamentally from other types of brand extensions, such as sequels and bestseller adaptations, and that it is thus unclear whether remaking movies is an economically viable strategy. The box office does not provide a straightforward answer: while Peter Jackson's 2005 remake of *King Kong* and Steven Spielberg's 2005 remake of *War of the Worlds* were big hits, Gus van Sant's 1998 remake of Alfred Hitchcock's classic horror movie *Psycho* and the *Conan the Barbarian* remake from 2011 recouped only a fraction of their costs.

We aim to shed light on this question by developing a conceptual framework of brand extension success in the movie industry based upon the sensations and familiarity that a movie offers its audiences. While sequels and bestseller adaptations capitalize on the familiarity of an existing brand and simultaneously offer consumers a considerable degree of novel sensations, remakes offer familiarity but are generally limited in their sensation value, a major motivational driver of movie attendance (Eliashberg and Sawhney 1994). This lack exists because remakes do not present the continuation of a known story, as sequels do, or add specific new sensory experiences to a known book, as adaptations do. Remakes, by definition, tell a story again that has been told before, in the same modality in which it has been told before.

We complement the sensations-familiarity framework with a contingency model that identifies the factors that determine the success of movie remakes. The model introduces a number of contingency factors with which we expect the degree of sensations and familiarity to vary in the case of movie remakes and which thus are capable of explaining the differences between the success of *King Kong* and the failure of *Psycho*. The contingency model should be valuable for the movie industry, as it guides movie producers in their selection of movies that, if remade, should be more successful at the box office than the "average" movie remake.

The remainder of this work is structured as follows. After giving an overview of the academic findings on brand extensions in the motion picture industry and remakes in particular, we draw from this brand extension literature to introduce the sensations-familiarity framework, and subsequently, the contingency model of remake success. By comparing a dataset of 207 movie remakes released in North American theaters between 1999 and 2011 to a statistically matched subsample of non-remake movies, we then investigate whether remakes on average, as well as certain types of remakes, are more successful than matched non-remake movies in terms of revenues (i.e., box office) and financial risk. We study the effects of remakes on revenues through a series of regression analyses and the effects on risk through F-tests. The article closes with practical recommendations for movie producers.

2 A parsimonious review of brand extension research on movies

The extension of established brands for the release of a new product is a heavily applied approach in hedonic media industries. At the time of this writing, 22 of the top 25 all-time worldwide box office movies represent some type of brand extension (Boxofficemojo 2013). Of the different types of movie brand extensions, sequels have received the most attention from scholars; previously, research has found sequels to generate more revenues than non-sequels (Hennig-Thurau et al. 2009; Dhar et al. 2012) while exhibiting a lower degree of risk (Hennig-Thurau et al. 2009; Palia et al. 2008; Ravid 1999). Other sequel-related findings include the optimal degree of recency between an original movie and its sequel, the optimal number of sequels (Basuroy and Chatterjee 2008), the release week versus long-term effects (Dhar et al. 2012), and the contingency factors of sequels' perceived quality (Sood and Drèze 2006). Other studies have analyzed movie adaptations of novels; research on this type of movie brand extension has demonstrated that adaptations are more successful on average and points to several contingency factors of this effect (Joshi and Mao 2012) as well as its reciprocal nature (Knapp et al. 2014).

Regarding remakes, we are not aware of any empirical study that investigates remakes' impact on box office revenues or other measurements of commercial success. Some studies include remake characteristics in their measure of cultural familiarity (Hennig-Thurau et al. 2006a; b) or the continuation of prior movies (Marshall et al. 2013). Only studies by Hennig-Thurau et al. (2006b) and Elliott and Simmons (2008) shed any initial light on the economic role of remakes. The first study reports nonsignificant correlations between remakes and both opening weekend and long-term box office success ($r = .01$ and $r = .03$, respectively), which are considerably lower than those of sequels. The second study originally accounts for remakes but drops the variable from the main analysis because, again, no significant influence is found.

In summary, there are several studies that address brand extensions in the motion picture industry, especially sequels and literature adaptations, but very little is known about the link between remakes and motion picture success. This research tests the main effect of "average" remakes on movie success and offers a systematic investigation of contingency factors of that effect.

3 A sensations-familiarity framework of movie success

We argue that remakes affect movie success in a different way than other movie brand extensions or unbranded movies. We base this argument on a sensations-familiarity framework of movie success in which we consider success as a function of a movie's capability of satisfying two basal consumer motivations: sensations and familiarity (see Fig. 1).

As movies are hedonic products (Hirschman and Holbrook 1982), consumers choose them because of the sensations they provide by telling new stories in an unknown way. To produce these sensations, motion pictures must be innovative: "Tell the same story, and you've rendered yourself useless" (Mendelson 2013). At the same time, consumers value familiarity in movies, both as a way to reduce the consumption risk that results from movies' experience good character (Chang and Ki 2005) and to receive enjoyment through a sense of connection with familiar characters (Green et al. 2004). A branding perspective interprets the familiarity of a product as brand knowledge, which, everything else being equal, transforms into brand-related behavior and should favor the success of familiar films over other films (Aaker and Keller 1990; Völckner and Sattler 2006).

A movie's potential to provide moviegoers with sensations and familiarity is influenced by its connection to a pre-existing brand. While unbranded movies are unlimited in their potential to offer novel sensations, they cannot offer consumers familiar characters. The financial success of sequels and novel adaptations found in previous research can be linked to their ability to offer sensations (by inventing new

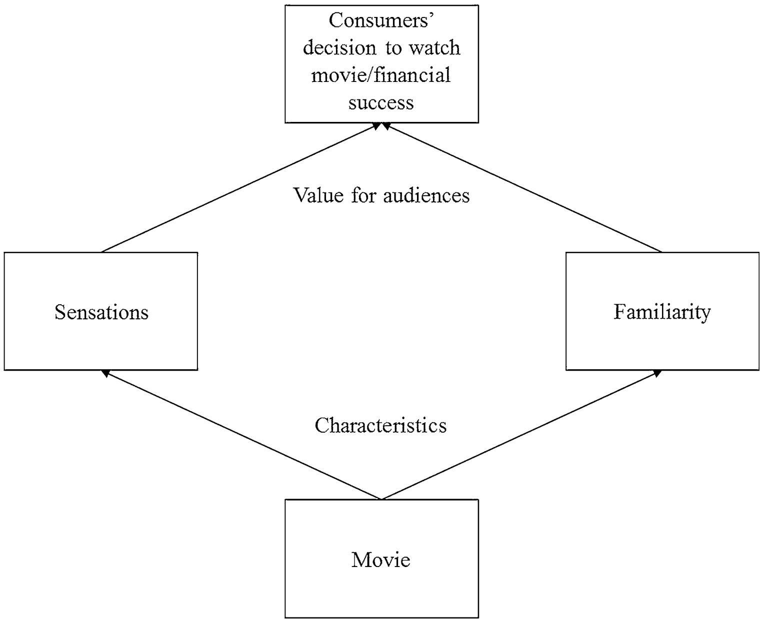

Fig. 1 Sensations-familiarity framework

adventures of well-known characters and by adding a new modality to an existent narrative, respectively) in combination with high levels of familiarity (a hero who is well-known from previous cinematic or literary adventures).

Remakes, however, are a special type of brand extension in that they retell an existing narrative in the same modality in which it has been told before. Like other brand extensions, remakes are of limited risk for consumers and offer audiences familiar “branded” attractions as a result of their established characters and story. However, their potential to offer sensations in the form of using novel story elements, introducing new characters, or adding new sensory dimensions is systematically limited, which should reduce their hedonic attractiveness for consumers and imply an economic disadvantage compared to unbranded films as well as other types of movie brand extensions. It is unclear whether the familiarity effect of remakes is generally strong enough to dominate this limited sensation potential. We empirically address this question by analyzing how remakes perform financially in terms of both revenues and risk.

4 A contingency model of remake success

We complement the general sensations-familiarity framework with a contingency model of movie remake success that takes into account the heterogeneity of remakes. The contingency model incorporates three sets of contingency factors which we derive from brand extension research (e.g., Völckner and Sattler 2006): the original movie’s brand awareness, the original movie’s brand image (both focal elements of parent brand knowledge; Keller 1993), and the relationship between the original movie and its remake extension (see Fig. 2). We argue that these contingency factors influence the level of familiarity and sensations that a remake offers audiences.

4.1 The original movie’s brand awareness

We expect the brand awareness of the original movie to moderate the remake-box office link in a nonlinear way. Generally, awareness of the remade brand is

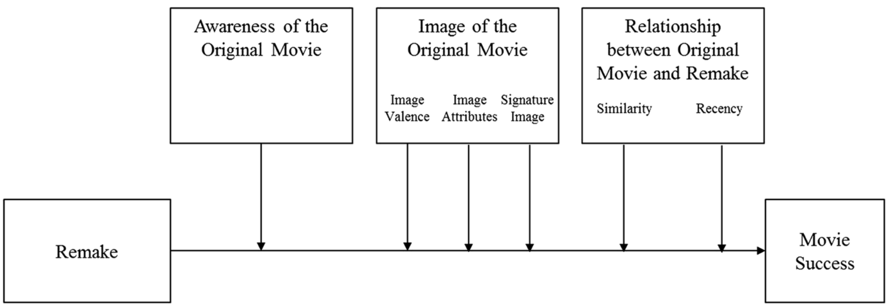

Fig. 2 Model of remake effects on movie success

advantageous because it helps to signal familiarity to audiences. If the awareness of the original is very low when the remake is announced, consumers do not recognize the connection to the original movie brand when evaluating the remake, and the movie remake cannot capitalize on its brand. However, if the remake is based on a very widely known original movie, the hedonic sensations the remake offers will be limited, as audiences have experienced the same sensations before and a satiation effect is likely to occur (Sood and Drèze 2006), which should reduce the attractiveness of the remake for audiences. Accordingly, we expect an inverted U-shaped relationship between consumers' awareness of the original movie when the remake is announced and the success of the remake.

4.2 The original movie's brand image

With regard to the image of the original movie, we distinguish between three facets of brand image as contingency factors: (a) image valence, (b) image attributes, and (c) signature image.

4.2.1 Image valence

Image valence captures the perceived quality of the original movie. Brand research suggests that extensions of high-quality brands are more successful than extensions of parent brands whose quality is perceived as low by consumers (Reddy et al. 1994), a finding that has been confirmed for movie sequels (Hennig-Thurau et al. 2009). However, the unique characteristics of remakes suggest a different effect. Specifically, if audiences perceive an original movie to be of very high quality, they might question the legitimacy of a remake and perceive it as a violation of a beloved piece of art (Thompson et al. 1994) instead of consuming it for its familiarity. As a consequence, we expect remakes of high-quality originals to perform less successfully than those of medium- and low-quality originals.

4.2.2 Image attributes

We presume that the success of a remake also varies with the image attributes of the original film. Specifically, some types of movies will tend to be perceived as modern or even timeless interpretations of a particular story, whereas others will tend to be considered old-fashioned and outdated. Remaking the latter type of movies could be a better approach because consumers are generally interested in greater cinematic realism (Bazin 1951) and will perceive the "updating" of old-fashioned stories, settings, and characters to be higher in sensation value compared to the retelling of movies that are considered up-to-date.

The degree to which a movie is perceived as modern or outdated should be a function of the original movie's genre. Genres whose attractions revolve around special effects or other production technologies (e.g., horror and action) will become outdated as a result of technological advancement. Therefore, remakes of movies of these genres should, all else being equal, be perceived by audiences as offering a high sensation value. In contrast, remakes of movies watched primarily for their story line and dialogue (e.g., drama and comedy) become outdated less easily, having a higher potential to be considered as "classics" (e.g., *Casablanca*). Thus, remakes of horror or action movies should be more successful than remakes of dramas or comedies.

4.2.3 Signature image

A movie's image also depends on the artists who have contributed to the movie. If the image of a movie is inextricably linked to a specific artist (such as the *Rocky* movies are to Sylvester Stallone, the *Dirty Harry* movies to Clint Eastwood, or most movies by Alfred Hitchcock to their legendary director), the movie is called a "signature movie" (Gelder 2004, p. 122). Remakes generally feature different artists than the original movies (which is another distinction from sequels); if the source of the adaptation is a signature movie, the remake lacks a core element of the parent brand image of the original movie. This should reduce the familiarity value of a remake for audiences (a *Rocky* movie cannot be a *Rocky* movie without Sylvester Stallone), so remakes of signature movies should be less successful.

4.3 Relationship between remake and original movie

The relationship between original movies and remakes has two facets that can have an impact on the success of the remake: similarity and recency.

4.3.1 Similarity between remake and original movie

Brand extension research has found that a high perceived similarity between the parent brand and the extension product leads to a more favorable attitude toward the extension (Dacin and Smith 1994). However, in studying movie sequels, Sood and Drèze (2006) have provided evidence of a satiation effect of similarity—a very high level of perceived similarity can be adversarial in the context of hedonic goods because it implies a limited extent of sensation value in terms of novelty and variety.

Although remakes are more restricted by the original movie on which they are based than sequels are, producers can still vary the level of similarity to a certain degree. Examples for such variations include the transfer of the story to a new place or time, or the addition of new supporting characters and new plot twists to the existing narrative. We expect that the success of remakes with audiences is influenced by the similarity of a remake to the original movie and that satiation effects also exist for remakes. Consequently, remakes that are perceived to be very similar to the movies they are based on will be less stimulating, and consequently, less successful than those that are less similar.

4.3.2 Recency of remake

A second facet of the relationship between a remake and its source is the time that separates the two movies' release dates, something we refer to as remake recency.

Research on movie brand extensions has reported that recency is positively linked with the success of sequels (Basuroy and Chatterjee 2008) and novel adaptations (Joshi and Mao 2012) in a linear way. The rationale for this conclusion is that a brand which has recently been extended is more vivid and remembered, which corresponds with higher familiarity levels.

In the case of remakes, this rationale needs to be adapted for the specifics of the remake concept. In general, recency can also be considered a good thing for remakes because old movies that are remade can often fail to offer sufficient familiarity; for example, a time gap of 30 years means that most of the moviegoers targeted by the remake were not even born when the original was released. However, if a remake is produced soon after the original, then novelty, and thus, the sensation value of the remake will be limited. Therefore, we expect an inverted U-shaped relationship, with medium-level remake recency being more successful than both very low- and very high-level remake recency.

5 Empirical testing

5.1 Data and measures

Our dataset consists of motion pictures theatrically released in North America between 1999 and 2011. To rule out result artifacts due to outliers, we limited our dataset to those movies produced in the USA and/or in the UK with a production budget of at least one million US dollars. The final dataset contains 2,168 movies that meet these conditions. To identify remakes, we used the classification of the Internet Movie Database (IMDb), the most authoritative collection of film-related information.[1] The dataset contains 207 remakes and 1,961 non-remake movies.

The variables used in this research comprise remake-specific variables as well as established movie success factors. The total box office revenues a movie received in North American theaters serve as our proxy for movie revenues.[2] To study the effect of remakes on risk, we used the standard deviations of movie revenues and a measure of the movies' rate of return (RoR; Palia et al. 2008). Regarding the latter, we calculated RoR by dividing the North American box office revenues by the sum of production costs and advertising spending for North America. Table 1 presents an overview of all of the variables used and their respective data sources.

Regarding remake-specific variables, we first had to identify the "original movie" for remakes that had more than one predecessor. We empirically defined the original movie as the previous version of a remake that had the highest awareness level when the remake was announced (i.e., was listed in the IMDb for the first time). We prefer the selection of the movie with the highest awareness to the one with the earliest release date because the former better reflects consumers'

[1] As the IMDb contains user-generated information, we manually checked every title in our database to ensure that the movies were perceived as remakes. The IMDb entries were mostly correct, so hardly any modifications were made.

[2] In the movie industry, the North American box office combines box office revenues from the USA and Canada; it is sometimes also referred to as the "domestic box office".

Table 1 Description and operationalization of variables used

Variable	Name	Description	Source
Determinants of movie success			
Remake	REMAKE	Binary variable taking the value of 1 if the movie is classified as a remake by the IMDb and perceived as a remake by critics	IMDb, Metacritic
Budget	BUDGET	Logarithm of the budget of the movie (inflation-adjusted)	e.g., IMDb, Boxofficemojo
Marketing support	MARKETING	Logarithm of the mean of pre-release advertising (inflation-adjusted, standardized) and distribution intensity as measured by the number of opening theaters in North America (standardized)	Kantar Media, TNS, Boxofficemojo
Star	STAR	Binary variable taking the value of 1 if at least one star who was listed on the movie poster participated in the movie; a star is defined as an actor who was on the "Top 10 Money-Makers Poll" list at least once preceding the year of the movie release	Quigley
Critics	CRITICS	Rating for the movie by professional movie critics	Metacritic
Sequel	SEQUEL	Binary variable taking the value of 1 if the movie is categorized as a sequel by the IMDb	IMDb
Bestseller	BESTSELLER	Binary variable taking the value of 1 if the movie was the adaptation of a book that was listed on the "USA Today" bestseller list at least once until 3 months before the movie release	USA Today
MPAA-rating	MPAA	Rating for the age restriction as published by the MPAA for the USA (1 = G, 2 = PG, 3 = PG-13, 4 = R)	IMDb
Comedy, action, drama, horror, thriller, Sci-Fi	GENRE	Binary variable taking the value of 1 if the genre of the movie belongs to the genre category of the respective variable	IMDb
Remake-specific variables			
Awareness of original movie	AWARENESS	Inverse of the mean of the MOVIEmeter rank of the original in the week of the remake's announcement as well as the 3 weeks prior, multiplied by 1,000	IMDb
Image valence of original movie	IMAGE VALENCE	Average of the IMDb user rating for the original movie	IMDb
Image attributes of original movie	IMAGE ATTRIBUTES	Binary variable taking the value of 1 if the genre of the original belongs to the respective genre category (Comedy, Action, Drama, Horror, Thriller, Sci-Fi)	IMDb

Table 1 continued

Variable	Name	Description	Source
Signature image of original movie	SIGNATURE IMAGE	Binary variable taking the value of 1 if (1) the director's/producer's name is placed very prominently on the original's poster and/or (2) an actor is explicitly assigned to his character on the poster(s) and/or (3) the main character is named as a signature role on the actor's official homepage. Posters were retrieved from Movieposterdatabase.com and Google picture search results (search key: "[movie title] [release year] USA official release poster")	IMDb, Movie poster database, Google
Similarity between original movie and remake	SIMILARITY	Multidimensional cumulative score that includes the continuity of the genre, main character, location setting, time setting, narrative perspective, and main conflict (thus ranging from 0 to 6)	IMDb
Recency of original movie	RECENCY	Difference in years between the release of the original and the release of the remake	Boxofficemojo
Measures of movie success			
Movie revenues	BOX OFFICE	Logarithm of North American box office gross revenues (inflation-adjusted)	Variety, IMDb, Boxofficemojo
Risk	RISK	Two measures: standard deviation of (a) movie revenues and (b) rate of return/RoR (quotient of movie revenues and sum of production costs and advertising spending for North America)	Variety, IMDb, Boxofficemojo, Kantar Media, TNS

perceptions and potentially resembles the movie with the highest degree of familiarity. As our measure of awareness, we used the IMDb's MOVIEmeter rank, which reflects the number of searches by IMDb users for a respective movie title. In cases where two or more earlier versions had similar MOVIEmeter ranks, we checked the first up to 20 critics on Metacritic.com and chose the version that most critics referred to as the "original". To smooth out outlier values, we collected the MOVIEmeter rank for the week in which the remake was listed for the first time and for the 3 weeks prior, and then used the arithmetic mean of the four data points as a measure of the original movie's brand awareness in our analyses. Following other scholars who have made use of MOVIEmeter information (e.g., Ho et al. 2009), we inverted this score and multiplied it by 1,000 so that higher values indicate higher awareness of the original.

We used the average IMDb user rating as our measure of the original movie's brand image valence (e.g., Hennig-Thurau et al. 2009; Dhar et al. 2012); we also ran post-hoc analyses with professional reviewers' image perceptions and combinations of consumer and reviewer perceptions, drawing on information from Rotten Tomatoes and other review sites (see footnote 11 for details). We measured brand image attributes as a set of binary genre variables of the original. The original movie's signature image was measured as a binary variable that takes the value of 1 if at least one of the three following conditions was met: (1) the director's or producer's name is placed very prominently on the original movie's official poster (e.g., "Cecil B. de Mille's The Ten Commandments"), (2) an actor is explicitly assigned to the original film's lead character on the poster (e.g., "Michael Caine is Alfie"), or (3) the main character is named as a signature role on the actor's official home page.

To assess the similarity between a remake and the original movie, we followed Verevis' (2006) approach and developed a formative measure that allows us to consider both the similarity of specific movie elements and the movies' structural similarity. We considered six binary variables measuring the similarity of genres, main characters, time setting, location setting, narrative perspective, and main conflict continuity.[3] The final composite score sums the different binary variables and ranges from 0 (=very dissimilar; continuity exists for none of the dimensions) to 6 (=very similar; continuity exists for all six dimensions). We calculated the recency measure as the difference in years between the release of the remake and the original movie.

[3] Specifically, genre similarity takes the value of 1 if the remake and the original movie cover the same genres. Main character similarity takes the value of 1 if the remake neither introduces new main characters nor drops existing characters and if the characters' key characteristics (gender, adult/child, hero/antihero) remain constant. Time setting similarity is 1 if the time discrepancy between the settings of the two movies is no more than 10 years. Location setting similarity is coded 1 if both movies take place in the same location setting. Narrative perspective similarity takes the value of 1 if both movies are narrated from the same perspective (an omniscient point of view versus a specific character's perspective). Finally, main conflict similarity receives the value 1 if the IMDb plot summaries describe equal plots. All information for this measure comes from IMDb; if information concerning characters, time settings, or location settings was missing, we double-checked it with more detailed plot summaries on Wikipedia.org.

To rule out an omitted variable bias, we also controlled for a number of variables previously identified by scholars as movie success factors (e.g., Hennig-Thurau et al. 2001; Basuroy et al. 2003; Ravid and Basuroy 2004). These variables are as follows: (a) production budget, (b) participation of a major star (i.e., an actor who appeared on the Quigley list of the "Top Ten Money-Making Stars" before the year of the movie release; Wallace et al. 1993), (c) whether a movie is a sequel to a previous movie, (d) whether it is an adaptation of a best-selling book (i.e., appeared at least once on the "USA Today" Bestseller list until 3 months before the movie's release), (e) the movie's quality according to professional movie critics, (f) its age rating by the MPAA, (g) a vector of different movie genres (i.e., action, comedy, drama, horror, science fiction, thriller), and (h) the marketing support the movie received. We measured marketing support as a composite score that encompasses advertising and distribution, two main marketing activities for movies for which decisions are made hand-in-hand with the producer.[4] Technically, our measure is the mean of z-standardized pre-release advertising spending (in US dollars) and distribution intensity (i.e., the number of opening weekend theaters).

We adjusted the monetary variables of budget, marketing support, and total box office revenues for inflation and used the logarithm of these variables to account for their skewed distribution (see, e.g., Gemser et al. 2012 for the same approach).

5.2 Procedure

Our approach to investigate the impact of remakes on movie success as well as the proposed contingency factors involved three steps. In the first step, we applied statistical matching to reduce a potential sample selection bias of remakes and to identify movies that are not remakes but are statistically comparable to our set of remakes with regard to critical success drivers. Statistical matching is an established approach to reduce a sample selection bias in a given dataset (Rubin 1973; Smith 1997). We considered the existence of such a bias probable, as research on movie sequels found sequels to systematically differ from non-sequel movies with regard to several variables, including budgets and advertising spending (Hennig-Thurau et al. 2009).

Specifically, we used propensity score matching to reduce the sample selection bias. Propensity score matching addresses the counterfactual question of how the box office revenues generated by a movie that has been selected to become a remake would have differed if the same movie had not been produced as a remake. To answer this question, propensity score matching identifies a proper substitute for the unobservable component of a remake movie being produced as a non-remake, conjuring a matched control sample out of the given 1,961 non-remake movies. We ran a binary logit model to obtain the individual propensity scores for each movie,

[4] Studios orient their advertising budgets to the number of theaters in which a movie is released and vice versa; no producer allocates high amounts of advertising to a movie that does not obtain a corresponding distribution. "The marketing and releasing plans are coordinated together and marketing executives work very closely with distribution executives" (Fellman 2006, p. 364f). Fellman was a leading manager at Warner Bros. Pictures at the time this statement was made. See also Friedman (2006, p. 292f) for a similar description. The two variables are highly correlated in our dataset ($r = .82$, $p < .01$).

with the dependent variable being 1 for remake movies and 0 for non-remakes.[5] As observed matching covariates, we used those movie success variables that we expected to differ between remakes and non-remakes, namely movie budget, marketing support, star participation, sequel, bestseller adaptation, critic rating, MPAA-rating, and several genres.

We then transformed the calculated propensity scores into matching weights using an Epanechnikov kernel function with a bandwidth parameter of .06.[6] In this step, each remake receives a weight of 1 (adding up to 207 cases), whereas each non-remake movie receives an individual weight (also adding up to 207 cases). The individual weights account for the propensity of a movie to be a remake; the kernel estimator thus upweights "close" (i.e., similar) movies and downweights "distant" (i.e., dissimilar) control cases (Heckman et al. 1998).

In the second step, we used the matched dataset of remakes and non-remake movies ($n = 414$) to study how an "average" remake performs in terms of movie revenues and risk compared to other movies. To analyze the effect of an "average" remake on movie revenues, we ran a weighted least squares (WLS) regression; the matching weights served as regression weights. To test whether the risk of producing an "average" remake is less than that of producing a movie which is not a remake, we ran F-tests to compare the standard deviations of all remakes and the "matched" non-remakes (Palia et al. 2008). In the third and final step, we then split our weighted sample into subsamples for all contingency factors listed in Fig. 2. For each contingency factor and the corresponding subsample, we repeated the analyses of remakes on movie revenues and risk. We ran WLS regressions for each category of a contingency factor and then applied a z-test to see whether the regression coefficients for the remake variable differed between the subsamples (Paternoster et al. 1998). We used three different approaches to generate the various subsamples, depending on the characteristics of the respective contingency factor. Specifically, for all binary contingency factors, we compared the remakes that featured the respective movie characteristic to those movies that did not feature it. For example, we compared the regression results for remakes that did feature a signature role (and all matched non-remake movies) to the regression results for remakes that did *not* feature a signature role (and again, all matched non-remake movies).

For continuous contingency factors, we split the sample using terciles to compare high-, medium-, and low-subsample groups based on the theoretical arguments provided above. That is, we split the brand awareness variable into terciles to account for the expected nonlinear nature of the factor. Because we propose that a medium level of brand awareness should have a higher success potential than high- and low-awareness levels, a tercile split is an adequate way to separate the respective subsamples. For image valence and similarity, we compare the tercile

[5] A propensity score is the conditional probability of the assignment to a particular treatment (i.e., a project being selected to become a remake) given a vector of observed covariates (in this case, budget, marketing support, etc.) (Rosenbaum and Rubin 1983).

[6] For detailed information on different types of matching estimators (including Epanechnikov kernel matching), please see, e.g., Heckman et al. (1997). We preferred the kernel approach over the nearest-neighbor approach because the former uses *all* control cases instead of relying solely on a 1:1 match, which chooses only the "closest" match (e.g., Heckman et al. 1998).

with the highest values with a combined sample of the other two terciles, as we expect the high-value subsample to differ from the remaining set of remake movies. For recency, we divided the variable into three time periods, covering high recency (1–10 years), medium recency (11–30 years), and low recency (more than 30 years). This split was preferred over terciles because of the skewed distribution of the recency variable.

5.3 Results

5.3.1 Statistical matching

Seven out of the thirteen matching variables significantly differed between remakes and non-remakes before the matching (i.e., budget, marketing, sequel, bestseller, and the horror, comedy, and thriller genres), providing evidence of a selection bias for remakes. After the matching, no significant differences remain, indicating that the applied matching procedure is able to reduce this bias substantially; Table 2 presents the detailed results.

Additional support for the effectiveness of the matching comes from a comparison of the bias before and after the matching (Rosenbaum and Rubin 1985); the matching reduces the mean bias from 17.8 to 2.8 and the Pseudo-R^2 from .085 to .003 (before and after the matching, respectively). All our cases are "on support" (see e.g., Smith and Todd 2001 for the relevance of common support), which confirms that a substantial overlap exists between our treated and untreated cases (i.e., remakes and non-remakes). This indicates that our dataset is well suited for the matching approach.

Table 2 Overview of matching results

	Mean comparison (pre-/post matching)			Bias	*t* test	
	Treated	Controls pre	Controls post	% reduction |bias|	*p* pre	*p* post
LN budget	3.6635	3.4035	3.6371	89.8	<.001	.758
LN marketing	.9921	.8888	.9802	88.5	.001	.739
Star	.2947	.2596	.2918	91.7	.275	.948
Critics	4.9493	5.0532	4.9443	95.2	.436	.977
Sequel	.0097	.1244	.0174	93.2	<.001	.495
Bestseller	.0338	.0765	.0376	91.2	.024	.837
MPAA	3.1884	3.2055	3.1767	31.3	.768	.876
Comedy	.3333	.4707	.3640	77.7	<.001	.514
Action	.2174	.2193	.2192	6.8	.950	.966
Drama	.5459	.5028	.5313	66.2	.238	.767
Horror	.1739	.0780	.1530	78.2	<.001	.566
Thriller	.4106	.2774	.3836	79.7	<.001	.575
Sci-Fi	.0870	.0918	.0899	40.1	.819	.918

Comparing the average box office results for remakes and unmatched/matched non-remake movies reveals first insights into the economic impact of the remake variable. While the average box office of remakes is significantly higher than that of all non-remakes (unmatched comparison: remakes = 34.820, non-remakes$_{unmatched}$ = 26.690, t-stat = 2.59, $p < .01$),[7] this difference becomes insignificant when only the matched sample of non-remakes is used (matched comparison: remakes = 34.820, non-remakes$_{matched}$ = 33.126, t-stat = .55, n.s.). Neither of these comparisons, however, accounts for the possible effects of controls and the contingency factors discussed above; we report this in the next section.

5.3.2 Results for revenues and risk for the full dataset: "Average" effects

Table 3 reports the descriptive statistics and correlations for the variables included in the regression. The left panel of Table 4 then lists the results for the average effect WLS regressions using the matched dataset. The model is well explained ($R^2 = .719$), and the small VIF values indicate that the results are not distorted by multicollinearity. We find no significant average effect of the remake variable on box office when accounting for controls ($b = .013$, $t = .497$).[8] This implies that, in contrast to other movie brand extensions such as sequels and bestseller adaptations, remakes on average do *not* enjoy an advantage in terms of box office revenues. We replicated our results with an ordinary least squares (OLS) regression of the unweighted dataset; although the parameter for the remake variable is slightly higher, it is once more insignificant (for details, see the right panel of Table 4).[9]

To test whether remakes are less risky than other movies, we adopted the procedure suggested by Palia et al. (2008) and compared the standard deviations of the success of remakes (i.e., movie revenues and RoR) with the standard deviations of the success of matched non-remakes and ran F-tests. We find that remakes have a lower standard deviation in terms of both movie revenues and RoR than other non-remake films, as reported in Table 5. This demonstrates that although remakes on average do not generate higher revenues, the risk of producing a remake is lower than that of producing a similar non-remake movie.

5.3.3 Subsample results for revenues and risk: Contingency effects

Table 6 reports the regression coefficients for the remake variable for the different subsample analyses and the F values for each subsample. We now discuss the results for each proposed contingency factor.

[7] Logged values are back-transformed and shown in million US$.

[8] As a robustness check, we conducted an OLS regression analysis with all movies that have received a wide release in North American theaters (i.e., were initially released on at least 800 screens). With again no significant effect found for remakes ($b = .008$, $t = .166$), our results remain robust across different samples and methods. See Table 7 in the Appendix for details.

[9] To check whether results are affected by possible interactions by movies that are both sequels and remakes, we ran a WLS and an OLS regression for a sample without sequels. Results remained unchanged. See Table 8 in the Appendix for details.

Table 3 Correlation table

	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Remake	.50	.501	1														
2. Budget	3.65	.871	.015	1													
3. Marketing	.99	.362	.016	.698***	1												
4. Star	.29	.456	.003	.322***	.238***	1											
5. Critics	4.95	1.737	.001	.052	−.090*	.147***	1										
6. Sequel	.01	.116	−.034	.051	.066	−.037	−.007	1									
7. Bestseller	.04	.186	−.010	.048	−.007	.019	.123**	.125**	1								
8. MPAA	3.18	.766	.008	−.214***	−.251***	.007	.034	−.032	−.004	1							
9. Comedy	.35	.477	−.032	.009	.129***	.065	−.081*	.021	−.082*	−.305***	1						
10. Action	.22	.414	−.002	.316***	.262***	−.010	−.082*	.012	−.068	.066	−.217***	1					
11. Drama	.54	.499	.015	−.083*	−.222***	.115**	.306***	−.010	.082*	.143***	−.291***	−.133***	1				
12. Horror	.16	.370	.028	−.151***	.007	−.191***	−.194***	.048	−.030	.239***	−.246***	−.111**	−.173***	1			
13. Thriller	.40	.490	.028	.018	.065	−.013	−.138***	.015	.000	.358***	−.467***	.189***	−.016	.411***	1		
14. Sci-Fi	.09	.284	−.005	.237***	.177***	.010	−.006	−.001	−.046	−.048	−.163***	.264***	−.124**	.002	.191***	1	
15. Box Office	3.55	1.179	.021	.640***	.797***	.263***	.174***	.080	.067	−.222***	.080	.183***	−.149***	.035	.032	.145***	1

The dataset was weighted with the matching weights before calculating the descriptives. Logarithmic values were used for budget, marketing, and box office

*** Statistical significance at the .01 level; ** statistical significance at the .05 level; * statistical significance at the .10 level (2-tailed)

Table 4 WLS and OLS regression: Average effects (full dataset)

	Matched data regression (WLS)				Unmatched data regression (OLS)			
	Coefficient	Beta	*t*-statistic	VIF	Coefficient	Beta	*t*-statistic	VIF
Intercept	−.019		−.170		−.198		−1.874*	
Remake	.013	.006	.497	1.004	.021	.005	.438	1.050
LN budget	.175	.129	7.378***	2.335	.154	.114	6.427***	2.976
LN marketing	2.273	.698	40.484***	2.277	2.403	.752	43.312***	2.858
Star	.117	.045	3.575***	1.230	.040	.013	1.144	1.188
Critics	.173	.255	20.455***	1.191	.177	.237	21.574***	1.145
Sequel	.195	.019	1.651*	1.030	.349	.081	7.475***	1.121
Bestseller	.245	.039	3.291***	1.056	.155	.030	2.785***	1.070
MPAA	−.069	−.045	−3.351***	1.355	−.032	−.019	−1.590	1.344
Comedy	.019	.008	.524	1.703	.048	.017	1.311	1.681
Action	−.001	.000	−.014	1.390	−.027	−.008	−.652	1.450
Drama	−.099	−.042	−3.100***	1.400	−.039	−.014	−1.109	1.563
Horror	.371	.116	8.271***	1.516	.260	.054	4.493***	1.361
Thriller	−.016	−.007	−.445	1.669	−.043	−.014	−1.087	1.638
Sci-Fi	−.047	−.011	−.915	1.177	−.016	−.003	−.289	1.221
R^2	.719				.773			
R^2 adjusted	.717				.771			
F-statistic	392.753				522.936			
Prob. (*F*-statistic)	<.001				<.001			

Dependent variable: LN box office

*** Statistical significance at the .01 level; ** statistical significance at the .05 level; * statistical significance at the .10 level

Table 5 Effects of remakes on risk

Dependent variable	Remakes		Non-remakes		Differences in SD	*F* value
	SD	*N*	SD	*N*		
Box office revenues	60.07912	207	69.59962	207	9.52050	1.342**
Rate of Return/RoR	.60975	207	1.03882	207	0.42907	2.903***

*** Statistical significance at the .01 level; ** statistical significance at the .05 level; * statistical significance at the .10 level

5.3.3.1 Original movie's brand awareness For medium-awareness remakes, we find a marginally positive effect ($b = .055$, $p = .10$), but there is no effect for high- and low-awareness remakes; the parameter for the high-awareness subsample is even negative. In addition, the remake parameter for medium-awareness remakes is

Table 6 Results of the subsample WLS regressions and risk analyses

Contingency factor	Feature of subsample	*N* (total) / *N* (subsample)	Remake coefficient	|z value|	Risk (Box Office)			Risk (Rate of Return/RoR)		
					SD	Difference in SD	*F* value	SD	Difference in SD	*F* value
Awareness of original movie	High awareness	2,031/70	−.026	High versus medium: 1.746**	68.714	.885	1.026	.673	.366	2.385***
	Medium awareness	2,030/69	.055*	High versus low: 1.071	58.444	11.156	1.418**	.579	.460	3.225***
	Low awareness	2,029/68	.024	Medium versus low: .660	49.270	20.330	2.000***	.564	.475	3.396***
Image valence of original movie	Good image	2,027/66	−.085**	3.591***	62.430	7.170	1.243	.606	.433	2.941***
	Medium or bad image	2,102/141	.071***		58.962	10.638	1.393**	.608	.431	2.922***
Image attributes of original movie	Action	1,992/31	.045	.841	78.444	−8.844	.7872	.554	.485	3.517***
	Horror	2,004/43	.107**	2.263**	46.531	23.069	2.237***	.720	.318	2.079***
	Sci-fi	1,980/19	−.052	.934	87.056	−17.456	.6392	.499	.540	4.328***
	Thriller	2,023/62	.000	.490	56.843	12.757	1.499**	.470	.569	4.892***
	Comedy	2,016/55	−.010	.396	59.125	10.475	1.386*	.589	.450	3.114***
	Drama	2,065/104	.001	.597	49.160	20.440	2.005***	.546	.493	3.625***
Signature image of original movie	Yes	1,980/19	−.321***	6.344***	27.344	42.256	6.479***	.596	.443	3.035***
	No	2,149/188	.049*		62.040	7.560	1.259*	.607	.432	2.932***
Similarity between original and remake	High similarity	2,018/57	−.097***	3.596***	41.102	28.497	2.867***	.769	.270	1.827***
	Medium or low similarity	2,111/150	.063**		64.937	4.662	1.149	.540	.499	3.700***

Table 6 continued

Contingency factor	Feature of subsample	*N* (total) / *N* (subsample)	Remake coefficient	|z value|	Risk (Box Office)			Risk (Rate of Return/RoR)		
					SD	Difference in SD	*F* value	SD	Difference in SD	*F* value
Recency of original movie	High recency (1–10 years)	2,007/46	−.032	High versus medium: 2.207**	46.955	22.644	2.197***	.499	.540	4.339***
	Medium recency (11–30 years)	2,019/58	.080**	High versus low: .642	45.231	24.369	2.368***	.741	.298	1.967***
	Low recency (>30 years)	2,064/103	−.001	Medium versus low: 1.755**	71.052	−1.452	.960	.557	.482	3.476***

SD standard deviation

Dependent variable for regressions: LN box office

For each regression, we used all independent variables described in Table 4. Each subsample includes all remake movies with the respective subsample feature (e.g., all remakes with a good image) and all non-remake movies. *N* (total) refers to all cases used in the respective regression; *n* (subsample) refers to the number of remake movies within that sample. For example, in the first regression analysis listed, 70 cases feature an original movie with high awareness which are added to 1,961 weighted non-remake cases and thus adds up to 2,031 cases in total (and a cumulated weight of 70 + 207 = 277). All remake cases across the three terciles add up to 70 + 69 + 68 = 207, which is the total of all remake cases in our sample. The unstandardized coefficient indicates whether the respective remake cases exhibit a significant influence on box office revenues in the respective regression. *Z* values are calculated with one-tailed *z*-tests. (We also checked for differences when using a two-tailed *z*-test; the results remained mainly robust.)

*** Statistical significance at the .01 level; ** statistical significance at the .05 level; * statistical significance at the .10 level significantly higher than for high-awareness remakes (z-stat $= 1.75$, $p < .05$); the difference between medium- and low-awareness remakes does not reach significance (z-stat $= .66$). Thus, medium-awareness remakes indeed perform better at the box office than high-awareness remakes do, with the moderating effect of brand awareness being asymmetrical.[10] RoR-related risk is lower for remakes across all levels of awareness, and revenue-related risk is lower for medium- and low-awareness remakes. Both types of remake risk are lowest for remakes of original movies with low awareness.

5.3.3.2 Original movie's image valence The remake coefficient for remakes of original movies with high-image valence is significant and negative ($b = -.085$, $p < .05$), whereas the coefficient for the combined subsample of medium- and low-image valence is significant and positive ($b = .071$, $p = .01$). The difference between the two parameters is also significant (z-stat $= 3.59$, $p < .01$), which suggests that a movie with a very positive quality perception is not the ideal candidate for being remade.[11] This is supported by our risk analyses; whereas both high- and medium-/low-image remakes are of lower RoR-related risk than non-remakes, revenue-related risk is only significantly lower for medium-/low-image remakes.

5.3.3.3 Image attributes Our subsample regression analyses for six different genres are generally in support of our theoretical arguments. Horror movies and action movies, which typically feature a high amount of technology-driven (and thus quickly outdated) elements, have higher remake coefficients than movies without these genre attributes, whereas story- and dialogue-driven remakes (i.e., dramas, comedies, and thrillers) show the opposite effect with very low coefficients. However, the horror genre is the only genre for which the remake coefficient reaches significance ($b = .107$, $p < .05$). Thus, the influence of a movie's genre on its "remakeability" tends to be rather limited, and producers should pay attention to other contingency factors instead. All genres outperform non-remakes in terms of RoR-related risk, and horror remakes, but also drama and thriller remakes involve less revenue-related risk than non-remakes.

[10] Please note that these results are somewhat sensitive to the definition of the subsamples; the reported effect of medium-awareness remakes fades when the subsample boundaries are moved by 10 percent or more. Thus, these results should be interpreted with care. We also conducted sensitivity analyses for the other metric variables (i.e., image valence and remake recency), but they were not influenced by such variations.

[11] We replicated this analysis using professional reviewers' image perceptions instead of those of consumers and also with combinations of image perceptions of professional critics and consumers. The results remained the same for every operationalization used; see Table 9 in the Appendix for details. For these replications, the ratings of professional critics were taken from Rotten Tomatoes; in cases where not enough information was available, we used information from Metacritic.com and MRQE.com. For those movies for which no information was available on any of these sites, we used the score expert Leonard Maltin reported in his film guide (Maltin 2013). For five original movies, no information was available from any of these sources; these movies were dropped from the replication analyses.

5.3.3.4 Signature image In line with the theoretical arguments, the results show a strong negative effect on revenues for remakes that are based on movies with a signature image ($b = -.321$, $p < .01$) and a positive effect for remakes with no-signature image ($b = .049$, $p < .10$). The two subsample regression parameters differ significantly (z-stat = 6.34, $p < .01$), which highlights the hurdles that are associated with remaking a signature film. Signature remakes exhibit less RoR-related and revenue-related risk than non-remakes, which suggests that there is limited variation in the lower revenues these remakes generate. For no-signature remakes, RoR-related risk is also lower, but revenue-related risk is only marginally lower than is the case with non-remakes.

5.3.3.5 Similarity We find a significant negative effect on revenues for remakes that are very similar to their originals ($b = -.097$, $p < .01$), while remakes with medium or low similarity exhibit a positive influence ($b = .063$, $p < .05$). The difference between the two remake parameters itself is also significant (z-stat = 3.60, $p < .01$). Highly similar remakes exhibit little variation in their RoR and revenues; remakes that are of medium or low similarity have an advantage over non-remakes in terms of RoR-related risk, but not significantly in terms of revenue-related risk.

5.3.3.6 Recency Again consistent with our arguments, we find remakes with a medium level of recency (i.e., a time gap of 11–30 years) to be most promising in terms of revenues: the remake parameter for this subsample is positive ($b = .080$, $p < .05$) and differs significantly from those of the other two subsamples, both of which are nonsignificant (z-stat = 2.21, $p < .05$ and z-stat = 1.76, $p < .05$, respectively). Medium recency remakes also offer advantages in terms of revenue- and RoR-related risk. High- and low-recency remakes vary less in terms of RoR, but low-recency remakes do not differ in terms of revenue-related risk from non-remakes.

6 Discussion

This article introduces a new sensations-familiarity framework of hedonic media products and uses it to investigate the economic potential of remakes, a unique type of movie brand extension and widely used phenomenon in the global movie industry. Drawing from a dataset of 2,168 movies and statistical matching, we find that remakes are, on average, not more successful at the box office than otherwise equal non-remakes, but carry less risk.

Based on a contingency model that we derive from the sensations-familiarity framework and brand extension research, we are also able to demonstrate that the economic potential of remakes differs due to several factors and that specific types of remakes are indeed more successful than other movies. The contingency model offers very concrete managerial guidelines about the types of remakes that are most promising for producers. Figure 3 presents a map that positions various remake

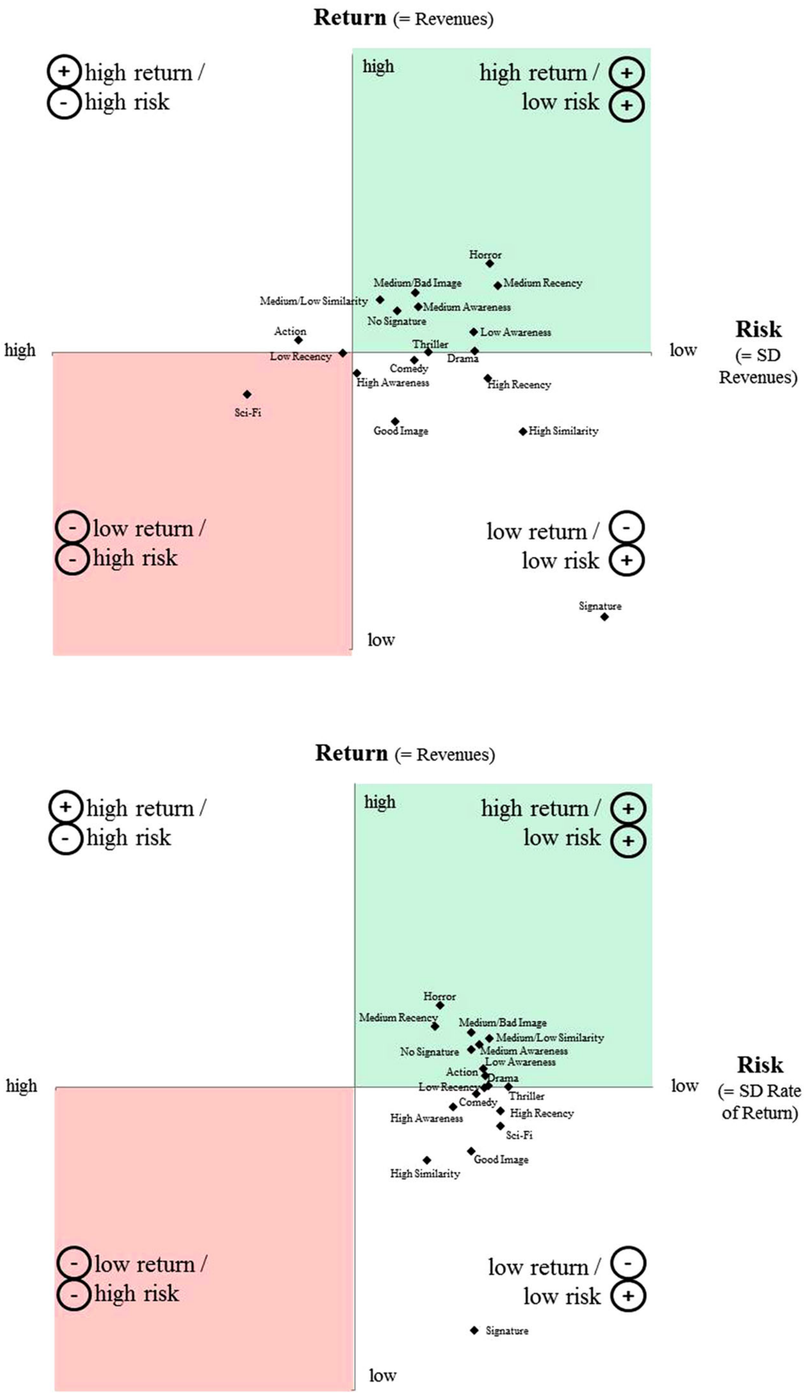

Fig. 3 Risk-return maps of different types of remakes

types based on their respective risk-return combination. Remakes that are placed in the upper right quadrant appear to be particularly promising investments, as they offer above-average revenues and are also less risky than the “average” non-remake movie. Such films include remakes based on films with medium awareness, a medium-/low-image, medium recency, movies that are considered horror movies, and movies that lack a signature. The figure also indicates that remakes should not be overly similar to their original.

Some limitations highlight avenues for future research. Our dependent measure concentrates on domestically generated box office revenues and does not account for international revenues or home entertainment sales, two revenue sources that are of growing importance to Hollywood. In home entertainment markets, remakes compete with their originals, which might cause divergent results. Additionally, this study only considers forward spillover effects (i.e., how the original impacts the remake) but not reciprocal spillover effects. Can a remake revitalize the home entertainment revenues of the original movie in the same ways a sequel does (Hennig-Thurau et al. 2009)?

Moreover, further research could extend the contingency model introduced herein. A potential addition is 3D—does adding a third dimension, and thus new sensorial sensations, improve the average returns of remakes? While our dataset only contains a limited set of 3D remakes, future data might shed light on this. Furthermore, our use of film-level data limits the scope of this study—experiments could yield insights concerning the decision-making processes of moviegoers and account for differences among consumers. For example, do fans of the original movie prefer to see (or to avoid seeing) a remake?

In our theoretical considerations, we compared remakes with other types of brand extensions that are relevant in the movie industry (i.e., sequels and literature adaptations). Future research could systematically compare contingency factors for different types of brand extensions. An exciting question is whether the findings also apply to other entertainment industries such as cover versions of famous hits in the music industry. Such investigations could further broaden the knowledge on remakes as a cultural phenomenon and extend brand extension research in general.

Appendix

See Tables 7, 8, and 9.

Table 7 OLS regression results for the main effect in a reduced sample (opening theaters ≥800)

	Coefficient	Beta	t-statistic	VIF
Intercept	−.176		−1.445	
Remake	.008	.002	.166	1.052
LN budget	.130	.106	4.769***	2.462
LN marketing	2.616	.607	29.053***	2.196
Star	.037	.017	1.077	1.196
Critics	.149	.253	16.585***	1.169
Sequel	.349	.117	7.838***	1.119
Bestseller	.142	.037	2.483**	1.090
MPAA	−.019	−.015	−.913	1.323
Comedy	−.042	−.020	−1.052	1.879
Action	−.040	−.017	−1.010	1.468
Drama	−.088	−.043	−2.474**	1.512
Horror	.255	.076	4.533***	1.415
Thriller	−.096	−.044	−2.367**	1.735
Sci-Fi	−.022	−.007	−.440	1.218
R^2	.657			
R^2 adjusted	.654			
F-statistic	235.652			
Prob. (F-statistic)	<.001			

Dependent variable: LN box office

*** Statistical significance at the .01 level; ** statistical significance at the .05 level; * statistical significance at the .10 level

Table 8 Regression results for the sample with sequels and without sequels

	Complete sample (unmatched, OLS)		Only non-sequels (unmatched, OLS)	
	Coefficient	t-statistic	Coefficient	t-statistic
Intercept	−.198	−1.874*	−.132	−1.158
Remake	.021	.438	.025	.496
LN budget	.154	6.427***	.139	5.442***
LN marketing	2.403	43.312***	2.420	41.708***
Star	.040	1.144	.054	1.455
Critics	.177	21.574***	.179	20.395***
Sequel	.349	7.475***	–	–
Bestseller	.155	2.785***	.159	2.601***
MPAA	−.032	−1.590	−.051	−2.257**
Comedy	.048	1.311	.060	1.544
Action	−.027	−.652	−.036	−.814
Drama	−.039	−1.109	−.029	−.782
Horror	.260	4.493***	.264	4.111***
Thriller	−.043	−1.087	−.013	−.309
Sci-Fi	−.016	−.289	−.071	−1.206

Table 8 continued

	Complete sample (matched, WLS)		Only non-sequels (matched, WLS)	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Intercept	−.019	−.170	−.039	−.334
Remake	.013	.497	.018	.620
LN budget	.175	7.378***	.176	7.001***
LN marketing	2.273	40.484***	2.274	38.172***
Star	.117	3.575***	.116	3.318***
Critics	.173	20.455***	.174	19.274***
Sequel	.195	1.651*	–	–
Bestseller	.245	3.291***	.281	3.439***
MPAA	−.069	−3.351***	−.068	−3.102***
Comedy	.019	.524	.022	.573
Action	−.001	−.014	−.002	−.059
Drama	−.099	−3.100***	−.095	−2.774***
Horror	.371	8.271***	.380	7.951***
Thriller	−.016	−.445	−.013	−.350
Sci-Fi	−.047	−.915	−.052	−.941

Dependent variable: LN box office

*** Statistical significance at the .01 level; ** statistical significance at the .05 level; * statistical significance at the .10 level

Table 9 Results of subsample WLS regression analyses for different measures of image valence

Contingency factor	Feature of subsample	*N* (total)/ *N* (subsample)	Remake coefficient	|*z* value|
Image valence of original movies (professional reviewers)	Good image	2,022/61	−.086**	3.152***
	Medium or bad image	2,102/141	.055**	
Image valence of original movies (additive combination of professional reviewers and consumers)	Good image	2,024/63	−.095***	3.666***
	Medium or bad image	2,100/139	.068**	

Table 9 continued

Contingency factor	Feature of subsample	N (total)/ N (subsample)	Remake coefficient	|z value|
Image valence of original movies (multiplicative combination of professional reviewers and consumers)	Good image	2,028/67	−.065*	2.826***
	Medium or bad image	2,096/135	.060**	

Dependent variable: LN box office

Five remakes had to be dropped due to missing values of the critics' evaluation of the original movie. For each regression, we used all independent variables described in Table 4. Each subsample includes all remake movies with the respective subsample feature (e.g., all remakes with a good image) and all non-remake movies. *N* (total) refers to all cases used in the respective regression; *N* (subsample) to the number of remake movies within that sample

*** Statistical significance at the .01 level; ** statistical significance at the .05 level; * statistical significance at the .10 level

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