Thorsten Hennig-Thurau, Mark B. Houston, & Torsten Heitjans

Conceptualizing and Measuring the Monetary Value of Brand Extensions: The Case of Motion Pictures

Brand extension value is the part of brand value that derives from a brand owner's right to introduce new products related to the brand. The authors draw on a theoretical conceptualization of brand extension success and present an approach to measure the monetary value of brand extension rights in the context of motion pictures (i.e., movie sequel rights) and to calculate the effect of variations of key extension product attributes, such as the continued participation of stars, on this value. Their measure incorporates both the forward spillover effect and the reciprocal spillover effect and accounts for differences between brand extensions and new original products in revenues and risk, thereby offering marketing scholars a novel approach for evaluating the riskiness of investment alternatives. With respect to the forward spillover effect of a parent brand on the extension product, the authors apply regression analysis to data from all 101 initial movie sequels released in North American theaters between 1998 and 2006 and to a matched subsample of original movies and calculate the risk-adjusted monetary brand extension value by comparing success predictions for both sequels and matched original movies. Regarding the reciprocal spillover effect by which the extension product affects the success of the parent brand, the authors use longitudinal data of parent-brand DVD sales to monetize the risk-adjusted impact of the brand extension on the parent. The usefulness of their approach is illustrated by calculating the monetary brand extension value for an actual movie title.

Keywords: brand value, motion picture industry, brand extension, forward spillover effect, reciprocal spillover effect

A brand extension strategy in which an existing brand name is attached to a new product can help companies raise consumers' interest in the new product at the time it is launched (Keller 2003). This is of particular importance for products whose diffusion functions follow an exponential-decay pattern and generate the highest revenues immediately after the new product has been made available to consumers, which is often the case with high-budget media products, such as motion pictures, books, music, and games (Ainslie, Drèze, and Zufryden 2005).

This research addresses a critical brand extension issue—namely, determining the monetary value of a brand extension right. By examining data from the motion picture context, in which sequels function as extensions of movie brands, we develop a practical and valid method that enables companies to calculate the financial value of their brands' extension rights, a fundamental but difficult-to-measure intangible capital asset (Srivastava, Shervani, and Fahey 1998). For example, NBC Universal holds the rights to produce a sequel to the classic film *E.T.: The Extra-Terrestrial*, and the value of the firm should reflect the value of those rights. But how much are the rights worth? Any company that owns a well-known brand might ask this question.

Beyond its balance sheet relevance, determining the value of a brand extension right is also essential for buying and selling such rights, a regular occurrence in many industries. For example, the Luxottica Group purchased the rights to design, produce, and globally distribute prescription frames and sunglasses under the Polo Ralph Lauren brand for \$200 million (*Business Edition* 2006). In the motion picture industry, studios compete aggressively to acquire "sequel rights to dormant or interrupted franchises" (Garg 2007). Intermedia Films paid \$14.5 million for the sequel rights to *The Terminator* in 2001 (Epstein 2005). Did this price exaggerate (or underestimate) the power of the *Terminator* brand?

Because extension products usually consist of multiple attributes that are not finalized at the time a firm acquires the extension right, it is also critical to know how changes in such attributes influence brand extension value. What would the sequel right for *The Terminator* have been worth if the original's star (Arnold Schwarzenegger) was not

Thorsten Hennig-Thurau is Professor of Marketing and Media Research, Bauhaus-University of Weimar, and Research Professor of Marketing, Cass Business School, London (e-mail: tht@medien.uni-weimar.de). Mark B. Houston is Eunice and James L. West Chair of American Enterprise and Professor of Marketing, MJ Neeley School of Business, Texas Christian University (e-mail: m.b.houston@tcu.edu). Torsten Heitjans is a doctoral student and a teaching and research assistant, Department of Marketing and Media Research, Bauhaus-University of Weimar (e-mail: torsten.heitjans@medien.uni-weimar.de). The authors thank the marketing scholars Robert P. Leone, Henrik Sattler, and Chris White; the finance scholar Shane Johnson; the operations research scholar Nada Sanders; the participants of the 8th Annual Workshop of the DeSantis Center for Motion Picture Industry Studies, Fort Lauderdale; and the anonymous *JM* reviewers for their constructive comments on this research.

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available? Would the release of a sequel have any reciprocal impact on the parent film's value (e.g., by stimulating its DVD sales)?

Although the paucity of research on monetizing brand extensions was first lamented more than 15 years ago (Smith and Park 1992), no studies have yet assessed the revenues created by individual brand extensions, despite a body of research on the determinants of the success of brand extensions. Because such information is critical for accurate firm valuations and for negotiations between potential buyers and sellers of brand extension rights, its lack constitutes an "important gap in extant approaches" (Srinivasan, Park, and Chang 2005, p. 1433).

Our objective is to develop a measure of monetary brand extension value that can be used to assess individual brand extension rights. We draw from the brand literature to identify the elements of brand extensions that determine their success and use this information to empirically calibrate a model of the brand extension value of individual brands that integrates both forward and reciprocal brand extension spillovers, with data on motion pictures. The model accounts for revenue- and risk-related effects of brand extensions. We illustrate the usefulness of the model by calculating the monetary brand extension value for an actual movie brand.

Brand Extension Value Research

Monetary Brand Extension Value

Extending existing brands is an important branding strategy. Although a large body of research has examined brand extensions (see Völckner and Sattler 2006), little is known about the monetary value of the strategy. Following the brand valuation logic of Simon and Sullivan (1993) would require a comparison of revenues for branded extensions and unbranded similar products. Although studies employ stock prices (Lane and Jacobson 1995) and market share (Smith and Park 1992), no study has directly measured revenues.

Teichner and Luehrman (1992) argue for the use of real options theory to measure brand extension value for motion picture sequels. Because options theory requires a multiperiodic, multiproduct perspective with relevant information added over time (Haenlein, Kaplan, and Schoder 2006), it implies that multiple options are valued before their parent brands are released. However, our study centers on determining the monetary value of individual brand extension rights after the parent's success is already known (i.e., for existing parent films).

Brand Extensions of Motion Pictures

Two articles have empirically investigated sequels as movie brand extensions. Sood and Drèze (2006) analyze consumers' psychological reactions to the nature of a sequel's title but do not measure economic success. Basuroy and Chatterjee (2008) test the impacts of sequel characteristics on box office success and find that sequels produce lower revenues and are less profitable than their parents and that a shorter time lag between original and sequel positively influences box office success. Neither study directly measures the monetary value of sequels or addresses reciprocal spillover effects.

Several other movie studies include a sequel dummy in their equations (e.g., Hennig-Thurau, Houston, and Walsh 2006) and find that sequels generate higher revenues. However, parameter estimates may be distorted because sequels are systematically allocated higher budgets and distributed to more theaters (Basuroy and Chatterjee 2008). Moreover, a single parameter for all sequels limits the ability to estimate the extension value of individual movies, particularly as parent-brand characteristics and the fit between parent and extension are not taken into account. The studies also do not assess reciprocal spillover effects.

A Conceptual Model of Monetary Brand Extension Value

We define forward spillover as the difference between the risk-adjusted revenues of a new brand extension and those of a similar original new product (Simon and Sullivan 1993; see Figure 1). Reciprocal spillover is the risk-adjusted change in revenues of the parent brand that can be attributed to the extension. We include key success factors that enable us to calculate a conditional extension value for a product that is based on varying levels of these factors (e.g., whether the parent movie's stars are in the sequel). To be able to estimate the value of a future brand extension, we consider only the factors that are known before the extension is produced or that can be altered by the brand owner.

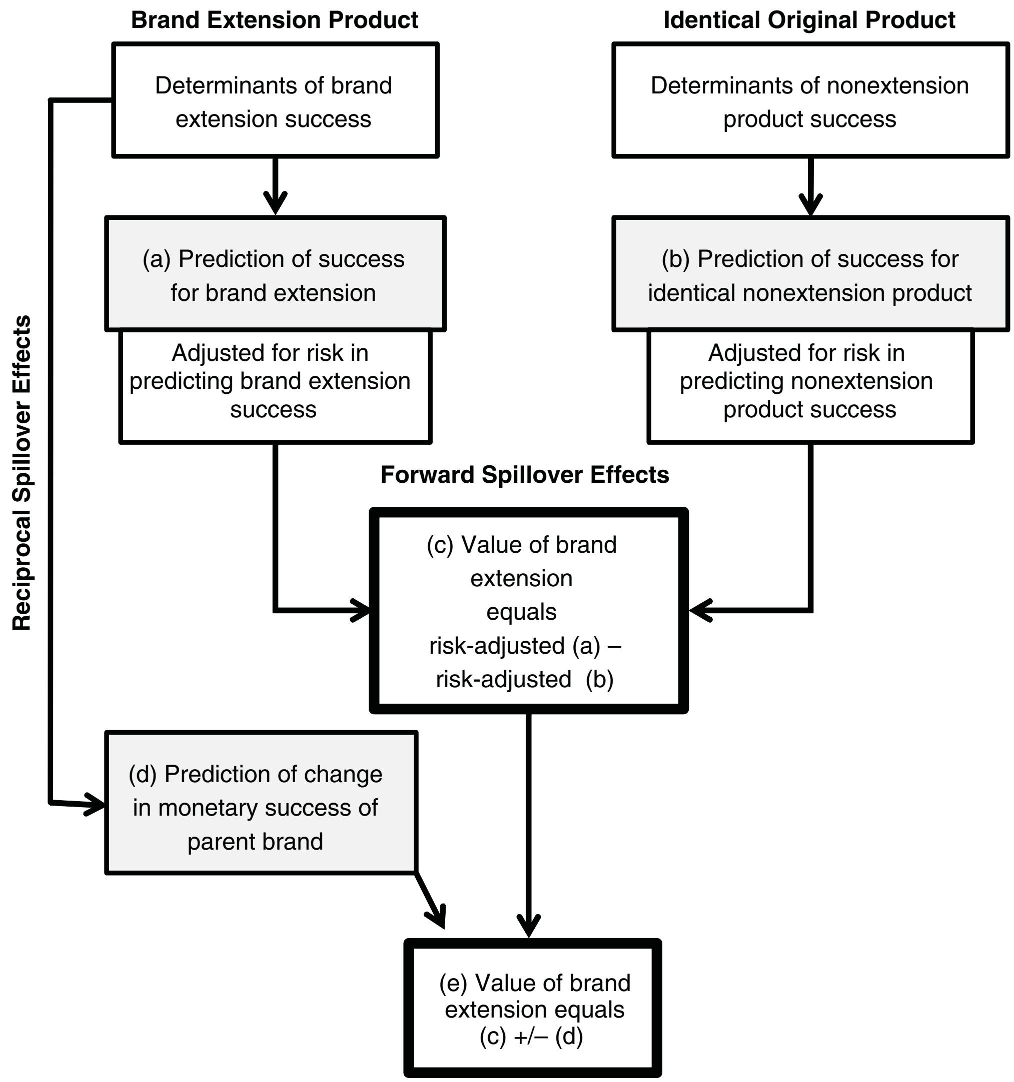
We now empirically calibrate and monetize the forward spillover effect of a movie brand on the extension product. We then report the empirical measurement and monetization of the reciprocal spillover effect of a movie brand extension on its parent.

Monetizing Forward Spillover Effects

Drawing from brand extension research (e.g., Keller 1993; Völckner and Sattler 2006), we distinguish four categories of factors that drive brand extension success: (1) parent-brand characteristics, (2) the fit between parent and extension, (3) the interaction of parent characteristics with fit, and (4) brand extension characteristics. Table 1 lists the drivers, their adaptations to the context of this research, and specific empirical operationalizations of the constructs.

First, with respect to parent-brand characteristics, the parent brand's image and brand awareness, and the interaction between the two, should influence an extension's success (Balachander and Ghose 2003; Keller 1993). As an industry-specific characteristic, we also include the parent movie's cultural familiarity (i.e., whether it is based on a familiar book, a comic, or a game; Hennig-Thurau, Houston, and Walsh 2006). Second, as brand research assigns a major role in extension success to the fit between the parent brand and the extension (Klink and Smith 2001), we include 11 fit variables that tap the consistency between parent and extension product on key facets such as stars, release date, budget, and title. This multifaceted treatment

FIGURE 1
A Conceptual Model of the Monetary Value of Brand Extensions



of fit informs detailed managerial implications that are not possible with a global measure of fit. Third, because interaction effects between parent-brand characteristics and fit should also affect extension success (Völckner and Sattler 2006), we create interaction-term variables for each facet of fit with each parent-brand characteristic, which results in 11 interaction-term variables for brand image and 11 for brand awareness. Fourth, regarding extension characteristics, we include marketing support (proxied by a sequel's budget) and retailer acceptance (distribution intensity) (Klink and Smith 2001; Völckner and Sattler 2006). We also include industry-specific extension characteristics (i.e., the sequels' ratings, genres, and star power; Elberse and Eliashberg 2003).

For original new products (i.e., nonsequels in the context of our study), we include the brand extension characteristics from the extension/sequels model—namely, budget, distribution intensity, rating, genres, and star power—as well as cultural familiarity, as this same information is available for both original new products and extensions.

Model Calibration and Parameter Estimation

Samples and matching procedure. Of all the movies released in U.S. theaters between January 1998 and December 2006, we collected data for all 101 initial movie sequels (only the first sequels in a series) released during the period and for a matched subsample of nonsequels that we drew from the 1536 theatrically released nonsequels from the same period, using a multivariate procedure. The matching approach identifies sequels and nonsequels that are similar in terms of key variables and removes sample bias that might result from skewed differences in studios' treatments of sequels and nonsequels (Smith 1997). Specifically, using key success predictors for sequels and nonsequels (i.e., budget, distribution intensity, rating, star power, cultural famil-

TABLE 1
General and Context-Specific Brand Extension Success Drivers

General Brand Extension Success Drivers	Corresponding Movie Brand Extension Success Drivers	Empirical Measures	Sources
Parent-Brand Characteristics			
Parent-brand image (PBI) (Keller 1993)	PBI of parent movie	Reflective score calculated by partial least squares, combining consumer quality ratings, critics ratings, industry experts ratings	IMDb (consumers); Metacritic and Leonard Maltin's Movie Guide (critics); AMPAS (industry experts; a weighted Academy Awards score, as used in Hennig-Thurau, Houston, and Walsh 2006)
Parent-brand awareness (PBA) (Keller 1993)	PBA of parent movie	Formative score calculated by partial least squares, combining inflation adjusted North American box office and number of theaters at North American opening weekend	*Variety* magazine (box office and theaters)
PBI–PBA interaction (e.g., Balachander and Ghose 2003)	PBI–PBA interaction	CPR of regression of latent variable scores of PBI and PBA on the CPT of the two constructs	See main effects
Not applicable	Cultural familiarity of parent movie	1 if original movie was a remake of another movie or based on a novel, comic, or video game and 0 if otherwise	IMDb
Fit Characteristics			
Fit (e.g., Aaker and Keller 1990)	Star continuity	"Starmeter" of the main actors of the parent movie appearing in the sequel in relation to the maximum possible "starmeter" if all main actors from the parent movie would have appeared in the sequel	IMDb Starmeter measure
Fit	Director continuity	Percentage of directors of the parent movie who are involved in the sequel	The Numbers
Fit	Writer continuity	Percentage of screenwriters of the parent movie who are involved in the sequel	The Numbers
Fit	Producer continuity	Percentage of producers of the parent movie who are involved in the sequel	The Numbers
Fit	Distributor continuity	Percentage of distributors of the parent movie who are involved in the sequel	IMDb
Fit	Genre continuity	1 if parent genre and sequel genre are equal and 0 if otherwise	The Numbers
Fit	Rating continuity	1 if parent rating and sequel MPAA rating are equal and 0 if otherwise	MPAA
Fit	Poster continuity	Similarity between parent and sequel poster from 1 = "very similar" to 5 = "very dissimilar," as coded by two independent judges, mean score used (94% agreement, r = .80)	Posters from Allposters.com and other sources
Fit	Title continuity	1 if the sequel's title can be recognized and 0 if otherwise; coded by two independent judges, mean score used (97% agreement, r = .90)	Not applicable

TABLE 1
Continued

General Brand Extension Success Drivers	Corresponding Movie Brand Extension Success Drivers	Empirical Measures	Sources
Fit	Budget continuity	Percentage deviation of the sequel's budget from the budget of the parent movie	Multiple sources, including *Variety*, IMDb, The Numbers, and Wikipedia
Fit	Season continuity (reversed)	Difference in month between month of release of parent movie and sequel (0–6)	IMDb
		Interaction Effects	
Interaction of parent-brand image with fit (e.g., Keller and Aaker 1992)	Interaction of PBI of parent movie and each fit variable	CPR of regression of PBI and each fit variable on the CPT of the two constructs	See main effects
Interaction of parent-brand awareness with fit (e.g., Völckner and Sattler 2006)	Interaction of PBA of parent movie with each fit variable	CPR of regression of PBA and each fit variable on the CPT of the two constructs	See main effects
		Brand Extension Characteristics	
Marketing support (e.g., Klink and Smith 2001)	Budget of sequel	Residual term of regression of PBA on inflation-adjusted budgets	Multiple sources for budgets, including *Variety*, IMDb, The Numbers, and Wikipedia
Retailer acceptance (e.g., Völckner and Sattler 2006)	Distribution intensity of sequel	Residual term of regression of PBA on number of opening-weekend theaters	*Variety*
Not applicable	Rating of sequel	MPAA rating, ranging from 1 = G to 4 = R	MPAA
Not applicable	Star power of sequel	Residual term of regression of PBA on inflation-adjusted star power	IMDb; a weighted score, as used in Hennig-Thurau, Houston, and Walsh 2006
Not applicable	Genre of sequel	Dichotomous variables for key genres (i.e., comedy, animation, drama, action, adventure, horror, thriller, romance, and crime)	IMDb

Notes: CPR = cross-product residuals, CPT = cross-product term, IMDb = Internet Movie Database, and MPAA = Motion Picture Association of America.

iarity, and genre) as matching variables, we calculated squared Euclidian distances between each sequel and all 1536 nonsequel movies and picked the three nearest neighbors for each sequel (Smith 1997). All variables were standardized before the matching.[1]

Operationalization. Given the importance of nontheatrical distribution channels in the film industry (Hennig-Thurau et al. 2007), our dependent variable is the sum of the actual revenues from theaters, home-video retail, and home-video rental on a title-by-title basis. All revenue data were inflation adjusted, and the total revenues variable was log-transformed. Our data comprise North American revenues, which serve as a solid basis for estimating global revenues for U.S. movies (Epstein 2005). Box office data were taken from *Variety*, video sales from Nielsen VideoScan, and rentals from Adams Media Research/Home Media Retailing.[2]

Parent-brand image and brand awareness were both measured with multiple items to account for the multicomponent nature of the constructs; latent variable scores were

[1]The specific sequel titles and nonsequel titles in our sample are available on request from the authors.

[2]Note that Nielsen VideoScan reports only the number of sold DVDs, not revenues. Thus, we multiplied the number by the average DVD retail price of $20, which was relatively stable for the sample period (Motion Picture Association of America 2007). In addition, because the Nielsen data include sales from reporting retailers that represent approximately 65% of total nationwide sales, we adjusted the data to project nationwide sales. Our video-rental data cover only the top-50 videos of each month; we made no adjustment for this variable because of the lack of reliable information. Post hoc tests suggest that the release of additional sequels does not affect the data.

generated using partial least squares.[3] For brand image, the score included assessments from consumers, professional critics, and industry experts as a reflective scale (α = .80) (Jarvis, MacKenzie, and Podsakoff 2003), consistent with an objectivist view that suggests that an overall aesthetic impression exists that determines each indicator (Hennig-Thurau, Houston, and Sridhar 2006).

On the basis of Jarvis, Mackenzie, and Podsakoff's (2003) criteria and a modest interitem correlation (r = .41), we measured brand awareness on a formative scale, with the parent movie's North American box office and the number of theaters in which the parent movie was shown at its release determining the level of awareness. Because the sample contained films from a wide time span, we needed to account for the loss in society's awareness of a movie over time. Thus, we discounted the brand awareness score of each movie with a forgetting-curve function (Wixted and Carpenter 2007), with function parameters being calibrated with data from an online survey of 761 consumers who were provided with a list of 39 movie titles (i.e., the tenth most successful title of each year from 1968 to 2006) and asked to indicate whether they were aware of each film.[4] The cross-product residuals of a regression of brand image and awareness on the cross-product term stood in as the interaction variable of brand image × brand awareness, making use of Lance's (1988) residual centering regression approach. Residual centering, which Bottomley and Holden (2001) use in a brand extension context, minimizes multicollinearity from the usual high correlatedness of regression variables with their product term while providing a "means to assess the predictability of some criterion from the *interaction* among predictors" (Lance 1988, p. 166).

For sequel characteristics, we separately regressed distribution intensity, budget, and star power on brand awareness and used the residuals from those regressions instead of raw values, thus using only the incremental information that is not explained by brand awareness of the parent. This procedure controls for endogeneity by accounting for established structural relationships between these constructs and the parents' brand awareness (Elberse and Eliashberg 2003) and reduces multicollinearity. The fit variables were directly calculated from secondary data (except for poster fit and title fit, which two research assistants coded). The 22 parent-brand characteristics × fit interaction variables were also created using residual centering.

Methods. We first replicate prior research with a combined sample analysis, using a dummy variable to identify sequels. The matching approach enables us to estimate unbiased treatment effects for the sequel dummy (Smith 1997). We use the sequel dummy, movie characteristics (i.e., budget, distribution intensity, rating, genres, star power, and cultural familiarity), and the interaction terms between the sequel dummy and the movie characteristics (generated with residual centering) as independent variables and estimate their impact on total revenues with ordinary least squares regression. The release year controls for unobserved heterogeneity.[5]

However, although the combined sample approach provides general evidence comparing sequels with nonsequels in terms of revenue generation, it prevents us from investigating some key aspects of monetary sequel value. Specifically, the variables that capture the fit between parent and extension are not available for nonsequels and therefore cannot be included. For example, star continuity (the product term of star continuity and the sequel dummy) takes a value of 0 if the stars from a parent film do not appear in the sequel (e.g., Jim Carrey and Jeff Daniels, the stars of the hit *Dumb and Dumber*, did not appear in the sequel, *Dumb and Dumberer: When Harry Met Lloyd*). In a combined sample approach, star continuity would also take a value of 0 for a nonsequel original movie. In other words, a combined sample procedure with a sequel dummy could not capture the conceptual differences between a nonsequel and a sequel in which none of the main stars of the parent film participated. This is crucial because the lack of star continuity is a characteristic that should attenuate the box office outcomes of a sequel because the audience would miss the stars (e.g., Carrey and Daniels) or might interpret their absence as a signal that the sequel is of poor quality. The mixing of fundamentally different phenomena introduces error and blurs the meaning of the star continuity coefficient.[6]

Moreover, with such key variables lacking, a combined sample approach could not go beyond the question whether sequels matter to predict variation in performance across sequels. Thus, the combined sample approach would prevent managers from testing finer-grained brand extension scenarios. In addition, as sequels and nonsequels are two distinct investment alternatives, it is essential to account for potential differences in project-specific risk. However, the combined sample approach does not allow for the comparison of the risk levels of sequels and nonsequels.

Therefore, we extend our analysis by applying a matched-subsample comparison approach in which we run two separate ordinary least squares stepwise regressions, one for sequels and one for nonsequels, using as regressors the respective variables identified in the prior section and total revenues as the dependent variable for both models.

[3]Covariance-based structural equation tools, such as LISREL, are not an alternative in this case for three reasons: (1) They do not generate determined latent variable scores that can be used for regression analysis, (2) they are less suited than partial least squares to handling formative constructs (see Diamantopoulos and Winklhofer 2001), and (3) they require a greater number of cases than are available in our data set.

[4]We fit several functions consistent with forgetting theory; the one that best fit the data was an s-curve function of the following kind: $F = 38.29 + (83.72 - 38.29) \times [t^{3.50}/(29{,}109.14 + t^{3.50})]$, where F = the percentage of respondents who did not know a certain movie title and t = the number of years since the movie title was theatrically released. When applying the function to our data, we set the minimum F = 0. Note that the discounting of brand awareness scores is similar to Basuroy and Chatterjee's (2008) time window effect. The addition of a time window variable does not affect our sample comparison analysis results, with the variable remaining insignificant.

[5]We thank an anonymous reviewer for suggesting this analysis.

[6]A similar argument can be made for the brand image of the parent movie (and any interaction terms associated with the construct); the variable does not exist for movies that are not extensions of an existing movie brand.

We apply a stepwise regression approach to reduce any concerns about multicollinearity and to achieve an acceptable level of degrees of freedom given our limited sample size. Critical F scores were set to .10 for entry and to .15 for removal to account for the limited sample size. In both regressions, we include the release year as a separate regression block. We then use the respective regression functions to predict overall revenues for all sequels and matched nonsequel movies.

Results

T-test results. The t-tests show that the sequel and nonsequel subsamples are similar with regard to the predictor variables—in other words, any sample bias has been successfully removed, a desired outcome of our matching procedure.[7] Specifically, the average number of opening theaters (M_{sequel} = 2618, $M_{nonsequel}$ = 2492), budget (M_{sequel} = \$57 million, $M_{nonsequel}$ = \$53 million), rating (3.0 for both subsamples), and star power (M_{sequel} = 40.6, $M_{nonsequel}$ = 38.4) do not differ significantly between the two subsamples. Despite these similar characteristics, we find that, on average, sequels outperform nonsequels in terms of overall revenues (M_{sequel} = \$175.0 million, $M_{nonsequel}$ = \$138.2 million; t = 2.07, $p < .05$).

Results of combined sample regression. The combined sample regression function explains overall revenues reasonably well ($R^2 = .72$) (see Table 2). The sequel dummy has a significant, positive effect ($\beta = .06$, $p < .05$), which provides further evidence that, on average, sequels produce higher revenues than nonsequels. Distribution intensity (i.e., number of theaters), budget, ratings, and the release year control also influence overall revenues.

Results of matched-subsamples regressions. The brand extension model explains overall sequel revenues well ($R^2 = .86$). With a weighted mean absolute percentage error (MAPE) of 24.76, a root mean square error (RMSE) of 63.76, and a coefficient of variation (CV) of .36, the model also predicts success adequately.[8] We find that nine variables remain significant in the final step of the estimation, thereby representing all four categories of brand extension drivers (i.e., parent-brand characteristics, fit characteristics, parent-brand characteristics × fit characteristics interactions, and brand extension characteristics) (see Table 3). Specifically, we find that both main effects from parent-brand awareness and brand image are significant; they are the strongest ($\beta = .71$) and third-strongest ($\beta = .18$) predictors of overall revenues, respectively. The two fit characteristics of star continuity and rating continuity are significant in the final regression ($\beta = .15$, and $\beta = .11$). The parent-brand awareness × star continuity ($\beta = .11$) and brand image × genre continuity ($\beta = .11$) interactions each explain significant variance. Finally, for brand extension characteristics, we find that distribution intensity and marketing effort are significant; the coefficient of theaters ($\beta = .35$) is more than three times that of budget ($\beta = .10$).

We now turn to the nonsequel model, which predicts the same dependent variable (the results are also reported in Table 3). The variance explained ($R^2 = .67$) is similar to that in other movie success studies (e.g., Hennig-Thurau, Houston, and Walsh 2006). Prediction accuracy is lower for nonsequels (weighted MAPE = 39.87, RMSE = 95.10, and CV = .69), and important to our calculation of brand extension value, the standard error of the estimate (a parameter similar to RMSE) is higher to an extent that is practically meaningful ($\sigma_{seq} = 67.17$, $\sigma_{nonseq} = 95.90$; on the comparison of predictions between subsamples, see Armstrong 1985). We find that three predictors are significant—the number of opening weekend theaters explains the most variance in revenues ($\beta = .77$), followed by budget ($\beta = .19$) and rating ($\beta = .13$).

Summary. Our analyses in the preceding sections suggest that for motion pictures, a brand extension provides two key advantages over an equal but original new product. First, t-test and combined sample regression results show that sequels generate higher average revenues than nonsequels. This is also supported when we apply the nonsequel regression function to the sequel subsample as a post hoc examination, which reveals how the sequels would have performed if they had been made as identical but original nonsequels. We calculate average revenues of \$142.71 million, which is less than the actual average revenues of sequels (and similar to the average revenues of the matched nonsequel subsample).

As a second advantage, and of equal importance for brand extension valuation, the prediction accuracy measures indicate that there is less risk when investing in a sequel than in an original new movie. Although there is no statistical test to empirically compare prediction accuracy across regressions, the differences in prediction accuracy are practically meaningful (weighted MAPE improved by 38%, RMSE by 33%, and CV by 48%), with the pattern of improvement being consistent across our subsamples and post hoc analyses.[9] We also compare the MAPE of our sequel subsample regression function with that of a nested model comprised of the independent variables from the nonsequel regression function (i.e., examining the subsample of sequels using only the variables that are also available for nonsequels). The weighted MAPE of this nested nonsequel model is 33.95%, or 37.1% worse than that of the full sequel model. This nested-model comparison demon-

[7]The correlation matrix is available from the authors on request.

[8]Because total revenues are widely spread among the movies in our samples, the ordinary MAPE (which weighs all sample elements equal) overrates high percentage errors for small movies, which are low in absolute terms. Therefore, we calculate the weighted MAPE, which weighs each case with its actual value and is defined as follows: weighted MAPE = $[(1/N)\,\Sigma_{n=1}^{N}|Y_n - \hat{Y}_n|]/[(1/N)\Sigma_{n=1}^{N}Y_n]$, where N = number of films in the sample, Y_n = actual values, and $\hat{Y}_n$ = predicted values. The weighted MAPE turns into the ordinary MAPE when actual values exhibit little dispersion.

[9]Because the matched character of our original-movies sample is essential for making comparisons, we also draw three different subsamples, each consisting of a random subset of 150 matched nonsequels. The patterns of results are consistent with the full nonsequel sample, and the revenue predictions for the sequels using the different nonsequel subsample regressions revealed similar results. The results for the sensitivity analyses are available on request.

TABLE 2
Combined Sample Analysis: Regression Results

Regressor	B	Beta	t (*p*)	VIF
Constant	117.708			
Sequel[a]	.131	.056	1.985 ($p < .05$)	1.05
Budget	.006	.249	5.489 ($p < .001$)	2.70
Opening weekend theaters	.001	.792	18.769 ($p < .001$)	2.35
Star power	–.001	–.044	–1.358 (n.s.)	1.39
Cultural familiarity[a]	–.003	–.001	–.037 (n.s.)	1.43
Rating	.182	.165	3.907 ($p < .001$)	2.36
Comedy_genre[b]	.060	.030	.775 (n.s.)	1.93
Animation_genre[b]	.064	.019	.573 (n.s.)	1.51
Drama_genre[b]	.055	.024	.722 (n.s.)	1.43
Action_genre[b]	–.105	–.049	–1.257 (n.s.)	2.02
Adventure_genre[b]	.030	.014	.382 (n.s.)	1.66
Horror_genre[b]	–.116	–.043	–1.008 (n.s.)	2.42
Sci_fi_genre[b]	–.043	–.014	–.451 (n.s.)	1.27
Thriller_genre[b]	.008	.004	.094 (n.s.)	2.20
Romance_genre[b]	.159	.050	1.629 (n.s.)	1.25
Fantasy_genre[b]	–.054	–.022	–.690 (n.s.)	1.36
Crime_genre[b]	.100	.032	1.001 (n.s.)	1.38
Sequel × budget[c]	.001	.020	.461 (n.s.)	2.39
Sequel × opening weekend theaters[c]	–.0002	–.071	–1.734 (n.s.)	2.21
Sequel × star power[c]	.002	.044	1.383 (n.s.)	1.35
Sequel × cultural familiarity[c]	.129	.028	.816 (n.s.)	1.50
Sequel × rating[c]	.076	.031	.759 (n.s.)	2.26
Sequel × comedy_genre[c]	.085	.018	.471 (n.s.)	1.94
Sequel × animation_genre[c]	.369	.044	1.285 (n.s.)	1.56
Sequel × drama_genre[c]	.020	.004	.108 (n.s.)	1.52
Sequel × action_genre[c]	–.066	–.014	–.342 (n.s.)	2.10
Sequel × adventure_genre[c]	.097	.019	.510 (n.s.)	1.82
Sequel × horror_genre[c]	.001	.0002	.004 (n.s.)	2.27
Sequel × sci_fi_genre[c]	–.012	–.002	–.050 (n.s.)	1.35
Sequel × thriller_genre[c]	.128	.026	.631 (n.s.)	2.24
Sequel × romance_genre[c]	.147	.017	.535 (n.s.)	1.32
Sequel × fantasy_genre[c]	.154	.027	.825 (n.s.)	1.43
Sequel × crime_genre[c]	–.281	–.043	–1.313 (n.s.)	1.44
Release year[d]	–.058	–.146	–4.766 ($p < .001$)	1.23
R^2	.721			
R^2 adjusted	.695			

[a]Dummy variable: original new film = 0, and sequel = 1.
[b]Dummy variable: not in this genre = 0, and in this genre = 1.
[c]The residual term was used for this variable.
[d]The release year was operationalized as the difference in years from 2007, so 2006 = 1, 2005 = 2, and so on.
Notes: Log-transformed inflation-corrected overall revenues are the dependent variable. n.s. = not significant at $p > .05$, and VIF = variance inflation factor.

strates the incremental value of the additional information contained in the sequel-specific variables in terms of risk reduction.

Calculating Brand Extension Value

The matched subsample regressions enable us to calculate the value of a movie brand extension from the forward spillover effect. We demonstrate our procedure for *Spider-Man*, assuming that no sequel for the brand has been filmed. Our approach enables an a priori estimation of the monetary value of a potential sequel. Because movie revenues are shared among studios, theaters, rental stores, and retailers, we consider only the share of the revenues that flows back to the producer. We calculate this share by multiplying the overall revenues by a weighted average of 48.86% (based on producers' revenue share for the theatrical channel ≈ 50%, retail channel ≈ 60%, rental channel ≈ 40%; Hennig-Thurau et al. 2007).

Risk-neutral scenario. We begin by taking the perspective of a risk-neutral investor to investigate how results dif-

TABLE 3
Forward-Spillover-Effect Regression Results

	Sequels				Original Movies			
Regressor	**B**	**Beta**	**t (*p*)**	**VIF**	**B**	**Beta**	**t (*p*)**	**VIF**
Constant	1.873				1.563			
Parent-brand image	.181	.175	4.022 ($p < .001$)	1.21	—			
Parent-brand awareness	.005	.714	16.890 ($p < .001$)	1.14	—			
Budget[a]	.003	.100	2.300 ($p < .05$)	1.22	.004	.191	4.696 ($p < .001$)	1.48
Opening-weekend theaters[a]	.001	.350	8.566 ($p < .001$)	1.07	.001	.768	17.279 ($p < .001$)	1.78
Star continuity	.004	.150	3.563 ($p < .001$)	1.14	—			
Rating continuity	.323	.106	2.565 ($p < .05$)	1.09	—			
Parent-brand awareness × star continuity	.00002	.109	2.647 ($p < .01$)	1.08	—			
Parent-brand image × genre continuity	.474	.109	2.717 ($p < .01$)	1.03	—			
Rating	—				.143	.126	3.478 ($p < .01$)	1.19
Release year[b]	.044	.105	2.586 ($p < .05$)	1.04	.053	.136	3.862 ($p < .001$)	1.11
R^2	.858				.671			
R^2 adjusted	.844				.666			

[a]The residual term was used for this variable in the sequel subsample regression.
[b]The release year was operationalized as the difference in years from 2007, so 2006 = 1, 2005 = 2, and so on.
Notes: Log-transformed inflation-corrected overall revenues are the dependent variable. VIF = variance inflation factor.

fer when accounting for risk. For a risk-neutral investor, investment decisions are based on the expected profit, μ, of alternative investment opportunities (e.g., sequels versus nonsequels), with the investor choosing the alternative with the highest expected profit (expected value criterion or Bayes criterion; Canada and White 1980). Risk neutrality implies that the risk of the investment alternatives is not considered. We calculate the forward spillover brand extension value (BEV^{FE}) for the brand *Spider-Man* (*S-M*) as the difference in expected revenues between alternative investments in a brand extension (i.e., sequel) and an otherwise identical original new movie (i.e., nonsequel). We insert the movie characteristics into the revenue equations of the sequel (revenue prediction sequel, or RPS) and the nonsequel (revenue prediction original, or RPO), and then we subtract the producer's share of RPO from the producer's share of RPS:

$$(1)\qquad \begin{aligned} BEV^{FE}_{S-M} &= (RPS_{S-M} - RPO_{S-M}) \times .4886 \\ &= (762.83 - 655.03) \times .4886 = 52.67. \end{aligned}$$

Accordingly, producing the sequel *Spider-Man 2* would generate approximately $53 million more revenues than would making an identical film (i.e., similar budget, distribution intensity, rating, star power, and genre) without the *Spider-Man* brand, which reflects the forward spillover effect of the parent brand. This amount can be exclusively attributed to the use of the *Spider-Man* brand and therefore measures this brand's forward spillover extension value.

Our approach also enables us to examine how the brand extension value would change if a sequel to *Spider-Man* were to be filmed without parts of the original cast and/or were to be differently distributed or budgeted (see Table 4). For example, we find that, all else being equal, were the sequel not to have starred Tobey Maguire (but an actor with identical star power and salary), the sequel's revenues would have decreased by $181.8 million and, consequently, would have resulted in a negative brand extension value of –$129.1 million. This implies that making an identical movie without using the brand would return more revenues to the producer than would a *Spider-Man* sequel without Maguire (i.e., it is not worth paying for the sequel rights unless Maguire's services can be contracted). The simulation reveals that the parent-brand awareness × star continuity interaction accounts for 64% (or $116.6 million) of the loss in brand extension value.

Considering risk. A firm faces two types of payoff risk when making investment decisions (Sharpe and Alexander 1990). Project-specific risk corresponds to the level of uncertainty surrounding the payoff of a project; thus, the standard error of predictions from a sample of similar projects captures it well (Campbell and Viceira 2002). In contrast, market risk is not project specific and is accounted for by the discount rate a firm chooses through normal capital budgeting and investment planning (Sharpe and Alexander 1990). As risk preferences vary across investors—influenced by personal and firm characteristics, the firm's cost of capital, and so on—the acceptable level of market risk cannot be objectively determined (Campbell and Viceira 2002). However, we demonstrate how project-specific risk can be determined and combined with an investor's personal risk preferences to value a brand extension or sequel right.

Risk-averse scenario. To determine how results differ when a rights owner is predisposed against risky investments, we draw from finance theory and apply the value-at-risk (VaR) approach of risk management to calculate a risk-adjusted brand extension value (Jorion 2001). The VaR approach measures the potential loss of a risky asset or

TABLE 4
Brand Extension Value for Different Variations of the *Spider-Man* Sequel

Variable	Sequel as Filmed	Sequel Without Toby Maguire	Sequel Without Toby Maguire (Main Effect Only)	Sequel Has PG Rating Instead of PG-13	Sequel Has R Rating Instead of PG-13	Sequel Opens in 20% Fewer Theaters
Total revenue: sequel[a]	762.83	390.79	629.35	552.42	552.42	461.28
Total revenue: nonsequel[b]	655.03	655.03	655.03	568.03	755.35	332.66
Producer revenue: sequel[c]	372.72	190.94	307.50	269.91	269.91	225.38
Producer revenue: nonsequel[c]	320.05	320.05	320.05	277.54	369.06	162.54
Brand extension value[d]	52.67	–129.11	–12.55	–7.63	–99.15	62.85
Risk-Adjusted Producer Revenues/Value						
60% Risk Averse						
Producer revenue: sequel[c]	364.52	182.74	299.29	261.71	261.72	217.18
Producer revenue: nonsequel[c]	308.33	308.33	308.33	265.82	357.35	150.82
Brand extension value[d]	56.19	–125.59	–9.04	–4.11	–95.63	66.36
75% Risk Averse						
Producer revenue: sequel[c]	350.73	168.95	285.51	247.92	247.92	203.39
Producer revenue: nonsequel[c]	288.65	288.65	288.65	246.14	337.67	131.14
Brand extension value[d]	62.08	–119.70	–3.14	1.78	–89.75	72.25
90% Risk Averse						
Producer revenue: sequel[c]	330.71	148.93	265.49	227.90	227.90	183.37
Producer revenue: nonsequel[c]	260.07	260.07	260.07	217.56	309.09	102.56
Brand extension value[d]	70.64	–111.14	5.42	10.34	–81.19	80.81

[a]U.S. dollar revenue estimate for the hypothetical sequel (based on the sequel regression).
[b]U.S. dollar revenue estimate for an identical nonsequel movie (based on the nonsequel regression).
[c]Producer's share of total revenues.
[d]Producer revenues for the sequel less producer revenues for the identical nonsequel.
Notes: Risk-adjusted figures are calculated by multiplying the unadjusted revenue prediction with the product of the standard error of the estimate σ (with $\sigma = 67.17$ for sequels and 95.90 for nonsequels) and the t-value for a certain level of risk. For example, the expected producer revenues for a 75% risk-averse producer in the case that the sequel was filmed as it actually was are calculated as follows: $[762.83 - (.67 \times 67.17)] \times .4886 = 350.73$.

portfolio over a defined period and enables investors to incorporate a confidence level that approximates their risk preferences when valuing these assets (Damodaran 2007). A standard approach for calculating VaR for a specific asset is the analytical variance–covariance method, which assumes that returns from such assets follow a probability distribution (usually a normal distribution).[10] Using the expected return on assets and their standard deviation in combination with distribution assumptions, the variance–covariance method determines the lower limit of a confidence interval for a given level of desired certainty (e.g., 90%), with the standard assumption that the investor is risk averse (Sharpe and Alexander 1990).

In our case, the risk-adjusted forward spillover brand extension value ($raBEV^{FE}$) of a movie brand i is defined as the difference between the VaR^{FE}_{sequel} estimated from the sequel subsample (i.e., the risk-adjusted revenues that can be expected when investing in a sequel) and the $VaR^{FE}_{original}$ estimated from the subsample of originals (i.e., investing in an identical nonsequel):

$$\text{(2)} \qquad raBEV_i^{FE} = VaR^{FE}_{i(sequel)} - VaR^{FE}_{i(original)},$$

$$\text{(3)} \qquad VaR^{FE}_{i(sequel)} = \hat{x}_{i(sequel)} - t_{1-\alpha} \times \sigma_{sequel}, \text{ and}$$

$$\text{(4)} \qquad VaR^{FE}_{i(original)} = \hat{x}_{i(original)} - t_{1-\alpha} \times \sigma_{original},$$

where $\hat{x}_{i(sequel)}$ represents the expected revenues of investment alternative i calculated from the sequel subsample, $\hat{x}_{i(original)}$ represents the expected revenues of investment alternative i calculated from the subsample of originals, $t_{1-\alpha}$ represents the parameter corresponding to a given confidence level $1 - \alpha$ (e.g., 90%) taken from Student's t distribution table, and σ is the standard error of the expected revenues of the sequel and original subsample, respectively, as estimated through regression analysis.

In summary, to incorporate risk in our assessment of the monetary value of a brand extension right, we use the project-specific risk parameters of an investment in a sequel and an alternative investment in a nonsequel, which we determined with our matched subsamples approach. For illustration, we return to *Spider-Man* and use three levels of investor risk preference: (1) 60% certainty (t = .25), 75% certainty (t = .67), and (3) highly risk-averse 90% certainty (t = 1.28). Applying Equations 2–4 to the *Spider-Man* sequel and a similar original for these levels of risk aversion leads to the results reported in Table 4, which reveal that the forward spillover brand extension value increases as the level of risk considered acceptable decreases, a result of the higher prediction accuracy (i.e., lower standard error) for sequels. Specifically, requiring 90% certainty, the brand extension value based on forward spillover effects for the *Spider-Man* brand is more than $70 million (for a sequel as actually filmed).

[10]Alternative approaches to empirically determine VaR include historical simulations and Monte Carlo simulations (Damodaran 2007). We refrained from including dynamic, multiperiodic effects and more than one investment alternative.

Monetizing Reciprocal Spillover Effects

Extensions have been argued to function as substitutes of their parents, cannibalizing parents' revenues (Balachander and Ghose 2003; Bottomley and Holden 2001), or as complements, enhancing consumers' desire for the parent (Aaker and Keller 1990). We expect sequels to function as complements to their parents because, if a consumer has not seen the parent film, doing so provides the context for interpreting the sequel. In addition, a consumer who has seen the parent film may still benefit from seeing it again to counteract forgetting (Lehmann and Weinberg 2000) or to relive a pleasurable experience (Hennig-Thurau, Houston, and Walsh 2006).

To assess empirically whether movie brand extensions have a reciprocal spillover effect on their parents and to monetize this effect's contribution to brand extension value, we follow the logic of the event study method. Event studies measure the effect of unanticipated events on stock prices by isolating the resultant abnormal changes in stock prices (McWilliams and Siegel 1997). Marketing phenomena that have been studied with event studies include joint ventures (Houston and Johnson 2000), movie-star value (Elberse 2007), and the forward spillover effect of brand extensions (Lane and Jacobson 1995). Although we do not use stock prices, we draw on event study logic to quantify the causal effect of the release of a sequel (the event in our design) on the DVD sales of its parent (the market reaction), thus isolating abnormal parent DVD sales. By running cross-sectional regression analyses on abnormal sales, we develop a prediction model of the monetary value of the reciprocal spillover that can be summed with predictions of forward spillover for a comprehensive value of brand extensions.

Calculating Abnormal Sales

Data and modeling approach. Identifying abnormal sales requires data that will enable us to predict the DVD sales of a parent movie that would have occurred if the sequel had not been released. We draw on proprietary weekly DVD sales data from Nielsen VideoScan for 76 of the 101 parent movies in our main sample (data were not available for 25 titles). We used the DVD sales for each individual movie from 24 months before the theatrical release of the sequel until 12 weeks before the sequel release (i.e., the estimation window) to fit a regression function that provides sales estimates for future periods unaffected by the sequel release (little advertising occurs more than 12 weeks before a theatrical release; Ho, Dhar, and Weinberg 2004).

We tested different regression functions for each movie and chose the one that best fit the data. We used cumulative sales (which are more robust than individual sales against outliers) as the dependent variable and number of weeks as the independent variable. In general, for movies that had been released on DVD within 24 months of the sequel, the logarithmic function $DVDsales_t = \alpha + \beta \times \ln(t)$ (where t is week and α and β are parameters) fit the data best, while for movies released more than 24 months before the sequel release (i.e., for which the DVD sales information was incomplete) the power-law function $DVDsales_t = \alpha \times t^\beta$ had the best fit. Both functions are in line with the well-known exponential-decay pattern of movie sales.

Because we expect the release of a sequel to influence parent DVD sales at the sequel's release at theaters and again, four to six months later, on DVD (Hennig-Thurau et al. 2007), we compare the cumulative predicted sales for the period from 12 weeks before the theatrical sequel release until one year after the release with the actual sales in the same period; we used a shorter postrelease window for the cases in which exogenous events unrelated to the sequel affected parent DVD sales (e.g., another sequel was announced or released). The difference between actual DVD sales and predicted DVD sales is our measure of abnormal sales.

Results. The regression function fits are satisfactory, with an average R-square of .97 (all individual R^2 values > .90, except for *The Santa Clause*, with $R^2 = .80$ as a result of seasonal outliers). The abnormal DVD sales (in units) vary widely, ranging from 219 (for *State Property*) to 1,365,718 (for *Shrek*), with a mean of 217,651.9, which is significantly different from zero ($t(75) = 7.11$, $p < .01$) and a standard deviation of 266,998.1. Abnormal sales are greater than zero for all 76 movies in the sample, which supports our assumption that movie sequels are complementary products. As an example of the typical pattern, Figure 2 shows the actual and predicted DVD sales for two movies and illustrates abnormal increases at the sequels' releases in theaters and on DVD.

Predicting Abnormal Sales

Modeling approach. To identify the variables that drive abnormal DVD sales of a parent in response to a sequel, we conduct a cross-sectional regression. As regressors, we use the same set of parent characteristics, brand extension characteristics, and fit characteristics that we used to estimate the forward spillover effect (see Table 1).

To rule out potential confounds, we also include industry-specific versions of control variables that reflect more general factors that apply to brand extensions across industries (e.g., timing, number of versions of parent, time lag between parent and extension, joint promotion or distribution efforts) (McWilliams and Siegel 1997). Specifically, in addition to a sequel's release year (the difference from 2007), we include the number of DVD versions (e.g., standard edition, collector's edition, director's cut) of the parent released before the sequel's release in theaters, the number of weeks between the parent DVD release and the sequel release, the weeks between the most recent DVD release of the parent and the sequel release, and whether a new DVD edition of the parent was released in concert with the sequel (as for 28 of our 76 titles).

For the latter variable, we created dummy variables for marginal and substantial rereleases (which contained the same transfer and/or similar bonus material as an earlier DVD release of the same title or a strongly improved transfer and/or substantial new bonus material, respectively); two coders judged each rerelease as marginal (n = 16) or substantial (n = 12) (89% agreement; coders resolved disagreements by discussion). Finally, we also created interaction-term variables of the marginal and substantial variables and parent-brand awareness using residual centering, and we include them in the regression model. We apply stepwise regression analysis and set critical F scores to .10 for entry and to .15 for removal.

Results. The final regression explains 53% of the parent movies' abnormal DVD sales and predicts success reasonably well (weighted MAPE = 65.24, RMSE = 180,285, standard error of the estimate = 187,446, and CV = .861). It contains four variables, three of which refer to the parent brand (see Table 5). Parent-brand awareness ($\beta = .56$) explains the most variance in abnormal DVD sales, followed by the parent-brand awareness × parent-brand image interaction, and the main effect of parent-brand image ($\beta = .39$ for each). No other brand extension variable plays a significant role. The year in which the sequel is released ($\beta = -.18$) also remains in the final regression model; its negative effect accommodates the increase in DVD sales over time in the sample period. Table 5 also shows that the majority of explained variance in abnormal DVD sales can be attributed to the success driver variables, not to the control.

Finally, we ran a post hoc regression that also included the sequel's box office revenues and its quality, as judged by professional critics (i.e., its metascore, a weighted composite score of reviews from approximately 40 influential sources calculated by metacritic.com) and consumers (IMDb user rating, averaged from up to 300,000 votes per movie). Although these variables are not available when planning a sequel, their addition enables us to examine the degree to which abnormal sales are related to different levels of success and quality. Table 5 shows that a sequel's quality does not explain additional variance, but the inclusion of its box office success is significant, adding 16 percentage points of variance explained ($R^2 = .70$). This model has a weighted MAPE of 50.99, an RMSE of 146,388, a standard error of 152,533, and a CV of .701.

Quantifying the Monetary Value

Entering the respective parameters into the abnormal-DVD-sales regression equation enables us to quantify the reciprocal spillover for a specific brand extension. For example, again assuming that no sequel had been filmed for *Spider-Man*, our prerelease information regression equation suggests that a sequel to the movie would have generated additional DVD sales of 818,018 units of the original movie at retailers that report to Nielsen VideoScan (or 65% of the total market), which corresponds to an estimated total of 1,258,489 additional DVDs sold across North America. An average price of $20 per copy (Motion Picture Association of America 2007) implies revenues of $25,169,780, with $15,101,868 (or 60%) of the revenues flowing back to the producer.

These numbers can also be adjusted for risk by applying the variance–covariance method. Accounting for the price per copy and revenue split, the risk-adjusted reciprocal spillover effect (RE) brand extension value ($raBEV^{RE}$) of a movie brand i can be calculated as follows:

FIGURE 2
Distribution of DVD Sales (in Units) for Two Movies

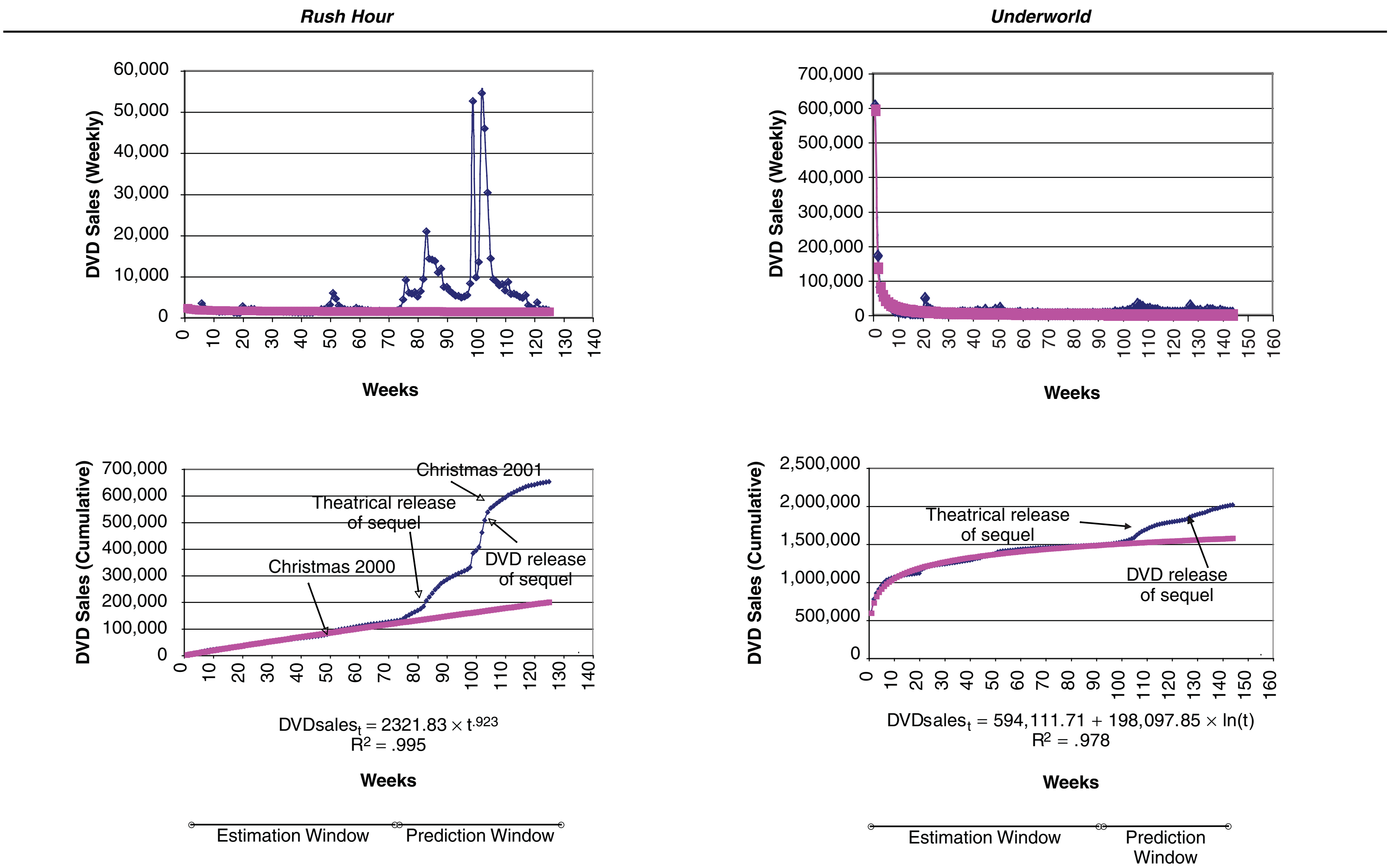


TABLE 5
Reciprocal-Spillover-Effect Regression Results

	Prerelease Information Model				Control Variables–Only Model			Postrelease Information Model			
Regressor	**B**	**Beta**	**t (p)**	**VIF**	**B**	**Beta**	**t (p)**	**B**	**Beta**	**t (p)**	**VIF**
Constant	–438,644.31		–4.115 ($p < .01$)		267,273.90		4.002 ($p < .01$)	–420,262.29		–4.842 ($p < .01$)	
PBA	1029.47	.556	6.466 ($p < .01$)	1.24	—	—	—	1,047.28	.565	8.081 ($p < .01$)	1.12
PBA × PBI[a]	640.76	.392	4.750 ($p < .01$)	1.04	—	—	—	641.07	.392	5.727 ($p < .01$)	1.08
PBI	109,285.88	.392	4.658 ($p < .01$)	1.08	—	—	—	109,731.80	.393	5.861 ($p < .01$)	1.04
Release year of sequel[b]	–30,180.35	–.211	–2.547 ($p < .05$)	1.04	–13,864,97	–.079	–.836	–37,376.23	–.261	–3.848 ($p < .01$)	1.06.
Box office sequel[a]	—	—	—	—	—	—	—	2,067.41	.405	6.101 ($p < .01$)	1.02
R^2	.533				.009			.695			
R^2 adjusted	.507				–.004			.674			

[a]The residual term was used for this variable in the sequel subsample regression.
[b]The release year was operationalized as the difference in years from 2007, so 2006 = 1, 2005 = 2, and so on.
Notes: PBA = parent-brand awareness, and PBI = parent-brand image.

$$\text{(5)} \qquad \text{raBEV}_i^{RE} = \left(\hat{x}_i^{AR} - t_{1-\alpha} \times \sigma\right) \times \frac{20 \times .6}{.65},$$

where $\hat{x}_i^{AR}$ is the expected abnormal revenues of a movie, $t_{1-\alpha}$ is the confidence parameter from the normal distribution table, and σ is the standard error of the expected abnormal revenues. For the movie *Spider-Man* and 90% risk aversion, we obtain the following results:

$$\text{(6)} \qquad \text{raBEV}_{S-M}^{RE} = \left(818{,}018 - 1.28 \times 187{,}446\right) \times \frac{20 \times .6}{.65} = \$10{,}776{,}194.$$

In other words, the rights owner of the brand *Spider-Man* can expect a sequel to generate, with 90% confidence, approximately \$10.8 million in abnormal-DVD-sales revenues.

Discussion and Implications

Findings and Limitations

To monetize brand extension value, we distinguish between forward spillover and reciprocal spillover effects. For forward spillover, we calibrated both a combined regression and separate subsample regressions for sequels and matched nonsequel movies. The regression results provide empirical evidence that for motion pictures, introducing a brand extension provides two advantages: (1) It generates higher average revenues (as evidenced by the combined sample regression parameter and a t-test), and (2) it reduces project-specific risk (as demonstrated by higher prediction accuracy and a lower standard error for sequels than for nonsequels). For reciprocal spillover, we found that sequels are complements to their parents, with abnormal (i.e., sequel-induced) DVD sales for the parent as high as 1.3 million copies. We explain more than 50% of abnormal DVD sales with the parent's brand awareness and image and up to 70% when including the theatrical success of the sequel.

In terms of limitations, our approach focuses on initial sequels and does not address the effects of additional sequels (e.g., *Spider-Man 3* and *Spider-Man 4*). The success of an initial sequel has a substantial impact on the value of additional sequels; for example, the big-budget *Remo Williams: The Adventure Begins* was intended to become a multimovie series similar to the James Bond franchise, but the idea was discarded after the original flopped. Thus, extending our model for additional sequels would require consideration of the relationships between the additional sequel and the original sequel and among all further sequels, which implies a level of complexity that is difficult to model because of the small number of multiple sequels. However, we acknowledge this as an intriguing direction for further research; perhaps researchers could apply real options theory to a sequential, multistage decision process.

To reduce concerns about multicollinearity and to achieve an acceptable level of degrees of freedom given our sample size, we employed stepwise regression. Because a search bias can affect stepwise regression results when there are a large number of variables (Wallace, Seigerman, and Holbrook 1993), we note that theory and/or prior empirical studies have justified all variables we included in the final model and that patterns of significance and directions of signs supported our approach.

Managerial Implications

Our models enable managers to estimate effectively the monetary value of brand extensions, an important intangible asset. We believe that the method provides transparency for stakeholders and can be used as a basis for financial negotiations for the legal right to produce movie sequels, thereby providing a more objective starting point than the gut-feeling approach that pervades the industry (Young, Gong, and Van der Steede 2008). Another practical use of the model is to evaluate alternative combinations of strategic brand elements. Our model includes parameters that managers can control when planning the extension product, thus enabling them to examine the impact of continuity or change in specific characteristics (e.g., stars, rating, genre) between the parent and the sequel. Because some variables (e.g., distribution intensity) will not be finalized when the valuation of a sequel right takes place, companies can use our approach to explore the sensitivities of outcomes to different levels of drivers. In addition, our results suggest that the release of complementary brand extensions causes consumers to reappraise parent brands (or at least increases their salience), and thus managers should refine marketing strategies to facilitate reciprocal spillover benefits.

Although the operationalizations and empirical evidence in this study are specific to the context of motion pictures, we believe that our general conceptual framework (derived from brand valuation theory) and estimation approach (derived from finance theory) are generalizable to brand extensions in other industries. Our method suggests that managers in other industries can determine the value of forward spillover by comparing predictions from models of brand extension revenues and nonbranded new product revenues. To run regression models for these two investment alternatives, our approach requires historical (or experimental) data for both brand extensions and similar nonextension new products. Although managers can employ the general types of brand extension drivers used in this research (e.g., parent-brand characteristics, extension characteristics, fit, interactions between fit and parent-brand characteristics), they also need to tailor these abstract categories to their respective industry's conditions. In addition, knowledge of industry-specific drivers is needed to create powerful substitutes for the film industry–specific equivalents used in this study.

Estimating reciprocal spillover value should be possible in other industries as well. Longitudinal sales data are needed for a sufficiently large number of earlier brand extensions as well as their parent brands. Regression equations can then be developed to explain any positive or negative abnormal sales, again using industry-specific operationalizations of parent and extension characteristics (and the fit between them) as independent variables. Control variables should include industry-specific measures of the release timing of the extension product (absolute and relative to the release of the parent brand) and the number of versions or models of the parent-brand product, among others. As with any forecasting approach that is based on regression coefficients that emerge from a prior time period, a stable market environment (e.g., competition, core technologies, customer preferences) will enhance confidence in predictions.

Implications for Theory and Further Research

The approach we use can be adapted for research in other industry contexts in which the monetization of brand extension rights is of similar importance. Our exclusive use of factors that are easily quantifiable and do not rely on the aesthetic dimensions of motion pictures supports the adaptability of our model.

Although our findings support many conclusions of extant brand extension research, several contrasts exist. While fit and marketing support have been found to explain the most variance in extension success (Völckner and Sattler 2006), brand awareness and retailer acceptance were the strongest predictors of extension success in our study. Perhaps the distinct contexts provide potential explanation—most extant work on brand extensions has explored fast-moving consumer goods, where a primary challenge for new products is gaining awareness in a crowded market, and in turn, marketing support is critical to inform consumers. In contrast, for hedonic media products, because of heavy media attention to the release of an extension of a popular parent film and consumers' intrinsic interest resulting from the product category's hedonic character, marketing support does not carry the full burden of educating and attracting customers. Given the short life cycle of films, distribution intensity is another critical factor in driving sequel success. An important direction for further research is the development of a comprehensive framework that identifies the contingencies that determine these relative impacts. Our study extends fit-related research, and our approach of using specific aspects instead of a global measure can stimulate future studies on the dimensions of fit in different contexts.

Our finding of a reciprocal spillover effect extends the work of Balachander and Ghose (2003). Although their study found that advertising effects for a brand extension spill over to the parent, we found that the parent brand's awareness and image primarily determine the strength of the reciprocal spillover effect and that extension characteristics play a lesser role. Given mixed emerging evidence for both a positive (Balachander and Ghose 2003; this study) and a negative (John, Loken, and Joiner 1998) impact of brand extensions on parent brands, further research on reciprocal spillover is desirable. Opportunities exist to explore consumers' reappraisals of parent brands in light of brand extensions and to study market reactions to the parent in response to alternative extension strategies.

In conclusion, this research introduces an approach for monetizing the brand extension value of products. Using proprietary data from the motion picture industry, we present an approach that brand owners and potential buyers can apply to determine the monetary value of a brand extension right. We demonstrate how both forward and reciprocal spillover effects can be considered to fully recognize the value of a brand extension.

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