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This article examines the effects of sequential movie releases on the dilution and enhancement of celebrity brands. The authors use favorability ratings collected over a 12-year period (1993–2005) to capture movement in the brand equity of a panel of actors. They use a dynamic panel data model to investigate how changes of brand equity are associated with the sequence of movies featuring these actors, after controlling for the possible influence from the stars' off-camera activities. The authors also examine the underlying factors that influence the magnitude and longevity of such effects. In contrast with findings from existing research in product branding, the authors find evidence that supports the general existence of dilution and enhancement effects on the equity of a celebrity brand through his or her movie appearances. They also find that star favorability erodes substantially over time. Finally, this research offers insights for actors regarding how to make movie selections strategically to maximize their brand equity.

Keywords: branding, celebrity brand, feedback effect, brand extension, line extension, movie

Dilution and Enhancement of Celebrity Brands Through Sequential Movie Releases

> In this celebrity-driven culture we inhabit, it might have been seen as inevitable that people would come to be viewed—and view themselves—as brands. (Ebenkamp 1999, p. 11)

In recent years, practitioners have begun to argue that the definition of "brand" should be broadened from relationships with products or companies to include anything that engages in emotional relationships with consumers (Bayley 2005; Reuters 2009). For example, A-list Hollywood stars such as Tom Hanks and Meryl Streep represent powerful Hollywood brands to worldwide movie viewers in every movie on which they stamp their names (Kramer 2003). As with traditional product brands, actors (and their agents) have begun to realize the importance of enhancing and protecting their celebrity brands (Mulholland 2007). According to our analysis in Appendix A, actors with a high degree of brand equity enjoy substantial financial returns on their movie salary. For Hollywood stars, "branding can mean simply identifying a career goal and implementing a game plan to achieve it" (Towle 2003).

Traditionally, branding research has been conducted in a product/service context. In this context, researchers have primarily studied the conditions under which positive and negative feedback effects occur when firms introduce brand or line extensions (e.g., Ahluwalia and Gürhan-Canli 2000; Gürhan-Canli and Maheswaran 1998; John, Loken, and Joiner 1998; Keller and Aaker 1992; Keller and Sood 2003; Milberg, Park, and McCarthy 1997; Swaminathan, Fox, and Reddy 2001). Despite some insightful findings, this line of research has yet to investigate the following issues.

First, though useful for understanding the phenomena of enhancement and dilution effects, these studies do not make

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general predictions about the magnitude or longevity of such effects. Second, because the vast majority of these studies were one-shot experiments in which consumers provided their instantaneous responses to hypothetical product extensions (cf. Swaminathan, Fox, and Reddy 2001), the dynamic movement of brand equity in response to a sequence of new product introductions has not been investigated. Third, previous research in this area has been conducted primarily in labs, and the external validity of their findings remains to be tested.

Addressing these issues within the traditional context of product branding has been hampered by methodological difficulty and a lack of viable data. In this article, we go beyond extant literature by empirically analyzing the magnitude, longevity, and dynamics of feedback effects in a real-world setting in which consumers' evaluations of a panel of brands can be traced over time. Because both celebrity names and product/service names are part of the "brand," the framework we introduce advances an understanding of the dynamic movement of brand equity for sequential new product introductions.

Specifically, we investigate the effects of sequential movie releases on the dilution and enhancement of celebrity brands in the movie industry. Similar to the use of an Intel microprocessor as a branded component in personal computers, we view movie stars as branded components and movies as new products that feature these celebrity brands. Because consumer attitudes represent a key dimension of brand equity (Aaker 1991; Keller 1993; Park, Jaworski, and MacInnis 1986), we use favorability ratings collected by a major U.S. entertainment company from 1993 to 2005 to represent changes in the brand equity of a panel of actors over time.[1] Because consumers' favorable attitudes toward a movie star may be affected by his or her off-camera activities (e.g., involvement with charities, relationships, scandals), we trace the media exposure of these movie stars' non-movie-related activities during the same time window. We further construct a dynamic panel data model to investigate how changes in the favorability ratings of these actors are associated with their movie appearances, after controlling for the influence of the stars' off-camera activities.

In contrast with previous findings that enhancement and dilution effects only occur under certain conditions for product brands, we find evidence of the general existence of dilution and enhancement effects for the equity of a celebrity brand through his or her movie appearances. In addition, although brand equity is stable and long lasting for product brands, the equity status of a celebrity brand erodes substantially over time. We also find that the volume (not valence) of media coverage of an actor's off-camera activities positively contributes to his or her brand equity.

We organize the rest of this article as follows: First, we discuss the relationship between our research and the existing literature. Second, we describe the key findings from two lab experiments in which we examine the underlying mechanism of consumers' evaluations of celebrity versus product brands. Third, we present empirical data collected from the field, demonstrate our dynamic panel data model, and present our findings. Fourth, we illustrate how our estimates can guide the strategic decision making of an actor in developing and protecting his or her celebrity brand. Fifth, we conclude by summarizing the key results, discussing the implications and limitations, and providing avenues for further research.

THEORETICAL BACKGROUND

Movie Stars as Brands and Movies as New Products Featuring Celebrity Brands

Because a brand name generally reduces a buyer's shopping effort by providing information about the product's expected quality, an increasing number of products are marketed with components that themselves are brand names (e.g., Geylani, Inman, and Hofstede 2008; Park, Jun, and Shocker 1996; Venkatesh and Mahajan 1997), such as personal computers with Intel microprocessors and brownie mixes with Hershey's syrup.

In a similar spirit, we view movie stars as branded components and movies as new products that feature these celebrity brands. Our rationale is as follows: First, in our study context, the brand name of the movie star not only provides the movie with some immediate consumer base (i.e., loyal fans of the movie star) but also serves as a signal to convey information about the expected quality of the movie. This rationale is consistent with previous findings that when a branded component appears in a new product, it facilitates the acquisition of initial consumer awareness and provides an endorsement of product quality (Rao, Qu, and Ruekert 1999; Rao and Ruekert 1994).

Second, as Ailawadi, Lehmann, and Neslin (2003) propose, the value of a brand lies in the revenue premium it generates for the product carrying the brand name. In the context of movies, the brand name of the movie star is a major force driving demand for a movie. Indeed, researchers have found that demand for a movie increases with the rank of the movie star appearing in it (e.g., Elberse 2007; Elberse and Eliashberg 2003).

Therefore, we view movie stars as celebrity brands and movies as new products that feature these brands. In the branding literature, some researchers view new product introductions in similar product categories as line extensions and those in dissimilar product categories as brand extensions. Thus, each movie can be a line extension of the celebrity brand because movie stars exist to make movies. However, Park, Jun, and Shocker (1996) refer to new products with branded components as composite brand extensions. Other researchers refer to new products in both the same and different product categories as brand extensions (e.g., Loken and John 1993). In the context of movies, Sood and Drèze (2006) conceptualize movie sequels as brand extensions of the original movies. Therefore, to be consistent with extant literature, we use the general terminology of extension (without the distinction of line or brand) to refer to each movie featuring the celebrity brand.

Dilution and Enhancement Effects in Branding Research

Extant branding research has primarily studied dilution and enhancement effects in a typical product branding context. With regard to the dilution effect, researchers have provided mixed evidence about whether an unsuccessful new

[1]Prior literature has defined and operationalized brand equity in myriad ways (e.g., Keller 1993; Park et al. 2010). For data availability reasons, we relied exclusively on favorability to measure brand equity. We do not claim that it is the only way to define and measure brand equity.

product launch dilutes the brand itself. Some research supports the existence of dilution effects (e.g., Milberg, Park, and McCarthy 1997), but other studies do not. For example, Keller and Aaker (1992) fail to find any evidence of brand dilution with dissimilar product extensions. Loken and John (1993) find that quality perceptions of the brand were unaffected when the proposed extension was in a dissimilar product category (though in a similar product category, dilution occurred). John, Loken, and Joiner (1998) report that dilution effects were less likely for flagship products.

Regarding enhancement effects, existing research suggests that their presence is highly situation specific. Park, Jun, and Shocker (1996) find that positive enhancement effects only occur in complementary but dissimilar cobranded extensions. Gürhan-Canli and Maheswaran (1998) discover that both the typicality of the extension and consumers' level of motivation determine the effect of extensions. Greater feedback effects occur when consumers are highly involved in evaluating products. In addition, Ahluwalia and Gürhan-Canli (2000) suggest that when extension information is more accessible, both enhancement and dilution effects occur, regardless of the extension category. With lower accessibility, however, category diagnosticity determines whether extension information enhances or dilutes the brand. Finally, Swaminathan, Fox, and Reddy (2001) examine the impact of extension introductions on choice using scanner data. Their results show a positive reciprocal (enhancement) effect of extension trial on parent brand choice, particularly among prior nonusers of the parent brand.

In general, the mixed findings on dilution effects make it difficult to foresee whether some movies will actually dilute the brand equity of an actor. Moreover, the situation-specific enhancement effects make it difficult to predict the extent of the enhancement effect in this context. Finally, because our research diverges from prior research by focusing on celebrity brands rather than product brands, the underlying mechanism behind consumers' evaluations of product brands and celebrity brands may differ. For product/service brands, consumers receive highly coordinated and consistent information about the brands (i.e., brand positioning). In contrast, consumers' memory of an actor is based on episodic exemplars that are not necessarily well connected to one another (e.g., movies with different plots, genres, and costars; various types of media coverage). Consequently, general findings in the traditional context of product brands may not be readily applicable to the context of celebrity brands.

In the next section, we describe two lab experiments in which we compared the two types of brands according to (1) consumers' memory structures for the brands and (2) the degree to which consumers were willing to update their views about the brands when extension products were introduced. We report the main findings here and leave the supplementary details to Appendix B.

LAB EXPERIMENTS

Lab Experiment 1

This experiment was designed to compare consumers' memory structures regarding celebrity brands versus product/service brands. A within-subjects pretest first identified pairs of celebrity and product/service brands with similar degrees of brand familiarity, favorability, identity clarity, and affect. Next, we employed a between-subjects study to investigate consumers' memory structures for these two types of brands. Depending on their condition type (celebrity versus product brands), the participants indicated, "What comes to your mind when you think about this actor/actress [brand]?" For each thought association, we also asked participants to indicate, on a seven-point scale, "How certain (strongly) do you feel about this thought?" Next, the participants answered two seven-point scale questions: "How many different types of thoughts come to your mind when you think about this actor/actress [brand]?" and "To what extent does this actor/actress [brand] represent a mix of highly different personas in her/his acting and personal life [a mix of highly different characteristics]?"

The key findings of this experiment can be summarized as follows: First, consumers have a greater number and more types of thought associations with celebrity brands than with product/service brands. Second, consumers feel less certain about their most salient thoughts about celebrity brands versus product/service brands. Third, consumers' understanding of celebrity brands is more multidimensional than their understanding of product/service brands. Therefore, our analyses indicate that consumers have different memory structures for celebrity brands versus product/service brands.

Lab Experiment 2

In this experiment, we investigated whether there is a difference between celebrity brands and product/service brands regarding how consumers modify their brand evaluations in response to product extension introductions. We first conducted a within-subjects pretest to identify product extensions that are perceived as equally far and equally close to the pairs of celebrity and product brands from Lab Experiment 1. For example, home audio speakers were equally close extensions for Keanu Reeves and Jaguar; stationery was an equally far extension for this pair. Table 1 provides a complete list of the extensions.

Using the pretest data, we conducted a 2 (brand type: celebrity versus product) × 2 (extension type: close versus far) between-subjects design. A total of 82 participants were randomly assigned to one of the four conditions. Within each condition, participants were presented with two scenarios regarding the same type of extensions. For example, in the celebrity-close condition, the participants were informed that Keanu Reeves was going to launch a line of home audio speakers under his name. Next, we asked the participants to indicate, on a seven-point scale (anchored by "strongly disagree" and "strongly agree"), whether they would like the actor more or less if the extension product succeeded or failed. A higher response score would demonstrate a greater degree of brand updating. In another sce-

Table 1

CLOSE AND FAR EXTENSIONS USED IN LAB EXPERIMENT 2

		Close Extension	*Far Extension*
Pair 1	Keanu Reeves Jaguar	Home audio speaker	Stationery
Pair 2	Leonardo DiCaprio Godiva	Wine	Wallpaper

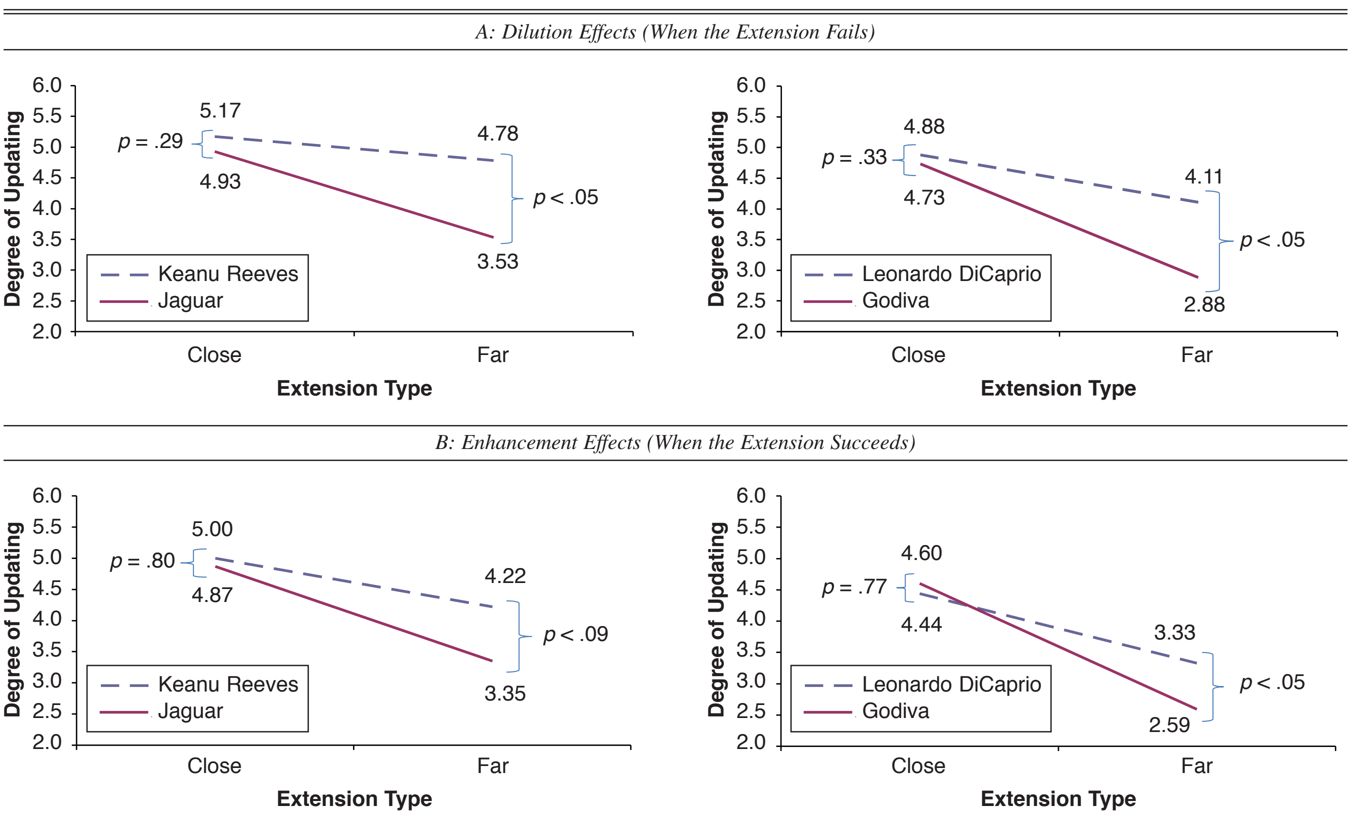
nario, we asked the same questions for a case in which Leonardo DiCaprio was launching a line of wines. In a similar fashion, participants in the three other conditions answered corresponding questions.

Figure 1, Panels A and B, illustrates the results of our study. The two-way interaction of brand type and extension type was marginally significant for pair 1 ($F(1, 78) = 3.01$, $p < .09$) and significant for pair 2 ($F(1, 78) = 4.12$, $p < .05$) when the extension failed. Specifically, celebrity brands exhibited greater dilution effects than product brands when the extension was categorized as far apart (pair 1: $F(1, 78) = 4.80$, $p < .05$; pair 2: $F(1, 78) = 5.21$, $p < .05$). However, the effect disappeared in the close extension condition (pair 1: $F(1, 78) = 1.16$, $p = .29$; pair 2: $F(1, 78) = .96$, $p = .33$). Similarly, the two-way interaction was significant for both pairs when the extension succeeded (pair 1: $F(1, 78) = 3.99$, $p < .05$; pair 2: $F(1, 78) = 5.14$, $p < .05$). Celebrity brands exhibited significantly or marginally greater enhancement effects than product brands in the far extension condition (pair 1: $F(1, 78) = 3.09$, $p < .09$; pair 2: $F(1, 78) = 4.16$, $p < .05$), whereas such differences were absent in the close extension condition (pair 1: $F(1, 78) = .07$, $p = .80$; pair 2: $F(1, 78) = .09$, $p = .77$).

In summary, we found that for close extensions, the magnitude of dilution and enhancement effects was not significantly different between the two types of brands. Yet, for far extensions, consumers were more likely to update their views toward the celebrity brand than the product brand. To compare the differences in brand updating for the two types of brands when the typicality of the extensions was low (i.e., far extension), we also pooled the dilution and enhancement data from the two pairs in the far extension conditions. We found that consumers in general were more likely to update their evaluations of celebrity brands than product brands ($F(1, 158) = 21.03$, $p < .001$).

As a potential explanation for the differences between the two types of brands in the far extension condition, we propose that because consumers have relatively more certain associations with product brands (see Lab Experiment 1), a new piece of information (i.e., brand extension), particularly an inconsistent one, may be less likely to change consumers' view of the product brand. This explanation is in line with the proposition in the Bayesian updating literature (e.g., Boulding, Kalra, and Staelin 1999; Geylani, Inman, and Hofstede 2008; Rust et al. 1999). In the presence of tighter (diffuse) priors, new information exerts less (more) influence on the posterior belief. Therefore, when modifying their evaluation of a product brand, consumers exhibit less updating from the introduction of the extension products, particularly when the extension products are far apart (atypical). This rationale is also consistent with the findings in prior research that consumers seem to follow a subtyping model when they update their views of a product brand (e.g., Geylani, Inman, and Hofstede 2008; Park, McCarthy, and Milberg 1993). In the subtyping model (Weber and Crocker 1983), consumers tend to view far extensions as atypical instances of the parent brand and categorize them as subtypes. As a result, consumers generally resist changing their evaluations of a product brand when the extension is categorized as far apart.

Figure 1
CELEBRITY VERSUS PRODUCT BRANDS



In contrast, because celebrity brands are perceived as more multidimensional and the thought associations with celebrity brands are less certain, consumers are more likely to update their past beliefs about the celebrity brand when faced with new information. Consequently, the bookkeeping model (Weber and Crocker 1983) may better describe how consumers update their evaluations of a celebrity brand. According to this model, when actors introduce extension products, each piece of new information leads to an incremental modification of the schema (in Figure 1, Panels A and B, the slopes of the extension types are flatter for celebrity brands than for those of product brands). Therefore, consumers generally reveal greater susceptibility to changes for celebrity brand extensions.

EMPIRICAL INVESTIGATION

Data

The data in our empirical study were collected from multiple sources, including (1) a 12-year longitudinal survey of favorability rating data for a panel of 48 movie stars conducted by a major U.S. entertainment company,[2] (2) media coverage of these stars' off-camera activities in weekly *People* magazines and daily *Variety* magazines during the same time of the survey,[3] (3) the online movie database IMDb (www.imdb.com), (4) the online movie database Rotten Tomatoes (www.rottentomatoes.com), and (5) the TNS Media Intelligence database.

For each movie star in our panel, we observed the movement of his or her favorability ratings over time, releases of movies featuring this movie star, and news coverage about the star's off-camera activities during the same period. Thus, the duration of the longitudinal data for each movie star varied, depending on when that particular star entered the favorability polls (minimum time 2001–2005; maximum time 1993–2005; average time 9.92 years; median time 10.40 years). Our final sample included 48 stars with 1427 observations, namely, 614 movie appearances and 813 favorability ratings. Table 2 provides the complete list of the 48 movie stars we considered and the number of movie and favorability observations we gathered for each star.

The favorability ratings we used were collected through telephone interviews. Sixteen territories were carefully selected by a data collection agency to represent the entire U.S. market. Within each territory, a simple random sampling method yielded approximately 800 respondents for each favorability poll. These interviews were conducted in various months for different movie stars. In each favorability poll, a screening check ensured that the respondent was aware of the actor. The original question was as follows: "On a scale from 0 to 100, what is your favorability of this actor/actress?" The aggregate-level favorability score across survey participants served as a measure of star favorability at the time of the interview.[4]

Because we aimed to investigate the extent to which a movie's performance and characteristics affect the movie star's brand equity, we also gathered the following informa-

Table 2
MOVIE STAR PANEL DESCRIPTIONS

Movie Star	*Number of Movies*	*Number of Favorability Ratings*
Adam Sandler	13	18
Angelina Jolie	11	14
Antonio Banderas	16	15
Ben Affleck	18	25
Ben Stiller	19	17
Brad Pitt	14	19
Bruce Willis	19	21
Cameron Diaz	16	18
Catherine Zeta-Jones	9	19
Charlize Theron	12	15
Dennis Quaid	13	19
Denzel Washington	12	19
Drew Barrymore	17	20
Eddie Murphy	16	17
Gwyneth Paltrow	17	23
Halle Berry	14	19
Jack Nicholson	8	14
Jamie Foxx	11	14
Jennifer Connelly	9	12
Jennifer Lopez	11	20
Jim Carrey	12	15
Jodie Foster	5	12
John Travolta	17	18
Johnny Depp	12	18
Julia Roberts	18	19
Julianne Moore	13	13
Keanu Reeves	12	17
Kirsten Dunst	15	14
Leonardo DiCaprio	11	13
Martin Lawrence	12	18
Matt Damon	19	21
Mel Gibson	15	19
Meryl Streep	9	15
Natalie Portman	8	13
Nicolas Cage	16	22
Nicole Kidman	12	19
Reese Witherspoon	12	16
Renee Zellweger	12	14
Robert De Niro	19	20
Russell Crowe	8	15
Sandra Bullock	15	19
Sarah Michelle Gellar	5	14
Sharon Stone	11	13
Tom Cruise	9	20
Tom Hanks	12	16
Uma Thurman	12	14
Vin Diesel	5	14
Will Smith	13	16

[2]The primary purpose of this data collection was to facilitate the company's strategic decision making in areas such as screening actors for movie roles or negotiating contracts with movie stars. An actor becomes part of the favorability poll after receiving some initial market recognition. Some movie stars have a longer track record in the favorability poll than others. To construct a dynamic panel data model with sufficient favorability observations per longitudinal profile, we acquired data for actors with at least 12 favorability ratings between 1993 and 2005, which resulted in the 48 stars in our empirical study.

[3]The massive amount of news coverage about each movie star during the time period of the favorability poll made it infeasible for us to review all the news articles about the actors (e.g., there were 85,251 articles about Nicole Kidman during this time window in the Factiva database, most of which duplicated coverage about the same events). Therefore, we narrowed down our search to *People* and *Variety* because of their specialization in celebrity news. According to our discussions with executives in the movie industry, these two magazines provide the most comprehensive coverage of movie stars' off-camera activities.

[4]It is worth noting that the favorability ratings used in our study were analogous to the well-known Q scores (www.qscores.com). In a performer Q study, each respondent indicates whether a performer is one of his or her favorites on a five-point scale, similar to our 0–100 point scale.

tion for each movie in our data sample: (1) five indicators of movie success (i.e., total number of Oscar and Golden Globe nominations received by the movie, total number of Oscar and Golden Globe nominations received by the focal movie star, critic rating, viewer rating, and cumulative box office revenue) and (2) five indicators of movie characteristics (i.e., maximum number of screens, seasonality, whether it is a sequel, Motion Picture Association of America [MPAA] rating, and genre). Following Elberse and Eliashberg (2003), we defined seasonality as the average weekly box office revenue in each week of the year. Because these movie observations span a ten-year period from 1995 to 2005, we adjusted the monetary measures (i.e., box office revenue and seasonality) to the base year of 1995 using inflation indexes published by the Bureau of Labor Statistics. To control for the time trend in the number of screens, we regressed each movie's maximum number of screens on an intercept of yearly dummies from 1996 to 2005 and other movie-related characteristics. These yearly dummies measured the average time trend in the maximum number of screens compared with the base year of 1995. Accordingly, we controlled for the time trend by subtracting the yearly dummy from the actual number of screens.

In Figure 2, we provide an example of a series of favorability ratings and movie appearances for the movie star Cameron Diaz. As this figure shows, the favorability rating surveys were collected in various months of the year. In some occasions, there were one or more movie releases in between two adjacent favorability ratings. In other occasions, the movie star did not appear in any movie in between two consecutive favorability ratings.

Finally, to account for the influence of a star's off-camera activities on his or her favorability rating, for each star in our panel, we reviewed all news articles related to the star in *People* and *Variety* during the period of our longitudinal analysis. After screening out movie-related articles, we obtained 6228 articles reporting the off-camera activities of the 48 stars in our analysis.

To be consistent with previous research on the impact of buzz and word of mouth (e.g., Liu 2006; Mahajan, Muller, and Kerin 1984), we took into account both the volume and the valence of media coverage. We define the monthly volume as the number of non-movie-related articles that appeared in *People* and *Variety* magazines each month. Human raters coded these articles by valence. The raters read each article and assigned it to one of the following three categories: positive, negative, or neutral. Following Liu (2006), we used the percentage of positive and negative articles that appeared every month to measure the valence of the media coverage on the movie stars' off-camera activities.[5] We provide the summary statistics of our data sample in Table 3.

Model

The primary goal of our model was to examine the relationship between the movement of star favorability over time and the releases of various movies featuring these stars during the same period, after controlling for the possible influence of the stars' off-camera activities. We also examined the underlying factors that influence the magnitude and the longevity of such effects. We provide the specifics of the model next.

Favorability movement. Let M denote the movie, P stand for star favorability, and W represent media coverage about the star's off-camera activities. For star i, his or her favorability rating at time k, coded as P_{ik}, pertains to his or her most recent favorability rating, taken at time s (k > s); the movies appearances of star i between time k and s; and media coverage of the star's off-camera activities between these two consecutive favorability ratings. If star i does not have any movie appearance between k and s, the effect of the movie is absent. Similarly, if there is no media coverage about the star's off-camera activities between k and s, the influence of off-camera activities is zero. Using calendar months as a unit of time, we define P_{ik} as follows:

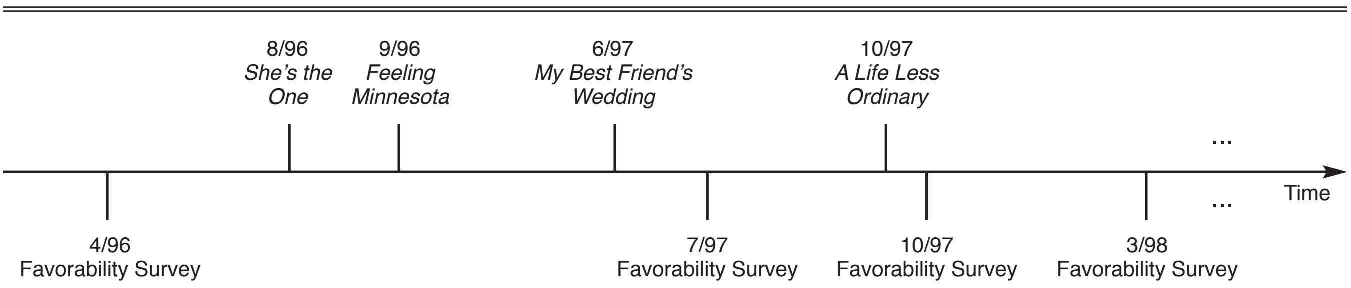
$$P_{ik} = \sum_{t=s}^{k-1}\left\{\left[\varphi(i,t)\rho_{iMt}M_{it} + \gamma(i,t)\theta W_{it}\right]\prod_{j=t}^{k-1} r_{ij}\right\} + \rho_{iPs}P_{is}\prod_{j=s}^{k-1} r_{ij} + \rho_{ik}, \tag{1}$$

[5]Because coding these articles according to their valence is extremely tedious and time consuming, two raters initially divided the task of reading the 6228 articles and classifying them into the three categories. To check the degree of interrater consistency, a third rater independently coded all the articles. The level of agreement between the third rater and the first two raters was as high as .90. When the third rater disagreed with the first two raters, an additional rater read the article, and the three independent ratings were integrated using the majority rule: If at least two raters assigned the same category, that category was used for that article.

Figure 2

EXAMPLE OF A SERIES OF FAVORABILITY AND MOVIE OBSERVATIONS

ACTRESS: CAMERON DIAZ



Notes: Media coverage of the movie star's off-camera activities is not shown

Table 3
DESCRIPTIVE STATISTICS OF PANEL DATA

Variable	*Total Number of Observations*	*M*	*SD*	*Minimum*	*Maximum*	*Mdn*
Star						
Number of favorability ratings	48	16.94	3.07	12.00	25.00	17.00
Number of movies acted	48	12.79	3.72	5	19	12
Favorability						
Favorability rating (0–100)	813	50.01	15.17	8.00	85.00	50.00
Movie						
Award Nominations_Movie	614	1.67	3.58	.00	22.00	.00
Award Nominations_Actor	614	.19	.52	.00	2.00	.00
Critic rating (1–10)	614	5.84	1.32	2.30	8.90	5.85
Viewer rating (1–10)	614	6.20	1.07	2.30	8.60	6.20
Cumulative box office (in millions of dollars)[a]	614	61.24	64.24	1.02	570.34	39.69
Maximum number of screens[b]	614	2222	893	43	3854	2220
Seasonality (in millions of dollars)[a]	614	3.12	.72	1.97	4.67	3.02
Sequel	614	.08	.27	.00	1.00	.00
PG	614	.11	.31	.00	1.00	.00
PG-13	614	.43	.49	.00	1.00	.00
R	614	.47	.50	.00	1.00	.00
Action	614	.29	.45	.00	1.00	.00
Comedy	614	.36	.48	.00	1.00	.00
Drama	614	.32	.47	.00	1.00	.00
Animation	614	.04	.20	.00	1.00	.00
Media Coverage of Stars' Off-Camera Activities						
Volume (monthly)	6228	1.38	1.33	0	9	1
Valence_Percentage_Positive (monthly)	6228	.23	.31	0	1	0
Valence_Percentage_Negative (monthly)	6228	.04	.12	0	1	0

[a]Adjusted for inflation, using 1995 as the base year.
[b]Adjusted for time trend, using 1995 as the base year.

where P_{ik} and P_{is} are the favorability ratings of star i at times k and s, respectively; $\varphi(i,t)$ is a dummy variable indicating whether a movie acted in by star i was released during month t, between times k and s; M_{it} denotes the effect of the movie released at time t; ρ_{iMt} is a scale characterizing the magnitude of such effects; $\gamma(i,t)$ is a dummy variable indicating whether there is media coverage of star i's off-camera activities in month t; W_{it} represents the vector of media coverage during month t (i.e., volume and positive and negative valence of media coverage); θ is the vector of parameter estimates associated with that effect; r_{ij} is the decay rate (i.e., 1 – depreciation rate) of the star's favorability during time j; ρ_{iPs} is a scale capturing the magnitude of the impact from P_{is} on P_{ik}; and ε_{ik} represents the error term.

Inspired by the commonly adopted idea of treating advertising and promotion as periodic shocks to the demand for a product (e.g., Leone 1995; Nijs et al. 2001), we view a star's movie appearances and off-camera activities as shocks to his or her favorability ratings. In line with this notion, the basic premises of our model can be explained as follows: A movie star's favorability erodes over time. Periodically, the star receives two types of shocks—namely, movie appearances and media coverage of off-camera activities. The star's favorability receives a bump at the time the shock occurs. Afterward, his or her favorability continues to depreciate.

Prior research has suggested that consumers' belief about a brand/product is a two-dimensional construct, with the mean reflecting the expected belief and the variance reflecting the degree of uncertainty consumers have about the brand/product (e.g., Boulding, Kalra, and Staelin 1999; Geylani, Inman, and Hofstede 2008; Rust et al. 1999). Therefore, we took into account both the mean and the variance of the most recent favorability measure in Equation 1. In particular, we defined the scale of P_{is} as $\rho_{iPs} = \exp(-a_P\sigma_{iPs})$, where σ_{iPs} represents the standard deviation of star i's favorability at time s. The magnitude of the impact from P_{is} is weighted by the degree of uncertainty consumers have toward the star. If the degree of uncertainty is high, the scale of the impact from P_{is} to P_{ik} should be relatively small. We used an exponential function to ensure that the range of the scale ρ_{iPs} was bounded between 0 and 1, with $\rho_{iPs} = 1$ when the standard deviation of the past favorability measure $\sigma_{iPs} = 0$. In the following, we provide further details on how we define the decay rate r_{ij}, the movie effect M_{it}, and the scale of the movie effect ρ_{iMt}.[6]

Decay rate. Inspired by the work of Lincoln and Allen (2004), we included gender and age in the decay rate function. In addition, we included the movie star's degree of

[6]We followed Liu (2006) and Mahajan, Muller, and Kerin (1984) to estimate the scale of the media effect (i.e., θ in Equation 1) at the aggregate level. It is likely that the magnitude of this effect is a function of the movie star's individual characteristics, such as gender, age, and degree of establishment (two of which also vary over time). We decided not to pursue this refinement for the following reasons: First, in Equation 1, the effect from the movie star's media coverage on favorability is defined as the product of θ and the decay rate r_{ij}, with the latter varying with the star's gender, age, and degree of establishment. If we also allow θ to vary as a function of these star-related characteristics, the effect of media coverage is likely to be overparameterized, so the resulting estimates would become unstable. Second, as we illustrated in the results section, our model estimates revealed that the relative impact of non-movie-related media coverage on star favorability was considerably smaller than the effects of movies. With these considerations, we simplified the scale of the media effect at the aggregate level.

establishment to capture the potential influence on decay rate. We adopted the widely used exponential decay function (e.g., Jedidi, Krider, and Weinberg 1998) in our model:

$$(2)\quad r_{ij} = \exp\Big[a_r + b_r\text{female}_i + \left(c_{r10} + c_{r11}\text{female}_i\right)\text{age}_{ij} + \left(c_{r20} + c_{r21}\text{female}_i\right)\text{age}_{ij}^2 + \left(d_{r10} + d_{r11}\text{female}_i\right)\text{sm}_{ij} + \left(d_{r20} + d_{r21}\text{female}_i\right)\text{sm}_{ij}^2 + \mu_{ij}\Big],$$

where a_r is a parameter capturing the baseline decay constant, female_i is a dummy variable indicating the gender of star i, age_{ij} is the age of the star i at time j, and sm_{ij} represents the star's degree of establishment (total number of movies acted in by star i at time j). Recognizing that some unobservable characteristics of the star also might influence the decay rate, we included a random error term μ_{ij} with distribution $\mu_{ij} \sim N(0, \sigma_\mu^2)$ in Equation 2.

In this equation, we used quadratic functions for the age and sm variables to capture the possibility of inverted U-shaped relationships between the carryover of star favorability and these two variables. The carryover of star favorability might increase as the movie star matures or he or she becomes more established. However, beyond a certain point, the carryover of star favorability should begin to decrease because the star cannot deliver as he or she has in the past. Furthermore, we included gender-specific interaction terms in the quadratic functions to account for different shapes of such relationships for actors of different genders. For any given star, the decay rate of his or her favorability is not only gender specific but also time variant.

Movie effect. To capture the overall impact of a movie on a star's favorability, we defined the movie effect, M_{it}, as a function of the movie's performance and characteristics metrics:

$$(3)\qquad M_{it} = \alpha + \beta Z_{it} + \xi_{it},$$

where Z_{it} is a vector including five indicators of movie success (i.e., number of award nominations received by the movie and focal movie star, critic rating, viewer rating, and cumulative box office sales) and five indicators of movie characteristics (i.e., maximum number of screens, seasonality, whether it is a sequel, MPAA rating, and genre) and ξ_{it} is a random-error term with distribution $\xi_{it} \sim N(0, \sigma_\xi^2)$.

Our selection of these movie performance and characteristic metrics was based on previous movie-related research (e.g., Ainslie, Drèze, and Zufryden 2004; Elberse and Eliashberg 2003). Some unobservable characteristics of the movie may affect a star's favorability, so we included a random-error term in Equation 3 to capture that effect.

Scale of movie effect. When a movie star receives a shock to his or her favorability from a new movie, the intensity of the bump may be affected by factors beyond the metrics of the movie itself. On the basis of extant behavioral literature, we included the typicality of the extension and the direction of the movie effect (i.e., positive or negative) as two such factors. In particular, we defined a scale parameter for the movie effect and modeled it as follows:

$$(4)\qquad \rho_{iMt} = \exp(a_M ng_{iMt} + b_M invg_{iMt} + c_M neg_{iMt}),$$

where ng_{iMt} denotes the number of previous movies acted in by the actor in the genre of the focal movie; $invg_{iMt} = 1/sg_{iMt}$, such that sg_{iMt} represents the relative share of the star's previous movie appearances in this genre; and neg_{iMt} is a dummy variable with $neg_{iMt} = 1$ if $M_{it} < 0$ and $neg_{iMt} = 0$ if otherwise.

In Equation 4, the variables ng_{iMt} and $invg_{iMt}$ measure the typicality of the extension product. If a star has appeared in many comedy movies or the majority of his or her previous movies are comedies, his or her appearance in a new drama movie would be considered an atypical extension. In particular, we define $sg_{iMt} = \max(ng_{iMt}, .01)/\Sigma_{g'=1}^{G} ng'$, where ng_{iMt} represents the number of previous movies in genre g and $\Sigma_{g'=1}^{G} ng'$ denotes the star's total movie appearances across different genres. To avoid the inversion of 0, we set $ng_{iMt} = .01$ when the number of previous movies in the genre equals 0 (i.e., $\max[ng_{iMt}, .01]$).

It has been widely recognized in branding literature that the typicality of an extension plays an important role in the magnitude of the feedback effect (e.g., Gürhan-Canli and Maheswaran 1998; Keller and Aaker 1992; Loken and John 1993). Therefore, our definition of movie scale also examines whether the typicality of the extension matters. For our study context, when a movie star appears in a new genre, the likelihood of his or her exposure to a broader audience may increase. Therefore, Equation 4 also indirectly measures whether an increase in star awareness through a movie appearance in a new genre alters the scale of the movie effect.

Furthermore, we used the dummy variable neg_{iMt} to examine whether negative and positive movie effects have asymmetric impacts on a star's favorability. Various researchers have suggested that because negative information is perceived as more diagnostic than positive information, consumers tend to give more weight to negative than positive experiences (e.g., Herr, Kardes, and Kim 1991). If this negativity bias also applies to our context, a negative movie effect should carry more weight for star favorability than a positive movie effect.

Estimation and causality check. Equations 1–4 constitute the empirical model we estimate. Past favorability ratings, movie effects, and the star's off-camera activities might be correlated with some unobservable idiosyncratic characteristics of the movie star (e.g., image, persona, acting skills), so Equation 1 is subject to endogeneity. We alleviate this issue by taking the first differences of Equation 1 to remove the time-invariant individual fixed effects and assuming that the time-variant individual effects are captured in the star's most recent favorability rating (see Appendix C).[7]

On a related note, our model implies that movie appearances influence star favorability. Star favorability also might determine movie appearances. We conducted a Ganger

[7]We acknowledge that our current approach may not completely address the potential endogeneity bias caused by the time-variant individual effects. A better approach is to construct a structural model that captures the entire decision process (e.g., how movie studios make casting decisions, how the popular press decides whom and what to report about celebrities' off-camera actives, how consumers develop favorability toward a star). Because of the lack of such data, we did not pursue such a refinement. Another way to address this issue would be to use instruments for the variables used to represent the movie effects and media effects. We searched literature on movies to look for candidates of such instruments. Although the vast majority of movie research suffers from similar endogeneity issues (e.g., the movie's cast, number of screens, advertising, and production budget are all endogenous), no existing research in this area has offered viable instruments to address this problem. It is probably a common limitation in this line of research, which also applies to our work.

causality check to test these two hypotheses. First, to assert a causal relationship from movie appearances to star favorability, we regressed favorability (P_{ik}) on the lagged value of favorability (P_{is}) and the number of movie appearances between times s and k. Using a Wald test, we found that movie appearances help explain star favorability (test statistic = 9.64, $p < .01$). Second, to examine the competing hypothesis, we regressed the number of movie appearances on the lagged values of movie appearances and star favorability. A Wald test revealed that the lagged value of star favorability added no information to movie appearances (test statistic = 2.12, $p > .10$), which implies that Granger causality is absent. Therefore, our data do not support the competing hypothesis.

We used a method of simulated moment procedure to estimate the set of parameters in Equations 1 and 4 simultaneously (Ahn and Schmidt 1995, 1997; Gourieroux and Monfort 1996). More details of our estimation procedure appear in Appendix C.

Empirical Findings

We next discuss our empirical findings. We provide the parameter estimates in Table 4.

Variance of past favorability. As we expected, the impact of lagged favorability was negatively related to its variance. This finding is consistent with the proposition in previous research that when the degree of uncertainty (i.e., variance) associated with the past belief (P_{is}) increases, the relative weight of the past belief decreases in the posterior belief (P_{ik}) (e.g., Boulding, Kalra, and Staelin 1999; Geylani, Inman, and Hofstede 2008; Rust et al. 1999).

Favorability decay. First, in line with the finding of Lincoln and Allen (2004), we found that the favorability of a female star depreciates faster than that of a male star. Second, we discovered that a star's age and degree of establishment both exhibit inverted U-shaped relationships to the carryover of star favorability. Third, we observed that some gender-specific interaction terms are significant in the two quadratic functions, which implies that the shapes of the inverted U relationships differed for actors of different genders.

Because the scale of the decay rate was small (i.e., monthly), we rescaled age to 1/10 of its original value and stage_movie to 1/100 of its original value to facilitate the model estimation. On the basis of our parameter estimates, we found that the maximum favorability carryover for a male actor occurs at age 33.3 years, when his total number of movie appearances reaches 14.4. At this point, the star's favorability depreciates less than 1% per year. However, for a young star at an early stage of his movie career, favorability is susceptible to considerable decay. For example, the favorability of a male actor of 25 years of age who has appeared in only two movies depreciates 5% per year, absent any movie appearances or media coverage. After the actor's age and degree of establishment move beyond the peak of his favorability carryover, the rate of favorability depreciation increases. For example, if a male actor were 55 years of age and appeared in 16 movies, his favorability would still depreciate 2.1% per year. For female stars, we found that maximum favorability carryover takes place when they are 20.8 years of age and have appeared in eight movies. At this point, the decay rate of favorability is approximately 3% per year. In general, the favorability carryover of female actors reaches the maximum point earlier and faster than that of male actors.

Table 4

MODEL PARAMETER ESTIMATES

Parameter	*Estimate*	*SE*
a_P (variance of past favorability)	.0017*	.0009
Favorability Decay		
Intercept	–.0085*	.0041
b_r (female)	–.0019*	.0008
c_{r10} (age)	.0021*	.0007
c_{r11} (female × age)	.0006*	.0002
c_{r20} (age^2)	–.0003*	.0001
c_{r21} (female × age^2)	–.0003$^{n.s.}$	.0021
d_{r10} (stage_movie)	.0686*	.0022
d_{r11} (female × stage_movie)	.0689$^{n.s.}$	.0142
d_{r20} (stage_movie^2)	–.2379*	.0932
d_{r21} (female × stage_movie^2)	–.6184*	.2142
Standard deviation of random error	.0001$^{n.s.}$	.0068
Movie Effect		
Intercept	.1380*	.0394
Indicators of Movie Success		
Award_movie	.0182$^{n.s.}$	.0131
Award_star	1.1858*	.5021
Critics rating	.1226*	.0602
Viewer rating	.3495*	.1545
Cumulated box office (in millions of dollars)	.0083*	.0003
Maximum number of screens	.0004*	.0001
Seasonality (in millions of dollars)	–.4621$^{n.s.}$	.2737
Sequel or Not		
Sequel	.3978*	.0612
MPAA Rating		
PG	–.3082*	.1170
PG-13	.4554*	.2302
Genre		
Action	–.4831*	.2022
Comedy	1.3434*	.6313
Animation	.7939$^{n.s.}$	.7832
Standard deviation of random error	.0711$^{n.s.}$	.1547
Scale of Movie Effect		
a_M (number of movies in same genre)	.0325$^{n.s.}$	.0501
b_M (invg)	–.0683*	.0316
c_M (shift due to negative movie effect)	2.0046*	.6862
Media Coverage of Star's Off-Camera Activities		
Volume (monthly)	.0656*	.0187
Valence_percentage_positive (monthly)	.1441$^{n.s.}$	.0831
Valence_percentage_negative (monthly)	.2161$^{n.s.}$	.1509

*Significant at .05.
Notes: n.s. = nonsignificant.

In the branding literature, the duration of brand equity has always been considered an important research topic. Although few studies have empirically examined the longevity of a brand's equity, there seems to be a consistent view that the equity of a product/service brand is relatively stable and lasting (Aaker 1991). Our results indicated that in the context of the movie industry, celebrity brands are subject to considerable erosion over time. This result is probably due to our finding in Lab Experiment 1 that, compared with their attitudes toward product/service brands, consumers are less certain in their thought associations for celebrity brands. Therefore, unless consumers are exposed to the celebrity brand on a regular basis, the equity status of the celebrity is susceptible to substantial decay.

Movie effect. The second panel in Table 4 presents the parameter estimates of the movie effect. We discovered that the total number of award nominations a movie has earned does not improve the star's favorability. This finding is not surprising, in that the popular press has increasingly criticized Oscar nominations as "deeply political" and "widely unpopular," because "academy voters have been trying to teach people what kind of movies they should like, rather than honoring the movies that people actually watch" (Hendrix 2006, p. 13). Each year's Golden Globe and Oscar nominations often coincide, and starring in an award-nominated movie is not necessarily associated with an improvement in favorability. In contrast, the total number of award nominations received by the star serves as a better indicator of increased star favorability. Critic and viewer ratings and cumulative box office sales all signify improvements in star favorability.

With regard to movie characteristics, we found that a movie's maximum number of screens contributes positively to star favorability. In contrast, seasonality does not affect the star's favorability rating. Our estimate also reveals that movie sequels improve the movie star's favorability. With sequels, movie stars can capitalize on the success of an original movie by reprising the same characters in a new situation.[8] In terms of ratings, PG-13 movies are best for an actor to boost his or her brand equity, which may reflect several factors. First, movies with PG-13 ratings can reach a broader audience than R-rated movies. Second, because PG-rated movies tend to sensor adult situations and language strictly to suit their younger audience, many moviegoers may perceive them as less attractive than PG-13 movies. Regarding genre, comedy is better than drama, action, or animation movies for improving an actor's brand equity. This finding was somewhat surprising; we expected drama movies to be the most beneficial for a movie star because they are often connected with deep emotions. A potential explanation for this is that, compared with other genres, the demographics and psychographics of the audience for comedy movies make them more willing to adjust their favorability toward the movie star upward. It is also possible that comedy elicits more positive affect in the minds of viewers, and this positive affect might enhance star favorability.

With the estimates in the second panel of Table 4, we can use Equation 3 and calculate an estimated movie effect for all the movies in our data set. Table 5 provides the descriptive statistics of the estimated movie effects (we mean-centered all continuous variables in the vector of M_{it}). Because these movie effects exhibit a wide dispersion from zero, we learned that each movie appearance can enhance or dilute the movie star's brand equity considerably. Among the 614 movies in our data, 414 exerted positive feedback effects, and the rest were negative. For an actor to protect and develop his or her brand favorability over time, the selection of movies is critical.

This result is particularly noteworthy because previous research about feedback effects in the context of product branding has indicated that dilution and enhancement effects occur only in certain conditions. Our empirical results reveal the general existence of feedback effects in a celebrity branding context. As a potential explanation of this difference, we note that the mechanisms underlying consumers' evaluations of celebrity and product brands differ (see Appendix B).

When a star appears in two or more movies between two favorability surveys, our model assumes that the joint impact of these movies on star favorability is additive (i.e., additive model). There are two alternatives to this assumption. First, a star's favorability rating could be driven mainly by his or her most recent movie appearance, just before the favorability measurement (i.e., recency model). Second, the favorability rating may be determined predominantly by the movie with the strongest effect (i.e., salience model). To test these alternative assumptions, we estimated two benchmark models. In the recency model, only the most recent movie preceding the current favorability measure appeared in the model estimation. In the salience model, we assumed that the subsequent favorability rating was driven only by the movie with the strongest effect at the time of the survey. To compare these alternative models, we computed the mean square error between the predicted and the actual favorability ratings for each model. The mean square error of the additive model was 43.76, that of the recency model was 46.91, and that of the salience model was 48.20. Therefore, the additive model better describes the joint impact of movies when there are multiple movies in between two favorability ratings.

Scale of movie effect. The estimates related to the scale of the movie effect appear in the third panel of Table 4. We found that a star's relative share of movies in a genre plays a significant role in the scale of movie effect. Specifically, when the movie star appears in a newer genre, the scale of the movie effect becomes relatively smaller, in contrast with our initial conjecture that a movie in a newer genre has a relatively larger impact on star favorability, because it increases awareness of the star. When the typicality of the extension is low, perhaps consumers are more resistant to updating their views of the star because the newer genre appears outside the star's focal expertise. Similarly, Loken and John (1993) propose that fewer feedback effects take place for atypical extensions because they do not reflect the parent brand's core competency. The absolute number of

[8]It is possible that movie sequels are more likely to be created for favorable stars, which implies an endogeneity problem. We checked the correlation between the star's appearance in a movie sequel and his or her most recent favorability rating in our data sample. This correlation was insignificant ($r = .04$, $p = .32$). Nevertheless, we acknowledge that this finding did not indicate an absence of potential endogenous bias. Appendix C provides more details regarding how we alleviate the issue of endogeneity in general.

Table 5

DESCRIPTIVE STATISTICS OF ESTIMATED MOVIE EFFECTS

Variable	*Number*	*M*	*SD*	*Minimum*	*Maximum*	*Mdn*
Movie effect	614	.71	1.40	–3.54	6.78	.60
Movie effects ≥ 0	414					
Movie effects < 0	200					

previous movies in the genre did not have a significant impact on the scale of the movie effect, possibly because the absolute number and relative share of the movies in the genre were somewhat correlated. Therefore, although each measure captures a unique aspect of extension typicality, the impact from the former gets absorbed by the latter in the estimation.

We also discovered that the scale of the movie effect is significantly greater when the overall impact of a movie on star favorability is negative. This finding conforms to the well-known negative bias theory. A negative movie viewing experience leaves a stronger impression than a positive movie viewing experience, so actors should avoid starring in movies that they believe are unlikely to be successful.

With the parameter estimates in the top three panels of Table 4, we also estimated the duration of a movie effect. An illustration is as follows: Assume that after we account for the scale of the movie effect, the bump a movie star receives from a particular movie is estimated to equal 3. For a male star who is 25 years of age and has appeared in two movies, the effect of the movie on his favorability drops to 2.86 a year after the movie's release. Thus, for each movie release, the movie star can estimate not only the magnitude of the movie effect but also the longevity of this effect on his or her brand equity.

Media coverage of the star's off-camera activities. Our analysis shows that the volume of media coverage had a significant, positive influence on a movie star's favorability. In contrast, the valence of the coverage (positive or negative) did not affect star favorability. Because movie stars' personal lives are often highly visible to the general public, it is not surprising that consumers' favorability toward an actor is driven not only by the star's movie appearances but also by his or her behind-the-camera activities. In an interesting contrast, the overall impact of a movie on favorability can be either positive or negative, but any media coverage about a star's off-camera activities reinforces the equity of that star. This finding likely emerges because only movies reflect the core skills of actors, not their off-camera activities. Therefore, a movie can either improve or hurt an actor's brand equity, but when it comes to off-camera activities, any publicity helps. Liu (2006) reports that the volume of word of mouth, not the valence, leads to greater movie box office revenue. Our empirical results support the general idea that for word of mouth, only the volume, not the valence, matters.

Because the volume of media coverage positively contributes to star favorability, our model can be used to examine the amount of media coverage needed to overcome a negative movie effect. If there are one or multiple negative movie effects between two consecutive favorability ratings, we can estimate how much media coverage is needed to offset these negative effects. Of the 614 movies in our data sample, 200 (released between 182 pairs of consecutive favorability ratings) were estimated to exert negative influences on star favorability. Using the actual volume as a base, we found that, on average, the amount of media coverage needed to increase 17.76 times to offset negative movie effects (M = 17.76, Mdn = 8.26, SD = 33.34, minimum = .02, maximum = 279.43) in the subsequent favorability poll. This finding suggests that movies exert significantly more influence than media coverage of the star's off-camera activities on star favorability. Movie stars should safeguard their brand equity by carefully choosing their movie appearances because, in general, it is difficult to offset the impact of a negative movie by increasing media coverage.

Managerial Applications

According to our model, the overall impact of a movie on star favorability is a joint function of (1) indicators of movie success, (2) movie characteristics, and (3) the time between a movie release and the favorability measure. Although it is reasonable to assume that the movie star can infer an increase in his or her brand equity from some indicators of movie success, the relationship between movie characteristics and star favorability may not be apparent. Furthermore, it is unclear if the magnitude of the positive movie effect is sufficient to offset favorability decay. Therefore, a potential managerial application of our research is that the parameters of our empirical analysis can be used to obtain estimates of movie effects and the rate of favorability decay, according to which a movie star can make strategic decisions about his or her future movie choices.

Our model is a reduced-form model by nature, so the well-known Lucas critique is relevant for the execution of our analyses. To minimize this concern, we followed Van Heerde, Dekimpe, and Putsis's (2005) suggestions by focusing on short-term predictions in which future policies (i.e., movies) closely mirror historically observed policies in the sample data. In the following, we provide two examples to illustrate how to conduct such an analysis.

Natalie Portman. Natalie Portman's favorability equaled 41 in June 2005, at the end of our longitudinal survey. Before this rating, her three most recent movies appearances were *Garden State* (released August 2004), *Closer* (released December 2004), and *Star Wars Episode II: Attack of the Clones* (released May 2005). With this recent history, we aimed to examine whether continuing to appear in similar movies shortly after June 2005 would help Natalie Portman build her brand equity further.

Without loss of generality, we assumed that she would follow the rate at which she released movies in the two years before her last favorability rating and thus star in three movies in the two years after June 2005. We also assumed that she would obtain offers to appear in movies similar to her previous three movies because movie stars often receive offers to appear in similar types of movies. We used the estimated movie effects for these three movies to approximate the potential feedback effects Portman could receive from the new movies if she decided to continue on a similar path in her movie selections. Assuming the three movies were released at six-month intervals and the effect of her off-camera activities was absent, our model estimates predicted that Portman's favorability would improve to 46.49 by June 2007 (i.e., two years after her last favorability survey). That is, the enhancement effects the actress should receive from these movies could not only offset the decay of her favorability but also enhance her brand equity. During the period after June 2005, if she received offers to star in movies similar to her most recent movies, Portman should have considered taking them.

Vin Diesel. Vin Diesel's favorability rating was 49 in July 2005, at the end of our longitudinal survey. His last three movies before this measure were *Knockaround Guys* (released October 2002), *A Man Apart* (released April 2003), and *The Pacifier* (released March 2005). After conducting a similar analysis, we found that if Vin Diesel continued along a similar path, two years later his favorability rating would have dropped substantially from 49 to 27.65. This finding implies that Diesel's movie career was not heading in the right direction at the time of his last favorability survey. To protect his brand equity, Diesel should have responded by declining offers to appear in movies similar to his previous three movies and seeking out opportunities to star in different types of movies and/or movies with better prospects. In a similar fashion, each actor in our panel could benefit from our model by predicting how his or her favorability would be affected if he or she were to take a similar path in his or her movie choices.

CONCLUSIONS

In this section, we highlight the key results, describe their theoretical and managerial implications, and discuss some limitations and avenues for further research. First, we found evidence in support of the general existence of enhancement and dilution effects on the equity of a movie star through movie releases. Previous research has typically indicated that these effects in a product branding context occur only under certain conditions. This disparity implies a difference between celebrity and product brands with regard to how consumers form brand evaluations. In particular, both our empirical results and the lab experiments suggest that the bookkeeping model better describes how consumers develop their evaluations of a celebrity brand, rather than the popular subtyping model supported by many prior studies (e.g., Milberg, Park, and McCarthy 1997; Park, McCarthy, and Milberg 1993).

Second, our results show that in contrast with the traditional view that brand equity is relatively stable in the short and medium runs (Aaker 1991), in the context of the movie industry, the favorability of a celebrity brand depreciates significantly over time. We attribute this effect to consumers' reduced certainty in their memory structures about celebrity brands compared with product/service brands. Unless consumers have been exposed to the celebrity brand regularly, the equity status of the celebrity is subject to substantial erosion over time.

Third, our dynamic model explicitly examines how a series of movie appearances jointly contribute to the brand equity of an actor. In the marketplace, it is common practice to launch a series of new products under a common brand name. However, existing literature has overlooked the timing, duration, and combination of multiple feedback effects through sequential new product introductions. Our framework can serve as a foundation for research investigating these effects in the traditional context of product branding.

Finally, our findings are useful for the strategic decision making of both actors and firms that use celebrities as spokespeople. In particular, our research provides actors (and their talent agents) with a better understanding of the dilution and enhancement of their celebrity brands and insight into strategies to maximize their brand equity. Regarding celebrity spokespeople, our findings suggest that firms need to invest in research that tracks the movement of star favorability over time, because a star's favorability can change considerably, conditional on each of his or her movie appearances, age, and level of establishment.

Our research also is not without limitations. First, our brand equity measure was limited to the degree of favorability attached to the brand. Keller (1993) conceptualizes brand equity as a multidimensional concept. Further research could examine how a sequence of brand or line extensions dynamically influences the other dimensions of brand equity. Second, because we have a reduced-form model, our approach did not eliminate the potential endogeneity bias caused by the time-variant individual effects. Additional research could construct a structural model to capture the decisions of the various agents involved in the process (e.g., movie studios, popular press, movie stars, moviegoers). More useful policy simulations could be developed with such a structural model. Third, we limited our analysis to celebrity brands in the movie industry. Further research could extend our approach to study the feedback effects of extension products on the equity of a celebrity/product brand in broader contexts.

APPENDIX A: FINANCIAL RETURN OF STAR FAVORABILITY

In this appendix, we analyze the impact of favorability on the star's salary. Using trade magazines such as *Variety* and online movie databases such as IMDb (www.imdb.com), we searched for the amount of salary the movie stars received from each movie in our sample data. We found salary information for 155 movies. With these salary data, we conducted a regression to analyze the financial return of star favorability.

To control for the influence of other movie-related characteristics on the star's movie salary, we regressed the log of the star's salary on the log of the star's favorability and several star- and movie-related characteristics (i.e., gender, age, the square of age, genre, rating, distributor, sequel, production budget, numbers of award nominations received by the movie and the star, critics rating, viewer rating, log[advertising expenditure], log[number of screens], number of weeks in theaters, and seasonality). The advertising expenditure information was collected from the TNS Media Intelligence Database. Seasonality was defined as the average weekly box office revenue for each week of the year. Other information was collected from the online movie databases IMDb (www.imdb.com) and Rotten Tomatoes (www.rottentomatoes.com). The movie-related characteristics were similar to those used in previous research (e.g., Ainslie, Drèze, and Zufryden 2004; Elberse and Eliashberg 2003).

The results of our regression suggest that, after we controlled for the influence of other star- and movie-related characteristics, a 1% increase in the star favorability rating contributed to a 3.07% increase in the salary the star received from a movie. The substantial financial return of star favorability provided some additional evidence indicating that actors with more brand equity benefited.

APPENDIX B: LAB EXPERIMENTS

Because our research diverges from prior branding literature by focusing on celebrity brands rather than product/service brands, we conducted two lab experiments to examine how consumers might evaluate these two types of brands differently. The primary purpose of Lab Experiment 1 was to compare consumers' memory structures about celebrity versus product/service brands. In Lab Experiment 2, we aimed to examine whether there was a difference between celebrity and product/service brands in terms of how consumers modify their brand evaluations after product extensions.

Lab Experiment 1

Pretest. We first ran a pretest to identify sets of celebrity and product/service brands that were sufficiently similar to each other on several dimensions so we could make further comparisons of these brands. A within-subjects study was conducted. Twenty-eight undergraduate students from a large West Coast U.S. university were asked to assess 20 celebrity brands and 20 product/service brands. For each brand, they responded to the following questions using seven-point scales: (1) "How easy is it for you to recall this actor/actress [product/service brand]?" (2) "How much do you like this actor/actress [product/service brand]?" (3) "How clear is the identity of this actor/actress [product/service brand] in terms of his or her main character [main characteristics]? and (4) "To what degree does the actor/actress [product/service brand] evoke positive emotions?" These four criteria were chosen to identify pairs of comparable celebrity and product/service brands. We selected the first three criteria on the basis of suggestions by Park, Milberg, and Lawson (1991). We chose the last criterion to ensure that the celebrity and product/service brands were comparable in terms of the affective dimension.

Data analyses revealed three pairs of celebrity and product/service brands comparable on the four dimensions (i.e., brand familiarity, favorability, identity clarity, and affect). Specifically, the paired samples t-tests revealed insignificant differences between the following three pairs on all four dimensions: (1) Keanu Reeves–Jaguar ($p > .250$), (2) Leonardo DiCaprio–Godiva ($p > .119$), and (3) Reese Witherspoon–Hershey's ($p > .305$). We used these three pairs of brands in the main study, reported next.

Main study. We conducted a between-subjects study to examine whether consumers had different memory structures for celebrity versus product/service brands. Two conditions were designed for this study. In condition 1, 43 participants completed a survey about the three celebrity brands. In condition 2, 44 participants filled out a similar survey for the three corresponding product/service brands. Participants were randomly assigned to one of the two conditions and answered several questions about each brand. First, we asked the participants the following open-ended question: "What comes to your mind when you think about this actor/actress [brand]?" For each thought association, we also asked participants to indicate on a seven-point scale "How certain (strongly) do you feel about this thought?" Second, the participants answered the following seven-point scale questions: (1) "How many different types of thoughts come to your mind when you think about this actor/actress [brand]?" and (2) "To what extent does this actor/actress [brand] represent a mix of highly different personas in her/his acting and personal life [mix of highly different characteristics]?"

We first analyzed the answers to the open-ended question to identify the different types of thought associations. For celebrity brands, seven themes of responses emerged (in descending order of frequency): celebrity image and abilities, physical characteristics, name of the movies, movie roles, personal life–related comments, movie image, and other associations with the celebrity. For product/service brands, only five types of responses emerged: product attribute–related evaluations, brand image associations, products under the brand, usage situations, and personal experiences.

For the open-ended question, we also counted the number of statements the participants provided for each brand. For two of the three pairs, the number of statements related to the celebrity brand were significantly more than those related to the product/service brand (Keanu Reeves = 4.42, Jaguar = 3.93, $p < .05$; Reese Witherspoon = 4.43, Hershey's = 3.70, $p < .05$). For the remaining pair, the difference was marginally significant (Leonardo DiCaprio = 4.42, Godiva = 3.85, $p = .09$).

In addition, we compared the degree of certainty (strength) of the three most salient thoughts for each celebrity–product pair (when the participant listed fewer than three thoughts, all the thoughts were included in this comparison). We found that, on average, consumers were significantly more certain about their most salient thought associations about the product brands than about the celebrity brands (Keanu Reeves = 5.81, Jaguar = 6.26, $p < .01$; Leonardo DiCaprio = 6.19, Godiva = 6.41, $p = .05$; Reese Witherspoon = 5.94, Hershey's = 6.24, $p < .05$).

Next, we analyzed participants' ratings on the two seven-point scale questions (i.e., different types of thoughts and mix of personas/characteristics). Because the two items revealed high correlations (.68), they were averaged to create an index, representing the multidimensionality of consumers' perceptions of each brand. For all three pairs of brands, consumers' perceptions of the celebrity brand were more multidimensional than the corresponding product brand (Keanu Reeves = 3.90, Jaguar = 3.30, $p < .05$; Leonardo DiCaprio = 4.69, Godiva = 3.46, $p < .001$; Reese Witherspoon = 4.91, Hershey's = 4.24, $p < .01$).

In summary, the results of this study confirmed that consumers have different memory structures for celebrity versus product/service brands. In particular, consumers have a greater number and more types of thought associations for celebrity than product/service brands. Furthermore, the most salient associations with celebrity brands were less certain compared with those with product/service brands. Finally, consumers tend to perceive the celebrity brands as more multidimensional than product/service brands.

Lab Experiment 2

Perceived similarity between the brand and the extension product is a key variable for evaluating brand extensions. Therefore, the primary goal of this pretest was to identify product extensions perceived as equally far and equally close to the pairs of celebrity and product brands from Lab Experiment 1. In a within-subjects study, 26 participants rated the perceived similarity of each of the 6 brands and 15 brand extensions on a seven-point scale (e.g., "If Keanu Reeves [Jaguar] is to launch … under his [its] name, what is your perceived similarity between the product and his [its] image?").

According to our pretest data, a home audio speaker was perceived as a close extension for both Keanu Reeves and

Jaguar. The degree of similarity was equal for both extension products (4.19 versus 4.61, $p = .28$). We also discovered that stationery was considered an equally far extension for Keanu Reeves and Jaguar (1.61 versus 2.03, $p = .25$). In addition, we found that wine was perceived as an equally close extension for the pair Leonardo DiCaprio and Godiva (4.07 versus 3.96, $p = .70$), and wallpaper was considered an equally far extension (1.88 versus 1.50, $p = .22$). Therefore, we used these four pairs of extension products (two close and two far) in our main study.

APPENDIX C: ESTIMATION PROCEDURE

Equations 1–4 describe the empirical model we need to estimate. This model takes the form of a dynamic model with unbalanced panel data. Substantial complications arise in the estimation of such a model for several reasons. First, the past favorability ratings in Equations 1 are correlated with the error terms (Greene 2000). Second, there could be an underlying selection process between some determinants of star favorability (e.g., movie appearances, movie sequels, media coverage of the star's off-camera activities) and the movie star. In other words, an actor's appearances in movies and movie sequels and the likelihood that the press reports about a star's off-camera activities might correlate with some unobservable idiosyncratic characteristics of the movie star (e.g., image, persona, acting skills). Therefore, past favorability ratings, movie effects, and the star's off-camera activities in Equation 1 are all potentially correlated with the error term, which implies an endogeneity problem.

We take the following steps to alleviate this issue: First, we assume that the error term in Equation 1 contains a time-invariant individual fixed effect and random noise. Without loss of generality, we use the following simplified expression to represent a general form of Equation 1:

$$\text{(C1)} \qquad P_{ik} = X_{ik}\Theta_{ik} + \delta_{is}P_{is} + \varepsilon_{ik},$$

$$\varepsilon_{ik} = v_i + \omega_{ik},$$

where $X_{ik}\Theta_{ik}$ represents the combined effects of movies and media coverage at time k, $\delta_{is}P_{is}$ denotes the undepreciated stock of star favorability, and the error term ε_{ik} includes the time-invariant individual fixed effect v_i and random noise ω_{ik}.

Second, given that some idiosyncratic characteristics of the movie star (e.g., acting skill) may evolve over time, we assume that at time k, the effects of all time-variant characteristics of the star to date are captured by the most recent favorability rating P_{is}, taken at time s. Therefore, we can take the first differences of Equation C1 to obtain the following equation:

$$\text{(C2)} \quad P_{ik} - P_{is} = (X_{ik}\Theta_{ik} - X_{is}\Theta_{is}) + (\delta_{is}P_{is} - \delta_{ig}P_{ig}) + (\varepsilon_{ik} - \varepsilon_{is}),$$

where g indicates the time the most recent favorability survey was taken before s.

In Equation C2, because the time-invariant individual fixed effect is swept away and the time-variant individual effects are captured in the most recent favorability ratings, we can estimate the reconstructed model by creating the following moment conditions (Ahn and Schmidt 1995, 1997):

$$\text{(C3)} \qquad E[P_{it}, (\varepsilon_{ik} - \varepsilon_{is})] = E[P_{it}, (\omega_{ik} - \omega_{is})] = 0,$$

where $t < s$.

By integrating over the random errors ξ_{it} and μ_{ij}, we generate a conditional moment coinciding with the generalized method of moments estimator (Gourieroux and Monfort 1996):

$$\text{(C4)} \qquad \int\{E[P_{it}, (\varepsilon_{ik} - \varepsilon_{is})]; \xi_{it}, \mu_{ij}\}dF(\xi_{it}, \mu_{ij}) = 0,$$

where $t < s$.

We then estimate the set of parameters in Equations 1 and 4 simultaneously under a method of simulated moment procedure.

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