

Dilution and Enhancement of Celebrity Brands through Sequential Movie Releases

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Abstract

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

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

“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.”

Becky Ebenkamp (*Brand Week*, Jun. 21, 1999)

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 (e.g. *New Statesman*, Oct. 3, 2005; *Reuters*, Mar. 26, 2009). Specifically, 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 (*Fox News*, Aug. 26, 2003). As with traditional product brands, actors/actresses (and their agents) have begun to realize the importance of enhancing and protecting their celebrity brands (*B&T Marketing and Media*, Feb. 9, 2007).¹ For Hollywood stars, “branding can mean simply identifying a career goal and implementing a game plan to achieve it” (*The Hollywood Reporter*, Nov. 18, 2003).

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

¹ According to our analysis in Appendix A, actors/actresses with a high degree of brand equity enjoy substantial financial return on their movie salary.

First, while useful for understanding the phenomenon of the enhancement and dilution effects, these studies do not make a general prediction about the magnitude or the longevity of such effects. *Second*, because the vast majority of these studies were one-shot experiments in which consumers provide their instantaneous responses to hypothetical product extensions (with the exception of Swaminathan et al. 2001), the dynamic movement of brand equity in response to a sequence of new product introductions has not been investigated. *Finally*, given that previous research in this area has been primarily conducted in labs, the external validity of their findings remains to be testified.

Addressing these issues within the traditional context of product branding has been hampered by the methodological difficulty and the lack of viable data. In this paper, we go beyond the scope of extant literature by empirically analyzing the magnitude, the longevity, and the dynamics of feedback effects in a real world setting in which consumers' evaluations towards a panel of brands can be traced over time. Since both celebrity names and product/service names are part of the "brand", the framework introduced here could advance our understanding of the dynamic movement of brand equity under 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 Intel microprocessor as a branded component in personal computers, we consider movie stars as branded components and movies as new products featuring 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 during from 1993 to 2005 to represent changes in the brand equity of a panel of actors/actresses

over time.² Given that consumers' favorability toward a movie star may also be affected by his/her off-camera activities (such as the star's involvements with charities, relationships, scandals, etc.), we also traced media exposure of these movie stars' non-movie related activities during the same time window. We further constructed a dynamic panel data model to investigate how changes in the favorability ratings of these actors/actresses are associated with their movie appearances, after controlling for the influence from these stars' off-camera activities.

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

The rest of the paper is organized as follows. First, we discuss the relationship between our research and the existing literature. Second, we describe the key findings from the two lab experiments in which we examine the underlying mechanism behind consumers' evaluations towards celebrity vs. product brands. Third, we present the empirical data collected from the field, demonstrate our dynamic panel data model, and present our findings. Next, we illustrate how our estimates can be used to guide the strategic decision making of an actor/actress in developing and protecting his/her celebrity brand. We conclude by summarizing key results, discussing implications, limitations and avenues for future research.

² In the literature, brand equity has been defined and operationalized in a myriad of ways (e.g. Keller 1993; Park, MacInnis, Drèze, and Lee 2009). Due to data availability, this paper relies exclusively on favorability to measure brand equity. We therefore do not claim this is the only way to define and measure brand equity.

Theoretical Background

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

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

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

Second, Ailawadi, Lehmann, and Neslin (2003) proposed that 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 has always been considered a major force driving the demand for a movie. Indeed, researchers found that demand for a movie increases with the rank of the movie star appearing in it (e.g. Elberse 2007 and Elberse and Eliashberg 2003).

Consequently, we deem movie stars as celebrity brands and movies as new products featuring these brands. In the branding literature, some researchers considered new product introductions in similar product categories as line extensions and those in dissimilar product

categories as brand extensions. It can be argued that each movie is a line extension of the celebrity brand because movie stars exist to make movies. On the other hand, Park et al. (1996) refer to new products with branded components as composite brand extensions. Additionally, some other researchers refer to new products in both same and different product categories as brand extensions (e.g. Loken and Roedder John 1993). In particular, in the context of movies, Sood and Drèze (2006) conceptualize movie sequels as brand extensions of the original movies. Therefore, to be consistent with the 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 research in the branding literature primarily studied the dilution and enhancement effects in the typical product branding context. With regards to dilution effect, researchers showed mixed evidence of whether an unsuccessful new product launch dilutes the brand itself. While some research reported evidence supporting the existence of dilution effects (e.g. Milberg et al. 1997), others did not. For example, Keller and Aaker (1992) failed to find any evidence of brand dilution with dissimilar product extensions. Additionally, Loken and Roedder John (1993) found that quality perceptions of the brand were unaffected when the proposed extension was in a dissimilar product category (however, in a similar product category dilution occurred). Furthermore, Roedder John et al. (1998) reported that dilution effects were less likely to be present with flagship products.

Regarding enhancement effect, existing research suggested that its presence is highly situation-specific. Park et al. (1996) found that positive enhancement effects only occur in complementary but dissimilar co-branded extensions. Gürhan-Canli and Maheswaran (1998) discovered that both typicality of the extension and consumers' level of motivation determined

the effect of extensions. Greater feedback effects occurred when consumers were highly involved in evaluating products. In addition, Ahluwalia and Gürhan-Canli (2000) suggested that, under higher accessibility of extension information, both enhancement and dilution effects occurred regardless of the extension category. Under lower accessibility, however, category diagnosticity determined whether extension information would enhance or dilute the brand. Finally, Swaminathan et al. (2001) examined the impact of extension introductions on choice using scanner data. Their results showed a positive reciprocal (enhancement) effect of extension trial on parent brand choice, particularly among prior non-users of the parent brand.

In general, due to the mixed findings on dilution effects, it is difficult to foresee whether some movies will actually dilute the brand equity of an actor/actress. Moreover, the situation-specific enhancement effects also make it difficult to predict the extent of the enhancement effect in our context. Finally, given that our research diverges from past research by focusing on celebrity brands rather than product brands, the underlying mechanism behind consumers' evaluations towards product brands and celebrity brands may differ. For product/service brands, consumers in general receive highly coordinated and consistent information about the brands (referred to as brand positioning). In contrast, consumers' memory organization of an actor/actress is based on episodic exemplars that are not necessarily well connected to one another (such as movies with different plots, genres, co-stars, in addition to the various types of media coverage about the star). Consequently, the 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 regarding: 1) consumers' memory structures of the brands; and 2) the degree to which

consumers are willing to update their views about the brands when extension products are introduced. We report the main findings here and leave the supplementary details in Appendix B.

Lab Experiments

Lab Experiment One

This experiment was designed to compare consumers' memory structures about celebrity versus product/service brands. A within-subject pretest was first conducted to identify pairs of celebrity and product/service brands with similar degree of brand familiarity, favorability, identity clarity, and affect. Next, we employed a between-subject study to further investigate consumers' memory structures towards these two types of brands. Depending on their condition type (celebrity vs. product brands), the participants answered the question "what comes to your mind when you think about this actor/actress (*or* this brand)". For each thought association, we also asked the participants to indicate on a 7-point scale "how certain (strongly) do you feel about this thought". Next, the participants answered the following 7-point scale questions: 1) "how many different types of thoughts come to your mind when you think about this actor/actress (*or* this brand)"; and 2) "to what extent does this actor/actress (*or* this brand) represent a mix of highly different personas in her/his acting and personal life (*or* 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 than product/service brands. Second, consumers feel less certain (strong) about their most salient thoughts with celebrity versus product/service brands. Finally, consumers' understanding of celebrity brands is more multi-dimensional than their understanding of product/service brands. Therefore, our

analyses from this experiment indicate that consumers indeed have different memory structures for celebrity versus product/service brands.

Lab Experiment Two

In this experiment, we further investigated whether there is a difference between celebrity and product/service brands regarding how consumers modify their brand evaluations when product extensions are introduced. A within-subject pretest was first conducted to identify product extensions that are perceived as equally far and equally close to the pairs of celebrity and product brands used in the first lab experiment. For example, home audio speaker is considered as an equally close extension for Keanu Reeves and Jaguar; and stationery is considered as an equally far extension for this pair. Table 1 provides a complete list of such extensions.

<Insert Table 1 around here>

Based on the pretest data, a 2 (brand type: celebrity vs. product) x 2 (extension type: close vs. far) between-subject design was conducted. A total of eighty-two participants were randomly assigned to one of the four conditions. Within each condition, participants were presented with two scenarios of the same type of extensions. For example, in the celebrity-close condition, the participants were informed that Keanu Reeves is going to launch a line of home audio speakers under his name. Next, we asked the participants to indicate on a 7-point scale (anchored at “strongly disagree” and “strongly agree”) whether they would like the actor more/less if the extension product succeeds/fails. Thus, a higher response score demonstrates a greater degree of brand updating. In scenario two, the same questions were asked for the case of Leonardo DiCaprio launching a line of wines. In a similar fashion, participants in the three other conditions were asked to answer the corresponding questions.

The results of our study are illustrated in Figures 1a and 1b. 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 fails. Specifically, celebrity brands exhibited greater dilution effect than product brands when the extension was categorized as far-away (for pair 1: $F(1, 78) = 4.80, p < .05$; for pair 2: $F(1, 78) = 5.21, p < .05$). However, such effect disappeared in the close extension condition (for pair 1: $F(1, 78) = 1.16, p = .29$; for pair 2: $F(1, 78) = .96, p = .33$). Similarly, the two-way interaction was significant for both pairs when the extension succeeds (for pair 1: $F(1, 78) = 3.99, p < .05$; for pair 2: $F(1, 78) = 5.14, p < .05$). Specifically, celebrity brands exhibited significantly or marginally greater enhancement effect than product brands in the far extension condition (for pair 1: $F(1, 78) = 3.09, p < .09$; for pair 2: $F(1, 78) = 4.16, p < .05$), whereas such differences were absent in the close extension condition (for pair 1: $F(1, 78) = .07, p = .80$; for pair 2: $F(1, 78) = .09, p = .77$).

<Insert Figures 1a and 1b around here>

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

One potential explanation for the differences between the two types of brands in far extension condition is as follows. Because consumers have relatively more certain/stronger

associations with product brands (as shown in lab experiment 1), a new piece of information (i.e. a brand extension), particularly inconsistent ones, is less likely to change the consumers' view towards the product brand. This is in line with the proposition in the Bayesian updating literature (e.g. Boulding, Kalra, and Staelin 1999; Geylani et al. 2008; Rust, Inman, Jia, and Zahorik 1999). This literature posits that, 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 (atypical). This rationale is also consistent with the findings in prior research that consumers seem to follow the subtyping model when they update their views towards a product brand (e.g. Geylani et al. 2008; Park et al. 1993). In the subtyping model (Weber and Crocker 1983), consumers have the tendency to consider far extensions as atypical instances of the parent brand and categorized them as subtypes. As a result, consumers are generally resistant in changing their evaluations of a product brand when the extension is categorized as far-away.

In contrast, because celebrity brands are perceived to be more multi-dimensional and the thought associations with celebrity brands are less certain/strong, consumers are more likely to update their prior beliefs of the celebrity brand when faced with new information. Consequently, the bookkeeping model (Weber and Crocker 1983) may better describe how consumers update their evaluations towards a celebrity brand. Under this model, when actors/actresses introduce extension products, each piece of new information leads to an incremental modification of the schema (as shown in Figures 1a and 1b, the slopes of the extension types are flatter for celebrity brands than those of product brands). Therefore, consumers generally reveal greater susceptibility to changes when it comes to celebrity brand extensions.

Empirical Investigation

Data

The data used 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 company³; 2) media coverage of these stars' off-camera activities in weekly *People* magazine and daily *Variety* magazine during the same time window of the survey⁴; 3) online movie database IMDb (www.imdb.com); 4) online movie database Rotten Tomatoes (www.rottentomatoes.com); and 5) TNS Media Intelligence database.

For each movie star in our panel, we observe the movement of his/her favorability ratings over time, the releases of movies featuring this movie star, and news coverage about the star's off-camera activities during the same time period. The duration of the longitudinal data for each movie star varies depending on when that particular star became included in the favorability polls (minimum time period: 2001 to 2005; maximum time period: 1993 to 2005; average time period: 9.92 years; median time period: 10.40 years). Our final sample includes 48 stars with 1427 observations. Among them, 614 are movie appearances and 813 are favorability ratings. Table 2 provides the complete list of the 48 movie stars we considered in this study. This table also gives the number of movie and favorability observations we have for each star.

³ The primary purpose of this data collection is to facilitate the company's strategic decision making in such areas as screening actors/actresses for movie roles, negotiating contracts with movie stars, and etc. An actor/actress became part of the favorability poll after he/she received some initial market recognition. Consequently, some movie stars have a longer track record in the favorability poll than others. In order to construct a dynamic panel data model with a sufficient number of favorability observations per longitudinal profile (i.e. the movie star), we only acquired data for actors/actresses with at least 12 favorability ratings between 1993 and 2005, which results in the 48 stars in our empirical study.

⁴ The massive amount of news coverage about each movie star during the time period of the favorability poll has made it infeasible for us to review all the news articles about the actor/actress (for example, there are 85,251 articles about Nicole Kidman during this time window in *Factiva* and most of them are 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 are known for providing the most comprehensive coverage of movie stars' off-camera activities.

<Insert Table 2 about here>

The favorability ratings used in our study were collected through phone interviews. Sixteen territories were carefully selected by the data collection agency to represent the entire U.S. market. Within each territory, a simple random sampling method was used. This method yielded approximately 800 respondents in each favorability poll. These interviews were conducted in various months for different movie stars. In each favorability poll, a screening check was used to ensure that the respondent was aware of the actor/actress. The original interviewing question was: “on a scale from 0-100, what is your favorability of this actor/actress?” The aggregate level favorability score across the survey participants was provided to us as a measure of star favorability at the time of the interview.⁵

Because we aim to investigate to what extent a movie’s performance and characteristics affect the movie star’s brand equity, the following information was collected for each movie in our data sample: 1) five indicators of movie success (i.e. the total number of Oscar and Golden Globe nominations received by the movie, the total number of Oscar and Golden Globe nominations received by the focal movie star, critics 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 sequel, MPAA rating, and genre). Following Elberse and Eliashberg (2003), seasonality was defined as the average weekly box office revenue in each week of the year. Given that 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 indices 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,

⁵ It is worth noting that the favorability ratings used in our study is analogous to the well-known Q scores (www.qscores.com). In a performer Q study, each subject is asked to indicate whether a performer is one of his/her favorites on a 5-point scale, which in essence is similar to our 0-100 point scale.

yearly dummies from 1996 to 2005, and other movie-related characteristics. These yearly dummies were used to measure the average time trend in the maximum number of screens as compared to the base year 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 actress Cameron Diaz. As shown in this figure, 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.

<Insert Figure 2 about here>

Lastly, in order to account for the influence from a star's off-camera activities on his/her favorability rating, for each star in our panel, we reviewed all news articles related to the star in *People* and *Variety* during the time period of our longitudinal analysis. After screening out movie-related articles, we obtained a grand total of 6,228 articles reporting the off-camera activities of the 48 stars in our analysis.

To be consistent with previous research on the impact of buzz/word of mouth (e.g. Liu 2006; Mahajana, Muller, and Kerin 1984), we took into account both volume and valence of media coverage. We define the monthly volume as the number of non-movie related articles appeared in *People* and *Variety* magazines within each month. Additionally, human raters were recruited to code these articles into valence. The raters read each article and assigned it to one of the following three categories: positive, negative, and neutral. Following Liu (2006), we used the

percentage of positive and negative articles appeared every month to measure the valence of the media coverage on these movie stars' off-camera activities.⁶

The summary statistics of our data sample are provided in Table 3.

<Insert Table 3 about here>

Model

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

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

⁶ Because coding these articles into valence is extremely tedious and time consuming, two raters initially divided up the task of reading the 6,228 articles and classifying them to one of the three categories. In order to check the degree of inter-rater consistency, a third rater was used to independently code all the articles. The level of agreement between the third rater and the first two raters was as high as 0.90. When the third rater disagreed with the first two raters, an additional rater was used 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.

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

where P_{ik} and P_{is} are the favorability ratings of star i at time k and s respectively, $\varphi(i,t)$ is a dummy variable indicating whether there is a movie acted by star i released during month t in between time 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 effect, $\gamma(i,t)$ 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. the volume, positive, and negative valence of the media coverage), θ is the vector of parameter estimates associated with such effect, r_{ij} is the decay rate (i.e. 1 - depreciation rate) of star 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 of a product (e.g. Leone 1995; Nijs, Dekimpe, Steenkamp, and Hanssens 2001), we consider a star's movie appearances and off-camera activities as shocks to his/her favorability ratings. Following 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 (i.e. movie appearances and media coverage of the star's off-camera activities) to his/her favorability. The star's favorability receives a bump at the time the shock occurs. Afterwards, his/her favorability continues to depreciate.

Past research suggested that consumers' belief toward 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 et al. 1999; Geylani et al. 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 taken at time s . The basic idea is that, the magnitude of the impact from P_{is} is weighted by the degree of uncertainty consumers have towards the star. If the degree of uncertainty is high, the scale of the impact from P_{is} on P_{ik} should be relatively small. We use an exponential function here to ensure that the range of the scale ρ_{iPs} is 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} .⁷

Decay Rate. Inspired by the work of Lincoln and Allen (2004), we included gender and age in the function of decay rate. Additionally, the movie star's degree of establishment was included to capture its potential influence on decay rate. In particular, we adopted the widely used exponential decay function (e.g. Jedidi, Krider, and Weinberg 1998) in our model:

$$(2) \quad r_{ij} = \exp \left(\begin{aligned} &a_r + b_r \text{female}_i + (c_{r10} + c_{r11} \text{female}_i) \text{age}_{ij} + (c_{r20} + c_{r21} \text{female}_i) \text{age}_{ij}^2 \\ &+ (d_{r10} + d_{r11} \text{female}_i) \text{sm}_{ij} + (d_{r20} + d_{r21} \text{female}_i) \text{sm}_{ij}^2 + \mu_{ij} \end{aligned} \right)$$

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 (measured as the total number of movies acted by star i at time j).

⁷It is worth noting that we followed Liu (2006) and Mahajan et al. (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 such 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 such a refinement given the following reasons. First, in Equation (1), the effect from the movie star's media coverage on his/her favorability is defined as the product of θ and the decay rate r_{ij} , with the latter varying depending on 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 the media coverage is likely to be over-parameterized so that the resulting estimates may become unstable. Second, as illustrated in the results section later on, our model estimates revealed that, by and large, the relative impact of the non-movie related media coverage on star favorability is considerably small as compared to the effects from movies. Under these considerations, the scale of the media effect is simplified at the aggregate level.

Recognizing that some unobservable characteristics of the star might also influence the decay rate, we include a random error term μ_{ij} with distribution $\mu_{ij} \sim N(0, \sigma_\mu^2)$ in Equation (2).

In this equation, we use quadratic functions for the variables *age* and *sm* to capture the possibility that there might be inverted-U shaped relationships between the carry-over of star favorability and these two variables. Namely, the carry-over of star favorability might increase as the movie star matures and/or he/she becomes more established. However, beyond a certain point, the carry-over of star favorability might start to decrease because the star may not deliver as he/she used to. Furthermore, we include gender-specific interaction terms in these quadratic functions to account for the fact that the shape of such relationships might differ for actors and actresses. To summarize, for any given star, the decay rate of his/her favorability is not only gender specific but also time variant.

Movie Effect. In order 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:

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

where Z_{it} is a vector including five indicators of movie success (i.e. number of award nominations received by the movie and the focal movie star, critics rating, viewer rating, and cumulative box office sales) and five indicators of movie characteristics (i.e. maximum number of screens, seasonality, whether it is 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 the movie performance and characteristics metrics listed above is based on previous movie-related research (e.g. Ainslie, Drèze, and Zufryden 2004; Elberse and

Eliashberg 2003). We recognize that some unobservable characteristics of the movie may also affect a star's favorability. A random error term is included in Equation (3) to capture such effect.

Scale of Movie Effect. When a movie star receives a shock to his/her favorability from a new movie, the intensity of the bump may be affected by factors above and 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:

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

where ng_{iMt} denotes the number of previous movies acted by the actor/actress in the genre of the focal movie, $invg_{iMt} = 1/sg_{iMt}$ with sg_{iMt} representing 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 $neg_{iMt} = 0$ otherwise.

In Equation (4), the variables ng_{iMt} and $invg_{iMt}$ are used to measure the typicality of the extension product. For instance, if a star has appeared in a number of comedy movies and/or the majority of his/her previous movies are comedies, his/her appearance in a new drama movie would be considered as an atypical extension. In particular, we define

$$sg_{iMt} = \max(ng_{iMt}, 0.01) / \sum_{g'=1}^G ng', \text{ with } ng_{iMt} \text{ representing the number of previous movies in genre}$$

g and $\sum_{g'=1}^G ng'$ denoting the star's total movie appearances across different genres. To avoid the

inversion of zero, we set $ng_{iMt} = 0.01$ when the number of previous movies in the genre equals to zero (i.e. $\max(ng_{iMt}, 0.01)$).

It has been widely recognized in the branding literature that the typicality of the 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 Roedder John 1993). Given its significant role in the literature, our definition of movie scale also examines whether the typicality of the extension matters in our study. Additionally, within our context, when a movie star appears in a newer genre, the likelihood of his/her exposure to a broader audience may increase. Therefore, our Equation (4) also indirectly measures whether an increase in star awareness via movie appearance in a newer genre impacts the scale of the movie effect.

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

Estimation and Causality Check. Equations (1) to (4) comprise the empirical model we need to estimate. Given that the past favorability ratings, the 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, and acting skills), our Equation (1) is subject to the problem of endogeneity. We alleviate this issue by taking the first differences of Equation (1) to remove the time-invariant individual fixed effect and assuming that the time-variant individual effects are captured in the star's most recent favorability rating (see more discussions in Appendix C).⁸

⁸ 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 capturing the entire decision process (e.g. how movie studios making casting decisions, how the popular press decides whom and what to report in terms of celebrities' off-camera actives, how consumers develop a certain degree of favorability towards a star).

On a related note, our current model implies that movie appearances influence star favorability. It is also likely that star favorability might determine movie appearances. We conducted a Granger causality check to test out 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 time s and k . Using a Wald test, we found that movie appearances indeed help explain star favorability (test statistic = 9.64, $p < 0.01$). 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 adds no information to movie appearances (test statistic = 2.12, $p > 0.10$), which implies that Granger causality is absent. Therefore, our data do not support the competing hypothesis.

A Method of Simulated Moment (MSM) procedure is used to estimate the set of parameters in Equations (1) and (4) simultaneously (Ahn and Schmidt 1995, 1997; Gouriéroux and Monfort 1996). More details of our estimation procedure are provided in Appendix C.

Empirical Findings

In the following paragraphs, we discuss our empirical findings. Our parameter estimates are provided in Table 4.

<Insert Table 4 about here>

Variance of Past Favorability. As expected, we found that the impact from the lagged favorability is negatively related with its variance. This finding is consistent with the proposition

Due to the lack of such data, we did not pursue such a refinement. Another way to address this issue is to use instruments for the variables used in movie effect and media effect. We searched the entire literature on movies to look for candidates of such instruments. We found that, although the vast majority of movie research suffers from similar endogeneity issue (e.g. a movie's cast, number of screens, advertising/production budget, and etc. are all endogenous), no existing research in this area was able to find viable instruments to address this problem. This is probably a common limitation in this line of research, which also applies to our work.

in previous research that, when the degree of uncertainty (i.e. variance) associated with the prior belief (i.e. P_{is}) increases, the relative weight of the prior belief decreases in the posterior belief (i.e. P_{ik}) (e.g. Boulding et al. 1999; Geylani et al. 2008; Rust et al. 1999).

Favorability Decay. Our findings about favorability decay are as follows. 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 with the carry-over of star favorability. Finally, we observed that some of the gender-specific interaction terms are significant in the two quadratic functions, which implies that the shapes of the inverted-U relationships do differ for actors and actresses.

Because the scale of the decay rate is 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 find that the maximum favorability carry-over for a male actor happens when he is 33.3 years old and the total number of his movie appearances reaches to 14.4. At this point, the star's favorability depreciates less than 1% per year. However, when the star is young and at an early stage of his movie career, the favorability of the star is susceptible to considerable decay. For example, if the actor's age is 25 and has only appeared in 2 movies, his favorability will depreciate 5% in a year with the absence of movie appearances and media coverage. On the other hand, after the actor's age and degree of establishment move beyond the peak of his favorability carry-over, the rate of favorability depreciation increases . For example, if an actor is 55 and has appeared in 16 movies, his favorability will still depreciate 2.1% per year. As for a female star, we find that her maximum favorability carry-over takes place when she is 20.8 years old and the total number of movie appearances is 8. At this point

the decay rate of her favorability is about 3% per year. In general, the favorability carry-over of female stars reaches the maximum point earlier and faster than that of male stars.

In the branding literature, the duration of brand equity has always been considered as an important research topic. Although very few studies empirically examined the longevity of a brand's equity, there appears to be a consistent view that the equity of a product/service brand is relatively stable and lasting (Aaker 1991). Interestingly, our results indicated that, within the context of the movie industry, celebrity brands are indeed subject to considerable erosion over time. This is probably related to our finding in lab experiment one that, as compared to product/service brands, consumers are less certain/strong in their thought associations with the 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 does not indicate an improvement in the star's favorability. This finding is not surprising given that the popular press has been increasingly criticizing every year's Oscar nominations as "deeply political" and "widely unpopular", because the "academy voters have been trying to teach people what kind of movies they should like, rather than honoring the movies that people actually watch" (*The New York Sun*, Mar. 3, 2006). As each year's Golden Globe and Oscar nominations often coincide, the above quote probably explains why starring in an award-nominated movie is not necessarily associated with an improvement in one's favorability. In contrast, the total number of award nominations received by the star serves as a better indicator of an increase in star favorability. Additionally, critics rating, viewer rating and cumulated box office sales all signify an improvement in star favorability.

With regard to movie characteristics, we found that a movie's maximum number of screens positively contributes to the favorability of the star. On the other hand, seasonality does not affect the star's favorability rating. Our estimate also reveals that movie sequel improves the movie star's favorability. This implies that, with sequels, movie stars can capitalize on the success of an original movie by reprising the same characters in a new situation in another movie.⁹ In terms of MPAA ratings, PG-13 rated movies are the best for an actor/actress to boost his/her brand equity. This result is possibly driven by the following facts. First, PG-13 rated movies can reach a broader audience than R-rated movies. Second, because PG-rated movies tend to strictly censor adult situations and language to suit their younger audience, many moviegoers may perceive them not as attractive as PG-13 rated movies. Regarding genre, comedy is better than drama, action, and animation movies in improving an actor/actress's brand equity. This finding is somewhat surprising as we have expected drama movies to be the most beneficial for a movie star, because they are often connected with deep emotions. One potential explanation for this is that, compared to other genres, the demographics and psychographics of the audience for comedy movies might be more willing to adjust their favorability towards the movie star upward. It is also possible that comedy elicits more positive affect in the mind of the viewers and this positive affect might enhance star favorability.

Given the estimates in the second panel of Table 4, we can use Equation (3) to calculate an estimated movie effect for all the movies in our data set. Table 5 provides the descriptive statistics of the estimated movie effects (all the continuous variables in the vector of M_{it} are mean centered in our estimation). Because these movie effects exhibit a wide dispersion from zero, we

⁹ 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/her most recent favorability rating in our data sample. This correlation turns out to be insignificant ($r = 0.04$, $p = 0.32$). Nevertheless, we acknowledge that this finding does not indicate the absence of the potential endogenous bias. Our Appendix C provides more details of how we alleviate the issue of endogeneity in general.

learned that each movie appearance can potentially enhance or dilute the movie star's brand equity considerably. Among the 614 movies in our data, 414 movies are estimated to have positive feedback effects while the rest are negative. Consequently, for an actor/actress to protect and develop his/her brand favorability over time, the selection of movies is critical.

<Insert Table 5 about here>

This result is particularly interesting because previous research about feedback effects within the context of product branding indicated that dilution and enhancement effects only occur under certain conditions. Our empirical results revealed the general existence of feedback effects in the celebrity branding context. One potential explanation of this difference is that the underlying mechanisms behind consumers' evaluations towards celebrity and product brands differ (see Appendix B for further discussion).

When a star appears in two or more movies in between two favorability surveys, our model currently assumes that the joint impact of these movies on star favorability is additive (referred to as additive model below). There are two alternatives to this assumption. First, it is possible that a star's favorability rating is mainly driven by his/her most recent movie appearance just before the favorability measurement (referred to as recency model below). Second, it is also likely that the favorability rating is predominantly determined by the movie with the strongest effect in between the two favorability measures (referred to as salience model below). In order to test out these alternative assumptions, we estimated two benchmark models. In the recency model, only the most recent movie preceding the current favorability measure was used in the model estimation. In the salience model, we assumed that the subsequent favorability rating is only driven by the movie with the strongest effect at the time of the survey. In order to compare these alternative models, we computed the mean squared error (MSE) between the predicted and

the actual favorability ratings for each of the three models. The MSE of the additive model is 43.76, that of the recency model is 46.91, and that of the salience model is 48.20. Therefore, the additive model seems to better describe the joint impact of movies when there are multiple movies in between two favorability ratings.

The Scale of Movie Effect. The estimates related to the scale of the movie effect are presented in the third panel of Table 4. We found that a star's relative share of movies in the 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 gets relatively smaller. This is opposite to our initial conjecture that, a movie in a newer genre might have a relatively larger impact on star favorability, because it might increase the awareness of the star. One possible explanation of this finding is that, when the typicality of the extension is low (i.e. a movie in a newer genre), the consumers are more resistant to update their views towards the star because the newer genre is considered outside of the star's focal expertise. This is similar to the proposition in Loken and Roedder John (1993) that less feedback effect takes place for atypical extensions as they do not reflect the parent brand's core competency. On the other hand, the absolute number of previous movies in the genre does not have a significant impact on the scale of the movie effect. This finding is possibly due to the fact that the absolute number and the relative share of movies in the genre are 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 larger when the overall impact of a movie on star favorability is negative. This finding conforms to the well-known negative bias theory. Given that negative movie viewing experience leaves a stronger

impression than positive movie viewing experience, an actor/actress should avoid starring in a movie when he/she believes that the movie is unlikely to be successful.

With the parameter estimates in the top three panels of Table 4, we can also estimate the duration of a movie effect. An illustration is provided as follows. Assuming that, after accounting for the scale of the movie effect, the bump a movie star receives from a particular movie is estimated to be 3. For a male star who is 25 years old and has appeared in 2 movies before, the effect of this movie on his favorability will reduce to 2.86 a year after the movie's release. As evident, for each of his/her movie release, the movie star can estimate not only the magnitude of the movie effect but also the longevity of such effect on his/her brand equity.

Media Coverage of Star's Off-Camera Activities. Our analysis showed that the volume of media coverage has a significant positive influence on a movie star's favorability. In contrast, the valence of the coverage (either positive or negative) does not affect star favorability. Given that movie stars' personal lives are often highly visible to the general public, it is not surprising that consumers' favorability toward an actor/actress is driven by not only the star's movie appearances but also his/her behind-the-camera activities. The interesting contrast is that, while the overall impact of a movie on favorability can be either positive or negative, any media coverage about a star's off-camera activities reinforces the equity of the star. This finding is likely to be caused by the fact that only movies reflect the core skills of the actors/actresses, not their off-camera activities. Therefore, although a movie can either improve or hurt an actor/actress's brand equity, when it comes to off-camera activities, any publicity helps. Liu (2006) has reported that the volume of word-of-mouth, not the valence, leads to greater movie box office revenue. Interestingly, our empirical results seem to support the general idea that, when it comes to word-of-mouth, only the volume, not the valence, matters.

As the volume of media coverage positively contributes to star favorability, our model can also be used to examine the amount of media coverage needed to overcome a negative movie effect. Specifically, 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. Among the 614 movies in our data sample, 200 movies (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 needs to increase 17.76 times to offset the negative movie effects (mean: 17.76; median: 8.26; standard deviation: 33.34; minimum: 0.02; and maximum: 279.43) at the subsequent favorability poll. This finding suggests that movies exert significantly more influence on star favorability than media coverage of the star's off-camera activities. Consequently, movie stars should safeguard their brand equity by carefully making movie appearances, as it is generally difficult to offset the impact of a negative movie by increasing media coverage.

Managerial Applications

According to our model, the overall impact a movie has on star favorability is a joint function of: 1) indicators of movie success; 2) movie characteristics; and 3) the time distance between movie release and favorability measure. Although it is reasonable to assume that the movie star can infer an increase in his/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 enough to offset favorability decay. Therefore, one potential managerial application of our research is that the parameters from our empirical analysis can be used to obtain estimates of movie effects and

the rate of favorability decay, based on which a movie star can make some strategic decisions about his/her future movie choices.

Given that our model is reduced-form by nature, the well-known Lucas critique is relevant in the execution of our analyses. To minimize this concern, we follow the suggestions of van Heerde, Dekimpe, and Putsis (2005) by focusing on short-term predictions in which the future policies (i.e. movies) closely mirrors historically observed policies in the sample data. In the following we provide two examples to illustrate how to carry out this analysis.

Natalie Portman. Natalie Portman's favorability was measured to be 41 on 6/05 at the end of our longitudinal survey. Prior to this rating, her three most recent movies appearances were *Garden State* (released on 8/04), *Closer* (released on 12/04), and *Star Wars Episode II: Attack of the Clones* (released on 5/05). Given this recent history of Natalie Portman's movie appearances, we aimed to examine whether continuing to appear in similar movies shortly after 6/05 would help Natalie Portman to further build up her brand equity.

Without loss of generality, we assumed that, similar to the rate at which she released movies in the two years before her last favorability rating, Natalie Portman will star in three movies during the two years after 6/05. We also assumed that she will obtain offers to appear in movies similar to the three movies mentioned above, given that movie stars often receive offers to appear in similar types of movies. Consequently, we used the estimated movie effects for these three movies to approximate the potential feedback effects Natalie Portman may receive from the new movies, if she decides to continue on a similar path in her movie selections.

Assuming that the three movies are released on a 6-month interval and the effect from her off-camera activities is absent, our model estimates predicted that Natalie Portman's favorability will improve to 46.49 on 6/07 (i.e. two years after her last favorability survey). This implies that, the

enhancement effects the actress will receive from these movies will not only offset the decay of her favorability, but also enhance her brand equity. Consequently, during the time period after 6/05, if receiving offers to star in movies similar to her most recent movies, Natalie Portman should certainly consider taking these offers.

Vin Diesel. Vin Diesel's favorability rating was 49 on 7/05 at the end of our longitudinal survey. His last three movies before this measure were *Knockaround Guys* (released on 10/02), *A Man Apart* (released on 4/03), and *The Pacifier* (released on 3/05). After conducting a similar analysis for Vin Diesel, we found that, if Vin Diesel continues along a similar path, two years later his favorability rating will drop substantially from 49 to 27.65. This finding implied that Vin Diesel's movie career was not heading towards the right direction around the time of his last favorability survey. In order to protect his brand equity, Vin Diesel should respond by declining offers to appear in movies similar to the three movies mentioned above and seeking out opportunities to star in different types of movies and/or movies with better prospect.

In a similar fashion, each actor/actress in our panel can benefit from our model by predicting how his/her favorability will be affected if he/she takes a similar path in his/her movie choices.

Conclusions

In what follows we highlight the key results, describe their theoretical and managerial implications, and discuss limitations and avenues for future research.

First, we found evidence supporting the general existence of enhancement and dilution effects on the equity of a movie star through movie releases. Previous research typically indicated that these effects in the product branding context only occur under certain conditions. This disparity implies that there is a difference between celebrity and product brands with

regards to how consumers form their brand evaluations. In particular, both our empirical results and the lab experiments seem to suggest that the bookkeeping model better describes how consumers develop their evaluations towards a celebrity brand. This distinguishes from the popular subtyping model supported by many past studies (e.g. Milberg, Park, and McCarthy 1997; Park, McCarthy, and Milberg 1993).

Second, our results showed that, in contrast to the traditional view that brand equity is relatively stable in the short and medium runs (Aaker 1991), within the context of the movie industry, the favorability of a celebrity brand depreciates significantly over time. We attribute this to the fact that consumers exhibit less certainty (strength) in their memory structures about the celebrity brands as compared to the product/service brands. Consequently, unless consumers are exposed to the celebrity brand regularly, the equity status of the celebrity is subject to substantial erosion over time.

Third, our dynamic model explicitly examined how a series of movie appearances jointly contributes to the brand equity of an actor/actress. In the marketplace, it is common practice to launch a series of new products under a common brand name. However, the 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 future research investigating these effects in the traditional context of product branding.

Finally, our findings are useful for the strategic decision making of both actors/actresses and firms using celebrities as spokespersons. In particular, our research is valuable in providing actors/actresses (and their talent agents) with a better understanding of the dilution and enhancement of celebrity brands and insight into strategies to maximize their brand equity. In the usage of a celebrity spokesperson, 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 over time conditional on each of his/her movie appearances, age, and how established he/she is.

Our research is not without limitations. First, our brand equity measure is limited to the degree of favorability attached to the brand. In Keller (1993), brand equity is conceptualized as a multi-dimensional concept. Future research may examine how a sequence of brand/line extensions dynamically influences the other dimensions of brand equity. Second, because we have a reduced-form model, our current approach does not eliminate the potential endogeneity bias caused by the time-variant individual effects. Future research may construct a structural model to capture the decisions of the various agents involved in the process (i.e. movie studios, popular press, movie stars, and the moviegoers). More useful policy simulations can be developed under such a structural model. Finally, we limit our analysis to celebrity brands in the movie industry. Future research can extend our approach to study the feedback effects of extension products on the equity of a celebrity/product brand in broader contexts.

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Figure 1a: Celebrity vs. Product Brands: Dilution Effects (When Extension Fails)

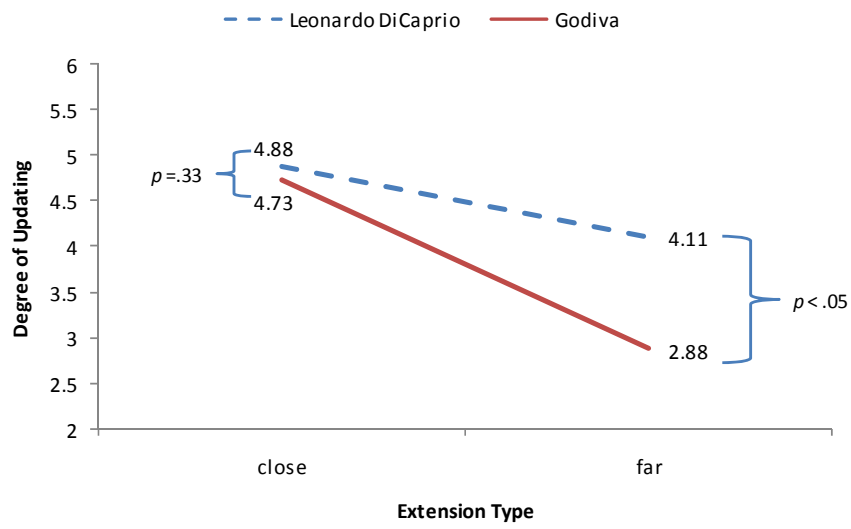
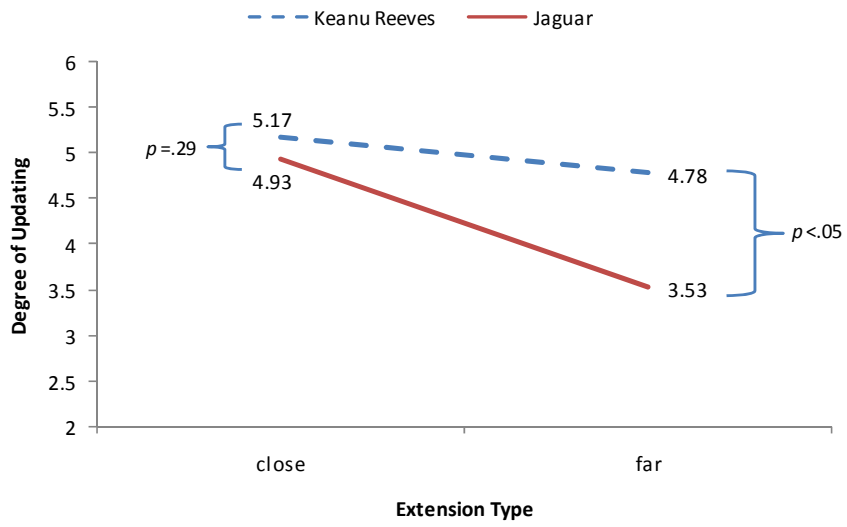


Figure 1b: Celebrity vs. Product Brands: Enhancement Effects (When Extension Succeeds)

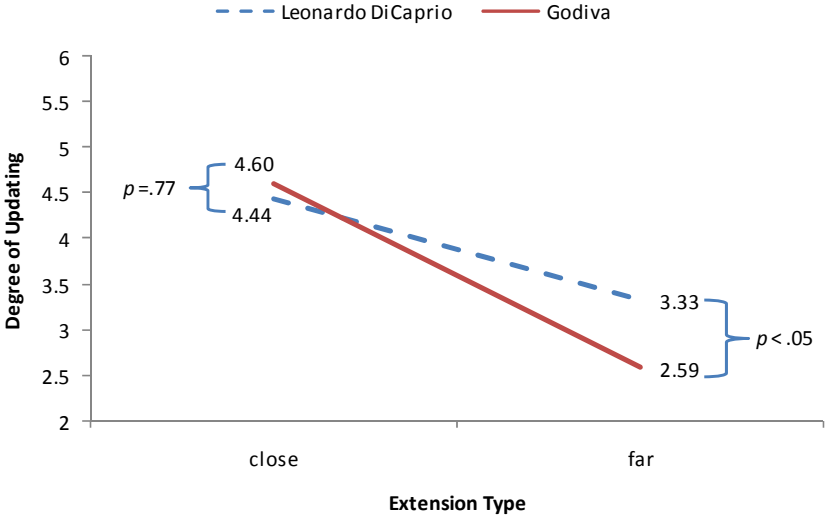
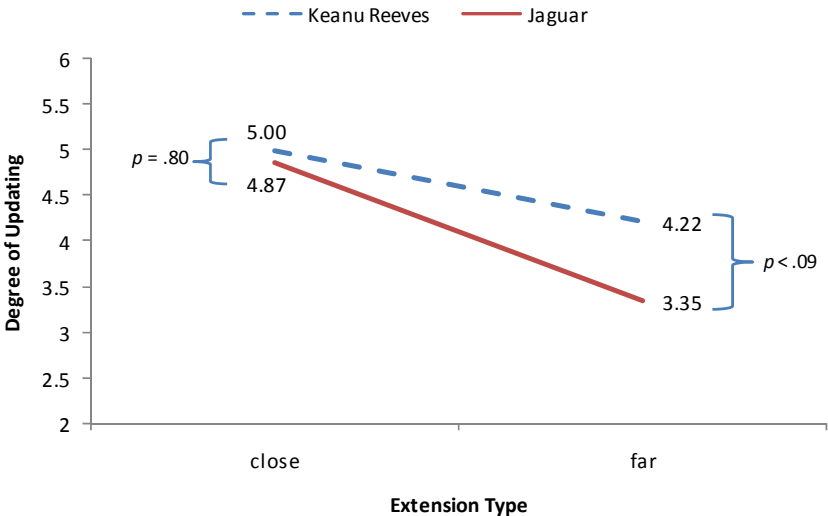
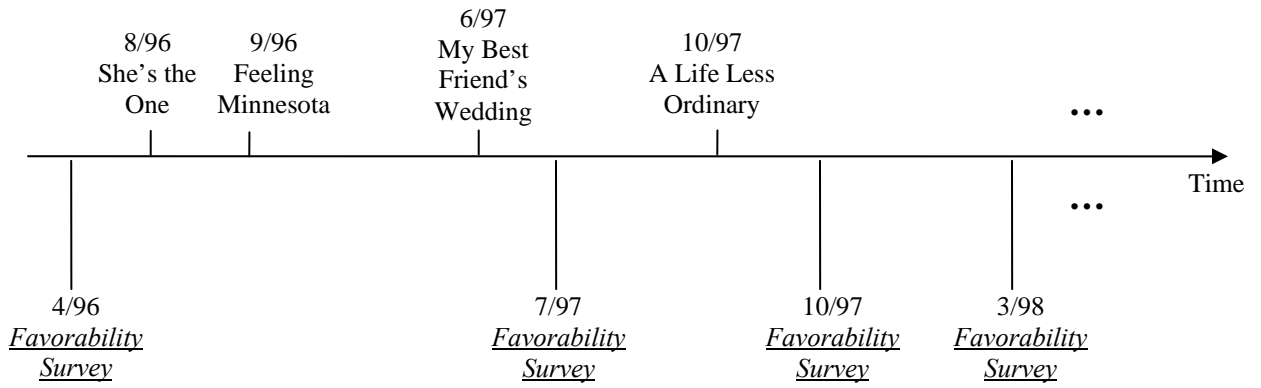


Figure 2: Example of a Series of Favorability and Movie Observations

Actress: Cameron Diaz*



*Media coverage of the movie star's off-camera activities is not shown in the figure

Table 1: Close and Far Extensions Used in Lab Experiment Two

		Close Extension	Far Extension
Pair 1	Keanu Reeves Jaguar	Home Audio Speaker	Stationery
Pair 2	Leonardo DiCaprio Godiva	Wine	Wallpaper

Table 2: Movie Star Panel Descriptions

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

Table 3: Descriptive Statistics of Panel Data

Variable	Total # of Observations	Mean	Std Dev	Minimum	Maximum	Median
<i>Star</i>						
# of Favorability Rating	48	16.94	3.07	12.00	25.00	17.00
# of Movies Acted	48	12.79	3.72	5	19	12
<i>Favorability</i>						
Favorability Rating (0-100)	813	50.01	15.17	8.00	85.00	50.00
<i>Movie</i>						
Award Nominations_Movie	614	1.67	3.58	0.00	22.00	0.00
Award Nominations_Actor	614	0.19	0.52	0.00	2.00	0.00
Critics 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
Cumulated Box Office (Million \$)*	614	61.24	64.24	1.02	570.34	39.69
Max. # of Screens**	614	2222	893	43	3854	2220
Seasonality (Million \$)*	614	3.12	0.72	1.97	4.67	3.02
Sequel	614	0.08	0.27	0.00	1.00	0.00
PG	614	0.11	0.31	0.00	1.00	0.00
PG13	614	0.43	0.49	0.00	1.00	0.00
R	614	0.47	0.50	0.00	1.00	0.00
Action	614	0.29	0.45	0.00	1.00	0.00
Comedy	614	0.36	0.48	0.00	1.00	0.00
Drama	614	0.32	0.47	0.00	1.00	0.00
Animation	614	0.04	0.20	0.00	1.00	0.00
<i>Media Coverage of Stars' Off-Camera Activities</i>						
Volume (Monthly)	6,228	1.38	1.33	0	9	1
Valence_Percentage_Positive (Monthly)	6,228	0.23	0.31	0	1	0
Valence_Percentage_Negative (Monthly)	6,228	0.04	0.12	0	1	0

* Adjusted for inflation, using 1995 as the base year.

**Adjusted for time trend, using 1995 as the base year.

Table 4: Model Parameter Estimates

Parameter	Estimate	Std. Error
a_P (variance of past favorability)	0.0017*	0.0009
<i>Favorability Decay</i>		
Intercept	-0.0085*	0.0041
b_r (female)	-0.0019*	0.0008
c_{r10} (age)	0.0021*	0.0007
c_{r11} (female*age)	0.0006*	0.0002
c_{r20} (age ²)	-0.0003*	0.0001
c_{r21} (female*age ²)	-0.0003 ^{ns}	0.0021
d_{r10} (stage_ movie)	0.0686*	0.0022
d_{r11} (female*stage_ movie)	0.0689 ^{ns}	0.0142
d_{r20} (stage_ movie ²)	-0.2379*	0.0932
d_{r21} (female*stage_ movie ²)	-0.6184*	0.2142
Std. dev. of random error	0.0001 ^{ns}	0.0068
<i>Movie Effect</i>		
Intercept	0.1380*	0.0394
<u><i>Indicators of Movie Success</i></u>		
Award_ movie	0.0182 ^{ns}	0.0131
Award_ star	1.1858*	0.5021
Critics rating	0.1226*	0.0602
Viewer rating	0.3495*	0.1545
Cumulated box office (million \$)	0.0083*	0.0003
<u><i>Maximum Number of Screens</i></u>	0.0004*	0.0001
<u><i>Seasonality (million \$)</i></u>	-0.4621 ^{ns}	0.2737
<u><i>Sequel or Not</i></u>		
Sequel	0.3978*	0.0612
<u><i>MPAA Rating</i></u>		
PG	-0.3082*	0.1170
PG13	0.4554*	0.2302
<u><i>Genre</i></u>		
Action	-0.4831*	0.2022
Comedy	1.3434*	0.6313
Animation	0.7939 ^{ns}	0.7832
Std.dev. of random error	0.0711 ^{ns}	0.1547
<i>The Scale of Movie Effect</i>		
a_M (# of movies in same genre)	0.0325 ^{ns}	0.0501
b_M (inv g)	-0.0683*	0.0316
c_M (shift due to negative movie effect)	2.0046*	0.6862
<i>Media Coverage of Star's Off-Camera Activities</i>		
Volume (monthly)	0.0656*	0.0187
Valence_percentage_positive (monthly)	0.1441 ^{ns}	0.0831
Valence_percentage_negative (monthly)	0.2161 ^{ns}	0.1509

* significant at .05; ns: non-significant

Table 5: Descriptive Statistics of Estimated Movie Effects

Variable	N	Mean	Std Dev	Minimum	Maximum	Median
Movie Effect	614	0.71	1.40	-3.54	6.78	0.60
<i>Movie Effects ≥ 0</i>	414					
<i>Movie Effects < 0</i>	200					

Appendix A: Financial Return of Star Favorability

In this appendix, we analyze the impact of favorability on the star's movie 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 were able to find the salary information for 155 movies. Given the salary data we have, a regression is conducted to analyze the financial return of star favorability.

In order to control for the influence of other movie-related characteristics on the star's movie salary, we regress the log of the star salary on the log of star favorability and a number of star- and movie-related characteristics (i.e. gender, age, the square of age, genre, MPAA 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 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 online movie databases IMDb (www.imdb.com) and Rotten Tomatoes (www.rottentomatoes.com). These movie-related characteristics are similar to the ones used in previous research (e.g. Ainslie et al. 2004; Elberse and Eliashberg 2003).

The results of our regression suggested that, after controlling for the influence of other star- and movie-related characteristics, 1% increase in star favorability rating contributes to 3.07% increase in the salary the star received from a movie. Therefore, the substantial financial return of star favorability provides us with some additional evidence indicating that actors/actresses with a higher degree of brand equity are indeed much better off.

Appendix B: Lab Experiments

Given that our research diverges from past 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.

Lab Experiment 1

The primary purpose of this lab experiment is to compare consumers' memory structures about celebrity vs. product/service brands.

Pretest

We first ran a pretest to identify sets of celebrity and product/service brands that are sufficiently similar to each other on a number of dimensions so that further comparisons can be made on these brands. A within-subject study was conducted. Twenty-eight undergraduates from a large west coast university were asked to assess twenty celebrity brands and twenty product/service brands. For each brand, the subjects responded to the following questions using 7-point scales: 1) how easy is it for you to recall this actor/actress (*or* product/service brand); 2) how much do you like this actor/actress (*or* product/service brand); 3) how clear is the identity of

this actor/actress (*or* product/service brand) in terms of his/her main character (*or* its main characteristics); and 4) to what degree does the actor/actress (*or* 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 based on the suggestions of Park, Milberg, and Lawson (1991). The last criterion was chosen to ensure that the celebrity and product/service brands are comparable in terms of the affective dimension.

Data analyses revealed three pairs of celebrity and product/service brands that are comparable on those 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. They are: 1) Keanu Reeves – Jaguar ($p_s > .250$); 2) Leonardo DiCaprio – Godiva ($p_s > .119$); and 3) Reese Witherspoon – Hershey’s ($p_s > .305$). These three pairs of brands were used in the main study reported next.

Main Study

A between-subject study was conducted to examine whether consumers have different memory structure for celebrity versus product/service brands. Two conditions were designed for this study. In condition 1, forty-three participants were asked to complete a survey about the three celebrity brands identified above. In condition 2, forty-four 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 an open-ended question “what comes to your mind when you think about this actor/actress (*or* this brand)”. For each thought association, we also asked the participants to indicate on a 7-point scale “how certain (strongly) do you feel about this thought”. Second, the participants answered the following 7-point scale questions: 1) “how many different types of thoughts come to your mind when you think about this actor/actress (*or* this brand)”; and 2) “to what extent does this actor/actress (*or* this brand) represent a mix of highly different personas in her/his acting and personal life (*or* a mix of highly different characteristics)”.

We first analyzed answers to the open-ended question to identify the different types of thought associations. For celebrity brands, the following 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 were identified (i.e. product-attributes-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. We found that, for two out of the three pairs, the number of statements related to the celebrity brand were significantly more than those related to the product/service brand (number of statements: Keanu Reeves vs. Jaguar = 4.42 vs. 3.93, $p < .05$; Reese Witherspoon vs. Hershey’s = 4.43 vs. 3.70, $p < .05$). And for the remaining pair, the difference was marginally significant (number of statements: Leonardo DiCaprio vs. Godiva = 4.42 vs. 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 less than 3 thoughts, all of the thoughts were included in this comparison). We found that, on average, consumers are significantly more certain about their most salient thought associations with the product brands than those with the celebrity brands (mean of certainty (strength): Keanu Reeves vs. Jaguar = 5.81 vs. 6.26, $p < .01$); Leonardo DiCaprio vs. Godiva = 6.19 vs. 6.41, $p = .05$; Reese Witherspoon vs. Hershey's = 5.94 vs. 6.24, $p < .05$).

Next, we analyzed participants' ratings on the two 7-point scale questions (i.e. different types of thoughts and a mix of different personas/characteristics). Because the two items revealed high correlation (correlation = .68), they were averaged to create an index, representing the multi-dimensionality of consumers' perceptions towards each brand. We found that, for all three pairs of brands, consumers' perceptions about the celebrity brand are more multi-dimensional than the corresponding product brand (mean of ratings: Keanu Reeves vs. Jaguar = 3.90 vs. 3.30, $p < .05$; Leonardo DiCaprio vs. Godiva = 4.69 vs. 3.46, $p < .001$; Reese Witherspoon vs. Hershey's = 4.91 vs. 4.24, $p < .01$).

In sum, results from this study confirmed that consumers indeed have different memory structures for celebrity versus product/service brands. In particular, consumers have a greater number and more types of thought associations with celebrity than with product/service brands. Furthermore, the most salient associations with celebrity brands were less certain (strong) as compared to those with product/service brands. Finally, consumers tend to perceive the celebrity brands as being more multi-dimensional than product/service brands.

Lab Experiment 2

In this study, we aim to examine whether there is a difference between celebrity and product/service brands regarding how consumers modify their brand evaluations when product extensions are introduced. In the following we focus on describing the pretest. The details of the main study are presented in the paper.

Perceived similarity between the brand and the extension product is a key variable for the evaluation of brand extensions. Therefore, the primary goal of this pretest is to identify product extensions that are perceived as equally far and equally close to the pairs of celebrity and product brands used in study 1. A within-subject study was conducted. Twenty-six participants were asked to rate the perceived similarity between each of the six brands and fifteen brand extensions on a 7-point scale (e.g. "If Keanu Reeves (*or* Jaguar) is to launch ... under his (*or* its) name, what is your perceived similarity between the product and his (*or* its) image?").

Based on our pretest data, we found that home audio speaker is perceived as a close extension for both Keanu Reeves and Jaguar. And the degree of similarity is equal for both extension products (4.19 vs. 4.61, $p = .28$). We also discovered that stationery is considered as an equally far extension for Keanu Reeves and Jaguar (1.61 vs. 2.03, $p = .25$). Additionally, we found that wine is perceived as an equally close extension for the pair Leonardo DiCaprio and Godiva (perceived similarity: 4.07 vs. 3.96, $p = .70$) and wallpaper is considered as an equally

far extension for this pair (perceived similarity: 1.88 vs. 1.50, $p = .22$). Therefore, these four pairs of extension products (2 close and 2 far extensions) were used in our main study.

Appendix C: Estimation Procedure

Equations (1) to (4) comprise the empirical model we need to estimate. This model has the form of a dynamic model with unbalanced panel data. Substantial complications arise in the estimation of such model due to the following 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 (such as movie appearances, movie sequels, and media coverage of the star's off-camera activities) and the movie star. In other words, an actor/actress's appearances in movies and movie sequels and the likelihood of the press reporting a star's off-camera activities might be correlated with some unobservable idiosyncratic characteristics of the movie star (e.g. image, persona, and acting skills). Therefore, the past favorability ratings, the 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 the issue of endogeneity. First, we assume that the error term in Equation (1) contains a time-invariant individual fixed effect and a random noise. Without loss of generality, we use the following simplified expression to represent a general form of Equation (1):

$$(A1) \quad \begin{aligned} P_{ik} &= X_{ik} \Theta_{ik} + \delta_{is} P_{is} + \varepsilon_{ik} \\ \varepsilon_{ik} &= v_i + \omega_{ik} \end{aligned}$$

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 a random noise ω_{ik} .

Second, given that some idiosyncratic characteristics of the movie star (e.g. acting skills) may evolve over time, we assume that, at time k , the effects of all the time-variant characteristics of the star to date are captured by the most recent favorability rating of the actor/actress, P_{is} , taken at time s .

Therefore, we can take the first differences of Equation (A1) to obtain the following equation:

$$(A2) \quad P_{ik} - P_{is} = (X_{ik} \Theta_{ik} - X_{is} \Theta_{is}) + (\delta_{is} P_{is} - \delta_{ig} P_{ig}) + (\varepsilon_{ik} - \varepsilon_{is})$$

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

In Equation (A2), 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):

$$(A3) \quad E[P_{it}, (\varepsilon_{ik} - \varepsilon_{is})] = E[P_{it}, (\omega_{ik} - \omega_{is})] = 0 \quad \text{where } t < s$$

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

$$(A4) \quad \int \{E[P_{it}, (\varepsilon_{ik} - \varepsilon_{is})]; \xi_{it}, \mu_{ij}\} dF(\xi_{it}, \mu_{ij}) = 0 \quad \text{where } t < s$$

The set of parameters in Equations (1) and (4) are then estimated simultaneously under a Method of Simulated Moment (MSM) procedure.