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Partner Selection in Brand Alliances: An Empirical Investigation of the Drivers of Brand Fit

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We investigate whether partners in a brand alliance should be similar or dissimilar in brand image to foster favorable perceptions of brand fit. Using a Bayesian nonlinear structural equation model and evaluations of 1,200 brand alliances, we find that the conceptual coherence in brand personality profiles predicts attitudes towards a brand alliance. More specifically, we find that similarity in Sophistication and Ruggedness and moderate dissimilarity in Sincerity and Competence result in more favorable brand alliance evaluations. Overall, we find that similarity effects are more pronounced than dissimilarity effects. Implications for brand alliance strategies and marketing managers are discussed.

Keywords: brand alliances; brand personality; brand management; nonlinear structural equation models; Bayesian analysis

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1. Introduction

Brand alliances involve all joint-marketing activities in which two or more brands are simultaneously presented to the consumer (Rao et al. 1999, Simonin and Ruth 1998). These simultaneous presentations appear in many different forms. For instance, BMW and Oracle are jointly presented on their co-sponsored sailing boat during the America's Cup; Red Bull and Nissan's Infinity are displayed on their Formula One race car, and the logos of the Qatar Foundation and the United Nations Children's Fund (UNICEF) are jointly displayed on F.C. Barcelona's soccer shirt. Brands are valuable assets and can be combined to form a synergistic alliance in which the sum is greater than the parts (Rao and Ruekert 1994). However, brand alliances do not always reinforce a brand's image. They may result in image impairment (Geylani et al. 2008) and may not always lead to win–win outcomes, as incongruity between the brands may drive consumers away (Venkatesh and Mahajan 1997). Selecting the right partner for a brand alliance strategy is therefore critical. In this research, we provide diagnostic insights for partner selection and investigate how partners can be optimally combined to profit from the synergies generated by pooling brands.

Selecting the right partner for a brand alliance is a complicated problem because the drivers of brand fit are not well understood (Helmig et al. 2008). One would expect that similarity between partner brands increases fit (Simonin and Ruth 1998), but moderate incongruity may foster favorable evaluations as well (Meyers-Levy and Tybout 1989). After all, puzzle pieces fit because they are complementary, not because they are similar. For instance, Red Bull uses Renault engines for their Formula One racing vehicles, but uses Nissan's Infinity brand as the team's title sponsor. Why is Red Bull teaming up with a somewhat dissimilar brand such as Nissan rather than with Ferrari, a successful Formula One team with a more similar brand image? Why is the Qatar Foundation sponsoring F.C. Barcelona's shirt, rather than being displayed next to the Emirates logo on Real Madrid's soccer shirt? Is the alliance between the Qatar Foundation and UNICEF a better combination than the Qatar Foundation and Emirates? Because the drivers of brand fit are not well understood, academic research does not provide rational procedures and decision tools for managers to select the ideal partner for brand alliances.

Methodological challenges to studying brand alliances are the most important reason for our limited knowledge of partner selection and the drivers of brand fit. As argued by Yang et al. (2009, p. 1095), "it is challenging (if it is even possible) to construct an appropriate data set of brand alliances for a robust empirical study." Therefore, in addition to its substantial contribution, this research aims to overcome methodological limitations by proposing an experimental procedure in which 100 existing brands are randomly combined into 1,200 alliances. In our approach, we collect data in two different studies. In the Brand Image Study, a large sample of raters evaluate 100 brands on brand personality (BP) dimensions. In the Brand Alliance Study, a different group of raters evaluate brand alliances randomly constructed from the 100 brands of the Brand Image Study. Instead of adopting the common approach using separate analyses to uncover the nonlinear relationships between BP and brand alliance evaluations, we use Bayesian nonlinear structural equation models (Arminger and Muthén 1998, Lee et al. 2007). To optimally control for measurement error in the latent variables and to recognize the repeated measurement structure, we extended previous nonlinear structural equation models to incorporate these additional error sources. Our results suggest that the conceptual coherence in brand images (as assessed by one sample of raters) affects brand alliance evaluations (by another sample of raters). Therefore this research provides diagnostic insights for selecting partners to form brand alliances.

2. Literature Review

2.1. (Dis)similarity as a Driver of Brand Fit

In this paper, we focus on the drivers of brand fit and investigate how brands can be optimally combined. For instance, we investigate whether Coca-Cola, rather than Pepsi, is a good partner for McDonald's, and whether McDonald's, rather than Burger King, is a good partner for Coca-Cola. The notion of fit, as entertained in the brand extension literature, needs to be distinguished from brand fit in a brand alliance context. When a brand alliance is presented, two families of brand associations are elicited. Brand fit issues (i.e., inconsistency, incoherence, incongruence between brand images) are unlikely to arise in the brand extension literature, as brand extensions involve only a single brand. Although alliances between brands with images that fit are generally recommended, prior research has not clearly elucidated the drivers of brand fit.

On one hand, one might expect that a brand alliance between two brands with very *similar* brand images would elicit favorable responses from consumers. Indeed, the more shared associations there are between brands, the greater the perception of fit. For instance, brand image consistency of the two partner brands is positively related to brand alliance evaluations (Simonin and Ruth 1998). Similar observations have been made in the brand extension literature (Park et al. 1991). For instance, overall similarity between brand and category personality is an important driver of brand extension success (Batra et al. 2010).

On the other hand, several scholars have argued that moderate *dissimilarity* fosters favorable evaluations (Meyers-Levy and Tybout 1989). It has been argued that an alliance makes sense when the strengths and weaknesses of the partner brands compensate for each other (Samu et al. 1999) and "when two brands are complementary in the sense that performance-level strengths and weaknesses of their relevant attributes mesh well" (Park et al. 1996, p. 455). A combination of two brands with complementary attribute levels is evaluated more favorably than a brand alliance consisting of two highly favorable but not complementary brands (Park et al. 1996).

Yet, to what extent is the conceptual coherence, congruence, or fit between brands in an alliance driven by similarity and/or dissimilarity between brands? Insights into the drivers of fit could lead to a comprehensive selection tool that would help brand managers determine and select appropriate partners for successful brand alliances. Based on the human alliance and corporate alliance literature, we will argue that successful alliances require the pursuit of partners with similar characteristics on certain dimensions ("*birds of a feather flock together*"), but dissimilar characteristics on other dimensions ("*opposites attract*"). We propose that the intrinsic versus extrinsic nature of BP determines whether similarity or dissimilarity increases brand fit.

2.2. Coherence in Brand Personality as a Driver of Brand Fit

Brands are frequently represented in the minds of consumers as a set of humanlike characteristics, called brand personalities. To provide a complete description of BP, Aaker (1997) created a measurement scale consisting of five dimensions. These dimensions include (1) Sincerity, represented by attributes such as down-to-earth, real, sincere, and honest; (2) Competence, represented by attributes such as intelligent, reliable, secure, and confident; (3) Excitement, typified by attributes such as daring, exciting, imaginative, and contemporary; (4) Sophistication, represented by attributes such as glamorous, upper-class, good looking, and charming; and (5) Ruggedness, typified by attributes such as masculine, Western, tough, and outdoorsy (see Table 1 for examples of brands).

Because both brands' specific associations are likely to be elicited when brands are presented jointly in an alliance (Broniarczyk and Alba 1994), we hypothesize that the conceptual coherence in brand personality profiles drives brand fit. This hypothesis is strengthened by research on the effects of human personality (HP) in human alliances. Indeed, (dis)similarity in personality ratings of human alliance partners affects fit measures (Gonzaga et al. 2007, Luo and Klohnen 2005, Shiota and Levenson 2007), such as marital satisfaction, likelihood of separation, etc. (for review articles see

Table 1 Examples and Definitions of Brand Personality Dimensions

Brand personality dimension	Reliability ICC(1, k)	Average rating in sample (SD)	Example brands: Low	Example brands: High
Sincerity captures a brand that is perceived as having a down-to-earth, real, sincere, and honest brand personality.	0.65	6.01 (1.96)	Red Bull ($M = 4.78$) Shell ($M = 4.63$)	Pampers ($M = 7.22$) IKEA ($M = 7.25$)
Competence captures a brand that is perceived as having an intelligent, reliable, secure, and confident brand personality.	0.79	6.78 (1.85)	Dr. Pepper ($M = 5.32$) Pizza Hut ($M = 5.23$)	Sony ($M = 7.74$) Mercedes ($M = 8.18$)
Excitement captures a brand that is perceived as having a daring, exciting, imaginative, and contemporary brand personality.	0.82	5.90 (2.11)	DHL ($M = 4.29$) Kleenex ($M = 3.87$)	MTV ($M = 7.60$) Red Bull ($M = 7.61$)
Sophistication captures a brand that is perceived as having a glamorous, upper-class, good looking, and charming brand personality.	0.92	5.88 (2.36)	Colgate ($M = 4.36$) KFC ($M = 3.33$)	Prada ($M = 8.30$) Chanel ($M = 8.84$)
Ruggedness captures a brand that is perceived as having a masculine, Western, tough, and outdoorsy brand personality.	0.88	5.18 (2.36)	Nivea ($M = 3.70$) Disney ($M = 2.69$)	Diesel ($M = 7.29$) Harley Davidson ($M = 9.06$)

Notes. M indicates the mean rating as measured in the Brand Image Study. Brand personalities are rated on a 10-point scale.

e.g., Heller et al. 2004, Karney and Bradbury 1995, Malouff et al. 2010). Generalizing the findings from the human alliance literature to branding is difficult because HP dimensions do not correspond to BP dimensions. Several scholars have criticized Aaker's loose definition of BP (e.g., Azoulay and Kapferer 2003, Geuens et al. 2009) because it embraces characteristics other than personality. For instance, human personality researchers deliberately exclude sociodemographic characteristics, such as culture, social class, and gender, from human personality assessments (McCrae and Costa 1987). In contrast, the BP scale includes items such as feminine, masculine, upper-class, glamorous, Western, etc. (Aaker 1997).

Because BP taps into characteristics beyond personality, only three of the five BP dimensions resemble personality dimensions that are also present in HP models. Sincerity (BP) is defined by attributes related to warmth and honesty and which are also present in Agreeableness (HP); Competence (BP) denotes dependability and achievement, similar to Conscientiousness (HP); Excitement (BP) captures the energy and activity elements of Extraversion (HP) (Aaker et al. 2001). Because Sincerity, Competence, and Excitement roughly correspond to HP dimensions (Aaker 1997, Aaker et al. 2001, Geuens et al. 2009), we refer to these dimensions as intrinsic aspects of BP. The other two BP dimensions, i.e., Sophistication and Ruggedness, do not relate to any of the HP dimensions. As a consequence, we refer to Sophistication and Ruggedness as extrinsic aspects of BP because they tap into sociodemographic features rather than into personality. We propose that the intrinsic versus extrinsic nature of BP determines whether similarity or dissimilarity increases brand fit.

2.3. Hypotheses Development and Conceptual Model

We hypothesize that brand alliances are evaluated favorably when partnering brands are *dissimilar* in *intrinsic* BP dimensions yet *similar* in *extrinsic* BP dimensions. These hypotheses are strengthened by observations in the human alliance literature and the corporate alliance literature. Although brands differ from humans and corporations in numerous ways, it is clear that successful alliances require partners with similar characteristics on certain dimensions, but dissimilar characteristics on others.

In romantic alliances, both similarity as well as dissimilarity are important principles in partner selection (e.g., Kerckhoff and Davis 1962). For instance, age, social status, and ethnic background show strong similarities between partners, but psychological variables, such as personality, show a much weaker assortment than sociodemographic variables (e.g., Buss 1985, Thiessen and Gregg 1980, Vandenberg 1972). Winch et al. (1954) were among the first to argue that in romantic partner selection, one first eliminates all those who are too dissimilar in sociodemographic characteristics, and then selects from the remaining similar individuals (i.e., the field of eligibles) a potential partner who is likely to complement oneself on the personality level. Similarity may therefore be important with respect to sociodemographic aspects of a partner, while dissimilarity may be important with respect to more intrinsic aspects of a partner, such as personality (Kerckhoff and Davis 1962, Vandenberg 1972).

The observations in the human alliance literature are remarkably consistent with findings in the corporate alliance literature. The value generated from alliances is typically enhanced when partnering firms share similarities in social, cultural, or institutional aspects and when they have different resource and capability profiles (Sarkar et al. 2001). For instance, an entrepreneur's intention to create an alliance is driven by similarity to oneself with respect to extrinsic sociodemographic characteristics (such as language or social status) and by dissimilarity with respect to more intrinsic functional task considerations (Vissa 2011). Both in the romantic as well as in the corporate alliance literature, successful alliances require the pursuit of partners with similar characteristics on certain dimensions, but dissimilar characteristics on other dimensions.

Although generalizing the findings from human and corporate alliances to brand alliances is difficult for obvious reasons, we speculate that any combination of brands should follow the principles that guide partner selection in other settings. Because the intrinsic BP dimensions relate to HP dimensions and tap more into skills and capabilities than into sociodemographic aspects (e.g., dependability, achievement, honesty, competence, sincerity, energy, etc.), we hypothesize that partner selection should be based on *dissimilarity* with respect to these dimensions. In contrast, because the extrinsic BP dimensions tap more into sociodemographic aspects (e.g., feminine, masculine, glamorous, upper-class, Western, etc.), we hypothesize that partner selection should be based on *similarity* with respect to these dimensions.

Hypothesis 1. *Dissimilarity in intrinsic brand personality dimensions fosters favorable evaluations of brand alliances.*

Hypothesis 2. *Similarity in extrinsic brand personality dimensions fosters favorable evaluations of brand alliances.*

Figure 1 summarizes our framework of the drivers of brand fit in brand alliances. Our conceptual framework represents two brands, *A* and *B*, that partner in a brand alliance. Following previous marketing research on brand alliances (Simonin and Ruth 1998), our dependent variable is the evaluation of brand alliance *A*&*B* by consumers. Both brand images of *A* and *B* are described by ratings (*Score*) on each of the five BP dimensions. Using BP ratings, we assess the conceptual coherence (*Dissimilarity*) for intrinsic and extrinsic BP dimensions, which is defined as the distance between, respectively, intrinsic and extrinsic personality dimensions of brand *A* and brand *B*. A short distance represents similarity, while a long distance represents dissimilarity.

3. Method

Investigating the drivers of successful brand alliances is challenging for several reasons. First, collecting data on existing alliances is difficult, if not impossible (Yang et al. 2009). Because managers do not choose partner brands randomly, establishing whether similarity drives alliance success or whether alliance success determines similarity is virtually impossible. Indeed, brand images in alliances may change due to spillover effects (Simonin and Ruth 1998). Ideally, partners are combined randomly because the direction of causality is difficult to establish. Second, because of the wide variety of brand alliances, from joint sales promotions to ingredient branding (Helmig et al. 2008), existing brand alliances are difficult to compare because product fit and brand fit are confounded. Investigating the drivers of brand fit is virtually impossible if the nature of the brand alliance is not held constant. Third, researchers have resorted to experiments using a few, frequently fictitious, brands to investigate brand alliances (e.g., Geylani et al. 2008, Monga and Lau-Gesk 2007, Rao et al. 1999, Samu et al. 1999). The use of fictitious brands makes it difficult to study the core associations evoked by a brand (e.g., BP) and to generalize findings to a large sample of real brands. An exception is Yang et al. (2009) who turns to the National Basketball Association (NBA) to investigate real alliances between basketball players and teams. However, the professional sports industry is very specific, which makes it difficult to generalize findings to other industries. Fourth, measures and variables used to study brand alliances (e.g., attitude towards an individual brand as a predictor of attitude towards the brand alliance) are typically provided by the same set of individuals (Simonin and Ruth 1998). This may lead to inflated estimates of the relationships between variables due to common method bias (Podsakoff et al. 2003).

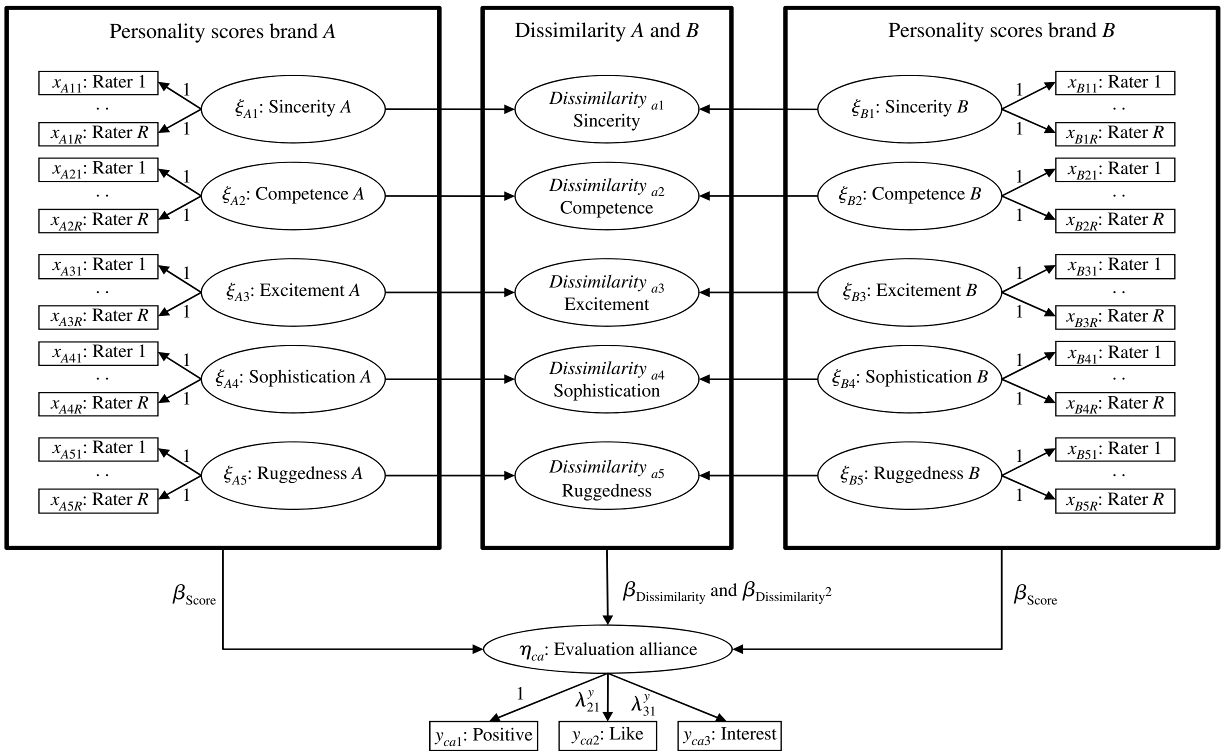
To overcome these challenges, we adopted a data collection procedure used in studies on aesthetical design (Henderson and Cote 1998, Orth and Malkewitz 2008, van der Lans et al. 2009) and applied in the brand extension literature (Batra et al. 2010). In this approach, data are collected in two studies. In the Brand Image Study, raters evaluate brand images of 100 well known global brands. In the Brand Alliance Study, different raters evaluate brand alliances randomly created from the same set of 100 brands. The brand image ratings of one set of participants are then linked to the brand alliance evaluations of another set of participants to understand how the conceptual coherence between brand images drives evaluations of brand alliances.

The 100 brands used in the studies were selected from the brand lists of Businessweek/Interbrand, Brandz, and Lovemarks. The selected brands (Web Appendix A (available as supplemental material at http://dx.doi.org/10.1287/mksc.2014.0859)) cover a wide range of industries, such as cars (e.g., Toyota, Mercedes, Ferrari), electronics (e.g., Microsoft, Apple, Nokia), entertainment (e.g., Disney, MTV), fast food chains (e.g., McDonald's, KFC, Starbucks), fast moving consumer goods (e.g., Coca-Cola, Heinz, Budweiser), financial services (e.g., AXA, American Express, Visa), luxury brands (e.g., Gucci, Chanel, Louis Vuitton), and online services (e.g., Google, Yahoo!, eBay). A more detailed description of the Brand Image and Brand Alliance studies is given next.

3.1. Brand Image Study

In the Brand Image Study, 204 participants (50% male; average age: 21 years, SD = 2.6) recruited at a large

Figure 1 **Model Specification**



Notes. This model specification deals with a brand alliance *a*, which consists of brands *A* and *B*. This brand alliance is evaluated by consumer *c*.

West-European university rated brand personalities of 100 selected brands. We followed extant literature on BP (Aaker 1997) and measured all five dimensions, i.e., the intrinsic dimensions Sincerity, Competence, and Excitement, and the extrinsic dimensions Sophistication and Ruggedness. Table 1 provides descriptions of each of the five BP dimensions, descriptive statistics, and examples of brands in our sample that score relatively low and high on each of these dimensions. Before participants assessed the brands, we provided a detailed description of each personality dimension. This procedure is similar to previous studies in design aesthetics in which raters are first confronted with a detailed description of the dimensions before rating a target on these dimensions (Henderson and Cote 1998, Orth and Malkewitz 2008, van der Lans et al. 2009). To not strain memory capacity, we always listed a few traits associated with the personality dimension during the actual rating task. In addition, we presented the brand name as well as the logo, such that BP ratings could also depend on the visual features of the brand logo. See Web Appendix B for an illustration of the measurement instrument.

Participants indicated the extent to which a set of traits (e.g., Ruggedness: "rugged, strong, rough, tough") described a specific brand (e.g., Canon) on a 10-point scale (1 = not at all descriptive, 10 = extremely descriptive). We randomly selected 10 brands from the pool of 100 brands and participants assessed these 10 brands on five BP dimensions. The 10 brands were first rated on one BP dimension before they were rated on another. To avoid order and fatigue effects, we randomized the order of BP dimensions across participants, as well as the order of brands within a BP rating. This approach led to reliable scores for each of the BP dimensions, with all intraclass correlations ($\text{ICC}(1, k)$, see Shrout and Fleiss 1979) well above the 0.6 cutoff (Glick 1985) (see Table 1). After each brand was rated on the BP dimensions, participants indicated their attitude towards each brand on a 10-point scale (1 = dislike very much, 10 = like very much; $\text{ICC}(1, k) = 0.77$).

3.2. Brand Alliance Study

In the Brand Alliance Study, 201 respondents (51% male; average age: 23 years, SD = 6.8) recruited at a large West-European university evaluated 1,206 brand alliances (i.e., each respondent rated six different brand alliances). We created brand alliances by randomly combining two brands from the Brand Image Study. In contrast to most experimental studies, this approach allows us to study a large sample of brand alliances and avoids selection bias, which is common in empirical studies of brand alliances. To create realistic brand alliances in a relevant marketing setting, we asked participants to imagine that two brands jointly sponsor an event (Ruth and Simonin 2003). Co-sponsorships are particularly useful for our research for three reasons. First, sponsorships are strategic vehicles for co-branding partnerships and provide an ideal platform from which co-branding can be leveraged. A sponsorship relationship can be conceptualized as a co-marketing alliance to optimize co-branding objectives (Farrelly et al. 2005, Ruth and Simonin 2003). Second, sponsorships represent significant investments, making them not only well suited but also an important context within which to study brand alliances. Indeed, global spending on sponsorship of sports, entertainment, and cultural events has increased over the past three years from \$44 billion annually in 2009 to \$51.1 billion in 2012 (International Events Group 2013). Finally and most important, co-sponsorships allow us to identify the drivers of brand fit rather than product fit. For instance, if we asked participants to rate an alliance between Porsche and Blackberry, ratings may greatly depend on whether participants imagine a car equipped with Blackberry technology or a phone designed by Porsche. Thus the ratings might depend on product fit. Because our research question deals with brand images and how they can be optimally combined, we deliberately minimized product fit issues and used co-sponsorships to measure brand fit in the purest possible form.

Participants in the Brand Alliance Study were first provided with background information on brand alliances and two examples of existing brand alliances. Subsequently, they imagined that two brands were organizing an event in a large city. To avoid systematic influences of brand-event interactions, we did not describe the event; respondents were told to think of any type of event. After these instructions, six different brand alliances were presented to respondents including brand logos. Respondents evaluated each brand alliance (i.e., "*What is your overall evaluation of the brand alliance*?") using three 7-point differential scales (very negative/very positive, dislike very much/like very much, very unfavorable/very favorable, Cronbach's alpha $= 0.91$) that measured their attitudes towards the brand alliance (Simonin and Ruth 1998), see Web Appendix B for an illustration of the measurement instrument.

To summarize, one sample of participants rated brands on five BP dimensions; another independent sample of participants rated randomly constructed brand alliances. The next section introduces our modeling approach that links the brand personalities of the individual brands, measured in the Brand Image Study, to the brand alliance evaluations as assessed in the Brand Alliance Study.

4. Model

Figure 1 presents the structural relationships between the latent BP dimensions and brand alliance evaluations. We use a Bayesian nonlinear structural equation approach to estimate our model (Arminger and Muthén 1998, Lee et al. 2007), which has the following features. First, we allow for nonlinear relationships between the latent BP dimensions and brand alliance evaluation, while simultaneously controlling for measurement error of the latent constructs. Estimation of nonlinear relationships is nontrivial and using conventional covariance structure analysis in standard packages such as LISREL is impossible (Arminger and Muthén 1998). Consequently, while previous research primarily used first factor analysis to compute latent variable scores as input for separate regressions to test nonlinear relationships (Bagozzi et al. 1992, Batra et al. 2010), we estimate latent variables and the nonlinear relationships simultaneously controlling optimally for parameter uncertainty. To do so, we use a Bayesian approach using the Metropolis-Hastings algorithm to sample the coefficients of the nonlinear relationships, which optimally estimates the model parameters (Lee et al. 2007). Second, while previous (nonlinear) structural equation models only control for one type of measurement error in the latent constructs, our approach also takes into account systematic measurement errors due to (1) response styles of the raters in the Brand Image Study, and (2) the repeated measurement design of the Brand Alliance Study. We do this by allowing for rater-specific intercepts and variance of the BP measures and a random effect specification for item intercepts of brand alliance evaluations.

4.1. Model Specification

Figure 1 summarizes our model based on our conceptual framework. BP dimensions $k \in \{1, \ldots, K\}$ for all brands $b \in \{1, \ldots, B\}$ are measured through ratings in the Brand Image Study ($K = 5$ and $B = 100$ in this study). The latent scores of these BP dimensions are used to compute *Score* and *Dissimilarity* of the randomly generated brand alliances in the Brand Alliance Study. The evaluations of the randomly generated brand alliances are measured by the responses of participants on $j = 1, \ldots, J$ items ($J = 3$ in this study). Our modeling approach links the computed latent scores of each brand alliance in the Brand Image Study to its evaluation in the Brand Alliance Study. To do this, our approach models rating x_{bkr} of rater r on personality dimension k for brand b as follows:

$$x_{bkr} = \tau_{rk} + \xi_{bk} + \varepsilon_{br} + \delta_{brk}. \tag{1}$$

In (1), τ_{rk} is a rater-specific intercept that controls for systematic differences across raters on each of the K BP dimensions. We use a random effects specification and assume that the $(K \times 1)$-vector τ_r is normally distributed with mean μ_τ and $(K \times K)$ covariance matrix Σ_τ. Term ε_{br} controls for rater-specific disturbances that are, for instance, caused by brand-specific halo effects; a rater that is very positive towards a brand may rate all dimensions more highly. Finally, δ_{brk} contains disturbance terms that are unexplained. We follow previous studies using Bayesian structural equation modeling (DeSarbo et al. 2006, van der Lans et al. 2009), and assume that the disturbance terms are normally distributed with mean zero and variances $\sigma^2_{\varepsilon r}$ and σ^2_{xk}, respectively. The $(K\times 1)$-vector with latent scores ξ_b on each of the personality dimensions are assumed to be normally distributed with mean zero and covariance matrix Σ_ξ.

Participant's c evaluation y_{caj} of item j of brand alliance a in the Brand Alliance Study is captured using the following measurement model:

$$y_{caj} = \upsilon_{cj} + \lambda_j \eta_{ca} + \varphi_{caj}. \quad (2)$$

In (2), υ_c is a $(J\times 1)$ respondent-specific vector with intercepts, and λ is a $(J\times 1)$-vector with factor loadings. φ_{caj} is an error term that is assumed to be normally distributed with mean zero and variance σ^2_{yj}. We take the repeated measures structure into account through a random coefficient specification for υ_c, and thus assume that this vector is normally distributed with mean μ_υ and covariance matrix Σ_υ.

Given Equations (1) and (2) that capture the measurement models for both studies, we specify the structural relationships between the latent brand personalities and brand alliance evaluations as follows:

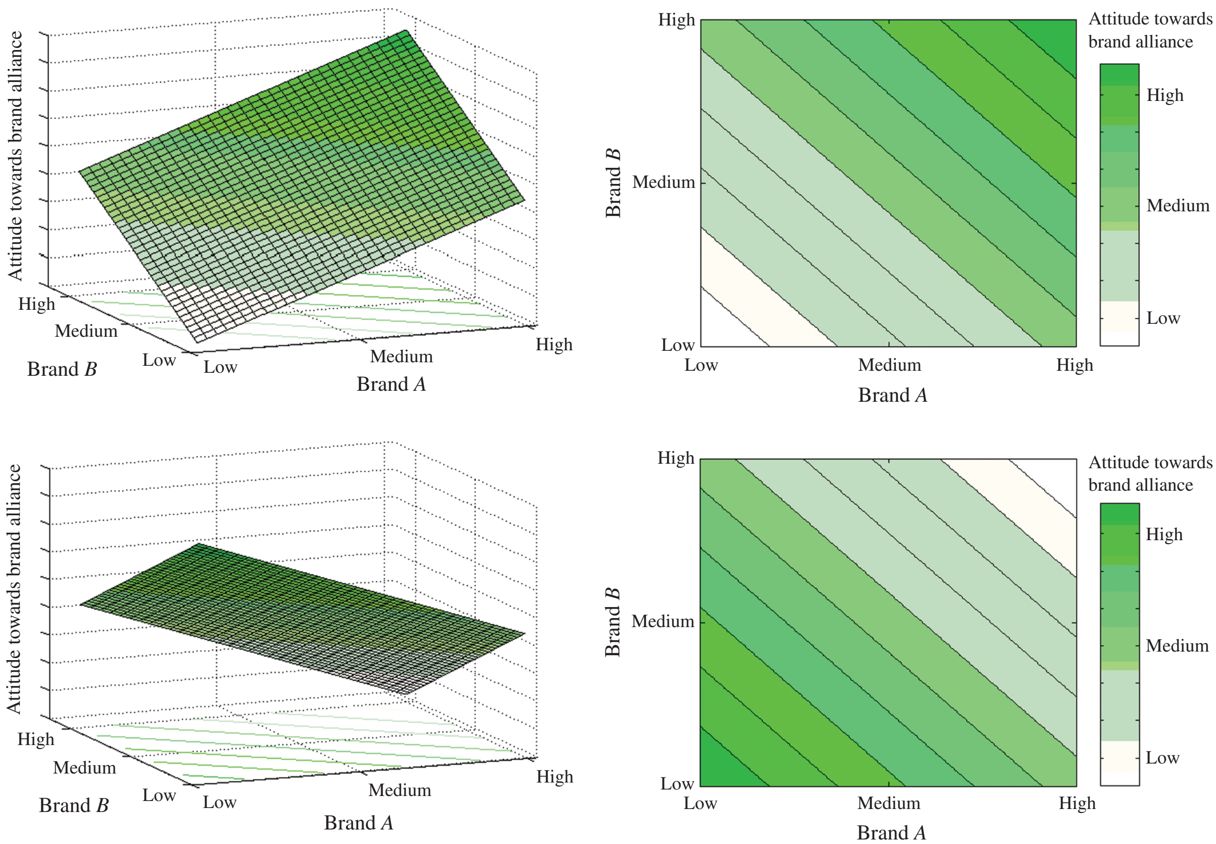
$$\eta_{ca} = \beta' g_{ca}(\xi, z_{ca}) + \zeta_{ca}. \quad (3)$$

In (3), $(L\times 1)$-vector β contains regression coefficients, and ζ_{ca} is an error term that is normally distributed with mean zero and variance σ^2_η. For brand alliance a evaluated by participant c, the deterministic function g_{ca} transforms the latent brand personalities ξ and possible control variables z_{ca} into a $(L\times 1)$ design matrix, including a constant. More specifically, following our conceptual model, g_{ca} represents (1) the average personality scores, (2) the dissimilarity of these scores, and (3) the squares of these dissimilarities to capture saturation effects. We include these squared dissimilarity variables based on Yang et al. (2009), who find that extreme dissimilarity between partners may be detrimental, leading to an inverted-U relationship between dissimilarity and performance ("low-medium" combinations perform better than "low–high" and "low–low" combinations). Similarly, Myers-Levy and Tybout (1989) find an inverted-U relationship between product and category dissimilarity on subsequent product evaluations. Given that brand alliance a evaluated by consumer c consists of brands A and B, we compute these measures as follows. The average personality score of brands A and B on personality dimension k is the mean of latent scores ξ_{Ak} and ξ_{Bk}, which equals $Score_{ak} = (\xi_{Ak}+\xi_{Bk})/2$. We compute the dissimilarity of personality dimensions in two ways. First, it is possible to compute the overall dissimilarity (Batra et al. 2010) between the brand personalities of A and B, which equals $\text{Overall\_dissimilarity}_a = \sqrt{\sum_{k=1}^{K}(\xi_{Ak}-\xi_{Bk})^2}$, i.e., the Euclidean distance between the two brand personalities. Second, as explained in our conceptual framework, it is likely that the effects of similarity/dissimilarity on brand alliance evaluations differ across personality dimensions. Therefore, we also compute dissimilarity for each dimension separately, which equals $Dissimilarity_{ak} = |\xi_{Ak}-\xi_{Bk}|$, for each dimension $k \in K$. Figures 2 and 3 illustrate the effects of these *Score* and *Dissimilarity* variables on brand alliance evaluation, respectively. The three-dimensional plots on the left in Figures 2 and 3 indicate the evaluation of the brand alliance (z-axis) as a function of brand personalities of alliance partners A and B in the (x, y)-plane. The plots on the right illustrate the same effects but using contour lines, similar to a map of mountains in a landscape, in which heights illustrate the brand alliance evaluation at the combination of the personalities of brands A and B. Obviously, because brands A and B are arbitrarily chosen and can thus be interchanged, the plots are symmetric on both sides of the diagonal $x = y$ line. Figure 2 shows that if brand A and/or B scores higher on a specific personality dimension, the overall evaluation of the brand alliances increases (top) or decreases (bottom), respectively, for positive ($\beta_{\text{Score}} > 0$) and negative effects ($\beta_{\text{Score}} < 0$) of the personality *Score*. Figure 3 represents, respectively, the situations where brand alliances consisting of similar (i.e., $\beta_{\text{Dissimilarity}} < 0$) versus dissimilar (i.e., $\beta_{\text{Dissimilarity}} > 0$) brands receive a higher evaluation. In the Results section, we use these plots to illustrate our results. In these plots we capture the entire personality dimension range by plotting the effects at $\pm 2\sigma_{\xi k}$ to represent high and low scores, respectively, where $\sigma_{\xi k}$ is the posterior estimate of the standard deviation of the score of brand personality k. Because personality scores are approximately normally distributed, the data generated in the Brand Alliance Study cover all plotted personality combinations.

Combining measurement Equations (1) and (2) and structural Equation (3), we obtain the following likelihood for our model:

$$\begin{aligned}
&L(x, y, \xi, \eta; \Theta)\\
&= \prod_{r=1}^{R}\prod_{b\in D_r}\{N_K(x_{br}; \tau_r + \xi_b + \varepsilon_{br}, \Sigma_x)\cdot N(\varepsilon_{br}; 0, \sigma^2_{\varepsilon r})\}\\
&\quad \cdot \prod_{r=1}^{R} N_K(\tau_r; \mu_\tau, \Sigma_\tau)\prod_{b=1}^{B} N_K(\xi_b; 0, \Sigma_\xi)\\
&\quad \cdot \prod_{c=1}^{C}\prod_{a=1}^{N(c)}\{N_J(y_{ca}; \upsilon_c + \lambda\eta_{ca}, \Sigma_y)\cdot N(\eta_{ca}; \beta' g_{ca}(\xi, z_{ca}), \sigma^2_\eta)\}\\
&\quad \cdot \prod_{c=1}^{C} N_J(\upsilon_c; \mu_\upsilon, \Sigma_\upsilon)
\end{aligned} \quad (4)$$

Figure 2 **Examples of Positive ($\beta_{\text{Score}} > 0$, Top) and Negative ($\beta_{\text{Score}} < 0$, Bottom) Score Effects on Brand Alliance Evaluation**



where Σ_x and Σ_y are diagonal with elements σ_{xk}^2 and σ_{yj}^2, respectively, and $\Theta = \{\tau_x, \tau_y, \mu_\tau, \mu_\upsilon, \varepsilon, \lambda, \beta, \Sigma_x, \Sigma_\varepsilon, \Sigma_\tau, \Sigma_\upsilon, \Sigma_\xi, \Sigma_y, \sigma_\eta^2\}$ contains the set of parameters, C represents the number of participants in the Brand Alliance Study, $N(c)$ represents the number of alliances evaluated by participant c (in this study $N(c) = 6$), and D_r indicates the set of 10 brands that is evaluated by rater r in the Brand Image Study.

4.2. Model Identification and Estimation

To identify our model, we restricted the means of the personality dimensions ξ to zero as indicated in likelihood (4). In addition, we restricted the factor loading of the first brand alliance evaluation item λ_1 to one, and the mean of the corresponding intercept $\mu_{\tau_y 1}$ to zero. We use a Bayesian procedure using an adaptive Metropolis-Hastings step (Browne and Draper 2000) to simultaneously estimate all parameters of likelihood (4) (Lee et al. 2007). This approach recognizes the uncertainty in latent variables and thus optimally estimates all model parameters[1] (see Web Appendix C for the complete MCMC algorithm and the specification of the prior distributions). To allow for comparisons of structural relationships across different variables, we standardized[2] BP scores (*Score*) and dissimilarities (*Overall_dissimilarity* and *Dissimilarity*) across all alliances. We used 100,000 draws to estimate our models. The first 50,000 were discarded as part of the burn-in-period; we used the final 50,000 draws, which we thinned to one in 10, for our parameter estimates. Plots of the posterior draws, as well as convergence diagnostics (Heidelberger and Welch 1983, Raftery and Lewis 1992) implemented in the BOA package (Smith 2007), showed that all runs converged long before the end of the burn-in period and that autocorrelations between draws were sufficiently low. Multicollinearity diagnostics were computed for all models; these did not signal problems. Correlations between independent variables in all draws never exceeded 0.8; condition numbers varied between 6.21 and 11.43, much smaller than 20 (as suggested by Mela and Kopalle 2002). Furthermore, synthetic data analysis

[1] We also estimated our model without allowing for measurement errors. All model fit statistics, including the log marginal density (LMD), strongly favor our model that incorporates measurement errors. The differences in LMD for all models were more than 10,000.

[2] We standardized the dissimilarity measures such that *dissimilarity* and *dissimilarity*^{2} (D and D^2, for short) are orthogonal by solving the following equality for m: $\text{cov}(D - m, (D - m)^2) = 0$. We obtained the following solution $m = \big[(\sum_{c=1}^{C} \sum_{a=1}^{n(c)} D_{ca})(\sum_{c=1}^{C} \sum_{a=1}^{n(c)} D_{ca}^2) - (\sum_{c=1}^{C} n(c)) \cdot (\sum_{c=1}^{C} \sum_{a=1}^{n(c)} D_{ca}^3)\big] / \big[(\sum_{c=1}^{C} \sum_{a=1}^{n(c)} D_{ca})^2 - (\sum_{c=1}^{C} n(c))(\sum_{c=1}^{C} \sum_{a=1}^{n(c)} D_{ca}^2)\big]$.

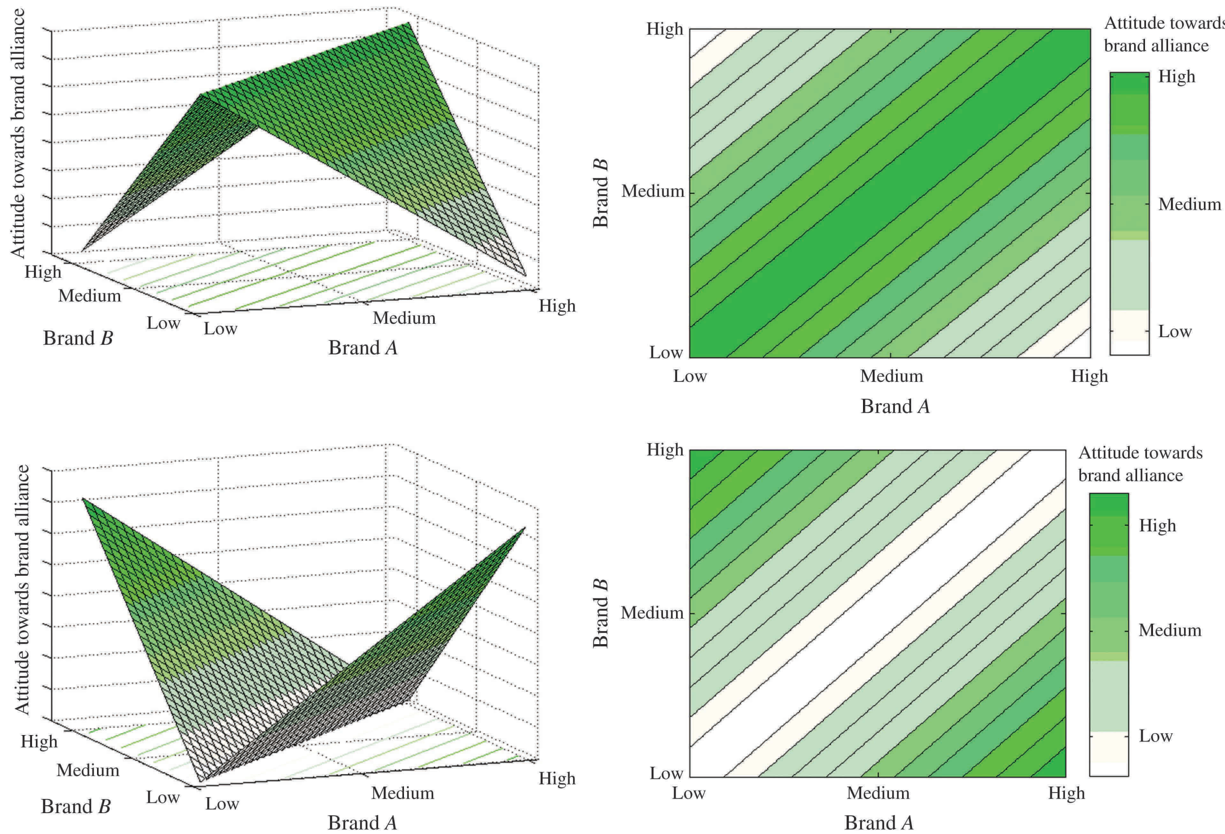


Figure 3 **Examples of Similarity ($\beta_{Dissimilarity} < 0$, Top) and Dissimilarity ($\beta_{Dissimilarity} > 0$, Bottom) Effects on Brand Alliance Evaluation**

revealed that our model recovers all model parameters within 95% posterior intervals.

5. Results

To test our conceptual model, we estimated four models that only differed in the structural relationships $g(\cdot)$ between the latent variables. All four models include the effect of the average score of each of the five personality dimensions and whether the two brands in the alliance are members of the same industry (e.g., both brands are car brands) on brand alliance evaluation. In addition to these effects, Model 2 incorporates the effect of overall dissimilarity and its square between BP dimensions, while Model 3 evaluates the effects of dissimilarities and their squares for each personality dimension separately. Finally, Model 4 determines the robustness of the models by adding two control variables: (1) the average Attitude[3] toward the two brand alliance members as indicated by the participants in the Brand Image Study, and (2) the average Brand Value[4] of the two brand alliance members as communicated in industry reports. Log marginal densities (LMD) were computed to assess the fit of each model (using the method suggested by Chib and Jeliazkov 2001). In addition, because the proposed models only differ in the structural relationships, and because these relationships are the focus of interest, we computed for each of these structural relationships the Bayesian version of the adjusted-R^2 (as proposed by Gelman and Pardoe 2006). We also computed the log likelihood (LL) of a holdout sample, which consisted of all evaluations of 20 randomly selected participants from the Brand Alliance Study. Table 2 summarizes the median estimates of the structural relationships between these four models, and indicates whether their 90%, 95%, and 99% posterior intervals contain zero. For each model, Table 2 also reports fit statistics of the corresponding benchmark models that do not incorporate measurement errors in the computation of the latent personality and alliance evaluation constructs.

[3] We incorporate the latent measure of brand attitudes in the same way as the average score of BP dimensions, thus controlling for the measurement error of brand attitudes.

[4] To compute Brand Value for each brand, we obtained publicly available brand values reported in dollar values by Interbrand (Best Global Brands 2009), Brand Finance plc (Brand Finance Global 500), and Millward Brown (Brandz Top 100: Most Valuable Global Brands 2009). We used a weighted average to compute Brand Value. If brand values were not reported, we imputed the minimum value as reported by the magazines.

Table 2 Median Estimates: Structural Paths

Variables	Model 1	Model 2	Model 3	Model 4
Score				
Sincerity	−0.17	−0.08	−0.02	−0.06
Competence	**0.50*****	**0.33****	**0.28***	0.20
Excitement	**0.40*****	**0.42*****	**0.41*****	**0.30*****
Sophistication	**−0.39****	**−0.24***	**−0.21***	−0.21
Ruggedness	**−0.19****	−0.10	0.05	0.01
Dissimilarity overall				
Overall		**−0.32*****		
Overall squared		0.00		
Dissimilarity dimensions				
Sincerity			−0.12	−0.11
Competence			0.01	−0.00
Excitement			**−0.11***	**−0.11***
Sophistication			**−0.17*****	**−0.17*****
Ruggedness			**−0.19*****	**−0.20*****
Dissimilarity squared dimensions				
Sincerity			**−0.13****	**−0.13****
Competence			−0.07	−0.07
Excitement			0.05	0.05
Sophistication			0.02	0.02
Ruggedness			0.04	0.04
Control variables				
Dummy category match (1 = brands in same category)	**0.36*****	**0.26*****	**0.24****	**0.24****
Attitude				**0.18***
Brand Value				−0.01
Bayesian adjusted-R^2	0.10	0.14	0.17	0.17
Log marginal density	−30,297	−30,299	−30,330[a]	−30,341
Log likelihood holdout sample	−1,072	−1,052	−1,065[b]	−1,049
Fit statistics for models without measurement error (benchmark models)				
Bayesian adjusted-R^2	0.04	0.05	0.05	0.05
Log marginal density	−41,878	−41,883	−41,921	−41,930
Log likelihood holdout sample	−1,569	−1,513	−1,536	−1,539

[a]The LMD with the insignificant parameter estimates of the match squared dimensions set to zero = −30,270.
[b]The holdout sample LL with the insignificant parameter estimates of the dissimilarity squared dimensions set to zero = −1,037.
*90% posterior interval does not contain zero (i.e., 95% of posterior draws are positive or negative); **95% posterior interval does not contain zero (i.e., 97.5% of posterior draws are positive or negative); ***99% posterior interval does not contain zero (i.e., 99.5% of posterior draws are positive or negative).

5.1. Model 1: Baseline Model Without Brand Personality Similarity

The results of the baseline Model 1 indicate that BP scores (*Score*) and whether brands belong to the same product category explain 10% of the variance of brand alliance evaluations (LMD = −30,297; holdout LL = −1,072). Given that these independent variables are measured by independent raters, brand personalities play an important role in explaining brand alliance evaluations. Irrespective of similarity between the partner brands, consumers evaluate alliances between Exciting ($\beta = 0.40$, 99.7% of posterior draws are positive) and Competent ($\beta = 0.50$, all posterior draws are positive) brands positively and alliances between Sophisticated and Rugged brands somewhat negatively ($\beta = -0.39$ and $\beta = -0.19$, with 99.9% and 99.1% of posterior draws negative for Sophistication and Ruggedness, respectively). We also find that alliances between brands from the same category receive on average higher evaluations ($\beta = 0.36$, all posterior draws are positive).

5.2. Model 2: Overall Brand Personality Similarity

Whereas Model 1 only estimates the effect of the personality of an alliance, Model 2 captures the effect of partner similarity. More specifically, in addition to BP scores and whether brands belong to the same product category, Model 2 includes the overall dissimilarity (*Overall_dissimilarity and Overall_dissimilarity*^{2}) between brand personalities. The addition of overall dissimilarity increases the explained variance of brand alliance evaluations from 10% to 14% (LMD = −30,299; holdout LL = −1,052). The results of Model 2 in Table 2 indicate a strong negative effect ($\beta = -0.32$, all posterior draws are negative) of overall dissimilarity between BP dimensions on the evaluation of brand alliances. The effect of *Overall_dissimilarity*^{2} is not significant ($\beta = 0.00$, 51.2% of posterior draws are positive). This indicates that partners with similar BP profiles receive on average higher evaluations compared to partners with dissimilar BP profiles. Although these results suggest that the evaluation of brand alliances increases when partner brands are more similar in BP, it does not indicate whether brand alliances should be similar on each BP dimension and whether similarity is equally important for all personality dimensions. The goal of Model 3 is to answer these questions.

5.3. Model 3: Specific Brand Personality Similarity

Instead of estimating the effect of overall dissimilarity between partners (Model 2), Model 3 incorporates dissimilarity (*Dissimilarity*) and its squares (*Dissimilarity*^{2}) for each brand personality dimension separately. As indicated by the Bayesian adjusted-R^2 measure, this increases the explanatory power of our model to 17%,[5] but the overall fit based on LMD and holdout LL predictions slightly decreases (LMD = −30,330; holdout LL = −1,064).[6]

[5] Additional analyses reveal that *Dissimilarity* and *Dissimilarity*^{2} of each personality dimension contributes to the additional explanatory power of the model. Compared to Model 1, adding only Dissimilarity and Dissimilarity^2 of Sophistication had the weakest impact on the Bayesian adjusted-R^2 (an increase from 0.10 to 0.119), while adding only Dissimilarity and Dissimilarity^2 of Sincerity had the strongest impact (Bayesian adjusted-R^2 increased from 0.10 to 0.135).

[6] The reason for this decrease in overall fit is four insignificant squared effects of dissimilarity. If only the significant dissimilarity effect of Sincerity is included, the overall fit increases (LMD = −30,270; holdout LL = −1,037).

Because the effects of personality dimensions are difficult to interpret from the parameter estimates, we illustrate their effects in Figures 4–8. These Figures are similar to Figures 2 and 3, and represent, within a personality dimension, all of the possible combinations of two brand alliance partners, brands A and B.

Sincerity. Model 3 shows that members of brand alliances do not need to be similar in Sincerity ($\beta = -0.12$, with 92.9% of the posterior draws are negative). Providing some support for Hypothesis 1, the squared effect of dissimilarity in Sincerity is negative[7] ($\beta = -0.13$ with 98.5% of the posterior draws are negative), implying that brands should try to find partners that are moderately dissimilar in Sincerity. Figure 4 illustrates this effect and suggests that brand alliances on the diagonal axis (i.e., brands with similar ratings on the BP dimension) receive lower evaluations compared to brands that are moderately dissimilar. This plot suggests that the optimal difference between two partnering brands is close to one standard deviation.

Competence. Similar to Models 1 and 2, we find a positive effect for Competent alliances ($\beta = 0.28$, 96.1% of posterior draws are positive). Although Model 3 suggests that members of brand alliances should be similar in BP, this is not the case for Competence ($\beta = 0.01$, 45.5% of the posterior draws are negative). Figure 5 even suggests that brand alliances on the diagonal axis receive lower evaluations compared to brands that are moderately dissimilar (consistent with Hypothesis 1), but the hypothesized dissimilarity effect for Competence could not be statistically supported.

Excitement. Similar to Models 1 and 2, we find a positive effect for Exciting alliances ($\beta = 0.41$, all posterior draws are positive). In contrast to Hypothesis 1, brands should be similar in Excitement ($\beta = -0.11$, 96.7% of posterior draws are negative), although the positive effect of the average Score of the two partnering brands is a more important driver of brand alliance evaluation, as illustrated in Figure 6.

Sophistication. Following Hypothesis 2, our results show that alliances are rated more favorably when partners are similar in Sophistication (effects of the dissimilarity: $\beta = -0.17$, with 99.9% of all posterior draws are negative). The corresponding effects of squared dissimilarities are nonsignificant ($\beta = 0.02$, 62.0% of posterior draws are positive). Figure 7 illustrates the negative effect for Sophisticated alliances ($\beta = -0.21$, 95.2% of posterior draws are positive) but also shows that brand alliances receive higher evaluations when partners are similar. This corroborates Hypothesis 2.

[7] Note that we standardized the *Dissimilarity* variables so that a negative squared effect corresponds to an inverted-U relationship.

Ruggedness. Consistent with Hypothesis 2, alliances are rated more favorably when partners are similar in Ruggedness (effects of the dissimilarity: $\beta = -0.19$, with 99.9% of all posterior draws negative; the effect of squared dissimilarities is nonsignificant: $\beta = 0.04$, with 84.9% of posterior draws positive). Figure 8 clearly illustrates that brand alliances receive higher evaluations when partners are similar in Ruggedness.

5.4. Model 4. Robustness of Results

In addition to the effects of the latent *Score* and *Dissimilarity* variables in Model 3, Model 4 tests whether these results are robust by adding (1) Attitude towards the individual brands as measured in the sample of participants in the Brand Image Study, and (2) the Brand Value of the individual brands reported in dollars as communicated in industry reports. Although our results show that the effect of Attitudes toward the individual brands on the evaluation of a brand alliance is positive ($\beta = 0.18$, 97.0% of posterior draws are positive), Brand Value does not explain any additional variation in brand alliance evaluations ($\beta = -0.01$, 44.1% of posterior draws are positive).[8] Most important, the parameter estimates of the latent *Score* and especially of the *Dissimilarity* variables are robust, while the addition of Attitude and Brand Value does not increase the Bayesian adjusted-R^2 (0.17). These results further illustrate the explanatory power of conceptual coherence in BP on brand alliance evaluations. Hence, a positive attitude toward each of the partner brands does not necessarily translate into favorable perceptions of a brand alliance. The conceptual coherence explains almost twice as much of the variance in brand alliance evaluations than attitude toward the individual brands.

While Model 4 illustrates that our results are robust in controlling for additional explanatory variables, Web Appendix D provides model-free evidence of our estimation results. This Web Appendix presents the estimation results of Models 1–4 using a three-step estimation approach. In step 1, we estimated personality scores by using only the data obtained from the Brand Image Study, while in step 2 we estimated the brand alliance evaluations using only data obtained in the Brand Alliance Study. Finally, in step 3, we regressed the average personality scores obtained from step 1 on the average brand alliance evaluations obtained from step 2. As illustrated in Web Appendix D, the parameter estimates are similar to the parameter estimates presented in Table 2. Moreover, the Bayesian-adjusted R^2 decreases from 0.10 to 0.06 (Model 1), from 0.14 to 0.09 (Model 2), from 0.17 to 0.09 (Model 3), and from 0.17 to 0.10 (Model 4). This highlights the power of our modeling approach.

[8] In a model with only Brand Value as the explanatory variable, Brand Value is positively related to brand alliance evaluations ($\beta = 0.20$, all posterior draws, except one, were positive; Bayesian adjusted-$R^2 = 0.01$).

Figure 4 Results Sincerity

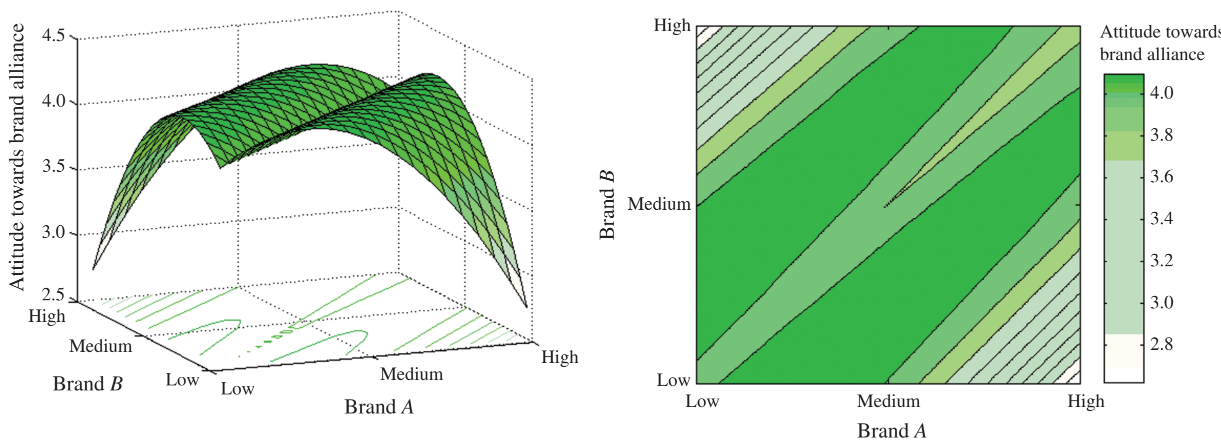


Figure 5 Results Competence

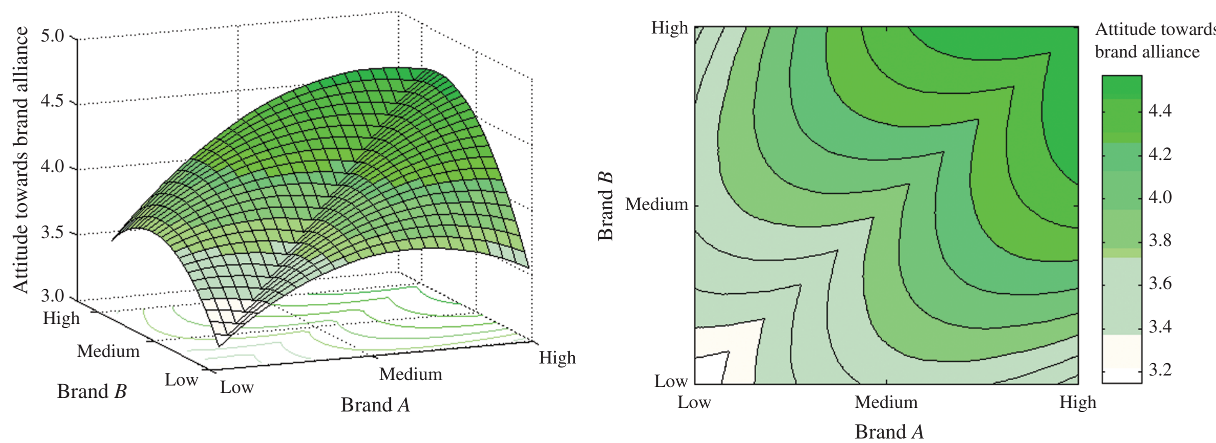
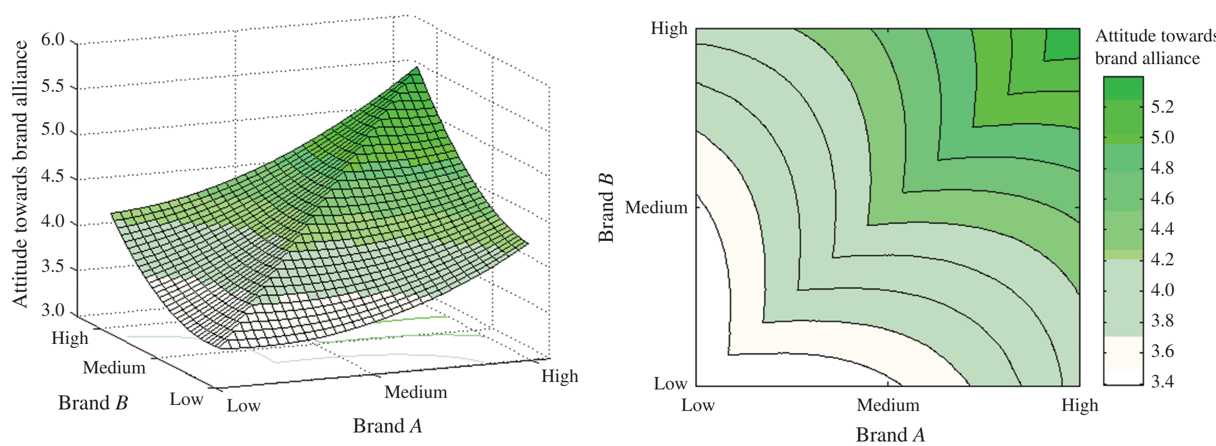


Figure 6 Results Excitement



6. General Discussion

Selecting a partner to form a brand alliance is an important marketing strategy to enhance brand image (e.g., a brand may benefit from the "halo of affection" that belongs to another brand), to increase market share (e.g., brand alliances enable partner brands to access each other's markets), or even to lower costs (e.g., joint advertising). Finding and selecting the right partner, however, is difficult. Although the academic literature stresses the importance of brand fit, to our knowledge, it does not provide insights into its underlying causes. In this research, we combined 100 existing brands

Figure 7 **Results Sophistication**

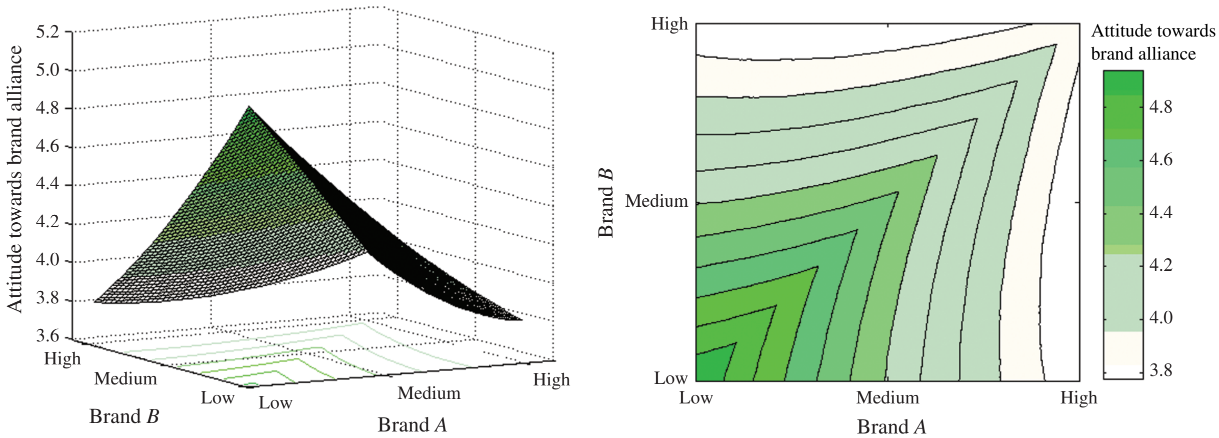
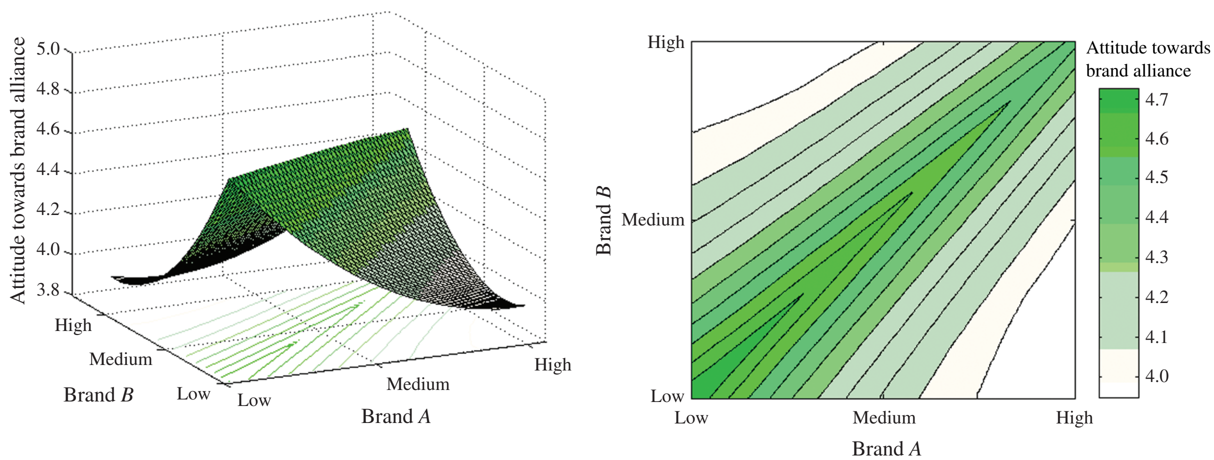


Figure 8 **Results Ruggedness**



in more than 1,000 brand alliances to uncover the drivers of brand fit. Using an extension of the Bayesian nonlinear structural equation modeling approach, we show that the conceptual coherence between BP profiles is a strong predictor of brand alliance evaluations.

Statements such as "opposites attract" or "birds of a feather flock together" are oversimplifications of a complex reality. In prior research, scholars have primarily aggregated dimensions to arrive at an overall conclusion of whether similarity or dissimilarity drives fit. Brand image, however, is a profile multidimensional construct and its dimensions cannot be aggregated or combined algebraically (Law et al. 1998). We propose that the conflicting views of the drivers of brand fit (i.e., similarity versus dissimilarity) are due to the aggregation of separate brand image dimensions. Hence, whether similarity or dissimilarity drives brand fit should be answered separately for each dimension.

Based on partner selection research in the human alliance and corporate alliance literatures, we hypothesized that similarity in extrinsic aspects and dissimilarity in intrinsic aspects of BP foster favorable brand alliance evaluations. Although we find strong support for our hypothesis related to extrinsic dimensions, our conclusions for intrinsic personality dimensions are mixed. We find that similarity in extrinsic dimensions (Sophistication, Ruggedness) and moderate dissimilarity in intrinsic dimensions (Sincerity, but only directionally for Competence) foster favorable evaluations of brand alliances. In addition, we find that combinations of Exciting brands, irrespective of (dis)similarity, result in favorable evaluations. In sum, it is as if partners should look the same on the outside (e.g., Sophisticated = feminine and upper-class; Ruggedness = masculine and Western), but different on the inside (e.g., Sincerity = honest and genuine; Competence = reliable and responsible), although the latter is less important.

Our study makes important methodological progress in brand alliance research. Scholars have resorted to experiments with a small sample of fictitious brands to investigate brand alliances. Generalizing from a limited set of brands (Simonin and Ruth 1998), from a specific industry (Yang et al. 2009) or from fictitious brands

(Geylani et al. 2008) is problematic for obvious reasons. We avoid these problems by randomly pairing 100 existing brands in more than 1,000 alliances. In addition, our approach allows us to establish causality, which is an important issue when trying to understand whether (dis)similarity drives brand fit. Indeed, when partners are not combined randomly, it is impossible to determine whether similarity drives alliance success (due to brand fit) or whether alliance success drives partner similarity (due to spillover effects, see Simonin and Ruth 1998). In sum, our study uses a methodology that makes significant methodological progress in brand alliance research (i.e., (1) real brands, (2) multiple industries or categories, (3) large set of brands, (4) establishing causality).

We not only provide an important contribution to the academic literature, but also to managerial practice. Although the aim of this research was to identify drivers of brand fit, our methodology allows managers to select ideal partners to form brand alliances. For instance, imagine that a car manufacturer wants to improve music playback, GPS navigation, entertainment and/or smartphone services in their car dashboards and that the brand manager seeks a partner to embark on a brand alliance. BMW has a history of working with Apple on iPod and iPhone integration; Ford maintained a long relationship with Microsoft in developing "carputer" integration features; Toyota recently teamed with Samsung for an in-vehicle infotainment system. Assuming that Apple, Microsoft, Nokia, Philips, Samsung, and Sony provide comparable services, brand managers may wonder which of these brands fits their car brand best. Table 3 displays scores on personality dimensions for car and technology brands as well as the expected brand alliance evaluations (on a 1–7 scale) based on our data and estimates from Model 3.

Table 3 indicates that the Mini-Apple alliance receives the highest evaluation ($\eta_{\text{Mini, Apple}} = 5.57$) and the Porsche-Nokia alliance the lowest ($\eta_{\text{Porsche, Nokia}} = 3.92$). Our model not only identifies which partners fit well (without inflated estimation due to common method bias) but also explains why some alliances are rated more favorably than others. Technology brands differ very little on the Sincerity and Ruggedness dimensions, and there are no strong differentiating aspects of the overall brand alliance evaluations. Table 3 demonstrates that Apple stands out on Excitement ($\xi_{3,\text{ Apple}} = 1.43$) and Sophistication ($\xi_{4,\text{ Apple}} = 1.84$). Because high scores on Excitement yield favorable brand alliance evaluations, Apple is an attractive partner for most car brands, but because brand alliances should be similar on Sophistication, Apple is especially attractive for sophisticated car brands, such as Mini, Audi, Mercedes, BMW, Ferrari, and Porsche. Because the Ferrari-Apple and Porsche-Apple alliances are characterized by dissimilarity on Ruggedness, these alliances are evaluated less favorably within the sophisticated car brands. Although exciting brands are attractive partners, this does not imply that Apple is always the most attractive. Indeed, Volkswagen, Ford, and Toyota gain more from alliances with Sony and Philips, while Honda, Nissan, and Hyundai gain more from alliances with Nokia. These examples highlight the importance of conceptual coherence in BP profiles. Indeed, attractive alliances do not result from simply pairing with an exciting brand such as Apple.

Most evidently, a brand cannot be reduced to the five dimensions we studied. Although it is clear that the coherence between BP profiles is a driver of brand fit, other dimensions may also contribute to perceived brand fit. For instance, Passion, Peacefulness, Responsibility, Activity, Aggressiveness, Simplicity, Emotionality, Masculinity, Femininity, etc., have been introduced as alternative or complementary dimensions of BP (Aaker et al. 2001, Geuens et al. 2009, Grohmann 2009). Future research may incorporate additional dimensions and further explore how the conceptual coherence between these or other dimensions contribute to brand fit. Because the perceptions and evaluations of these dimensions may differ across cultures (Aaker et al. 2001), future studies should test the generalizability of our conclusions. A brand cannot be reduced to its personality. The relative importance of BP dimensions as drivers of brand fit should be tested. For instance, we found that Brand Value is a predictor of alliance evaluations, but coherence in BP profiles was a more powerful predictor. Future research should explore other drivers of brand fit beyond BP (e.g., brand equity).

Note that our conclusions are restricted to perceptions of brand fit. Other benefits of alliances, such as cost-savings or access to a partner brand's market, may outweigh the cost of pairing two incongruent brands. Although brand fit may become more important when a brand alliance is more intense (e.g., a co-branded product versus simultaneously presenting two brands during a co-sponsored event), our conclusions may be limited to the evaluation of brand alliances in a co-sponsorship setting. Furthermore, we investigated the influence of BP on alliance fit for an unspecified one-time event in a large city. Future research should investigate whether these results also hold in different contexts or in an enduring long-term brand alliance, as selecting a partner for a one-night stand is critically different from selecting one for marriage. Indeed, it may be that the ideal personality profile of a brand providing a temporary gift in a Happy Meal box differs from the ideal profile of a partner for a 10-year contract when common use of a McDonald's location is negotiated. Additionally, brands within a pair may have varying strengths leading to asymmetries in the benefits associated with alliances. For instance, an unknown brand may benefit more from an alliance with a high

Table 3 Expected Alliance Evaluations between Car and Technology Brands

	Apple [0.25; 1.16; 1.43; 1.84; 0.07]	Microsoft [0.23; 0.35; −0.28; −0.05; −0.04]	Nokia [0.31; 0.30; −0.37; −0.71; −0.03]	Philips [0.35; 0.74; 0.43; 0.22; 0.16]	Samsung [0.06; 0.35; 0.90; 0.32; 0.29]	Sony [0.58; 0.94; 0.49; 0.48; 0.31]
Mini [−0.25; 0.43; 1.45; 2.03; 0.25]	**5.57**	4.56	4.49	4.92	5.05	5.01
Audi [0.19; 1.10; 1.20; 1.83; 1.20]	**5.31**	4.52	4.48	4.90	5.08	5.03
Mercedes [0.23; 0.92; 0.45; 2.10; 0.58]	**5.06**	4.53	4.46	4.86	4.92	4.99
BMW [0.09; 1.15; 1.37; 2.32; 1.94]	**5.15**	4.29	4.24	4.63	4.83	4.72
Ferrari [−0.25; 0.91; 1.97; 2.53; 2.84]	**5.02**	4.23	4.19	4.43	4.57	4.44
Porsche [−0.45; 0.41; 1.07; 2.37; 1.74]	**4.99**	4.02	3.92	4.43	4.64	4.47
Honda [0.11; −0.19; −0.59; −0.99; 0.75]	4.41	4.53	4.64	4.62	4.55	**4.64**
Nissan [−0.12; −0.42; −0.36; −1.27; 0.63]	4.40	4.63	**4.74**	4.70	4.61	4.64
Hyundai [0.29; −0.31; −0.59; −1.12; −0.54]	4.38	4.59	**4.71**	4.57	4.44	4.51
Ford [0.07; −0.16; −0.08; −0.56; 0.59]	4.59	4.69	4.75	4.92	4.79	**4.95**
Toyota [0.41; 0.23; −0.11; −0.55; 0.41]	4.75	4.84	4.83	4.98	4.87	**5.01**
Volkswagen [0.67; 0.79; 0.12; 0.07; 0.63]	4.89	4.94	4.86	**5.16**	5.10	5.15

Note. Numbers between brackets represent personality scores [Sincerity, Competence, Excitement, Sophistication, and Ruggedness].

equity brand than vice versa, as the unfamiliar brand can benefit from the "halo of affection" that belongs to the high equity brand (Rao and Ruekert 1994). Likewise, brands may differ in what they contribute to, rather than receive from, brand alliances. Investigating the asymmetries in the spillover effects from brands to alliances or from alliances to brands may be a fruitful area of research. Finally, future research should explore whether the conceptual coherence between brand images influences hard metrics such as sales or market share. Although constructing such a database is challenging and causality is difficult to establish, it would increase the validity of the present research.

Supplemental Material
Supplemental material to this paper is available at http://dx.doi.org/10.1287/mksc.2014.0859.

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