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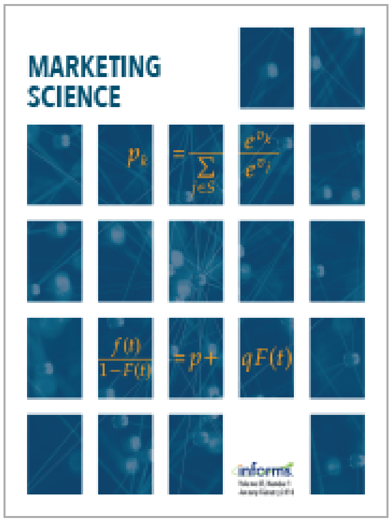

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Image Reinforcement or Impairment: The Effects of Co-Branding on Attribute Uncertainty

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Co-branding is often used by companies to reinforce the image of their brands. In this paper, we investigate the conditions under which a brand's image is reinforced or impaired as a result of co-branding, and the characteristics of a good partner for a firm considering co-branding for image reinforcement. We address these issues by conceptualizing attribute beliefs as two-dimensional constructs: The first dimension reflects the expected value of the attribute, while the second dimension reflects the degree of certainty about the attribute. We argue that these parameters are updated after consumers are exposed to a co-branding activity, and we develop an analytical model that incorporates these notions. An analysis of the model leads to several propositions, which we test in an experiment. Our findings indicate that it is not necessarily in a brand's best interest to choose an alliance partner that is of the highest performance possible. Moreover, we find that, while expected values of the brand attributes may improve as a result of co-branding, under certain conditions the uncertainty associated with the brands increases through the alliance. Implications for co-branding researchers and practitioners are discussed.

Key words: brand alliances; spillover effects; co-branding; image reinforcement; brand positioning
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1. Introduction

Co-branding is a brand alliance strategy in which two or more brands are simultaneously presented to consumers. There is a wide range of co-branding activities in the marketplace, ranging from advertising several brands in a single ad (e.g., Shell and Ferrari ads featuring both brands simultaneously, or ads showing the complementary consumption of McDonald's fries and Coca-Cola) to jointly branded products (e.g., Lexus Coach Edition or Kellogg's Healthy Choice cereal). With an annual 40% growth rate (Blackett and Boad 1999), co-branding has become increasingly prevalent (Keller and Lehmann 2006). For instance, it has been reported that 43% of the credit cards in circulation are co-branded (Punch 2001).

There are a variety of factors driving the surge in co-branding, ranging from the desire to gain access to new markets to the attempt to signal unobservable quality (Rao et al. 1999, Rao and Ruekert 1994). However, evaluations of the co-branded product may have an impact on consumers' perceptions of the partner brands[1] (e.g., Simonin and Ruth 1998). For example, Renault, partnering with the pamas fashion designer brand KENZO, launched its Renault-Twingo KENZO car to reinforce its image of being stylish, hoping that consumers would update their perceptions of Renault as a result of the co-branded product (Kapferer 1999). Sun formed an alliance with Google in 2005 to promote and distribute their products, presumably to improve customers' perceptions of Sun as a cutting-edge innovator.

Unfortunately, brand alliances do not always reinforce a brand's image. They may result in image impairment instead. For example, when Intel experienced quality problems with its Pentium microprocessors, Dell and Gateway were concerned about negative spillover effects on their brands (Simonin and Ruth 1998). Venkatesh and Mahajan (1997) show that branded components may suppress their partners' value. Thus, a strategic approach to identify the right partner is essential for firms considering alliances (Blackett and Boad 1999).

In this research, we focus on conditions under which co-branding drives image reinforcement versus image impairment for the partner brands. We define brand image as a cluster of beliefs associated with the brand, and assume that each of these beliefs has two dimensions—location and reliability. We define

[1] We use the terms *partner brands* and *partners* to refer to the brands forming an alliance via a co-branded product.

location as the mean and *reliability* as the inverse of the variance of the beliefs' distribution. We denote improvement or decline in either of these dimensions as image reinforcement or impairment, respectively. Our approach to incorporating attribute reliability is analogous to previous work in attribute uncertainty (e.g., Meyer 1981, Meyer and Sathi 1985), where uncertainty or unreliability is present within attributes, and consumers update their beliefs via experience.

Our contribution stems from the answers to two major questions of importance to firms considering co-branding as a possible image-reinforcement strategy for their brands. First, how does co-branding affect consumers' uncertainty about the co-branded product as well as uncertainty about the partner brands? We find that the expected performance of the partner brands improves as a result of co-branding, suggesting that alliance brands reinforce the partners' images. However, we also find that, under certain conditions, uncertainty spills over from the co-branded product to the partner brands, possibly tainting consumers' perceptions.

Second, which partner is right for a firm that considers co-branding for image reinforcement? We argue that it is not necessarily in a brand's interest to choose the best-performing partner on the attribute of interest. Rather, it is better to collaborate with a brand that is perceived to be of only moderately higher performance. This is somewhat counterintuitive, as a brand might naturally seek to collaborate with the best partner it can find. However, when the co-branded product involves brands with inconsistent images, consumers tend to regard the co-branded product as inconsistent with the brands' existing products and only slightly revise their prior beliefs.

The remainder of this paper is organized as follows. In §2, we review the relevant research on co-branding and alliances. We then develop a mathematical model in §3, and generate several empirically testable propositions that follow from our model in §4. In §5, we present an experiment that tests our propositions. Results from these tests are presented in §6. In §7 we conclude with a discussion of the managerial implications of our findings, together with limitations and directions for future research.

2. Related Co-Branding Research

To our knowledge, prior research has not explored the effects of co-branding on attribute uncertainty of partner brands. Park et al. (1996) investigate the effects of partner brand position in a composite brand extension (e.g., Slim-Fast chocolate cake mix by Godiva vs. Godiva chocolate cake mix by Slim-Fast) and the influence of complementarity between the partners' attributes on the attribute profiles of the co-branded product as well as the constituent brands. They show that, by combining two brands with complementary attribute levels, a composite brand extension has a better attribute profile than either a direct extension of the dominant brand or an extension that consists of two highly favorable but noncomplementary brands.

Simonin and Ruth (1998) report that consumers' attitudes toward a co-branded product affect their post-alliance attitudes of the partner brands, but these effects are moderated by brand familiarity. Samu et al. (1999) examine the effectiveness of advertising alliances for introducing new brands. They explore the effects of different advertising strategies on awareness, accessibility, beliefs, and attitudes, and show that product complementarity plays an important role in choosing the right advertising strategy. Finally, Desai and Keller (2002) compare different ingredient branding strategies, branding the target attribute ingredient as a self-branded ingredient versus branding it as a co-branded ingredient. They show that co-branded ingredients facilitate initial acceptance of expansions.

All of the above-mentioned studies investigate attribute or affect transferal that occurs as a result of co-branding. In this study, we construct a mathematical model based on behavioral theory that helps us analyze not only attribute transferal, but also how co-branding affects attribute uncertainty of the partner brands and the co-branded product. Several propositions follow from our model, which we test in an experiment.

3. A Model of Brand Alliances

A central tenet of our model is that consumers base their evaluations of a brand on the confluence of the brand's evaluation at a previous point in time and the new information that has become available since that point (e.g., Johar et al. 1997). In our case, the new information comes from the consumer's experience with the co-branded product. In the following paragraphs, we develop our model and articulate the underlying rationale.

First, we adopt the view that consumers use individual products of a brand to construct a distribution of products under that brand name. Leclerc et al. (2005) argue that brands with several product offerings are used as categories, due to their association with specific attributes (e.g., Boush and Loken 1991, Gurhan-Canli and Maheswaran 1998, Loken and John 1993). For example, Neutrogena has many products (e.g., shampoo, moisturizer, conditioner). A consumer may perceive a different level of mildness for each of these products. The distribution of these perceptions forms her belief distribution about Neutrogena's mildness.

Second, we view a brand belief as a two dimensional construct, captured by its location and its reliability. A brand's *location* is represented by the mean of its belief distribution (i.e., expected performance of the brand on the attribute), and its *reliability* is represented by the inverse of its variance (i.e., perceived uncertainty). For example, if the brand's location implies high quality and the brand is reliable on quality, then consumers are certain that quality is high. This assumption is based on the well-known expected utility mean-variance models (e.g., Markowitz 1959, 1987).

In our mathematical formulation we consider two brands, brand X and brand Y, that form an alliance. Let $i = 1, 2$ denote two attributes that characterize brands X and Y, and X_i and Y_i as consumer's beliefs on attribute i of brands X and Y respectively. We assume that X_i is normally distributed with mean μ_{X_i} and variance $\sigma^2_{X_i}$, and that Y_i is normally distributed with mean μ_{Y_i} and variance $\sigma^2_{Y_i}$:

$$f_{X_i}(x_i) = \frac{1}{\sqrt{2\pi\sigma^2_{X_i}}}\exp\left(-\frac{(x_i-\mu_{X_i})^2}{2\sigma^2_{X_i}}\right),$$
$$f_{Y_i}(y_i) = \frac{1}{\sqrt{2\pi\sigma^2_{Y_i}}}\exp\left(-\frac{(x_i-\mu_{Y_i})^2}{2\sigma^2_{Y_i}}\right).^2 \tag{1}$$

Park et al. (1996) argue that an alliance makes sense when the partner brands are complementary. In line with Park et al., we define two brands as complementary when the two brands have a common set of salient attributes, such that the two brands differ in terms of the attribute with which they are most strongly associated,[3] and the brand for which the attribute is most strongly associated has a higher performance rating on that attribute. Without loss of generality, we consider the case where the brands are complementary such that Attribute 1 is salient to brand X, Attribute 2 is salient to brand Y, $\mu_{X_1} > \mu_{Y_1}$, and $\mu_{Y_2} > \mu_{X_2}$. In the absence of other information, consumers should base their beliefs of the co-branded product primarily on their beliefs about the partner brands. Moreover, we expect the salient partner attribute belief to have a greater influence on the formation of the alliance belief than the nonsalient partner belief, as discussed below. To capture these notions, we formulate the distribution of the co-branded product beliefs $f_{A_i}(\cdot)$ as mixtures of the distributions of partner brand beliefs $f_{X_i}(\cdot)$ and $f_{Y_i}(\cdot)$:

$$f_{A_1}(a_1) = w_1 f_{X_1}(a_1) + (1-w_1) f_{Y_1}(a_1), \tag{2}$$
$$f_{A_2}(a_2) = w_2 f_{X_2}(a_2) + (1-w_2) f_{Y_2}(a_2), \tag{3}$$

with weights w_1 and w_2, such that $0 < w_2 < 0.5 < w_1 < 1$.

Of course, information stored in memory must be retrieved before making a judgment. Connectionist models of brand associations (e.g., Janiszewski and van Osselaer 2000) model association strength as a function of the predictive value of salient cues (e.g., brand names, product attributes). Researchers have found that the greater the strength of the association, the greater its accessibility from memory (e.g., Anderson 1983, Posavac et al. 1997). Studies of information accessibility show that as the accessibility of a piece of information increases, the likelihood of its use in encoding subsequent information concomitantly increases (e.g., Yi 1990). Accordingly, in Equations (2) and (3), we argue that the partner attribute belief that is most salient will contribute more to the formation of the alliance belief. This is why we assume $0 < w_2 < 0.5 < w_1 < 1$. This is consistent with information integration theory (e.g., Anderson 1971), wherein each piece of information is assigned a weight representing its relative importance. That is, salience drives attribute weighting in our model.

Equations (1) through (3) represent a finite mixture of normal distributions, so the first two moments, μ_{A_i} and $\sigma^2_{A_i}$, can be obtained in closed form (see Appendix A for the derivation):

$$\mu_{A_i} = w_i\mu_{X_i} + (1-w_i)\mu_{Y_i}, \tag{4}$$
$$\sigma^2_{A_i} = w_i\sigma^2_{X_i} + (1-w_i)\sigma^2_{Y_i} + w_i(1-w_i)(\mu_{X_i}-\mu_{Y_i})^2. \tag{5}$$

As Equations (4) and (5) suggest, the mean μ_{A_i} and variance $\sigma^2_{A_i}$ of the co-branded product are functions of the first two moments of the distributions of beliefs of brands X and Y. The location of the co-branded product on an attribute is a weighted average of the two brand locations, where the weights are determined by the salience of the brands on the attribute.

The perceived variance of the co-branded product in (5) is also a weighted sum, augmented with a term that depends on the weight and distance between the partner brand locations (i.e., $|\mu_{X_i} - \mu_{Y_i}|$). When the co-branded product involves belief distributions with different locations, consumers' attempts to merge the information from the partner beliefs induce an increased variance for the co-branded product's belief distribution. In other words, there are two sources of the co-branded product's variance, the variances of the partner brands and their locations.

[2] Note that we assume the two attributes of each of the partner brands to be independent of each other. In a more general model, perceptions of a brand could be modeled using a joint normal distribution of the perceptions of attributes where these attributes are allowed to be correlated.

[3] Hereafter, to be consistent with Park et al. (1996), we use the term *salience* to refer to this differential attribute-brand association.

We argue that if the co-branded product information is perceived as inconsistent, that is, when the co-branded product is perceived to be located far away from the partner brand, it will have little effect on the partner brand beliefs. The importance of consistency in images is recognized in similar contexts. For example, Shugan (2006) indicates that it is important for advertising content to be consistent with the brand image. Inconsistency discounting from information integration theory suggests a similar process (Anderson and Jacobson 1965).[4] It posits that inconsistent information, even from a credible source, is discounted if it is perceived as inconsistent with prior cues (Lynch and Ofir 1989). We measure inconsistency in terms of the Euclidian distance between the locations of partner brands and the co-branded product in multiattribute space, and specify weights Γ_{X_i} and Γ_{Y_i} as functions of this distance. Specifically, we formulate the distribution of the posterior beliefs of the partner brands after the alliance (X_i' and Y_i') as a mixture of the distributions of co-branded product beliefs and of pre-alliance beliefs of the partner brands with weights Γ_{X_i} and Γ_{Y_i} $(0 < \Gamma_{X_i}, \Gamma_{Y_i} < 1)$:

$$f_{X_i'}(x_i') = \Gamma_{X_i} f_{A_i}(x_i') + (1-\Gamma_{X_i}) f_{X_i}(x_i'), \tag{6}$$

$$f_{Y_i'}(y_i') = \Gamma_{Y_i} f_{A_i}(y_i') + (1-\Gamma_{Y_i}) f_{Y_i}(y_i'). \tag{7}$$

Thus, consumers use their perceptions of the co-branded product to update their beliefs about the partner brands. The weights Γ_{X_i} and Γ_{Y_i} capture the extent to which the co-branded product plays a role in updating the partner brand's posterior beliefs (i.e., the extent to which the co-branded product information is considered relevant). Accordingly, $1-\Gamma_{X_i}$ and $1-\Gamma_{Y_i}$ capture the level of inconsistency between the co-branded product and the partner brands.

Recall that Γ_{X_i} and Γ_{Y_i} capture the weight that the co-branded product has on the formation of the partner brand's posterior belief. The weights Γ_{X_i} and Γ_{Y_i} should decrease as a function of the distance between the co-branded product and the partner brands because inconsistency discounting increases with psychological distance between the partner brand and the co-branded product. Specifically, we expect:

$$\frac{\partial \Gamma_{X_i}}{\partial d_{A-X}} < 0 \quad \text{and} \quad \frac{\partial \Gamma_{Y_i}}{\partial d_{A-Y}} < 0, \tag{8}$$

where

$$d_{A-X} = \sqrt{\sum_{i=1}^{2} (\mu_{A_i} - \mu_{X_i})^2} \quad \text{and} \quad d_{A-Y} = \sqrt{\sum_{i=1}^{2} (\mu_{A_i} - \mu_{Y_i})^2}$$

are the distances between the co-branded product and the partner brands.[5, 6]

Our objective is to derive the post-alliance distributions of attribute beliefs, $f_{X_i'}(x_i')$ and $f_{Y_i'}(y_i')$. We therefore substitute $f_{A_i}(x_i') = w_i f_{X_i}(x_i') + (1-w_i) f_{Y_i}(x_i')$ and $f_{A_i}(y_i') = w_i f_{X_i}(y_i') + (1-w_i) f_{Y_i}(y_i')$ into Equations (6) and (7), which gives the posterior distributions:

$$f_{X_i'}(x_i') = (1-\Gamma_{X_i}(1-w_i)) f_{X_i}(x_i') + \Gamma_{X_i}(1-w_i) f_{Y_i}(x_i'), \tag{9}$$

$$f_{Y_i'}(y_i') = \Gamma_{Y_i} w_i f_{X_i}(y_i') + (1-\Gamma_{Y_i} w_i) f_{Y_i}(y_i'). \tag{10}$$

Equations (9) and (10) represent finite mixtures of normal distributions similar to the formation of co-branded product belief distribution as given in (2) and (3). Thus, in line with the proof in Appendix A, the first two moments can be obtained by inserting the weights of Mixtures (9) and (10) into Equations (4) and (5). Accordingly, the posterior means reduce to:

$$\mu_{X_i'} = (1-\Gamma_{X_i}(1-w_i))\mu_{X_i} + \Gamma_{X_i}(1-w_i)\mu_{Y_i}, \tag{11}$$

$$\mu_{Y_i'} = \Gamma_{Y_i} w_i \mu_{X_i} + (1-\Gamma_{Y_i} w_i)\mu_{Y_i}, \tag{12}$$

And the posterior variances reduce to:

$$\begin{aligned}\sigma^2_{X_i'} &= (1-\Gamma_{X_i}(1-w_i))\sigma^2_{X_i} + \Gamma_{X_i}(1-w_i)\sigma^2_{Y_i} \\ &\quad + (1-\Gamma_{X_i}(1-w_i))\Gamma_{X_i}(1-w_i)(\mu_{X_i}-\mu_{Y_i})^2, \end{aligned}\tag{13}$$

$$\begin{aligned}\sigma^2_{Y_i'} &= \Gamma_{Y_i} w_i \sigma^2_{X_i} + (1-\Gamma_{Y_i} w_i)\sigma^2_{Y_i} \\ &\quad + \Gamma_{Y_i} w_i (1-\Gamma_{Y_i} w_i)(\mu_{X_i}-\mu_{Y_i})^2. \end{aligned}\tag{14}$$

Using this formulation, we are able to describe how consumers update the prior distribution of the partner brand beliefs with the perceived distribution of the co-branded product and derive the moments of these posterior distributions. The posterior means are averages of prior means, weighted by the mixing weights w_i and Γ_{X_i} and Γ_{Y_i}. The posterior variances are weighted averages of the prior variances plus a term that is a function of the distance between the locations of the partner brands on the attribute. As mentioned earlier, consumers' attempts to merge the information from different partner brand beliefs induces an increased variance for the co-branded product's belief distribution. This uncertainty reflects back on the perceptions of the partner brands, resulting in higher posterior variances (i.e., lower perceived reliability).

[4] Other behavioral theories capture notions similar to inconsistency discounting (e.g., assimilation-contrast [Sherif et al. 1958] and subtyping [Weber and Crocker 1983]).

[5] Previous branding research has investigated brand schema change in terms of the number of inconsistent attributes (Loken and John 1993, Gurhan-Canli and Maheswaran 1998). We measure inconsistency in terms of the Euclidian distance between the locations of partner brands and the co-branded product in multi-attribute space.

[6] Note that in our formulation, we allow the effect of the co-branded product on the formation of posterior beliefs of the partners to be different ($\Gamma_{X_i} \neq \Gamma_{Y_i}$). However, these two effects will be equal to each other ($\Gamma_{X_i} = \Gamma_{Y_i} = \Gamma_i$) if consumers perceive the co-branded product to be equally consistent with the two partner brands.

We believe that our model represents an updating mechanism that best suits our theoretical approach to co-branding. An alternative updating mechanism is linear updating (Boulding et al. 1993). However, linear updating treats beliefs as points, while our updating approach involves distributions. Although Bayesian updating (Boulding et al. 1999, Rust et al. 1999) involves a distribution rather than a point, the Bayesian approach would be more suitable if we were interested in only the direct updating of the priors with the most recent information. However, our interest is in not only the post-alliance beliefs, but also the intermediating mechanisms that lead to these post-alliance beliefs. Thus, our model has two stages. The first stage describes the belief formation mechanism where the belief distributions of the two partner brands are *mixed*. This is not an updating process, so Bayesian updating is less suitable. Furthermore, the extent of updating in the Bayesian approach depends on the prior belief distribution and consumers' most recent information, which in our case can be considered as the perceived distribution of the co-branded product. In our model, updating depends not only on the prior partner brand and the co-branded product belief distributions, but also on the extent to which consumers discount the co-branded product information.

4. Propositions

Several empirically testable propositions follow from the co-branded product and posterior partner brand parameters given in Equations (4), (5), and (11) through (14). While some of these propositions (1 and 3) concern perceptions of the co-branded product, others (2, 4, 5, 6, and 7) pertain to the spillover effects of the co-branded product on partner brand beliefs. In this section, we list and discuss these propositions. The mathematical proofs are shown in Appendix A.

Proposition 1. *On each attribute, the location of the co-branded product is between the locations of the partner brands, and is closer to the brand for which the attribute is salient.*

That is, if Attribute 1 is salient to brand X, Attribute 2 is salient to brand Y, $\mu_{X_1} > \mu_{Y_1}$, and $\mu_{Y_2} > \mu_{X_2}$, then $\mu_{X_1} < \mu_{A_1} < \mu_{Y_1}$, $\mu_{X_2} < \mu_{A_2} < \mu_{Y_2}$, $|\mu_{A_1} - \mu_{X_1}| < |\mu_{A_1} - \mu_{Y_1}|$, and $|\mu_{A_2} - \mu_{Y_2}| < |\mu_{A_2} - \mu_{X_2}|$. This follows from the salient brand belief being more accessible in memory and therefore contributing more to the formation of the co-branded product belief. Consider the Slim-Fast and Godiva co-branding example of Slim-Fast–Godiva Chocolate Cake Mix (Park et al. 1996). If Slim-Fast's salient attribute is healthiness and Godiva's is taste, then their co-branded product will reflect the healthiness of Slim-Fast and the taste of Godiva. The co-branded product will be perceived to be healthy and to taste good.

Proposition 2A. *On each attribute, partner brands attract each other through the alliance* (*i.e., the difference between the locations-means of the brands decreases through an alliance*).

Proposition 2B. *Given that the partner brands are complementary and the co-branded product is equally consistent with the partner brands, if Attribute* 1 *is salient to Brand X and Attribute* 2 *is salient to Brand Y, then X attracts Y more than Y attracts X on Attribute* 1, *and vice versa for Attribute* 2.

In other words $|\mu_{X_i} - \mu_{Y_i}| > |\mu_{X'_i} - \mu_{Y'_i}|$, and given that the brands are complementary such that Attribute 1 is salient to Brand X and Attribute 2 is salient to Brand Y and $\mu_{X_1} > \mu_{Y_1}$, $\mu_{Y_2} > \mu_{X_2}$, and if $\Gamma_{X_i} = \Gamma_{Y_i}$, then $|\mu_{Y'_1} - \mu_{Y_1}| > |\mu_{X'_1} - \mu_{X_1}|$ and $|\mu_{Y'_2} - \mu_{Y_2}| < |\mu_{X'_2} - \mu_{X_2}|$. The theoretical motivation is given by Equations (11) and (12), which state that the new location of each partner brand is a convex combination of the brands' locations prior to the alliance. The weights are determined by the relative attribute salience for the brands and their distance from each other before the alliance. Because the co-branded product reflects the performance of the brand to which the attribute is salient, the brand for which the attribute is salient has more *pull* than the other brand. In our Slim-Fast and Godiva example, we would expect Slim-Fast to pull more on the healthiness attribute and Godiva to pull more on the taste attribute. A nice implication of this proposition is that, because the brand for which the attribute is salient will typically perform higher than the partner on that attribute, both partners improve on each attribute. That is, $(\mu_{X'_i} + \mu_{Y'_i}) - (\mu_{X_i} + \mu_{Y_i}) > 0$. Thus, Propositions 1 and 2 suggest possible synergies that can be achieved between the partner brands through co-branding. The attribute profile of the co-branded product reflects the performance of the better-performing brand on each attribute, and the net perceived mean of the partner brands improves through co-branding. While Proposition 1 and Proposition 2A replicate the findings of Park et al. (1996), it is interesting to note that we reach the same conclusions using different theories, offering a rigorous mathematical derivation of these propositions. To our knowledge, the remaining propositions (including Proposition 2B) and our attribute uncertainty perspective are new to the marketing literature.

Proposition 3. *The farther apart the partner brands are on an attribute* (*i.e., the greater the difference between the means of the brands' belief distributions*) *prior to the alliance, the greater the uncertainty associated with the co-branded product on that attribute.*

Mathematically, this proposition asserts that $\partial\sigma^2_{A_i}/\partial|\mu_{X_i} - \mu_{Y_i}| > 0$. As the difference between the partner brands' locations increases, consumers become more uncertain about the co-branded product. For example, if the expected taste difference between Hershey's and Slim-Fast is not as great as that between Godiva and Slim-Fast, the uncertainty associated with a Slim-Fast–Godiva co-branded product will be higher than the uncertainty associated with a Slim-Fast–Hershey's co-branded product on the taste attribute.

Proposition 4. *On each attribute, as the pre-alliance distance between the partner brands increases, the location change of each of the partner brands (relative to the original distance between them) through co-branding decreases.*

Mathematically speaking, $\partial(|\mu_{X_i'} - \mu_{X_i}|/|\mu_{X_i} - \mu_{Y_i}|)/\partial|\mu_{X_i} - \mu_{Y_i}| < 0$ and $\partial(|\mu_{Y_i'} - \mu_{Y_i}|/|\mu_{X_i} - \mu_{Y_i}|)/\partial|\mu_{X_i} - \mu_{Y_i}| < 0$. That is, when the co-branded product involves brands that are located far apart, consumers regard the information on the co-branded product as being inconsistent with the prior partner brand beliefs (i.e., inconsistency discounting). Thus, there will be less updating.

Proposition 5. *On each attribute, the uncertainty associated with the more reliable partner increases after the alliance.*

Mathematically, if $\sigma^2_{X_i} < \sigma^2_{Y_i}$, then $\sigma^2_{X_i'} > \sigma^2_{X_i}$. The uncertainty associated with the more reliable brand increases because of consumers' considering the greater uncertainty associated with the less reliable brand. That is, the co-branded product in essence acts as a conduit to transfer the less reliable brand's high uncertainty to the more reliable brand. We refer to this process as *uncertainty transfer*. Specifically, when the co-branded product involves a partner about which consumers are highly uncertain, this induces increased uncertainty about the co-branded product. Because consumers use their beliefs about the co-branded product to revise their prior beliefs, the high uncertainty about the co-branded product in turn increases their perception of uncertainty associated with the reliable brand. This insight is reflected in the first two terms of Equations (13) and (14). Also, as we mentioned in §3, another source of the co-branded product's variance in addition to the variances of the partner brands is that the partner brands have different locations. This increased variance reflects back on the partner brands when consumers update their prior brand beliefs with their beliefs about the co-branded product. This location effect is seen in the last terms of Equations (13) and (14).[7]

Proposition 6. *If the partner brand to which an attribute is salient is the less reliable one, then the uncertainty associated with the less reliable partner may increase after the alliance.*

Mathematically speaking, if Attribute 1 (2) is salient to brand X (Y), and brand X (Y) is the less reliable partner on this attribute, that is $\sigma^2_{X_1} > \sigma^2_{Y_1}$ ($\sigma^2_{Y_2} > \sigma^2_{X_2}$), and if $(\mu_{X_1} - \mu_{Y_1})^2/2 > \sigma^2_{X_1} - \sigma^2_{Y_1}$ ($(\mu_{Y_2} - \mu_{X_2})^2/2 > \sigma^2_{Y_2} - \sigma^2_{X_2}$), then $\sigma^2_{X_1'} > \sigma^2_{X_1}$ ($\sigma^2_{Y_2'} > \sigma^2_{Y_2}$). When the difference between the locations of the brands is large in comparison to the difference between their variances, uncertainty associated with the less reliable brand increases. Co-branding has two opposing effects on the variance of the less reliable partner. First, the less reliable (high variance) brand is associated with a more reliable (low variance) brand through co-branding. This reduces the variance of the less reliable brand. Second, the location effect described above increases its variance. When the difference between the variances of the partner brands is sufficiently small, the latter effect dominates and the variance of the less reliable brand increases. In our Slim-Fast–Godiva co-branding example, Propositions 5 and 6 predict that the reliability of Godiva and Slim-Fast could decrease on both attributes.

Proposition 7. *Given that the co-branded product is equally consistent with the partner brands, if the partner brand to which the attribute is salient is the less reliable one, then the total post-alliance uncertainty associated with both brands increases.*

In other words, $\sigma^2_{X_i'} + \sigma^2_{Y_i'} > \sigma^2_{X_i} + \sigma^2_{Y_i}$ if attribute i is salient to the less reliable partner and $\Gamma_{X_i} = \Gamma_{Y_i}$. Total uncertainty associated with both brands may increase due to uncertainty transfer and the location effect discussed above.

5. Experiment

5.1. Overview

While the theoretical model forms a mathematically rigorous way of explaining the effects of co-branding, we tested whether consumers behave in correspondence with the propositions (e.g., Amaldoss and Rapoport 2005). Two hundred and sixty one undergraduate students participated in the experiment in return for extra credit. The experiment consisted of the construction of a history of experiences with two fictitious and complementary brands that form a brand alliance. The partner brands were a luggage brand (*L*'s) and a clothing brand (*C*'s). Their

[7] The extent of the uncertainty transfer and location effect depends on weights of the second mixture Γ_{X_i} and Γ_{Y_i} which capture the weight that the co-branded product plays in the partner brands' posterior beliefs. In the limit, when the brands are very far away, although consumers' uncertainty about the co-branded product will be very high, Γ_{X_i} and Γ_{Y_i} will go to 0, and consumers will disregard the co-branded product information. Therefore, there will not be any change in partner brand variances through co-branding. We thank the Area Editor for pointing this out.

co-branded product was *L's-C's* Briefcase. Subjects were exposed to histograms representing their previous experiences with the two hypothetical brands through their distributions of two attribute beliefs (durability and style).[8] *L*'s salient attribute was durability, and *C*'s salient attribute was style, so *L*'s (*C*'s) corresponds to X (Y) in our model and durability (style) to Attribute 1 (2).

The experiment was a $2 \times 2 \times 2 \times 2$ between-subjects design. The first factor was the distance between the locations (means) of the brands on durability (*L*'s expected durability greater [much greater] than *C*'s). The second factor was the distance between the brands on style (*C*'s expected style greater [much greater] than *L*'s). The other two factors were the ordering of the standard deviations of the partners on the two attributes (*L*'s standard deviation greater [less] than *C*'s on durability; *C*'s standard deviation greater [less] than *L*'s on style). These factors were manipulated using histograms of the brands' durability and style distributions (see Table 1 for the specific experiment conditions).[9] We used a balanced design with approximately the same number of subjects per cell.

5.2. Procedure

To make sure that subjects knew how to read histograms, we included a brief tutorial preceding the experiment. The tutorial reviewed the interpretation of a histogram by providing an example. In the tutorial, a histogram was shown, and the exact counts corresponding to the bins of the histogram were provided. Then subjects were asked if the interpretation of the histogram was clear to make sure that everyone knew how to read it.[10]

Table 1 Experimental Conditions*

Cell	$\mu_{L's_{durability}}$	$\mu_{C's_{durability}}$	$\mu_{L's_{style}}$	$\mu_{C's_{style}}$	$\sigma_{L's_{durability}}$	$\sigma_{C's_{durability}}$	$\sigma_{L's_{style}}$	$\sigma_{C's_{style}}$
A	80	60	60	80	7.5	5.0	5.0	7.5
B	80	30	60	80	7.5	5.0	5.0	7.5
C	80	60	30	80	7.5	5.0	5.0	7.5
D	80	30	30	80	7.5	5.0	5.0	7.5
E	80	60	60	80	5.0	7.5	5.0	7.5
F	80	60	60	80	5.0	7.5	7.5	5.0
G	80	60	60	80	7.5	5.0	7.5	5.0
H	80	30	60	80	5.0	7.5	5.0	7.5
I	80	30	60	80	5.0	7.5	7.5	5.0
J	80	30	60	80	7.5	5.0	7.5	5.0
K	80	60	30	80	5.0	7.5	5.0	7.5
L	80	60	30	80	5.0	7.5	7.5	5.0
M	80	60	30	80	7.5	5.0	7.5	5.0
N	80	30	30	80	5.0	7.5	5.0	7.5
O	80	30	30	80	5.0	7.5	7.5	5.0
P	80	30	30	80	7.5	5.0	7.5	5.0

*The scores are out of 100.

In the experiment, subjects were first shown a description for each partner brand, then the salience of the two attributes was measured by asking the subjects to indicate the importance of each attribute in brand evaluation on a seven-point scale. Brand descriptions served two purposes: to make the experiment more realistic, and to manipulate salience. We tried to ensure that durability was salient for *L*'s and style was salient for *C*'s by using two methods. First, similar to Yi (1990), we used cognitive priming by constructing the brand descriptions so that they would activate *L*'s durability and *C*'s style. Second, according to Shavitt and Fazio (1990), a particular attribute may be spontaneously salient. A post-test verified our belief that durability is naturally salient for luggage products, and style is naturally salient for clothing.[11]

After the brand description and salience measurement, subjects were presented with two histograms that depicted previous durability and style perceptions with different products of the brand. After each histogram, subjects' perceived means and standard deviations on that attribute were measured. Similar to Rust et al. (1999), perceived mean was measured by the question, "I would expect the style (durability) of a product of *L*'s (*C*'s) to be ____," and perceived standard deviation was derived by measuring the 95% confidence interval, using the question, "About 95% of the time, style (durability) of *L*'s (*C*'s) products is between ____ and ____."

[8] We conducted a pretest on 59 subjects to ensure that the attributes were uncorrelated. Subjects indicated on a seven-point rating scale whether they thought durability and style of clothing and luggage products were related. Our results showed that subjects did not perceive a significant correlation between these two attributes in these product categories. The differences between the average relatedness ratings for clothing and luggage products and the scale midpoint were not statistically significant (for clothing products $z = 0.5$, for luggage products $z = 1.5$).

[9] Location and reliability may be dependent in practice. For example, extreme beliefs might be associated with lower variance. Our model is general enough to incorporate such dependence. Except for Proposition 3, all of our propositions continue to hold even if the dimensions are dependent.

[10] In addition, we used a manipulation check to make sure that subjects understood our histograms. The manipulation check was based on responses to questions which asked the subjects to give the counts corresponding to the bins of the histograms for *L*'s and *C*'s style and durability (e.g., "____ products of *L*'s received a style score between 50 and 55"). Across the sample, 97% of our subjects demonstrated a complete understanding of the histograms (i.e., they entered the correct counts).

[11] Salience was measured by asking 57 subjects to indicate on a 7-point scale the importance of each attribute in product evaluation for both clothing and luggage products. For clothing products, the average style rating was 1.6 points higher than the durability rating ($t_{56} = 8.80$, $p < 0.01$). For luggage products, the average durability rating was 1.5 points ($t_{56} = 7.03$, $p < 0.01$) higher than the style rating.

Following the presentation of these histories of experiences for the two brands, subjects were exposed to ad stimuli that depicted the alliance between the brands (shown in Appendix B). We then assessed the perceived mean and standard deviation of the co-branded product on both attribute dimensions. To clear short-term memory, subjects then completed an unrelated filler task for about 10 minutes. The subjects were asked to again report their perceived mean and standard deviation scores for each brand on each attribute, then were debriefed and released.

6. Results

6.1. Manipulation Checks

Before testing the propositions, we tested whether we had successfully manipulated perceived distance between the locations (means) of the partner brands before the alliance. Average distances were 19.4 and 49.6 for the small and large durability distance conditions, and 19.3 and 49.1 for the small and large style distance conditions, respectively. The differences between these distances across the conditions were statistically significant ($t_{260} = 39.61$, $p < 0.01$ for the durability distance conditions and $t_{260} = 46.62$, $p < 0.01$ for the style distance conditions). We also checked the standard deviation conditions. The average stated standard deviation difference on durability was 2.0 (average of std. dev.(L's) − std. dev.(C's)) for the condition in which L's standard deviation was greater than C's ($t_{131} = 18.66$, $p < 0.01$), and −2.5 for the condition in which L's standard deviation was less than C's ($t_{128} = 23.10$, $p < 0.01$). Similarly, the average stated standard deviation difference (average of std. dev.(C's) − std. dev.(L's)) on style was 2.4 for the condition in which C's standard deviation was greater than L's ($t_{127} = 38.2$, $p < 0.01$) and −2.3 for the condition in which C's standard deviation was less than L's ($t_{132} = 34.33$, $p < 0.01$). These results indicate that our manipulations were successful. (See Table 2 for average pre-alliance stated means and standard deviations for each of the experimental conditions.)

We also wanted to ensure that the brands were perceived as complementary. We first checked complementarity in performance. On the durability dimension, the perceived mean of L's was on the average 34.5 points higher than that of C's ($t_{260} = 34.11$, $p < 0.01$). On the style dimension, the perceived mean of C's was on the average 34.3 points higher than that of L's ($t_{260} = 34.98$, $p < 0.01$). We then checked complementarity in salience. On average, L's durability importance rating was 1.8 points (out of 7) higher than its style importance rating ($t_{260} = 15.60$, $p < 0.01$), and C's style rating was 1.5 points (out of 7) higher than its durability rating ($t_{260} = 15.00$, $p < 0.01$). These results confirm the complementarity of the two partnering brands.[12]

6.2. Tests of Propositions

In this section, we test the propositions that are generated from our mathematical model. Unless otherwise specified, the tests involve all the cells of our experimental design. Proposition 1 predicts that, on each attribute, the location of the co-branded product will fall between the locations of the partner brands and will fall closer to the brand for which the attribute is salient. The test of Proposition 1 consists of two parts. We first checked whether subjects considered the location of the co-branded product to lie between the locations of the partner brands. On each of the attribute dimensions, the 95% confidence interval for the location of the co-branded product was between the average pre-alliance locations of the partner brands. On the durability attribute, the 95% confidence interval for the location of the co-branded product was [67.2, 70.7], and the average pre-alliance locations for L's and C's were 80.2 and 45.7, respectively. On style, the 95% confidence interval for the co-branded product's location was [63.3, 67.6], and the average pre-alliance locations for L's and C's were 45.8 and 80.1, respectively.

For the second part of Proposition 1, we checked whether subjects considered the location of the co-branded product to be closer to the brand for which the attribute is salient. On the durability dimension, the distance between the pre-alliance location of C's and the co-branded product was on average 11.9 points larger than that between L's and the co-branded product ($t_{260} = 6.29$, $p < 0.01$). Specifically, the average distance between C's pre-alliance location and the co-branded product was 23.2, while the average distance between L's pre-alliance location and the co-branded product was 11.3. On the style dimension, the distance between L's and the co-branded product was on average 5.0 points larger than that between C's and the co-branded product ($t_{260} = 2.37$, $p < 0.02$). The average distance between L's and the co-branded product was 19.6, while the mean distance between C's and the co-branded product was 14.6 (see Table 2 for average perceived locations for the co-branded product and the partner brands for all subjects). Thus, Proposition 1 is supported.

Proposition 2 predicts that partner brands attract one another on each attribute via the alliance (Proposition 2A), with the brand for which the attribute is salient attracting the poorly performing brand more (Proposition 2B). The distance between the brands decreased both on the durability dimension (by 18.8

[12] A posttest verified that style and durability are equally salient for briefcases. We thank an anonymous reviewer for suggesting this.

points, $t_{260} = 13.57$, $p < 0.01$) and on the style dimension (by 17.9 points, $t_{260} = 13.80$, $p < 0.01$). On durability, the average distance between the brands before and after the alliance was 34.5 and 15.7, respectively. On style, these distances were 34.2 pre-alliance and 16.3 post-alliance. (See Table 2 for average perceived locations of the partner brands before and after the alliance for all subjects.) This provides support for Proposition 2A.

Turning to Proposition 2B, on the durability dimension, the distance between the post- and pre-alliance locations of *C*'s was on average 8.4 points larger than the shift in *L*'s (high durability salience) location ($t_{260} = 5.59$, $p < 0.01$). Specifically, the average shift in locations for *C*'s was 13.6, while the shift in *L*'s location was 5.2. On the style dimension, the distance between the post- and pre-alliance locations of *L*'s was on the average 3.1 points greater than that for *C*'s (high style salience) ($t_{260} = 2.11$, $p < 0.05$). Specifically, the shift in *L*'s location was 10.5, compared to *C*'s shift of 7.4. (See Table 2 for average perceived locations of the partner brands before and after the alliance across subjects.) We therefore conclude that Proposition 2B is supported.[13]

Proposition 3 predicts that the farther apart the partner brands prior to the alliance, the greater the uncertainty associated with the co-branded product. This proposition is supported. On each attribute dimension, we conducted an analysis of variance (ANOVA). The distances on each of the attribute dimensions (small-large distance on durability and small-large distance on style) and the ordering of the standard deviations of the partners on the two attributes (*L*'s standard deviation greater [less] than *C*'s on durability; *C*'s standard deviation greater [less] than *L*'s on style) were the independent variables, and the perceived standard deviation of the co-branded product was the dependent variable. On durability, this analysis revealed a significant effect only for distance on the durability dimension ($F_{1,245} = 11.03$, $p < 0.01$). Subjects in the large durability distance condition had an average perceived standard deviation for the co-branded product of 8.7, while those in the small durability distance condition had an average perceived standard deviation of 6.9. A similar analysis for the style dimension revealed a significant effect only for distance on the style dimension ($F_{1,245} = 10.67$, $p < 0.01$). The average perceived standard deviation for the co-branded product across subjects in the large style distance condition was 8.8, versus 7.0 in the small style distance condition.

[13] Strictly speaking, Proposition 2B requires the co-branded product to be equally consistent with the partner brands. Thus, we also tested this proposition in those cells where the co-branded product was perceived to be equidistant from the partner brands (cells A, D, E, F, G, N, O, and P). The results were substantively identical.

Proposition 4 investigates the effect of pre-alliance distance between the partner brands on their relative location change (i.e., $|\mu_{X_i'} - \mu_{X_i}|/|\mu_{X_i} - \mu_{Y_i}|$ and $|\mu_{Y_i'} - \mu_{Y_i}|/|\mu_{X_i} - \mu_{Y_i}|$). On balance, our results provide evidence in support of the inconsistency discounting predicted by Proposition 4. We conducted four ANOVAs, with the relative location change of *C*'s and *L*'s on each attribute as the dependent variables and all factors in our design as independent variables. We then test whether the effect of pre-alliance distance between the brands is significant.

The ANOVA with relative location change of *C*'s on the style attribute as the dependent variable reveals a significant effect only for distance ($F_{1,242} = 6.82$, $p < 0.01$). The average relative location change across subjects in the large style distance condition was 0.23, versus 0.42 in the small style distance condition. A similar ANOVA for *L*'s on style also reveals a significant effect only for distance ($F_{1,242} = 9.35$, $p < 0.01$). The average relative location change across subjects in the large style distance condition was 0.35 versus 0.54 in the small style distance condition.

On the durability dimension, an ANOVA with the same independent variables and relative location change of *L*'s as the dependent variable reveals a significant effect only for distance ($F_{1,243} = 13.13$, $p < 0.01$). The average relative location change across subjects in the large durability distance condition was 0.16 versus 0.32 in the small durability distance condition. The ANOVA with the relative location change of *C*'s as the dependent variable, however, did not indicate a significant effect ($F_{1,243} = 0.67$, *NS*) of distance. The average relative location change was 0.47 in the large durability distance condition versus 0.53 in the small durability distance condition. Because Proposition 4 is statistically supported in three of the four comparisons, with the fourth providing directional support, we conclude that the inconsistency discounting tenet underlying Proposition 4 is supported. Future research is needed to confirm these results.

Our results also support Proposition 5, which predicts that the perceived standard deviation of the more reliable brand increases through co-branding. On the durability dimension, when *L*'s was the more reliable brand (cells E, F, H, I, K, L, N, O in Table 1), the standard deviation of *L*'s increased by an average of 1.3 points ($t_{129} = 5.72$, $p < 0.01$). Similarly, when *C*'s was the more reliable brand (cells A, B, C, D, G, J, M, P), the standard deviation of *C*'s increased by an average of 1.7 points ($t_{131} = 6.18$, $p < 0.01$). Turning to the style dimension, when *L*'s was the more reliable brand (cells A, B, C, D, E, H, K, N), its standard deviation increased by 1.5 points ($t_{127} = 5.60$, $p < 0.01$). Likewise, when *C*'s was the more reliable brand (cells F, G, I, J, L, M, O, P), its standard deviation increased by an average of 1.9 points ($t_{132} = 6.35$, $p < 0.01$). See Table 2 for the average perceived standard deviations

Table 2 **Average Perceived Means (Locations) and Standard Deviations for the Co-Branded Product and Brands Before and After the Alliance***

	Pre-alliance								Co-branded product				Post-alliance							
	L's				*C*'s								*L*'s				*C*'s			
	Mean		Std. dev.		Mean		Std. dev.		Mean		Std. dev.		Mean		Std. dev.		Mean		Std. dev.	
Experimental condition**	Dur	Sty	Dur	Sty	Dur	Sty	Dur	Sty	Dur	Sty	Dur	Sty	Dur	Sty	Dur	Sty	Dur	Sty	Dur	Sty
A	78.7	61.3	6.9	4.7	60.7	78.7	4.9	7.5	69.7	70.0	6.6	6.2	76.1	67.9	6.4	5.5	70.9	73.1	5.5	6.2
B	80.9	51.9	6.1	4.1	30.3	80.9	4.1	6.3	71.3	75.6	8.3	5.7	82.1	69.4	5.6	4.8	58.6	79.3	5.4	5.2
C	80.3	34.1	6.3	4.6	61.2	80.3	4.6	6.8	73.9	55.0	6.7	8.6	74.7	54.2	6.8	6.2	70.9	70.2	5.4	7.1
D	80.3	30.0	7.4	4.9	30.0	80.0	8.0	7.4	66.7	61.7	8.4	8.9	74.8	47.4	9.1	8.7	50.7	74.8	5.0	9.2
E	80.6	60.3	4.6	4.6	60.0	80.0	6.9	6.8	73.5	76.2	6.2	7.5	75.8	70.9	5.3	4.9	65.7	75.5	6.5	6.5
F	80.6	62.8	4.8	7.0	63.4	80.6	7.0	4.6	73.9	73.9	6.6	7.2	79.4	66.1	5.9	6.6	68.0	77.9	6.3	6.5
G	81.1	61.5	6.3	6.8	60.5	79.7	4.5	4.7	70.4	70.3	6.2	6.3	76.4	69.0	6.0	6.3	69.9	74.3	5.4	5.2
H	80.0	60.0	4.9	4.8	30.0	80.0	8.3	7.3	65.3	66.0	9.7	7.9	74.1	65.3	7.0	6.5	54.7	66.9	6.8	6.8
I	80.6	60.3	4.7	7.2	30.3	80.3	7.3	4.9	64.7	68.2	11.5	8.7	72.2	65.9	6.8	8.3	53.0	76.5	8.3	7.9
J	79.7	60.0	7.0	7.0	30.4	80.0	6.5	6.1	71.8	62.9	8.6	6.8	76.8	62.1	7.3	6.1	60.2	72.7	4.6	4.5
K	80.0	33.4	4.6	4.6	60.9	80.6	7.3	7.0	68.6	67.2	6.6	8.1	73.1	43.3	5.3	5.3	58.3	75.5	6.7	6.7
L	80.0	29.7	4.8	7.3	60.0	80.0	7.2	4.7	65.3	53.4	7.4	10.6	75.0	40.9	5.3	6.6	59.0	73.8	6.5	6.0
M	80.6	30.0	6.5	6.8	60.0	80.0	4.8	4.6	72.7	64.7	9.0	10.0	76.0	43.9	8.3	9.4	58.8	74.7	7.8	8.4
N	80.0	30.0	4.6	4.6	28.9	80.0	7.0	7.1	61.4	65.5	9.0	9.1	69.5	47.0	6.3	7.4	52.9	65.6	7.7	7.3
O	80.0	30.0	4.6	7.2	30.0	80.0	7.0	4.8	69.1	56.6	6.1	6.6	76.4	43.2	5.9	8.4	47.6	63.3	8.2	6.2
P	79.4	30.9	7.0	7.0	34.1	80.3	4.9	4.7	64.1	60.6	8.0	8.5	68.2	45.6	8.0	7.7	49.4	69.1	6.9	6.7
Small durability distance	80.3	46.5	5.6	5.8	60.8	80.0	5.9	5.8	71.1	66.3	6.9	8.1	75.8	57.0	6.2	6.4	65.2	74.3	6.3	6.6
Large durability distance	80.1	45.2	5.8	5.9	30.5	80.2	6.0	5.8	66.8	64.6	8.7	7.8	74.2	55.7	7.0	7.2	53.4	71.1	7.2	6.9
Small style distance	80.3	60.8	5.7	5.8	45.7	80.0	5.9	5.8	70.1	70.4	7.9	7.0	76.6	67.1	6.3	6.1	62.6	74.6	6.4	6.3
Large style distance	80.1	31.0	5.8	5.9	45.8	80.2	5.9	5.9	67.8	60.6	7.7	8.8	73.5	45.8	6.9	7.5	56.0	70.9	7.1	7.2
L's (*C*'s) reliable (less reliable) on durability	80.2	45.9	4.7	5.9	45.6	80.2	7.2	5.9	67.8	66.0	7.9	8.2	74.4	55.5	6.0	6.7	57.4	72.0	7.1	6.7
C's (*L*'s) reliable (less reliable) on durability	80.1	45.8	6.7	5.8	45.9	80.0	4.7	5.8	70.1	65.0	7.7	7.7	75.6	57.3	7.2	6.8	61.1	73.5	6.4	6.8
L's (*C*'s) reliable (less reliable) on style	80.1	45.9	5.7	4.6	45.5	80.1	6.0	7.0	68.9	67.1	7.7	7.8	75.0	58.1	6.5	6.1	60.4	72.7	6.5	6.9
C's (*L*'s) reliable (less reliable) on style	80.3	45.8	5.7	7.0	46.0	80.1	5.9	4.7	69.0	63.9	7.9	8.1	75.0	54.7	6.7	7.4	58.2	72.8	7.0	6.6
All subjects	80.2	45.8	5.7	5.8	45.7	80.1	5.9	5.8	68.9	65.5	7.8	7.9	75.0	56.4	6.6	6.8	59.3	72.7	6.7	6.8

*Dur corresponds to the durability attribute and Sty corresponds to the style attribute.

**Small durability distance condition includes subjects in cells A, C, E, F, G, K, L, M; large durability distance condition cells B, D, H, I, J, N, O, P; small style distance condition cells A, B, E, F, G, H, I, J; large style distance condition cells C, D, K, L, M, N, O, P; *L*'s (*C*'s) reliable (less reliable) on durability condition cells E, F, H, I, K, L, N, O; *C*'s (*L*'s) reliable (less reliable) on durability condition cells A, B, C, D, G, J, M, P; *L*'s (*C*'s) reliable (less reliable) on style condition cells: A, B, C, D, E, H, K, N; and *C*'s (*L*'s) reliable (less reliable) on style condition cells: F, G, I, J, L, M, O, P.

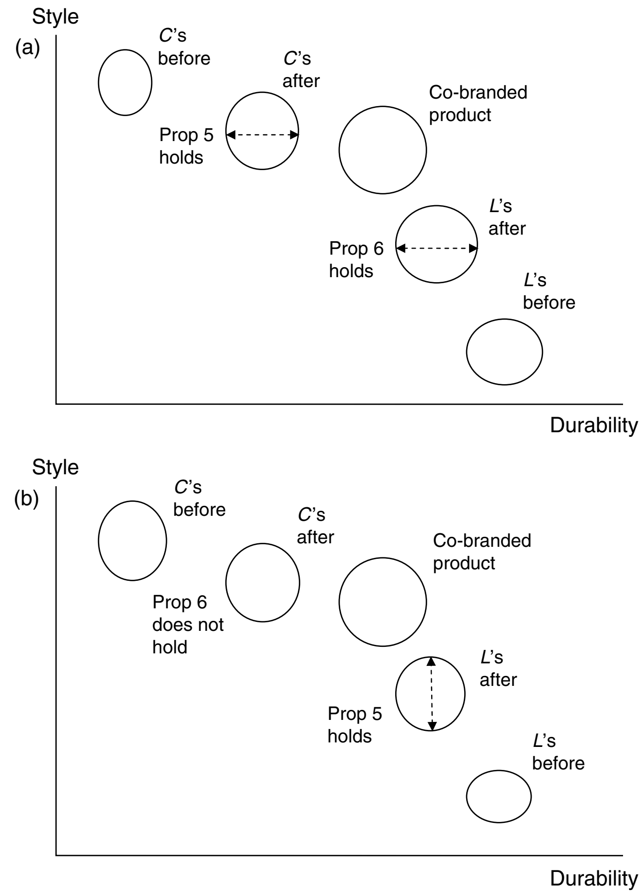
when L's was the reliable brand on durability and style and when C's was the reliable brand on these dimensions.

Proposition 6 predicts that the perceived standard deviation of the less reliable partner will increase on the attribute for which it is salient. This proposition is not supported. When L's was the less reliable brand on the durability dimension (cells A, B, C, D, G, J, M, P), its standard deviation on durability increased by an average of 0.5 points through the alliance ($t_{131} = 1.72$, $p < 0.1$). When C's was the less reliable brand on the style dimension (cells A, B, C, D, E, H, K, N),[14] its standard deviation on style decreased by an average of 0.1 points through the alliance ($t_{127} = 0.47$, *NS*).

Figures 1(a) and 1(b) visually depict the results of our experiment for Propositions 5 and 6. Figure 1(a) represents the condition in which C's is more reliable than L's on durability, and Figure 1(b) shows the case where L's is more reliable than C's on style. In these figures, the partner brands and the co-branded product are represented as ellipses. While the centers of the ellipses illustrate the average perceived mean (location) of the brands, the diameters along each attribute dimension represent the average perceived standard deviation on that dimension. The larger the diameter, the higher the perceived standard deviation. According to both Figures 1(a) and 1(b) on each attribute, the average perceived location of the co-branded product was between the average perceived locations of the partner brands and closer to the brand for which the attribute is salient. Furthermore, the partner brands attracted each other on each attribute, but the brand for which a given attribute is most salient attracted the other brand more. In these figures, dashed arrows demonstrate the change in perceived standard deviation as a result of the alliance. As shown for the durability case in Figure 1(a), when C's was the reliable brand (smaller diameter along durability dimension) and L's was the less reliable brand (larger diameter along durability), the diameters of both C's and L's increased along this dimension, suggesting an increase in average perceived standard deviation for both brands. Turning to Figure 1(b) for the style attribute, when L's was the reliable brand and C's was the less reliable brand, the diameter of only L's increased through the alliance, indicating empirical support for only Proposition 5.

Finally, Proposition 7 predicts that the total perceived standard deviation of the partners on an attribute will increase if the brand to which this attribute is salient is the less reliable one. This proposition is supported. When L's was the less reliable brand on the durability dimension (cells A, B, C, D, G, J, M, P), the total standard deviation of the partners (on durability) increased by an average of 2.2 points via the alliance ($t_{131} = 4.60$, $p < 0.01$), as indicated by the increase in the total diameter of the partner brands along the durability dimension in Figure 1(a). Similarly, when C's was the less reliable brand on the style dimension (cells A, B, C, D, E, H, K, N), the total standard deviation of the partners (on style) increased by an average of 1.4 points through the alliance ($t_{127} = 2.73$, $p < 0.01$). (See the increase in the total diameter along the style dimension in Figure 1(b).)[15]

Figure 1 **Illustration of Results: (a) *C*'s (*L*'s) Reliable (Less Reliable) on Durability; (b) *L*'s (*C*'s) Reliable (Less Reliable) on Style**



7. Conclusions

In this paper, we propose a new analytical framework of co-branding that allows marketers to gain a better

[14] Note that the distance requirement of the proposition was satisfied in the cells that we used to test this proposition (i.e., the brands were sufficiently far apart on each of the attributes).

[15] Strictly speaking, this proposition, as is the case for Proposition 2B, requires the co-branded product to be equally consistent with the partner brands. Thus, we also tested this proposition in those cells where the co-branded product was perceived to be equidistant from the partner brands (cells A, D, G, and P when L's was the less reliable brand on durability, and cells A, D, E, and N when C's was the less reliable brand on style). The results were substantively identical.

understanding of the effects of co-branding on the images of their brands. Our analysis provides insights into when allying for image reinforcement is a viable strategy for brands. We identify conditions in which a brand's image can be reinforced by borrowing from the higher performance of its partner brand, or impaired through increased uncertainty of consumers introduced through dissimilar brand images. We obtain these insights through the notion that consumers use individual products of a brand to construct a distribution of a brand's beliefs.

We conceptualize an attribute belief as a two-dimensional construct with location reflecting the expected value of the attribute and reliability reflecting the degree of certainty about the attribute. We argue that these constructs are updated when consumers are exposed to a co-branding activity, and we develop an updating mechanism involving a mixture formulation. We formalize the formation of beliefs of co-branded products using the notion that the greater the salience of an attribute to a brand, the greater the likelihood of accessing associations from memory. Our model generates a number of propositions, which were tested in an experiment. Six of the seven propositions are confirmed. We feel that the combination of theory and data provides a sound and reliable basis for our results. The major implications of our research are threefold:

1. *It is not always in a brand's interest to choose a partner brand that is of the highest performance possible*. Our model predicts that partner brands attract each other through an alliance. That is, the difference between the locations (means of the belief distributions) of the brands decreases through an alliance. This was supported by the experiment that showed attraction of brands through co-branding, and that the location of the co-branded product is between the locations of the partner brands. Therefore, co-branded product perceptions will improve with a high performance partner.

The result that partner brands attract each other through an alliance successfully replicates the findings of Park et al. (1996). However, we also find a significant increase in the uncertainty associated with the co-branded product as the difference between locations of the partner brands increases. This occurs because the partner's location tends to increase consumers' uncertainty about the co-branded product, thereby making the partner a less favorable option relative to alternative, less distant partners. Our results also show that the updating process of the partner brand beliefs is less acute when the distance between the brands is large, due to the discounting of the co-branded product information. Thus, when the co-branded product involves brands with inconsistent images, consumers revise their prior beliefs only slightly. Considering that partner brands attract each other through an alliance, it is best to collaborate with a brand that is perceived to have a moderately higher performance. With a partner performing moderately higher, attribute belief of the brand will be enhanced with less discounting.

2. *Co-branding for image reinforcement may not be a viable strategy for a reliable brand.* Both our analytical derivations and our empirical results imply this. The uncertainty associated with the more reliable brand increases as a result of co-branding. There are two reasons behind this result. First, there is a transfer of uncertainty from the less reliable brand to the more reliable brand. Second, consumers are likely to be more uncertain about a co-branded product that is somewhat inconsistent with the prior brand belief. This perception reflects back on the partner brands, resulting in higher posterior variances. Although the location of a reliable brand may improve when it co-brands with a brand that is moderately better performing, its reliability decreases no matter what partner it chooses. Managers of reliable brands should carefully consider the trade-off between this risk of image impairment and the advantages of collaboration.

3. *Co-branding may improve locations of the partner brands, while increasing the uncertainty associated with them.* Our results show that under certain conditions, while the combined reliability of the partner brands decreases, their combined location improves through the alliance. Although total uncertainty may increase due to the increase in the uncertainty associated with the more reliable partner, the overall location of the brands may improve because the brand for which the attribute is salient attracts the other brand. Because each partner salient on a particular attribute will typically outperform the partner on that attribute, this complementary salience effect improves both partners' positions. Thus, one cannot say whether co-branding generally results in image impairment or image reinforcement. While co-branding is likely to result in image reinforcement from the perspective of location or average performance, it is likely to result in image impairment from the perspective of reliability.

In this paper, we consider the type of brand alliances that are driven by the need to leverage complementary brand attribute strengths. We recognize that some other factors beyond the scope of this manuscript might explain some brand alliances. The partner brands may be aiming to fortify abstract similarities via their alliance. Lexus and Coach (Lexus Coach Edition), for instance, are similar in their upscaleness. Companies can also use brand alliances to gain access to proprietary markets (e.g., Northwest Airlines and KLM), and brand alliances can serve as quality signals when an individual brand is unable to successfully signal quality by itself. For example, concerns about NutraSweet's potential harmful health effects were only allayed after it co-branded with Coca-Cola and Pepsi (Rao et al. 1999). Finally, co-branding arrangements enable businesses to offer their customers enhanced benefit packages, often at a minor additional cost to their mainstream operations. A wide range of companies (e.g., retailers, hotels, airlines) use these types of arrangements to offer widely accepted credit cards that they cannot offer on their own (Blackett and Boad 1999).

As in any research, our work is not without limitations. First, our model assumes normal distributions for attribute beliefs. It is possible that consumer beliefs are better represented by other distributions. Second, our stylized model does not take into account possible unobserved synergies between the brands that could cause posterior means of both of the two partner brands to be more positive or more negative than the prior means. Third, it is worth exploring the variables that affect the mixture weights of the belief formation process of the co-branded product and of perception updating. For example, investigating variables like the need for cognition (Cacioppo and Petty 1982) and brand familiarity (Simonin and Ruth 1998) may provide more insights. We expect consumers with low need for cognition to be less concerned about incorporating new information into their beliefs and a result should be slower to revise their beliefs about the partner brands than high need for cognition consumers. Prior familiarity with the brands, on the other hand, is likely to affect the extent to which the attribute beliefs of the partner brands change through an alliance. For familiar brands, consumers have well-established and extensive associations, while for unfamiliar brands these associations are weaker (Simonin and Ruth 1998). Thus, one can expect more movement for a less familiar brand for which attribute beliefs are more malleable than for a better-known brand through an alliance. In this research, we used a stylized model that investigates brand alliances for which the consumers are as familiar as they are with the partner brands.[16] Future research should examine alliances that involve partner brands that differ in familiarity.

We felt that it was important that the experiment have structure, because internal validity was important in testing our propositions. However, future research should test the insights from our research in a less-restrictive context. For example, one might survey frequent shopper card holders about their beliefs of partner brands prior to the launch of a co-branded product, then compare the updated partner beliefs of purchasers of the co-branded product versus the partner beliefs of non-purchasers.

[16] We thank an anonymous reviewer for pointing this out.

It is important to point out that we have not examined brand choice in this research. Rather, we have examined effects of alliances on the beliefs about each attribute and the reliability thereof. Even a small shift in the partner's position can have a significant effect on choice probability if the weight on the attribute is high. Because we focus on salient attributes, presumably this would be the case. The frequent shopper card holder data discussed above could be used to empirically assess the effect of the updated beliefs on choices after the co-branded product has been introduced.

Appendix A

Derivation of the mean and variance of a mixture of two normal distributions:[17] Using (2) and (3), the first moment of $f_{A_i}(a_i)$, $\mu_{A_i} = \int_{-\infty}^{\infty} a_i f_{A_i}(a_i)\,da_i$, can be written as:

$$\mu_{A_i} = w_i \int_{-\infty}^{\infty} a_i f_{X_i}(a_i)\,da_i + (1-w_i)\int_{-\infty}^{\infty} a_i f_{Y_i}(a_i)\,da_i. \quad \text{(A1)}$$

This reduces to:

$$\mu_{A_i} = w_i \mu_{X_i} + (1-w_i)\mu_{Y_i}. \quad \text{(A2)}$$

Again using (2) and (3), the second central moment, $\sigma^2_{A_i} = \int_{-\infty}^{\infty} (a_i - \mu_{A_i})^2 f_{A_i}(a_i)\,da_i$, can be written as:

$$\begin{aligned}\sigma^2_{A_i} &= w_i \int_{-\infty}^{\infty} (a_i-\mu_{A_i})^2 f_{X_i}(a_i)\,da_i \\ &\quad + (1-w_i)\int_{-\infty}^{\infty} (a_i-\mu_{A_i})^2 f_{Y_i}(a_i)\,da_i. \quad \text{(A3)}\end{aligned}$$

Inserting (A2) into (A3) and rearranging, we get:

$$\begin{aligned}\sigma^2_{A_i} &= w_i \int_{-\infty}^{\infty} (a_i-\mu_{X_i} + (1-w_i)(\mu_{X_i}-\mu_{Y_i}))^2 f_{X_i}(a_i)\,da_i \\ &\quad + (1-w_i)\int_{-\infty}^{\infty} (a_i-\mu_{Y_i} + w_i(\mu_{Y_i}-\mu_{X_i}))^2 f_{Y_i}(a_i)\,da_i.\end{aligned}$$

It follows that:

$$\begin{aligned}\sigma^2_{A_i} &= w_i(1-w_i)^2(\mu_{X_i}-\mu_{Y_i})^2 + w_i\int_{-\infty}^{\infty}(a_i-\mu_{X_i})^2 f_{X_i}(a_i)\,da_i \\ &\quad + w_i^2(1-w_i)(\mu_{X_i}-\mu_{Y_i})^2 \\ &\quad + (1-w_i)\int_{-\infty}^{\infty}(a_i-\mu_{Y_i})^2 f_{Y_i}(a_i)\,da_i.\end{aligned}$$

Thus, the variance of the mixture can be written as:

$$\sigma^2_{A_i} = w_i\sigma^2_{X_i} + (1-w_i)\sigma^2_{Y_i} + w_i(1-w_i)(\mu_{X_i}-\mu_{Y_i})^2. \quad \text{Q.E.D.}$$

Proof of Proposition 1. According to (4) $\mu_{A_i} = w_i\mu_{X_i} + (1-w_i)\mu_{Y_i}$ with $0 < w_i < 1$. Thus, the location of the co-branded product is a convex combination of the locations of the partner brands. Hence μ_{A_i} is between μ_{X_i} and μ_{Y_i}.

Since $0 < w_2 < 0.5 < w_1 < 1$, then $w_1 > (1-w_1)$ and $w_2 < (1-w_2)$. Thus, on Attribute 1 $|\mu_{A_1} - \mu_{X_1}| < |\mu_{A_1} - \mu_{Y_1}|$, and on Attribute 2 $|\mu_{A_2} - \mu_{Y_2}| < |\mu_{A_2} - \mu_{X_2}|$. Q.E.D.

[17] Although mean and variance of a mixture of two normal distributions given by (4) and (5), respectively, are well known in statistics (see for example Cohen 1967, pp. 15–16), to our knowledge these results have not been used in the marketing literature before. Therefore, we present their derivation in this appendix.

Proof of Proposition 2. According to (11) and (12), the post-alliance locations of the partner brands are functions of their pre-alliance locations:

$$\mu_{X'_i} = (1-\Gamma_{X_i}(1-w_i))\mu_{X_i} + \Gamma_{X_i}(1-w_i)\mu_{Y_i}, \tag{A4}$$

$$\mu_{Y'_i} = \Gamma_{Y_i} w_i \mu_{X_i} + (1-\Gamma_{Y_i} w_i)\mu_{Y_i}. \tag{A5}$$

Notice that $(1-\Gamma_{X_i}(1-w_i))$, $\Gamma_{X_i}(1-w_i)$, $\Gamma_{Y_i} w_i$, and $(1-\Gamma_{Y_i} w_i)$ are all bounded by zero and one, and that $(1-\Gamma_{X_i}(1-w_i)) + \Gamma_{X_i}(1-w_i) = 1$ and $\Gamma_{Y_i} w_i + (1-\Gamma_{Y_i} w_i) = 1$. So the post-alliance means of the partner brands are convex combinations of their pre-alliance means. Therefore, $\mu_{X'_i}$ and $\mu_{Y'_i}$, are contained in a smaller interval than μ_{X_i} and μ_{Y_i}, hence $|\mu_{X_i} - \mu_{Y_i}| > |\mu_{X'_i} - \mu_{Y'_i}|$.

Rearranging terms in Equations (A4) and (A5), we obtain:

$$|\mu_{X'_i} - \mu_{X_i}| = \Gamma_{X_i}(1-w_i)|\mu_{X_i} - \mu_{Y_i}|, \tag{A6}$$

$$|\mu_{Y'_i} - \mu_{Y_i}| = \Gamma_{Y_i} w_i |\mu_{X_i} - \mu_{Y_i}|. \tag{A7}$$

If Attribute 1 is salient to Brand X ($1 > w_1 > 0.5$), and if the co-branded product is equally consistent with the partner brands ($\Gamma_{X_1} = \Gamma_{Y_1}$), (A6) and (A7) imply $|\mu_{Y'_1} - \mu_{Y_1}| > |\mu_{X'_1} - \mu_{X_1}|$. If Attribute 2 is salient to Brand Y ($1 > 1 - w_2 > 0.5$), this time (A6) and (A7) imply $|\mu_{Y'_2} - \mu_{Y_2}| < |\mu_{X'_2} - \mu_{X_2}|$. Q.E.D.

Proof of Proposition 3. Taking partial derivative of (5) with respect to the squared distance gives:

$$\frac{\partial \sigma^2_{A_i}}{\partial(\mu_{X_i} - \mu_{Y_i})^2} = w_i(1-w_i) > 0.$$

Note that $0 < w_i < 1$ implies $w_i(1-w_i) > 0$. Therefore, the uncertainty (variance) associated with the co-branded product on an attribute increases with increasing distance between the brands. Since $|\mu_{X_i} - \mu_{Y_i}|$ is a monotonic transformation of $(\mu_{X_i} - \mu_{Y_i})^2$, this proves Proposition 3. Q.E.D.

Proof of Proposition 4. Rearranging Equations (A6) and (A7) gives:

$$\frac{|\mu_{X'_i} - \mu_{X_i}|}{|\mu_{X_i} - \mu_{Y_i}|} = \Gamma_{X_i}(1-w_i), \tag{A8}$$

$$\frac{|\mu_{Y'_i} - \mu_{Y_i}|}{|\mu_{X_i} - \mu_{Y_i}|} = \Gamma_{Y_i} w_i. \tag{A9}$$

Taking partial derivatives of (A8) and (A9) with respect to Γ_{X_i} and Γ_{Y_i} gives:

$$\partial \frac{|\mu_{X'_i} - \mu_{X_i}|}{|\mu_{X_i} - \mu_{Y_i}|} \Big/ \partial \Gamma_{X_i} = (1-w_i) > 0, \tag{A10}$$

$$\partial \frac{|\mu_{Y'_i} - \mu_{Y_i}|}{|\mu_{X_i} - \mu_{Y_i}|} \Big/ \partial \Gamma_{Y_i} = w_i > 0. \tag{A11}$$

Let $d_{X_i - Y_i} = |\mu_{X_i} - \mu_{Y_i}|$ and

$$d_{A-X} = \sqrt{\sum_{i=1}^{2} (\mu_{A_i} - \mu_{X_i})^2} \quad \text{and} \quad d_{A-Y} = \sqrt{\sum_{i=1}^{2} (\mu_{A_i} - \mu_{Y_i})^2}$$

as mentioned in the main text. Given that $\mu_{A_i} = w_i \mu_{X_i} + (1-w_i)\mu_{Y_i}$ observe $\partial d_{A-X}/\partial d_{X_i - Y_i} > 0$ and $\partial d_{A-Y}/\partial d_{X_i - Y_i} > 0$.

Equations (A10), (A11), and (8) imply $\partial(|\mu_{X'_i} - \mu_{X_i}|/|\mu_{X_i} - \mu_{Y_i}|)/\partial|\mu_{X_i} - \mu_{Y_i}| < 0$ and $\partial(|\mu_{Y'_i} - \mu_{Y_i}|/|\mu_{X_i} - \mu_{Y_i}|)/\partial|\mu_{X_i} - \mu_{Y_i}| < 0$. Q.E.D.

Proposition 5. Rearranging terms in (13) and (14) gives:

$$\sigma^2_{X'_i} - \sigma^2_{X_i} = \Gamma_{X_i}(1-w_i)[(1-\Gamma_{X_i}(1-w_i)) \cdot (\mu_{X_i} - \mu_{Y_i})^2 - (\sigma^2_{X_i} - \sigma^2_{Y_i})] \quad \text{and} \tag{A12}$$

$$\sigma^2_{Y'_i} - \sigma^2_{Y_i} = \Gamma_{Y_i} w_i [(1-\Gamma_{Y_i} w_i)(\mu_{X_i} - \mu_{Y_i})^2 - (\sigma^2_{Y_i} - \sigma^2_{X_i})]. \tag{A13}$$

From (A12) and (A13), it is readily observable that $\sigma^2_{X'_i} - \sigma^2_{X_i} > 0$ if $\sigma^2_{X_i} < \sigma^2_{Y_i}$, and $\sigma^2_{Y'_i} - \sigma^2_{Y_i} > 0$ if $\sigma^2_{Y_i} < \sigma^2_{X_i}$. Q.E.D.

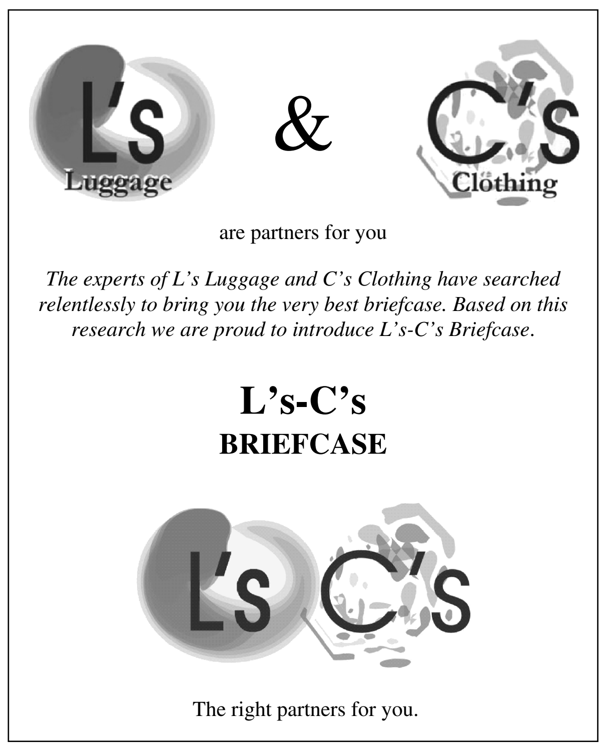
Proposition 6. Assume Attribute 1 is salient to Brand X and $\sigma^2_{X_1} > \sigma^2_{Y_1}$. According to (A12), $\sigma^2_{X'_1} > \sigma^2_{X_1}$ if $(\mu_{X_1} - \mu_{Y_1})^2 > (\sigma^2_{X_1} - \sigma^2_{Y_1})/(1 - \Gamma_{X_1}(1-w_1))$. Given $0.5 < w_1 < 1$ and $0 < \Gamma_{X_1} < 1$, $1 - \Gamma_{X_1}(1-w_1)$ will always be larger than 0.5. Therefore, we can write $\sigma^2_{X'_1} > \sigma^2_{X_1}$ if $(\mu_{X_1} - \mu_{Y_1})^2/2 > \sigma^2_{X_1} - \sigma^2_{Y_1}$. Assume Attribute 2 is salient to Brand Y and $\sigma^2_{Y_2} > \sigma^2_{X_2}$. According to (A13), $\sigma^2_{Y'_2} > \sigma^2_{Y_2}$ if $(\mu_{Y_2} - \mu_{X_2})^2 > (\sigma^2_{Y_2} - \sigma^2_{X_2})/(1 - \Gamma_{Y_2} w_2)$. Given $0 < w_2 < 0.5$ and $0 < \Gamma_{Y_2} < 1$, $1 - \Gamma_{Y_2} w_2$ will always be larger than 0.5. Therefore, we can write $\sigma^2_{Y'_2} > \sigma^2_{Y_2}$ if $(\mu_{Y_2} - \mu_{X_2})^2/2 > \sigma^2_{Y_2} - \sigma^2_{X_2}$. Q.E.D.

Proposition 7. Using (A12) and (A13) and assuming $\Gamma_{X_i} = \Gamma_{Y_i} = \Gamma_i$ one can write:

$$(\sigma^2_{X'_i} + \sigma^2_{Y'_i}) - (\sigma^2_{X_i} + \sigma^2_{Y_i}) = \Gamma_i(1-2w_i)(\sigma^2_{Y_i} - \sigma^2_{X_i}) + \Gamma_i(1 - \Gamma_i(1 - 2w_i + 2w_i^2))(\mu_{X_i} - \mu_{Y_i})^2.$$

Notice that the second term on the right-hand side is always greater than 0. The first term is also greater than 0, if Attribute 1 is salient to Brand X ($0.5 < w_1 < 1$) and $\sigma^2_{X_1} > \sigma^2_{Y_1}$, or if Attribute 2 is salient to Brand Y ($0 < w_2 < 0.5$) and $\sigma^2_{Y_2} > \sigma^2_{X_2}$. Q.E.D.

Appendix B. Ad Stimulus



Note. This ad stimulus is inspired by the one that was used by Simonin and Ruth (1998).

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