

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

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Abstract

Co-branding is often used by managers to reinforce the image of their brands. In this paper, we investigate when a brand's image is reinforced or impaired as a result of co-branding, and which partner is right for a firm that considers co-branding for image reinforcement. We address these issues by examining the effects of co-branding on attribute uncertainty of partner brands. We conceptualize 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 develop an analytical model that incorporates these notions. Based on categorization theory, the model describes the updating mechanism of partner brand beliefs that occur as a result of co-branding. 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 a 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, uncertainty associated with the brands increases through the alliance, increasing the risk of image impairment.

(Brand alliances; Co-Branding; Image Reinforcement; Brand Positioning)

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, 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). In recent years, with an annual 40% growth rate, co-branding has become a strategic tool for many companies to attain higher market shares (Dignam 1999). For instance, it has been reported that 43% of the credit cards in circulation are co-branded (Punch 2001).

There are a variety of reasons driving the surge in co-branding, ranging from the desire to gain access to new markets to the attempt to signal unobservable quality (Rao and Ruekert 1994; Rao, Qu, and Ruekert 1999). In this research, we focus on conditions under which co-branding drives image reinforcement versus image impairment for the partner brands. Our contribution stems from the answers to two major questions that we seek to address. First, when does image reinforcement or impairment occur as a result of co-branding? Second, which partner is right for a firm that considers co-branding for image reinforcement? These questions are of great importance for managers considering co-branding as a possible image reinforcement strategy for their brands. For example, Renault launched its Twingo-Kenzo car to reinforce its image of being stylish (Kapferer 1999). Consumers may update their perceptions of Renault as a result of this co-branded product.

Brand alliances may 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 (Fisher 1994, Simonin and Ruth 1998). Venkatesh and Mahajan (1997) show that branded components may suppress the value of their partners (1997). According to a recent study, almost half of strategic alliances fail (Dyer et al. 2001). “Who you are associated with is a key question,” says John Hagel, a McKinsey Consultant (Mitchell 1997). Thus, a strategic approach to identify the right partner is essential for firms considering alliances (Blackett and Boad 1999).

Consider the Slim-Fast and Godiva co-branding example (Slim-Fast-Godiva Chocolate Cake Mix) from the brand alliances literature (Park, Jun, and Shocker 1996). Assume that consumers perceive Godiva as a good tasting but unhealthy brand and Slim-Fast as a poor tasting but healthy brand. When these inconsistent beliefs are combined via an alliance, this may result in confusion about the co-branded product. This uncertainty may in turn reflect back upon the perceptions of the partner brands, resulting in an increase in consumers’ uncertainty about Slim-Fast being a healthy brand and Godiva being a good tasting brand. Thus, rather than being a win-win for Godiva and Slim-Fast, such an alliance may hurt the positioning of Godiva as a good tasting brand and Slim-Fast as a healthy brand.

One important result of our research is that it is not necessarily in a brand’s interest to choose the best performing partner on the attribute of interest. Rather, it is optimal to collaborate with a brand that is perceived to be of only moderately higher performance. We find that inconsistent images of the partner brands may result in confusion about the co-branded product and cause high uncertainty about the alliance. Moreover, when the brands are far apart, the co-branded product is regarded as an exception, and thus does not substantially affect the formation of posterior partner beliefs. Another important result is that the overall perception of both partner brands improves as a result of co-branding, suggesting that alliance brands reinforce the partners’

images. This is due to the pull of the higher performing brand. However, under certain conditions, uncertainty associated with the brands increases through co-branding. This is due to uncertainty transfer between the brands and to possible consumer confusion that can arise from a co-branded product that is inconsistent with the partner brands' prior image.

The remainder of this paper is organized as follows. In section 2, we review the relevant research on co-branding and alliances. We develop an analytical model based on theories from the behavioral literature in section 3, and generate several empirically testable propositions that follow from our model in section 4. In section 5, we present an experiment and test our propositions. We conclude with a discussion of the managerial implications of our findings, together with limitations and directions for future research.

2. Related 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 of complementarity of the partners' attributes on the attribute profiles of the composite brand extension (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 not complementary brands. Simonin and Ruth (1998) suggest that consumer attitudes toward a co-branded or allied

product¹ affect their post-alliance attitudes of the partner brands and that these effects are moderated by brand familiarity.

Samu, Krishnan and Smith (1999) examine the effectiveness of advertising alliances for introducing new brands. They explore the effects of different advertising strategies on brand awareness, brand accessibility, brand beliefs, belief accessibility and brand attitudes and show that product complementarity plays an important role in choosing the right advertising strategy. Finally, Desai and Keller (2002) analyze how different ingredient branding strategies, namely, branding the target attribute ingredient as a self-branded ingredient and as a co-branded ingredient influence consumer acceptance of brand expansions. They show that co-branded ingredients facilitate initial acceptance of expansions.

All of the above-mentioned studies investigated attribute or affect transferal that occurs as a result of co-branding. We not only analyze attribute transferal but also how co-branding affects *attribute uncertainty* of the partner brands and that of the co-branded product. We conceptualize a specific attribute belief as a two-dimensional construct with location reflecting the expected value of the attribute (i.e., the mean of the belief's distribution) and reliability reflecting the degree of certainty that consumers have about the performance of the brand on the attribute (inverse of the variance of the belief's distribution). We argue that these parameters are updated after consumers are exposed to the co-branding activity. We incorporate behavioral theories in a mathematical formulation for updating the location and degree of certainty in a multi-attribute co-branding model in which partner brands complement one another in terms of attribute performances and saliencies. Several propositions follow from our model, which we test in an experiment.

¹ We use co-branded product and allied product interchangeably.

3. A Model of Brand Alliances

Several studies have looked at consumers' use of new information to update their prior perceptions. In Boulding et al. (1993), cumulative quality perceptions were updated by a linear updating scheme while Rust et al. (1999) and Boulding et al. (1999) use Bayesian updating. In all of these studies, consumers update their prior quality beliefs with the perceived quality of the most recent transaction to come up with posterior beliefs. In our paper, consumers update their attribute beliefs of partner brands with their perceptions of the co-branded product.

Specifically, we assume that consumers use individual products of a brand to construct a distribution of products under that brand name. That is, consumers do not consider specific attribute beliefs of a brand name as points but rather as distributions. Brands with several product offerings come to be associated with a number of specific attributes ("quality," "gentleness," "mildness") based on the attributes associated with the brand's individual offerings (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). For each of these products, a consumer may have a different level of perceived mildness. The distribution of these perceptions forms her belief about Neutrogena's mildness.

This formulation is analogous to the research in cognitive psychology regarding category acquisition and representation, the most prominent of which are exemplar models and prototype models (see Smith and Medin 1981 for a review). In the exemplar view of categorization, the category is represented through separate descriptions of the category members (e.g., Hintzman 1986). Classification of a new instance is based on its similarity to individual items in the alternative categories. The prototype view holds that previous exposures lead to a summary

description, or central tendency (e.g., Posner and Keele 1968). Classification of new instances is based on their similarity to prototypes of alternative categories.

While these models capture the central tendency of category members with respect to a given dimension, Posner and Keele (1968) argue that subjects also acquire and store variability information. Fried and Holyoak (1984) propose a “category density model” in which individual exemplars are used to construct a category density function along certain attribute dimensions. According to Fried and Holyoak, these density functions are stored in memory via their means and variances and are continuously updated as newly presented instances occur. Park and Hastie (1987) validate this framework by showing that perceptions of variability influenced subjects’ tendency to generalize the traits of a single member to the entire group.

We view a brand belief as a two dimensional construct, captured by its *location* and *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 quite certain that quality is high.

In our mathematical formulation we consider two brands, X and Y that form an alliance. Let $i = 1, 2$ denote two attributes of brands X and Y which are forming an alliance. We assume that attribute beliefs X_i and Y_i are normally distributed with μ_{xi} and σ_{xi}^2 being the mean and variance of brand X , and μ_{yi} and σ_{yi}^2 being the mean and variance of brand Y on attribute i :

$$X_i \sim N(\mu_{xi}, \sigma_{xi}^2), Y_i \sim N(\mu_{yi}, \sigma_{yi}^2) \quad (1)$$

Park et al. (1996) argue that an alliance makes sense when the partner brands are complementary, in that performance level strengths and weaknesses mesh well. In line with Park

et al., we assume that complementarity is present when (1) two brands have a common set of relevant attributes, (2) the two brands differ in terms of the attribute with which they are most strongly associated², and (3) the brand for which the attribute is most strongly associated has a higher performance rating on that attribute.

Assuming the brands are complementary brands such that attribute 1 is salient to brand X and attribute 2 is salient to brand Y , and $\mu_{x1} > \mu_{y1}$ and $\mu_{y2} > \mu_{x2}$, we formulate the distribution of the allied product (co-branded product) beliefs (A_i) as mixtures of the partner brand beliefs:

$$P(A_1|X_1, Y_1) = w_1 P(X_1) + (1 - w_1) P(Y_1) \quad (2)$$

$$P(A_2|X_2, Y_2) = w_2 P(X_2) + (1 - w_2) P(Y_2) \quad (3)$$

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). Further, the greater the strength of the association, the greater its accessibility from memory (e.g., Anderson 1983; Posavac, Sanbonmatsu, and Fazio 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). This suggests that the greater the association between a particular attribute and a brand, the greater the probability that the attribute will be activated in memory upon exposure to the brand. Accordingly, in equations (2) and (3), we assume that the partner attribute belief that is most

² Hereafter, to be consistent with Park et al. (1996), we use the term ‘salience’ to refer to this differential attribute-brand association.

salient will be more likely to contribute to the formation of the alliance belief than the partner belief which is less salient.

Equations (1) through (3) represent a finite mixture of normal distributions, so the first two moments can be obtained in closed form (Bowman and Shenton 1973). The mean $E(A_i)$ and variance $Var(A_i)$ of the allied product are functions of the first two moments of the distributions of beliefs of brands X and Y :

$$E(A_i) = w_i \mu_{xi} + (1 - w_i) \mu_{yi} \quad (4)$$

and

$$Var(A_i) = w_i \sigma_{xi}^2 + (1 - w_i) \sigma_{yi}^2 + w_i (1 - w_i) (\mu_{yi} - \mu_{xi})^2 \quad (5)$$

The location of the allied product on an attribute is a weighted average of the two brand locations with the weights determined by the salience of the brands on the attribute. Since the location of the co-branded product is determined by multiplying the poorer performing brand of each attribute with w_i (see Equations (2) and (3)), a perceptual synergy between the partners is formed in the sense that the attribute profile (i.e., location of the co-branded product on each attribute) of the co-branded product reflects the performance of the partner that is most salient on each attribute. The perceived variance of the allied product is also a weighted sum, augmented with a term that depends on the weight and distance between the partner brand locations. That is, greater distance between the partner brands reduces the reliability of the allied product, capturing increased consumer confusion due to inconsistent brand images.

In line with the formation of beliefs of the co-branded product in Equation (2), we formulate the posterior beliefs of the partner brands after the alliance (X_i' and Y_i') as a mixture

of the allied product beliefs and the pre-alliance beliefs of the partner brands with weights Γ_{xi} and Γ_{yi} ($0 < \Gamma_{xi}, \Gamma_{yi} < 1$):

$$P(X_i') = \Gamma_{xi}P(A_i|X_i, Y_i) + (1 - \Gamma_{xi})P(X_i) \quad (6)$$

$$P(Y_i') = \Gamma_{yi}P(A_i|X_i, Y_i) + (1 - \Gamma_{yi})P(Y_i) \quad (7)$$

Thus, in this formulation consumers use their perceptions of the co-branded product to update their beliefs about the partner brands. In specifying the mixture weights, we need a model of stereotype change. Prior research has used models of stereotype change to model the modification of brand schemas in response to new information (e.g., Loken and John 1993; Gurhan-Canli and Maheswaran 1998). The two models of stereotype change that have found support from previous research are the bookkeeping model and the subtyping model (e.g. Weber and Crocker 1983, Loken and John 1993). The bookkeeping model assumes that all evidence is used to revise the stereotype (attribute belief in this case) and that only the amount of evidence determines the magnitude of change (Weber and Crocker 1983). Thus, the more distant the alliance from the partner brand, the greater the effect of the alliance on the formation of posterior beliefs.

According to the subtyping model, when instances are so incongruent that they cannot be assimilated by established stereotypes, subtypes develop. Because subtyped individuals differ from the other group members, they may be regarded as exceptions and therefore unrepresentative of the overall group (Weber and Crocker 1984). If subtyped, the new instance (i.e., co-branded product) will have little or no effect on the stereotype (beliefs of the partners). In our posterior belief formulation, we can use the mixture weights to capture the probability that subtyping will occur. The more distant the alliance from the partner brand, the greater will be the

probability of subtyping and, therefore, the greater the probability that the allied product will not contribute to the formation of posterior brand beliefs.

In line with these considerations, we can specify the mixture weights for the posterior belief formation. If the bookkeeping model is in effect, we should have:

$$\frac{\partial \Gamma_{xi}}{\partial d_{A-X}} > 0 \text{ and } \frac{\partial \Gamma_{yi}}{\partial d_{A-Y}} > 0, \quad (8)$$

and if the subtyping model is in effect, we should have:

$$\frac{\partial \Gamma_{xi}}{\partial d_{A-X}} < 0 \text{ and } \frac{\partial \Gamma_{yi}}{\partial d_{A-Y}} < 0 \quad (9)$$

where $d_{A-X} = \sqrt{\sum_{i=1}^2 (E(A_i) - \mu_{xi})^2}$ and $d_{A-Y} = \sqrt{\sum_{i=1}^2 (E(A_i) - \mu_{yi})^2}$ are the Euclidian distances between the co-branded product and the partner brands.^{3, 4}

We are interested in deriving the post-alliance distributions of attribute beliefs X_i' and Y_i' . Substituting $P(A_i|X_i, Y_i)$ from equations (2) and (3) into equations (6) and (7) gives the conditional distributions, given the prior beliefs of X and Y :

$$P(X_i'|X_i, Y_i) = (1 - \Gamma_{xi}(1 - w_i)) \cdot P(X_i) + \Gamma_{xi}(1 - w_i) \cdot P(Y_i) \quad (10)$$

$$P(Y_i'|X_i, Y_i) = \Gamma_{yi} w_i P(X_i) + (1 - \Gamma_{yi} w_i) P(Y_i) \quad (11)$$

Equations (10) and (11) again represent finite mixtures of normal distributions. So the posterior means can be obtained as:

³ Previous research has investigated brand schema change in terms of the number of inconsistent attributes when using subtyping and bookkeeping models (Loken and John 1993, Gurhan-Canli and Maheswaran 1998). In this research, we measure inconsistency in terms of the Euclidian distance between the locations of partner brands and the allied product in the multi-attribute space.

⁴ Note that in the above formulations, we allow the effect of the allied product on the formation of posterior beliefs of the partners to be different ($\Gamma_{xi} \neq \Gamma_{yi}$). However, these two effects will be equal to each other ($\Gamma_{xi} = \Gamma_{yi} = \Gamma_i$) if the co-branded product is perceived to be equally important to the partners.

$$E(X_i') = (1 - \Gamma_{xi}(1 - w_i))\mu_{xi} + \Gamma_{xi}(1 - w_i)\mu_{yi} \quad (12)$$

$$E(Y_i') = \Gamma_{yi}w_i\mu_{xi} + (1 - \Gamma_{yi}w_i)\mu_{yi} \quad (13)$$

and the posterior variances as:

$$Var(X_i') = \Gamma_{xi}(1 - w_i)\sigma_{yi}^2 + (1 - \Gamma_{xi}(1 - w_i))\sigma_{xi}^2 + (1 - \Gamma_{xi}(1 - w_i))\Gamma_{xi}(1 - w_i)(\mu_{yi} - \mu_{xi})^2 \quad (14)$$

$$Var(Y_i') = \Gamma_{yi}w_i\sigma_{xi}^2 + (1 - \Gamma_{yi}w_i)\sigma_{yi}^2 + \Gamma_{yi}w_i(1 - \Gamma_{yi}w_i)(\mu_{yi} - \mu_{xi})^2 \quad (15)$$

Using this formulation, we are able to 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 beliefs, weighted by the mixing weights w_i and Γ_{xi} or Γ_{yi} . The posterior variances are weighted averages of prior beliefs plus a term that is a function of the distance between the locations of the partner brands. The farther the partner brand locations prior to the alliance, the greater the likelihood that consumers will become confused about the allied product. This confusion reflects back on the perceptions of the partner brands, resulting in higher posterior variances (i.e., lower reliability).

4. Propositions

Several empirically testable propositions follow from the co-branded product and posterior partner brand parameters given in equations (4), (5), and (12) through (15). While some of these propositions concern perceptions of the co-branded product (Propositions 1 and 2), others pertain to the spillover effects of the allied product on partner brand beliefs (Propositions 3, 4, 5, 6 and 7). 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 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 , $\mu_{x1} > \mu_{y1}$, and $\mu_{y2} > \mu_{x2}$, then $\mu_{xi} < E(A_i) < \mu_{yi}$, $|E(A_1) - \mu_{x1}| < |E(A_1) - \mu_{y1}|$, and $|E(A_2) - \mu_{x2}| > |E(A_2) - \mu_{y2}|$. This follows from the salient brand belief being more accessible in memory. Thus, it contributes more to the formation of the allied product belief. For example, if Slim-Fast's salient attribute is healthiness and Godiva's is taste, then their co-branded product will reflect more the healthiness of Slim-Fast and taste of Godiva. The allied product will be perceived to be healthy and good taste.

PROPOSITION 2: The farther apart the partner brands on an attribute (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 $\frac{\partial \text{Var}(A_i)}{\partial |\mu_{xi} - \mu_{yi}|} > 0$. When the brands are located far apart, the inconsistent images of the partners are likely to confuse consumers. This gives rise to increased uncertainty about the allied product ($\text{Var}(A_i)$ increases). 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 3: On each attribute, partner brands attract each other through the alliance. Further, given that the allied product is equally important to the partners, 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 the reverse applies to attribute 2.

That is $|\mu_{xi} - \mu_{yi}| > |E(X_i') - E(Y_i')|$, and given that the brands are complementary brands such that attribute 1 is salient to brand X , attribute 2 is salient to brand Y , and

$\mu_{x1} > \mu_{y1}$, $\mu_{y2} > \mu_{x2}$, and if $\Gamma_{xi} = \Gamma_{yi}$ then $|E(Y_1') - \mu_{y1}| > |E(X_1') - \mu_{x1}|$ and

$|E(Y_2') - \mu_{y_2}| < |E(X_2') - \mu_{x_2}|$. The theoretical motivation is given by equations (12) and (13), which state that the new location of each partner brand is a convex combination of the brands' locations prior to the alliance, where the weights are determined by the salience of the attribute 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 (assuming that both partners bring a different salient attribute to the alliance). That is, $E(X_i') + E(Y_i') - (\mu_{x_i} + \mu_{y_i}) > 0$.⁵

PROPOSITION 4

- a) *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 increases.*
- b) *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.*

This proposition investigates which model of stereotype change (i.e., bookkeeping or subtyping) is in effect in the updating process of partner beliefs through co-branding.

Mathematically speaking, Proposition 4a states: $\partial\left(\frac{|E(X_i') - \mu_{x_i}|}{|\mu_{y_i} - \mu_{x_i}|}\right) / \partial|\mu_{y_i} - \mu_{x_i}| > 0$ and

$\partial\left(\frac{|E(Y_i') - \mu_{y_i}|}{|\mu_{y_i} - \mu_{x_i}|}\right) / \partial|\mu_{y_i} - \mu_{x_i}| > 0$ while Proposition 4b states $\partial\left(\frac{|E(X_i') - \mu_{x_i}|}{|\mu_{y_i} - \mu_{x_i}|}\right) / \partial|\mu_{y_i} - \mu_{x_i}| < 0$

⁵ Note that proposition 3 holds, even if $\Gamma_{X_1} \leq \Gamma_{Y_1}$ and $\Gamma_{Y_2} \leq \Gamma_{X_2}$.

and $\partial\left(\frac{|E(Y_i') - \mu_{yi}|}{|\mu_{yi} - \mu_{xi}|}\right) / \partial|\mu_{yi} - \mu_{xi}| < 0$. Proposition 4a of the proposition claims the bookkeeping

model is in effect, while Proposition 4b claims that the subtyping model is in effect. When the allied product has brands that are located far apart, the bookkeeping model predicts considerable updating because of the highly inconsistent information the co-branded product brings. However, according to the subtyping model, this highly inconsistent information results in a greater probability of subtyping and thus, the updating will be less.

PROPOSITION 5: *On each attribute, the uncertainty associated with the more reliable partner increases through the alliance.*

Mathematically, if $\sigma_{xi}^2 < \sigma_{yi}^2$, then $Var(X_i') > \sigma_{xi}^2$. The uncertainty associated with the more reliable brand increases because of uncertainty transfer from the less reliable brand. Also, the brands' inconsistent images (the distance between the locations of the partners) causes an increase in the uncertainty associated with the more reliable brand.

PROPOSITION 6: *If the two brands are sufficiently apart on an attribute (i.e., $|\mu_{xi} - \mu_{yi}| / \sigma_{yi} > \sqrt{(\max\{\sigma_{xi}^2, \sigma_{yi}^2\} / \min\{\sigma_{xi}^2, \sigma_{yi}^2\} - 1)}$) and if the brand to which this attribute is salient is the less reliable partner, the uncertainty associated with the less reliable partner increases through the alliance.*

Uncertainty associated with the less reliable brand increases because of the brands' inconsistent images (i.e., $\mu_{xi} - \mu_{yi}$ is large relative to σ_{yi}). Based on propositions 5 and 6, in our Godiva-Slim-Fast co-branding example, the uncertainty associated with both attributes of Godiva and Slim-fast may increase through their alliance.

PROPOSITION 7: *Given that the allied product is equally important when updating the partner beliefs, on an attribute, the total post-alliance uncertainty associated with both brands increases if the brand to which the attribute is salient is the less reliable one.*

In other words, $Var(X_i') + Var(Y_i') > \sigma_{xi}^2 + \sigma_{yi}^2$, if attribute i is salient to the less reliable partner and $\Gamma_{xi} = \Gamma_{yi}$. Total uncertainty associated with both brands increases due to the uncertainty transfer from the less reliable brand to the more reliable brand and the brands' inconsistent images.

We illustrate these propositions in Figure 1. The arrows represent the change of the partner brand positions as a result of an alliance. The centers of the circles represent the locations or the means of belief distributions of the brands, while the area of a circle illustrates the variances of the corresponding brands and the allied product. That is, the more reliable the brand, the smaller the circle. Our propositions are based on the distances between these centers and the areas of the circles. We see in Figure 1 that on each attribute, the location of the allied product is between the locations of the brands and closer to the brand for which the attribute is salient (Prop. 1). This effect pulls the allied product off of a line connecting the partner brands. On each attribute, the partner brands attract each other but the brand for which a given attribute is most salient attracts the other brand more (Prop. 3). Further, the uncertainty associated with both brands increases through co-branding, as reflected by the area of the circle representing the more reliable brand (brand X) increasing through co-branding (Prop 5). However, the variance of the less reliable brand (brand Y) increases only along its salient attribute dimension, turning the circle representing the less reliable brand into an ellipse (Prop 6).

[Insert Figure 1 here]

While the theoretical model forms a mathematically rigorous way of thinking about the effects of co-branding, to evaluate its usefulness we must test whether consumers behave in correspondence with the propositions. In the following section, we present the results of an

experiment in which the propositions were subjected to an empirical test. We conclude with a discussion of the implications of these results and directions for future research.

5. Experiment

5.1. Overview

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 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). Means and standard deviations of the histograms were manipulated based on the experimental conditions. The salient attribute to *L's* was durability and *C's* salient attribute was style.

The experiment was a 2 x 2 x 2 x 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). We used a balanced design with approximately the same number of subjects per cell.

[Insert Table 1 here]

5.2. Procedure

Before the experiment started, a histogram example was shown to the subjects to make sure that they understood the histograms used in the experiment (see Appendix B for a histogram example). After the example, subjects were shown a description for each partner brand, then the salience of the two attributes was measured by asking the subjects to indicate on a seven point scale the importance of each attribute in brand evaluation.⁶ Brand descriptions were used for 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 the durability of *L*'s and style of *C*'s. Second, according to Shavitt and Fazio (1990), for some product categories a particular attribute may spontaneously be salient. We believed durability to be the naturally salient attribute for luggage products and style to be naturally salient for clothing.

After the brand description and salience measurement, two histograms that depicted subjects' previous durability and style perceptions with different products of the brand were presented. 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

⁶ Direct ratings of importance are one of the methods used to measure attribute salience (Onkvisit and Shaw 1994; Engel et al. 1990). Park et al. (1996) also measure salience by asking the importance of each attribute (with a specific value) in brand evaluations. To increase our confidence in our salience measure we conducted a pretest (N=40) which showed that direct ratings of importance and strength of association (between brands and attributes) are highly correlated. Importance of attributes in brand evaluation was measured by the question: How important is the ___ (attribute) of ___ (brand)'s products for your overall evaluation of ___ (brand)? Strength of association was measured by the question: How strongly do you associate ___ (brand) with ___ (attribute). We calculated the correlation coefficients between these two measures for 3 different brands (Samsonite, Hush Puppies and Sean John) and for 2 different attributes (durability and style). The six correlation coefficients ranged between 0.62 and 0.85 (for all of the coefficients: $p < 0.01$) with an average correlation of 0.76.

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 ___”.

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 (see Appendix C). 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 unrelated filler for about 10 minutes. The subjects were asked to again report their perceived mean and standard deviation scores for each brand on each attribute, 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 $\text{std. dev.}(L's) - \text{std. dev.}(C's)$) 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 suggest that the differences of stated means and standard deviations were very close to those underlying our experiment and that our manipulations were successful (see Table 2 for average pre-alliance stated means and standard deviations for each of the experimental conditions).

[Insert Table 2 here]

We also wanted to ensure that the brands were perceived as complementary to each other. 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 (importance) rating was 1.5 points (out of 7) higher than its durability (importance) rating ($t_{260} = 15.00, p < 0.01$). These results confirm the complementarity of the two partnering brands.

6.2 Tests of Propositions

Proposition 1 predicts that on each attribute, the location of the co-branded product will be between the locations of the partner brands and closer to the brand for which the attribute is salient. This proposition is supported. On each of the attribute dimensions, the 95% confidence

interval for the location of the allied 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 allied 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 location of the allied product was (63.3, 67.6), and the average (pre-alliance) locations for *L*'s and *C*'s were 45.8 and 80.1 respectively.⁷

Moreover, 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 allied product ($t_{260} = 6.29, p < 0.01$). Specifically, the average distance between (pre-alliance location of) *C*'s and the co-branded product was 23.2, while the average distance between (pre-alliance location of) *L*'s and the allied product was 11.3. On the style dimension, the distance between *L*'s and the co-branded product was on average 5.00 points larger than that between *C*'s and the allied product ($t_{260} = 2.375, p < 0.02$). 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 means (locations) for the allied product and the partner brands for all subjects).

Proposition 2 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 the durability dimension, an ANOVA with distance conditions and the standard deviation conditions as the independent variables, and the perceived standard deviation of the co-branded product as the dependent variable revealed only a significant effect of the distance on the

⁷ On durability, the average location of the allied product was 68.9, and the 95% confidence intervals for the locations of *L*'s and *C*'s were (79.8, 80.6) and (43.8, 47.7) respectively. On style, the average location of the allied product was 65.9, and the 95% confidence intervals for the locations of *L*'s and *C*'s were (43.9, 47.8) and (79.8, 80.4) respectively.

durability dimension ($F_{1,245} = 11.03, p < 0.01$). Subjects in the large durability distance condition had an average perceived standard deviation of 8.7, while those in the small durability distance condition had an average perceived standard deviation of 6.9.

Similarly, on the style dimension, an ANOVA with distance conditions and the standard deviation conditions as the independent variables, and the perceived standard deviation of the co-branded product as the dependent variable revealed only a significant effect of the distance on the style dimension ($F_{1,245} = 10.67, p < 0.01$). Subjects in the large style distance condition had an average perceived standard deviation of 8.8, while those in the small durability distance condition had an average perceived standard deviation of 7.0.

Proposition 3 predicts that, on each attribute, partner brands attract each other through the alliance, with the brand for which the attribute is salient attracting the poorly performing brand more than vice versa.⁸ This proposition is also supported. The distance between the brands decreased both on the durability dimension (by 18.8 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 before the alliance and 16.3 post-alliance.

Moreover, 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 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-

⁸ Note that as we mentioned in section 4, this proposition holds only if the co-branded product has a symmetric effect on the partner brands ($\Gamma_{xi} = \Gamma_{yi}$). We believe that an asymmetric effect will occur if the co-branded product is not equally important to the partner brands. Since in our experiment we have used hypothetical brands, there is no reason to assume that the allied product will not have symmetric effects.

alliance locations of *L*'s was on the average 3.1 points greater than that for *C*'s locations ($t_{260} = 2.11, p < 0.05$). Specifically, the shift in *L*'s location was 10.5, compared to *C*'s shift of 7.4 (see Table 2 for average perceived means (locations) of the partner brands before and after the alliance for all subjects). We therefore conclude that Proposition 3 is supported.

Proposition 4 investigates the effect of pre-alliance distance between the partner brands on their relative location change ($\frac{|E(X_i') - \mu_{xi}|}{|\mu_{yi} - \mu_{xi}|}$). Propositions 4a and 4b predict competing models of belief change (bookkeeping versus subtyping). On balance, our results provide evidence in support of subtyping (Proposition 4b). On the durability dimension, an ANOVA with the distance conditions and standard deviation conditions as the independent variables, and relative location change of *L*'s as the dependent variable revealed only a significant effect of the durability distance condition ($F_{1,243} = 13.13, p < 0.01$). Subjects in the large durability distance condition had an average relative location change of 0.16, while those in the small durability distance condition had an average location change of 0.32. However, a similar ANOVA with the relative location change of *C*'s as the dependent variable did not find a significant effect ($F_{1,243} = 0.67, NS$) of durability distance condition. Subjects in the large durability distance condition had an average relative location change of 0.47, while those in the small durability distance condition had an average location change of 0.53.

On style, an ANOVA with the same independent variables and relative location change of *C*'s as the dependent variable revealed only a significant effect of the style distance condition ($F_{1,242} = 6.82, p < 0.01$). Subjects in the large style distance condition had an average relative location change of 0.23, while those in the small style distance condition had an average location change of 0.42. A similar ANOVA for *L*'s on style also revealed a significant effect for

only the style distance condition ($F_{1,242} = 9.35, p < 0.01$). Subjects in the large style distance condition had an average relative location change of 0.35, while those in the small style distance condition had an average location change of 0.54, supporting Proposition 4b.

Proposition 4a predicts a greater shift in the large distance condition and is rejected in all four comparisons. In contrast Proposition 4b predicts the opposite and is statistically supported in three of the four comparisons, with the fourth providing directional support. Thus, we conclude that the subtyping model underlying Proposition 4b is more consistent with our results. Future research should explore possible conditions under which the bookkeeping model holds.

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 brand⁹, the standard deviation of *L*'s increased by an average of 1.3 points through the alliance ($t_{129} = 5.72, p < 0.01$). Similarly, when *C*'s was the more reliable brand, 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, *L*'s standard deviation increased by 1.5 points through the alliance ($t_{127} = 5.60, p < 0.01$). Finally, when *C*'s was the more reliable brand, its standard deviation increased by an average of 1.9 points ($t_{132} = 6.35, p < 0.01$) (see Table 2 for average perceived standard deviations when *L*'s is the reliable brand on durability and style and when *C*'s is the reliable brand on durability and style).

Proposition 6 predicts that the perceived standard deviation of the less reliable partner will increase as well, but this result only holds for the attribute for which it is salient and when the distance between the brands is large. When *L*'s was the less reliable brand on the durability

⁹ In our experimental design (see Table 1) on the durability dimension, *L*'s was the more reliable brand in cells E, F, H, I, K, L, N, O, and *C*'s was the more reliable brand in cells A, B, C, D, G, J, M, P. On the style dimension, *L*'s was the more reliable brand in cells A, B, C, D, E, H, K, N, and *C*'s was the more reliable brand in cells F, G, I, J, L, M, O, P.

dimension,¹⁰ 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, its standard deviation (on style) decreased by an average of 0.1 points through the alliance ($t_{127} = 0.47, NS$). Thus, this proposition is not supported (see Table 2 for average perceived standard deviations when *C*'s is the reliable brand on durability-that is *L*'s is the less reliable brand on durability- and *L*'s is the reliable brand on style-that is *C*'s is the less reliable brand on style).

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, the total standard deviation of the partners (on durability) increased by an average of 2.2 points through the alliance ($t_{131} = 4.60, p < 0.01$). When *C*'s was the less reliable brand on the style dimension, total standard deviation of the partners (on style) increased by an average of 1.4 points through the alliance ($t_{127} = 2.73, p < 0.01$).

7. Conclusions

In this paper, we propose a new analytical framework of co-branding that allows marketers to gain a better understanding of the effects of co-branding on the images of their brands. Our analysis provides answers as to whether allying for image reinforcement is a viable strategy for brands, and, if so, the optimal partners to choose. We identified conditions in which a brand's image can be reinforced by borrowing from the higher performance of its partner brand, or

¹⁰ In our experiment, *L*'s was the less reliable brand on the durability dimension in cells A, B, C, D, G, J, M, P, and *C*'s was the less reliable brand on the style dimension in cells A, B, C, D, E, H, K, N.

impaired through the confusion of consumers introduced through dissimilar brand images. We obtained these insights through the notion that consumers use individual products of a brand to construct a distribution of a brand's beliefs. We conceptualized an attribute belief as a two dimensional construct with location or the mean of the belief's distribution 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 co-branding activity and suggested an updating mechanism involving a mixture formulation. We formalized 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 results show that the updating of brand beliefs as a result of a co-branding activity relies on the occurrence of subtypes when the expected beliefs of two brands are very different.

Our model generated a number of propositions, which were tested in an experiment. Six of the seven propositions are confirmed, which supports our analytical model and analytical findings. We feel that the combination of theory and data provide 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 which showed significant 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.

However, we find a significant increase in the uncertainty associated with the co-branded product when the difference between locations of the brands is large. Inconsistent images of the partner brands may confuse consumers, thereby increasing their uncertainty about the co-branded product. Our results also show that the updating process of the partner brand beliefs is adversely affected when the distance between the brands is large due to the subtyping of the co-branded product. When the co-branded product involves brands with inconsistent images, consumers regard the co-branded product as an exception to the brands' already existing products, and thus, they are less likely to use their co-branded product perceptions to update their partner brands beliefs. 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, expected attribute belief of the brand will be enhanced with a lower likelihood of subtyping and without an increase in uncertainty about this attribute, because consumers will not get confused about the inconsistent images of the partner brands when the brands are only moderately apart.

2. *Co-branding for image reinforcement may not be a viable strategy for a reliable brand.*

Our analytical derivations and empirical results imply this. The experiment shows a significant increase in the uncertainty associated with the more reliable brand through 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 get confused with a co-branded product that is inconsistent with the partner brand's prior image. This confusion reflects back on the perceptions of 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 location of the partner brands improves, their combined reliability decreases through the alliance. The overall location of the brands improves because the brand for which the attribute is salient attracts the other brand. Since each partner salient on a particular attribute will typically outperform the partner on that attribute, this complementary salience effect improves both partners' position. However, total reliability decreases because of uncertainty transfer from the less reliable brand to the more reliable brand and of consumers' confusion due to the brands' inconsistent images. Thus, one cannot say with certainty whether co-branding generally results in image impairment or reinforcement. While from the perspective of location or average performance, it is likely to result in image reinforcement, from the reliability or uncertainty perspective it is likely to result in image impairment.

As in any research, our work is not without limitations. First, our model assumes normal distributions for attribute beliefs. It is possible however, that consumer beliefs are better represented by other distributions. Second, it may be 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 need for cognition (Cacioppo and Petty 1982) and brand familiarity (Simonin and Ruth 1998) may provide more insights. Third, while our results support the subtyping model, future research should consider the possibility that certain

attribute types (e.g., hedonic) lead to bookkeeping, while others (e.g., functional) lead to subtyping. Finally, we tested our propositions in a lab context. To increase confidence in our results, there is a need to further test the propositions in other settings. For example, beliefs about product attributes tend to be stronger when based on actual use of the product. Moreover, prior beliefs might become weaker due to forgetting because the time between the pre- and post-alliance evaluations of the partner brands will be typically larger in a field setting.

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. Since we focus on salient attributes, presumably this would be the case. Thus, it is imperative that managers understand the potential effects before adopting co-branding as a strategy for image reinforcement.

Appendix A Proofs of Propositions

Proposition 1

According to equation (4) in the paper:

$$E(A_i) = w_i \mu_{xi} + (1 - w_i) \mu_{yi}$$

with $0 < w_i < 1$ and $w_i > (1 - w_i)$ if attribute i is salient to brand X .

Thus, the location of the allied product is a convex combination of the locations of the partner brands. Hence $\mu_{xi} < E(A_i) < \mu_{yi}$, and since $w_i > (1 - w_i)$, the allied product is located closer to brand X than brand Y on attribute i ($|E(A_i) - \mu_{xi}| < |E(A_i) - \mu_{yi}|$). This proves Proposition 1.

Proposition 2

Taking partial derivatives of (5) with respect to the squared distance gives:

$$\frac{\partial \text{Var}(A_i)}{\partial (\mu_{yi} - \mu_{xi})^2} = w_i (1 - w_i) > 0.$$

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

Proposition 3

According to equations (12) and (13) the post-alliance locations of the partner brands are functions of their pre-alliance locations:

$$E(X_i') = (1 - \Gamma_{xi}(1 - w_i))\mu_{xi} + \Gamma_{xi}(1 - w_i)\mu_{yi} \quad (\text{A1})$$

$$E(Y_i') = (1 - \Gamma_{yi}w_i)\mu_{yi} + \Gamma_{yi}w_i\mu_{xi} \quad (\text{A2})$$

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

$$|E(X_i') - E(Y_i')| < |\mu_{xi} - \mu_{yi}|.$$

Rearranging terms in equations (A1) and (A2), we obtain:

$$|E(X_i') - \mu_{xi}| = \Gamma_{xi} \cdot (1 - w_i) |\mu_{yi} - \mu_{xi}| \quad (\text{A3})$$

$$|E(Y_i') - \mu_{yi}| = \Gamma_{yi} \cdot w_i |\mu_{yi} - \mu_{xi}| \quad (\text{A4})$$

If attribute i is salient to brand X ($1 > w_i > 0.5$), and if the effect of the co-branded product on the partner brands is assumed to be symmetric ($\Gamma_{xi} = \Gamma_{yi}$), (A3) and (A4) implies:

$$|E(Y_i') - \mu_{yi}| > |E(X_i') - \mu_{xi}|.$$

This proves Proposition 3. Note that this proposition also holds for the domain $\Gamma_{x1} \leq \Gamma_{y1}$ and

$$\Gamma_{y2} \leq \Gamma_{x2}.$$

Proposition 4

Rearranging equations (A3) and (A4) gives:

$$\frac{|E(X_i') - \mu_{xi}|}{|\mu_{yi} - \mu_{xi}|} = \Gamma_{xi} \cdot (1 - w_i) \quad (\text{A5})$$

$$\frac{|E(Y_i') - \mu_{yi}|}{|\mu_{yi} - \mu_{xi}|} = \Gamma_{yi} \cdot w_i \quad (\text{A6})$$

Taking partial derivatives of (A5) and (A6) with respect to Γ_{xi} and Γ_{yi} gives:

$$\partial\left(\frac{|E(X_i') - \mu_{xi}|}{|\mu_{yi} - \mu_{xi}|}\right) / \partial\Gamma_{xi} = 1 - w_i > 0 \quad (\text{A7})$$

$$\partial\left(\frac{|E(Y_i') - \mu_{yi}|}{|\mu_{yi} - \mu_{xi}|}\right) / \partial\Gamma_{yi} = w_i > 0 \quad (\text{A8})$$

Let $d_{yi-xi} = |\mu_{yi} - \mu_{xi}|$. Note that one can write $\frac{\partial d_{A-X}}{\partial d_{yi-xi}} > 0$ and $\frac{\partial d_{A-Y}}{\partial d_{yi-xi}} > 0$. Thus, based

on equations (8) and (9) in the main text, if the bookkeeping model is in effect we should have the following,

$$\frac{\partial\Gamma_{xi}}{\partial d_{yi-xi}} > 0 \text{ and } \frac{\partial\Gamma_{yi}}{\partial d_{yi-xi}} > 0 \quad (\text{A9})$$

While if the subtyping model is in effect we should have:

$$\frac{\partial\Gamma_{xi}}{\partial d_{yi-xi}} < 0 \text{ and } \frac{\partial\Gamma_{yi}}{\partial d_{yi-xi}} < 0. \quad (\text{A10})$$

Equations (A7), (A8) and (A9) imply:

$$\partial\left(\frac{|E(X_i') - \mu_{xi}|}{|\mu_{yi} - \mu_{xi}|}\right) / \partial d_{yi-xi} > 0 \text{ and } \partial\left(\frac{|E(Y_i') - \mu_{yi}|}{|\mu_{yi} - \mu_{xi}|}\right) / \partial d_{yi-xi} > 0 \text{ (Proposition 4a).}$$

and equations (A7), (A8) and (A10) imply:

$$\partial\left(\frac{|E(X_i') - \mu_{xi}|}{|\mu_{yi} - \mu_{xi}|}\right) / \partial d_{yi-xi} < 0 \text{ and } \partial\left(\frac{|E(Y_i') - \mu_{yi}|}{|\mu_{yi} - \mu_{xi}|}\right) / \partial d_{yi-xi} < 0 \text{ (Proposition 4b).}$$

This proves Proposition 4.

Proposition 5

Rearranging terms in equations (14) and (15) gives:

$$\text{Var}(X_i') - \sigma_{xi}^2 = \Gamma_{xi} \cdot (1 - w_i) \left[(1 - \Gamma_{xi} \cdot (1 - w_i)) (\mu_{yi} - \mu_{xi})^2 - (\sigma_{xi}^2 - \sigma_{yi}^2) \right] > 0, \text{ if } \sigma_{xi}^2 < \sigma_{yi}^2 \quad (\text{A11})$$

and

$$\text{Var}(Y_i') - \sigma_{yi}^2 = \Gamma_{yi} w_i \left[(1 - \Gamma_{yi} w_i) (\mu_{yi} - \mu_{xi})^2 - (\sigma_{yi}^2 - \sigma_{xi}^2) \right] > 0, \text{ if } \sigma_{yi}^2 < \sigma_{xi}^2. \quad (\text{A12})$$

This proves Proposition 5.

Proposition 6

If attribute i is salient to brand X and $\sigma_{xi}^2 > \sigma_{yi}^2$, according to (A11), $\text{Var}(X_i') - \sigma_{xi}^2 > 0$ if

$$\frac{|\mu_{xi} - \mu_{yi}|}{\sigma_{yi}} > \sqrt{\left(\frac{\sigma_{xi}^2}{\sigma_{yi}^2} - 1 \right)} = \sqrt{\left(\frac{\max\{\sigma_{xi}^2, \sigma_{yi}^2\}}{\min\{\sigma_{xi}^2, \sigma_{yi}^2\}} - 1 \right)}. \quad (\text{A13})$$

If attribute i is salient to brand Y and $\sigma_{yi}^2 > \sigma_{xi}^2$, according to (A12), $\text{Var}(Y_i') - \sigma_{yi}^2 > 0$ if

$$\frac{|\mu_{xi} - \mu_{yi}|}{\sigma_{yi}} > \sqrt{\left(1 - \frac{\sigma_{xi}^2}{\sigma_{yi}^2} \right)} = \sqrt{\left(1 - \frac{\min\{\sigma_{xi}^2, \sigma_{yi}^2\}}{\max\{\sigma_{xi}^2, \sigma_{yi}^2\}} \right)}. \quad (\text{A14})$$

Note that $\sqrt{\left(\frac{\max\{\sigma_{xi}^2, \sigma_{yi}^2\}}{\min\{\sigma_{xi}^2, \sigma_{yi}^2\}} - 1 \right)} > \sqrt{\left(1 - \frac{\min\{\sigma_{xi}^2, \sigma_{yi}^2\}}{\max\{\sigma_{xi}^2, \sigma_{yi}^2\}} \right)}$. This proves Proposition 6.

Proposition 7

Using equations (A11) and (A12) and assuming $\Gamma_{xi} = \Gamma_{yi} = \Gamma_i$ one can write

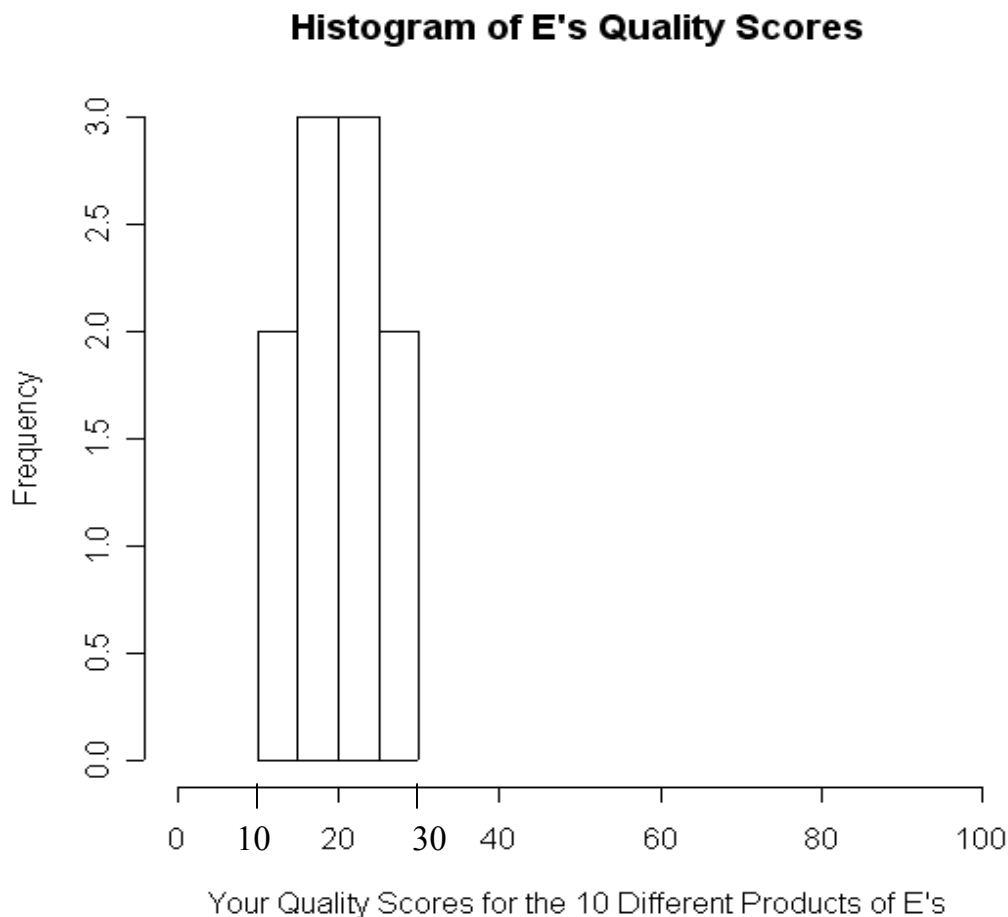
$$\text{Var}(Y_i') + \text{Var}(X_i') - (\sigma_{xi}^2 + \sigma_{yi}^2) = (\sigma_{yi}^2 - \sigma_{xi}^2) \Gamma_i (1 - 2w_i) + (\mu_{yi} - \mu_{xi})^2 (\Gamma_i - \Gamma_i^2 (1 - w_i))$$

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 i is salient to brand Y ($0 < w_i < 0.5$) and $\sigma_{yi}^2 > \sigma_{xi}^2$, or if attribute i is salient to brand X ($0.5 < w_i < 1$) and $\sigma_{xi}^2 > \sigma_{yi}^2$. This proves proposition 7.

Appendix B

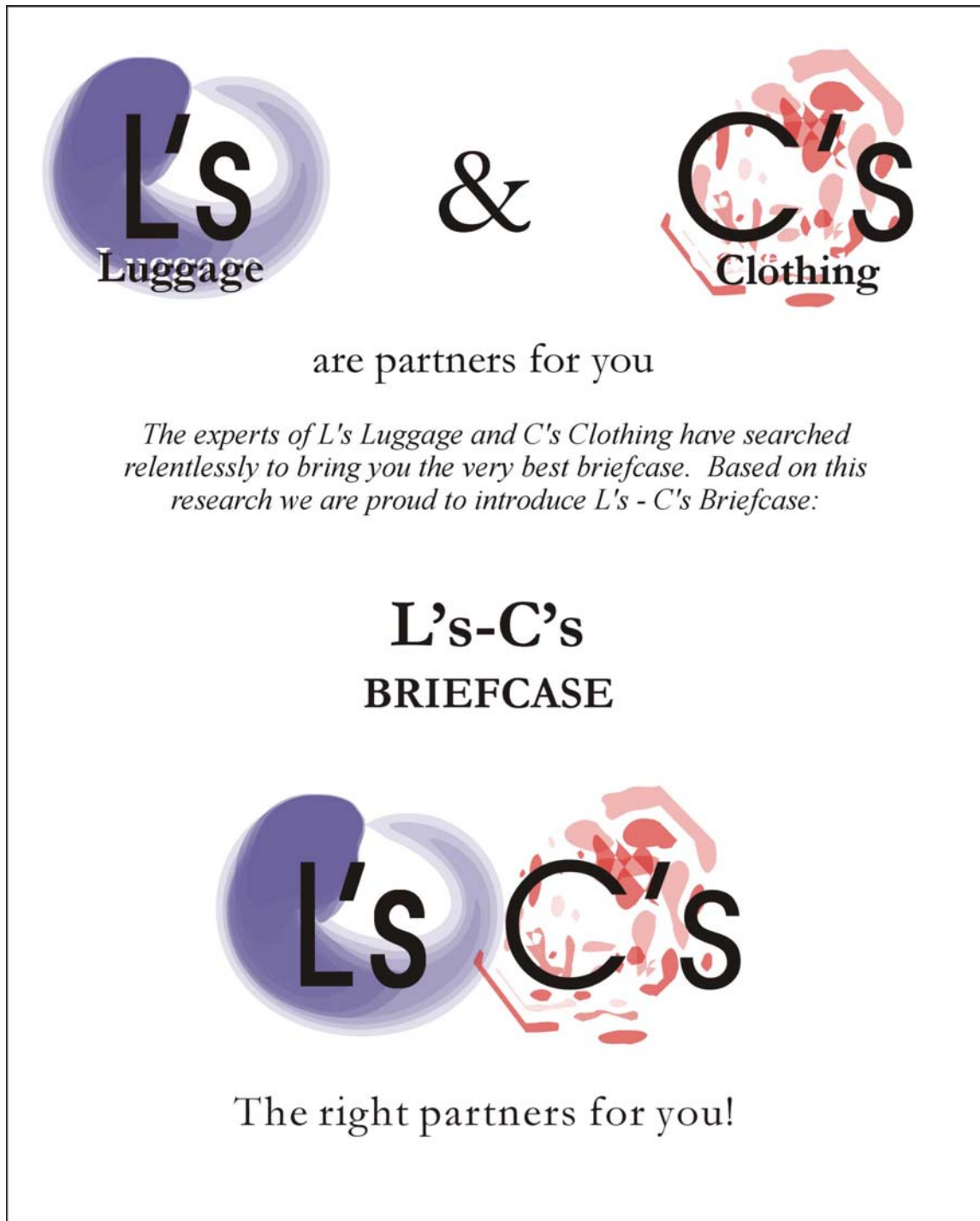
Histogram Example Shown to the Respondents Prior to the Experiment

Suppose you used 10 different products of an electronics brand E's (some of its products are mp3 players, home theater systems, DVD players and TV's). Your perceptions of the quality of these 10 products of E's are given below as a histogram. (The scores in the histogram are out of one hundred, 100 being the highest score.) The horizontal axis of the histogram gives your quality scores for the 10 different products of E's while the vertical axis shows the frequency of these scores, that is how many times each of these scores occurred.



According to this histogram you gave to
2 products a quality score between 10 and 15,
3 products a quality score between 15 and 20,
3 products a quality score between 20 and 25,
2 products a quality score between 25 and 30.

Appendix C
Ad Stimulus*



L's
Luggage

&

C's
Clothing

are partners for you

The experts of L's Luggage and C's Clothing have searched relentlessly to bring you the very best briefcase. Based on this research we are proud to introduce L's - C's Briefcase:

L's-C's
BRIEFCASE

L's **C's**

The right partners for you!

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

Figure 1
Illustration of Propositions

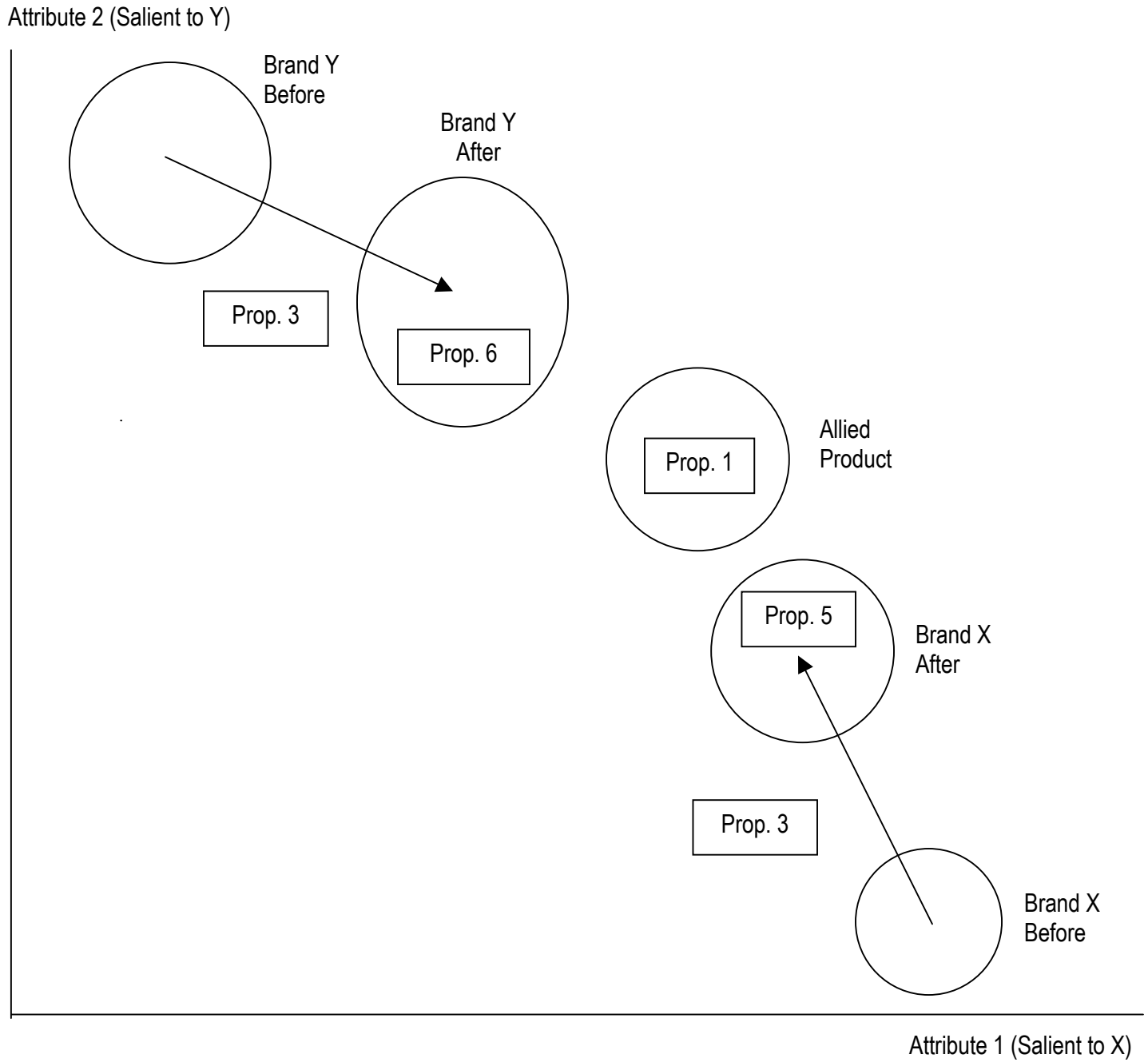


Table 1: Experimental Conditions*

| 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 | 5 | 7.5 |
| B | 80 | 30 | 60 | 80 | 7.5 | 5 | 5 | 7.5 |
| C | 80 | 60 | 30 | 80 | 7.5 | 5 | 5 | 7.5 |
| D | 80 | 30 | 30 | 80 | 7.5 | 5 | 5 | 7.5 |
| E | 80 | 60 | 60 | 80 | 5 | 7.5 | 5 | 7.5 |
| F | 80 | 60 | 60 | 80 | 5 | 7.5 | 7.5 | 5 |
| G | 80 | 60 | 60 | 80 | 7.5 | 5 | 7.5 | 5 |
| H | 80 | 30 | 60 | 80 | 5 | 7.5 | 5 | 7.5 |
| I | 80 | 30 | 60 | 80 | 5 | 7.5 | 7.5 | 5 |
| J | 80 | 30 | 60 | 80 | 7.5 | 5 | 7.5 | 5 |
| K | 80 | 60 | 30 | 80 | 5 | 7.5 | 5 | 7.5 |
| L | 80 | 60 | 30 | 80 | 5 | 7.5 | 7.5 | 5 |
| M | 80 | 60 | 30 | 80 | 7.5 | 5 | 7.5 | 5 |
| N | 80 | 30 | 30 | 80 | 5 | 7.5 | 5 | 7.5 |
| O | 80 | 30 | 30 | 80 | 5 | 7.5 | 7.5 | 5 |
| P | 80 | 30 | 30 | 80 | 7.5 | 5 | 7.5 | 5 |

* The scores are out of 100.

Table 2: Average Perceived Means (Locations) and Standard Deviations for the Allied product and Brands Before and After the Alliance¹¹

| Experimental Condition | Pre-alliance | | | | Allied Product | | Post-alliance | | | |
|--|--------------|-----------|-----------|-----------|----------------|----------|---------------|-----------|-----------|-----------|
| | L's | | C's | | Mean | Std.Dev. | L's | | C's | |
| | Mean | Std. Dev. | Mean | Std. Dev. | | | Mean | Std. Dev. | Mean | Std. Dev. |
| 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 | 7.7,1 | 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 ¹² | 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 ¹³ | 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 ¹⁴ | 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 ¹⁵ | 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 Reliable on Durability ¹⁶ | 80.2,45.9 | 4.7,5.9 | 80.2,45.6 | 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 Reliable on Durability ¹⁷ | 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 Reliable on Style ¹⁸ | 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 Reliable on Style ¹⁹ | 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 |

¹¹ The first figure in each of the cells indicates the average on the durability dimension while the second figure indicates the average on the style dimension.

¹² This row contains averages for all the subjects in the small durability distance condition which includes cells A, C, E, F, G, K, L, M in our experiment.

¹³ Large durability distance condition includes cells: B, D, H, I, J, N, O, P.

¹⁴ Small style distance condition includes cells: A, B, E, F, G, H, I, J.

¹⁵ Large style distance condition includes cells: C, D, K, L, M, N, O, P.

¹⁶ This row contains averages for all the subjects in cells E, F, H, I, K, L, N, O in which L's is the more reliable and C's is the less reliable brand on durability.

¹⁷ On the durability dimension, C's is the more reliable brand and L's is the less reliable brand in cells A, B, C, D, G, J, M, P.

¹⁸ On the style dimension, L's is the more reliable brand and C's is the less reliable brand in cells A, B, C, D, E, H, K, N.

¹⁹ On the style dimension C's is the more reliable brand and L's is the less reliable brand in cells F, G, I, J, L, M, O, P.

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