Determinants of Trademark Dilution

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A hierarchical Bayes associative network model for brand information is developed and tested to measure the extent of harm from trademark dilution. In the proposed model, category activation thresholds are modeled in terms of brand/category familiarity, activation flows are modeled in terms of relative category knowledge, and consumer confusion and its correlates are used to capture the asymmetric fan effects on retrieval probabilities for first and second users.

Owners of well-known brand names want to maintain the strength and selling power of these valuable but intangible assets. While brand managers have direct control over how their brand names are used in brand extensions, they have considerably less control over how they are used by other entities. If another firm were to use a famous brand name in such a way as to cause consumer confusion or deception regarding product source, the original owner of the brand name could sue the "second user" on the basis of trademark *infringement*. But the imitative use of a brand name does not always cause confusion among consumers, particularly when it is used in a product category completely unrelated to that of the original brand user. For example, the introduction of Kodak pianos, DuPont shoes and Buick aspirin might cause confusion among some consumers about product origin, but many would likely correctly infer these products were not affiliated with the original or "first" users of the brand names. These products might nevertheless reduce the value of the brand names for their original owners by weakening the strength and uniqueness of mental associations consumers had created between the brand names and their original product categories, a result referred to by legal scholars as trademark *dilution* (Peterson, Smith and Zerrillo 1999).

In 1995 the Federal Trademark Dilution Act (FTDA) was passed by Congress to address this issue. The FTDA, which applies only to famous trademarks, describes the harm that can be caused by trademark dilution as a lessening of the capacity of a famous mark to "identify and distinguish" its goods and services, even when consumers aren't confused as to product origin (15 U.S.C. Section 1125(c)(1); para 1127). In terms of memory theory, this might indicate a weakening of association strength between the brand and its original product category. The basic notion is that if you allow Rolls-Royce restaurants, Rolls-Royce cafeterias, Rolls-Royce pants, and Rolls-Royce candy, then eventually you won't have the Rolls-Royce

mark any more, as the name's strong and exclusive association with the luxury car product category will have been significantly diminished (Schechter 1927).

Demonstrating harm to brands from instances of trademark dilution and understanding the contextual factors that contribute to it have been the foci of intense inquiry and discussion by legal and marketing scholars, especially since passage of the FTDA. Indeed, these issues were considered of sufficient importance to be taken up by the Supreme Court, which recently ruled that, henceforth, owners of brand names will need to demonstrate actual harm, rather than just a likelihood of harm, to their brands in cases of trademark dilution in order to prevail in court under the FTDA (*Moseley v. V Secret Catalogue, Inc.*, 2003). While this ruling was helpful to litigants in clarifying the need to provide evidence of actual brand harm in court cases, it did not provide insight regarding how such harm might be measured or demonstrated, or what factors should be considered as contributing to harm from dilution.

The goal of this research is to explore the impact of various contextual factors on the extent of harm from dilution by developing and empirically testing an associative network model of brand memory. While brand dilution caused by extensions has received considerable attention from researchers (e.g., Aaker and Keller 1990, Gurhan-Canli and Maheswaran 1998, Keller and Sood 2003, Loken and John 1993), trademark dilution has not (c.f., Morrin and Jacoby 2000, Peterson, Smith and Zerillo 1999, Simonson 1993). We add to the existing literature by proposing a model structure for trademark dilution and empirically assessing the impact of contextual factors such as consumer confusion on the extent of harm.

Our analysis focuses on factors that enhance or inhibit a consumer's ability to activate, from long-term declarative memory, a target product category node when prompted with a brand name that has been utilized by both a first user (often the original user of the brand name)

and a second user (typically, a chronologically later user of the brand name). This type of association weakening is referred to by Simonson (1993) as typicality dilution and could negatively impact choice likelihood, even without changes to brand attitudes (Nedungadi 1990). Broadly speaking, we expect that harm from dilution will be a function of two major factors: elements of consumer expertise and consumer beliefs regarding product origin (i.e., confusion). A hierarchical Bayes model of category recall is developed that incorporates respondent heterogeneity in expertise, beliefs and associated parameters so that the effects of these factors are accurately measured.

One of the key issues addressed in the present research that has not been addressed previously (e.g., Morrin and Jacoby 2000), is the role of consumer confusion on the extent of dilution. Although the FTDA clearly states that consumer confusion is not necessary for a finding of dilution, several courts have issued rulings that indicate they believe the presence of confusion is an indication that dilution has also occurred (e.g., *Nabisco, Inc. v. PF Brands, Inc.* 1999; *Ringling Bros.-Barnum & Bailey Combined Shows, Inc. v. Utah Div. of Travel Dev.*, 1999). While Morrin and Jacoby (2000) showed that brand recognition and recall decline after exposure (versus no exposure) to trademark diluting advertisements, they did not provide insight regarding the role of consumer confusion.

PROPOSED MODEL

Prior research (Van Osselaer and Janiszewski 2001) has shown that two types of associative network models can be fruitfully applied to consumer brand information learning depending on contextual and individual factors – i.e., cue-independent models such as ACT-R (Anderson 1993, Anderson and Labiere 1998, Anderson et al. 2005), and cue-interdependent

models (Gluck and Bower 1988, Pearce 1994). Because the present study represents a low-motivation learning task and involves the presentation of a single (versus multiple) cue at test, a cue-independent model was chosen as the more appropriate basis for the model. These models hold that information is stored in long-term declarative memory in networks of nodes (items of information) connected by associations (relationships among the nodes). An individual remembers an item of information if a summed amount of activation flows to the target node sufficient to exceed its threshold level of activation.

The activation process is modeled in a form similar to other activation models (Anderson et al. 2005), simple feed-forward neural networks (McCulloch & Pitts 1943), and pattern recognition models (Ripley 1996). Neurons for product category nodes (e.g., beer) are thought to operate in a binary on/off fashion and are modeled as:

$$y_n(t) = I\left(\sum_{m \to n} w_{m,n} \cdot y_m(t-1) > \theta_n\right) \qquad \textbf{(1)}$$

where $y_n(t)$ is a binary (0,1) variable indicating whether or not the target product category node n is "on" and originating from the mth brand node, and t denotes time. I is an indicator function, taking on the value of 1 if the "test" in the parentheses is satisfied (node n is recalled), and zero otherwise. The summation sign (Σ) implies that the test is additive over the associations leading to node n. θ_n is the category threshold level that needs to be surpassed for activation of node n, and the w_{mn}, or activation flow, reflects the strengths of associations among nodes in the network.

We utilize category activation thresholds, θ, to capture the impact of the recency and frequency of previous activations. Rather than attempt to measure empirically the recency and frequency of prior activation, we operationalize thresholds for consumer i and brand k using

consumers' self-reported, pre-existing levels of familiarity with the brand names in product categories (e.g., Bass beer, Bass shoes). The proposed model allows for individual consumers to have different category thresholds as a function of previous exposure and experience and this is modeled in the form:

$$\theta_n^{ik} = \beta_{0i} + \beta_{1i} \cdot fam_n^{ik} \text{ [category threshold]} \quad \textbf{(2)}$$

where β_{0i} and β_{1i} are individual respondent-level parameters.

Association flow, *w*, is associated with an individual's level of knowledge about the first user's product category *relative to* the second user's product category. These weights determine the strength of activation flow when cued with a brand name. This aspect of the model captures what Anderson et al. (2005) refer to as attentional weighting of the current goal, and the relative measure allows some aspects of cue interdependency to be captured. Thus, if the consumer is very knowledgeable about the first user's category compared to the second user's category (e.g., beer versus shoes), the probability of retrieval interference from the second user decreases (i.e., dilution of Bass beer is less likely). The impact of the second user of a brand ("*s*") on the probability of recall of the first user category ("*f*") is captured with two alternative specifications:

$$w_f^{ik} = \frac{\exp[\alpha_f (know_f^{ik} - know_s^{ik})]}{\exp[\alpha_f (know_f^{ik} - know_s^{ik})] + \exp[\alpha_s (know_s^{ik} - know_f^{ik})]} \quad \textbf{(3)}$$

and

$$w_f^{ik} = \alpha_f \cdot (know_f^{ik} - know_s^{ik}) \text{ [activation flow]} \quad \textbf{(4)}$$

In equation (3), values of w_f near zero indicate that knowledge of the first user's product category is weak relative to that of the second user category, and thus that the second user is more likely to dilute or interfere with recall of the first user. When w_f approaches zero it also

implies that the second user's category is more likely to be recalled. The logit transformation ensures that the *w*'s add up to one. Equation (4) relaxes the relationship between the association weights by allowing them to be independently related to category knowledge and not sum to one.

The probability that an individual recalls a first user product category is defined as the probability that the activation flow along the association exceeds the category threshold:

$$\Pr(y_f^{ik} = 1) = \Pr(w_f^{ik} > \theta_f^{ik} + \varepsilon) \qquad \textbf{(5)}$$

where, if ε is distributed normal, then the choice probability is expressed as a probit model, and an extreme value distribution for ε leads to the logit model.

We include confusion and its correlates in this model to capture the well-known fan effect (Anderson 1974, 1983). Prior research demonstrates that even irrelevant information can dilute brand benefit beliefs (Meyvis and Janiszewski 2002). We hypothesize that a fan effect caused by an increase in the number of nodes in the original brand network will result in retrieval interference to the extent that consumers are confused about product origin. If a consumer is confused about product origin (i.e., believes the two products come from the same manufacturer), he will store the second user's information in the same brand network as that of the original user. When later cued with the brand name, some of activation will be siphoned off to the second user's category node. If instead, the consumer correctly infers the second user is made by a different manufacturer, that information will be stored in a brand network separate from that of the first user, and will interfere less with activation flow and retrieval for the first user. Conversely, a second user will benefit in terms of retrieval probability, when confusion exists, as the second user brand benefits from the activation siphoning off process.

Confusion is operationalized as the degree to which the consumer indicates it likely that the two products sharing a brand name come from the same manufacturer. Logo similarity and category similarity are similarly operationalized in a self-report manner. Based on the work of Loken, Ross and Hinkle (1986), who found that brands that exhibit a similar physical appearance tend to lead to perceptions of a common business origin, we expected that the effect of category similarity and logo similarity would contribute to confusion and thus operate in a similar manner.

Structurally, our model fitting efforts indicated that consumer confusion and its correlates, namely logo similarity and category similarity, best belonged in the model as a link to the scale of the error distribution:

$$\sigma^{ik} = \exp[\gamma_{i1}(confuse^{ik}) + \gamma_{i2}(\text{logosim}^{ik}) + \gamma_{i3}(catsim^{ik})] \text{ [fan effect]} \qquad \textbf{(6)}$$

That is, σ is included as the scale of a common noise for both the first and second users, and the associated variables are assumed to either enhance or diminish the ability to recall first or second user product categories, depending on the algebraic signs of the coefficients. For ε distributed extreme value, the choice probability associated with equations (5) and (6) is:

$$\Pr(y_f^{ik} = 1) = p_f = \frac{\exp[(w_f^{ik} - \theta_f^{ik})/\sigma^{ik}]}{1 + \exp[(w_f^{ik} - \theta_f^{ik})/\sigma^{ik}]}. \qquad \textbf{(7)}$$

The likelihood for our data is the joint probability of recalling the first user and second user product categories for all brands (k) given as:

$$\Pr\left(\{y_f\},\{y_s\} \mid \{\alpha_i\},\{\beta_i\},\{\gamma_i\}\right) = \prod_{i=1}^{N}\prod_{k=1}^{K}[p_f^{y_{ik}}(1-p_f)^{1-y_{ik}}]\cdot[p_s^{y_{ik}}(1-p_s)^{1-y_{ik}}] \qquad \textbf{(8)}$$

Finally, we allowed for heterogeneity in all model coefficients using a multivariate normal distribution with full covariance matrix:

$$(\alpha_i', \beta_i', \gamma_i')' \sim MVN(\mu, \Omega) \quad \textbf{(9)}$$

Our model generalizes existing specifications in the literature (see for example, Anderson et al., 2004, p.1042) in that covariates are related to model components (category thresholds, activation flow and fan effects) whose association is heterogeneously estimated. Thus, analysis based on the model does not require pre-specification of effect sizes (e.g., the value of the error scale, σ, as in Anderson, 2004) and allows for an assessment of the predictive relationship to the covariates. We note that several alternative covariate associations were explored (e.g., category knowledge related to category thresholds rather than activation flow), but are not reported because they resulted in inferior model fit.

METHOD

Participants were exposed to diluting brand logos and then tested on whether or not they could freely recall the original product categories associated with the brand names. We measured a set of contextual factors for each participant based on a set of factors often used in prior cases to establish circumstantial proof of dilution (*Mead Data Central, Inc. v. Toyota Motor Sales, U.S.A., Inc.* 1989): perceptions of logo similarity between the first and second users, perceptions of product category similarity between the first and second users, knowledge of first and second user product categories, and familiarity of first and second users, as well as consumer confusion regarding the affiliation between the first and second users.

Participants and Procedure

212 undergraduates enrolled in marketing courses participated for extra course credit. Participants were randomly assigned to either a control group (i.e., undiluted, n = 53) or an experimental group (i.e., diluted, n = 159). Each participant received a 35-page booklet

containing two parts. They were instructed to proceed through Part I of the booklet at their own pace and stop when they reached Part II. In Part I, participants evaluated a number of real-world brand logos, each of which was affiliated with a product category (e.g., Bass ale). The participant saw a visual of each logo underneath which was typewritten the product category. For each logo/category pair, participants were asked the extent to which they agreed that “This is a high quality product” and “I like this product" on a 9-point scale.

Participants then completed Part II together with the experimenter. The first phase of Part II consisted of a 2-minute distracter task to clear out short-term memory. Participants were then provided with a page listing the eight target brand names and were asked which product categories came to mind for each brand name. They were given 1 minute to complete this task. Participants then completed the remainder of the booklet at their own pace. The remaining sections measured the contextual factors of consumer confusion (1 = Different Manufacturers to 9 = Same Manufacturer), familiarity with the first user and second user brands (1 = Not at all familiar to 9 = Very familiar), similarity of logo appearance between the first user and second user brands (1 = Not at all similar to 9 = Very similar), product category similarity between the first user and second user brands (1 = Not at all similar to 9 = Very similar), knowledge about the first user and second user product categories (1 = Not at all knowledgeable to 9 = Very knowledgeable), and basic demographic information. When finished, participants were debriefed and thanked for their participation.

Stimuli

Eight real-world target brands were chosen from among those appearing in a commercially available software package (*Lots O' Logos* 1998). Brands were chosen whose names were used by more than one manufacturer. The eight first user brands and target categories were: Parker

pens, Ace hardware stores, Kiwi shoe polish, Bass ale, Gibson greeting cards, Viking computer components, Mercury automobiles, and Pioneer audio equipment. All participants were exposed to these eight first user brand logos embedded among ten filler brands. Participants in the experimental condition were subsequently exposed to these second users (also real brands): Parker games, Ace uniforms, Kiwi airlines, Bass shoes, Gibson housewares, Viking pest control, Mercury aircraft, and Pioneer chain saws. Control participants were exposed to eight filler brands instead of the second users of brand names.

Descriptive Statistics

In table 1 we examine what we refer to as brand-exclusive recall, which refers to the proportion of consumers who, when prompted with a brand name, recall only the first user's product category. Brand-exclusive recall is a desirable result for a first user brand as it suggests that the first user "owns" that brand name in the consumer's memory, rather than having to share associations with other product categories. One measure of dilution is the extent to which brand-exclusive recall declines after exposure to a diluting logo from a second user. From table 1, which compares brand-exclusive recall scores for respondents in the diluted versus undiluted conditions of this study, we see that, on average, brand exclusive recall scores fall by 20.9 points (from 65.0 to 44.2 points), or by about a third, as a result of a single exposure to brand diluting logos. Thus, the deleterious effects of trademark dilution are evident in simple category recall measures, a result in accord with previous research. The proposed statistical model, described in detail below, is based only on respondents in the diluted condition (i.e., n = 159).

[Tables 1 and 2 about here]

RESULTS

We compared the proposed model to a standard logit model and to a model that restricts the association strengths to sum to one. The results in table 3 indicate that the proposed model best fits the data. Table 4 shows the contextual factors generally have the effects predicted. The threshold (θ) for category activation declines as brand familiarity increases (β = -1.63), as predicted. We also found the predicted relationship between association strength (w) and relative category knowledge ($know_f^{ik} - know_s^{ik}$). The parameter mean ($\alpha$) for first users is smaller than that for second users (0.47 versus 1.51). The parameters for confusion (γ_1), logo similarity (γ_2), and category similarity (γ_3) have positive algebraic signs, implying that as confusion and its correlates increase, the scale factor (σ) increases and recall probabilities become less extreme. Finally, the diagonal elements of the covariance matrix (Ω) indicate substantial heterogeneity among respondents.

[Tables 3 and 4 about here]

Figure 2 presents boxplots summarizing the distribution of the effect sizes of the contextual factors. The boxplots for brand familiarity and relative category knowledge indicate that nearly all respondents have positive effect sizes, and this result applies to both first and second user brands. The average effect sizes for a one-unit change in the brand familiarity rating scale is 0.0266 and 0.018, respectfully, for first and second user brands in the study. This implies that a four-point increase in brand familiarity is associated with an eight to ten percent increase in average category recall probability.

The boxplots for source confusion and logo similarity indicate asymmetric effects for the first and second users, as predicted, and in accord with a fan effect result. We note that this asymmetric affect is not detected in the standard logit model specification because the same

coefficients are present for both first and second user brand recall, and as a result the associated effect-sizes have the same algebraic sign. An increase in the response ratings for these variables is associated with a decrease in recall probability for first users, but an increase in recall probability for second users. Thus, when the brand logos are similar in appearance, or when consumers think the two products with the same brand name are made by the same manufacturer (i.e., are confused), the probability of recalling the first user's product category declines, whereas the probability of recalling the second user's product category increases.

The boxplots for category similarity have mass in both the positive and negative intervals for both first and second users. An increase in category similarity results in an increase in recall probability for half of the respondents, and a decrease for the other half. These results indicate that category similarity does not have a reliable impact on category recall. It may be that category similarity (i.e., feature overlap) may not be the determining factor impacting perceptions of product origin, but rather fit based on more conceptual bases (e.g., Broniarczyk and Alba 1994).

[Figure 2 about here]

DISCUSSION

Passage of the FTDA in 1995 was an important milestone in the effort to protect brand names from trademark dilution. But there has been inconsistency and controversy in understanding the underlying consumer memory processes associated with trademark dilution and in finding ways of demonstrating brand harm in order to effectively use the FTDA to protect well-known brand names. In this paper we demonstrated how consumer exposure to brand diluting logos tends to reduce brand-exclusive recall levels. Just a single exposure to

diluting brand stimuli was found to have a damaging effect on brands, reducing brand-exclusive recall by about a third, on average.

More importantly, we show how the effects of exposure to diluting brand stimuli can be modeled in terms of a hierarchical Bayesian associative network theory. To the extent that consumers are highly familiar with a brand/category pair, they will be more likely to recall that brand's category after exposure to diluting stimuli. The legal implication of this result is that if the level of fame required by the courts for application of the FTDA is held extremely high, then few of the brands to which it applies may ever be able to demonstrate harm, at least from single instances of trademark dilution.

The results also indicate that a factor not typically considered by the courts, the consumer's relative knowledge about the two product categories involved, also may have an impact on retrieval. Relative category knowledge acted as the best measure for the association weights determining the impact that exposure to a diluting brand structure would have for a particular consumer. To the extent that a consumer possesses greater knowledge of the first user's product category relative to knowledge of the second user's product category, the first user is better insulated from the harm of trademark dilution. This finding implies that the sample of respondents chosen for consumer surveys in trademark dilution cases should be accorded considerable thought. If respondents are chosen who are more familiar with the second user's product category than the first user's product category, evidence of dilution as measured by recall inhibition is more likely to emerge. The courts may therefore want to issue specific guidelines regarding sampling issues for trademark dilution surveys.

We also determined that consumer confusion and logo similarity have asymmetric effects on first and second user retrieval probabilities. When consumers are confused about the

sources of the two products, or when they believe the two logos are similar in appearance, the first user's category is less likely to be recalled, while the second user's category is more likely to be recalled. This result is a natural result of an associative network framework that predicts a fan effect with damaging implications for first user brands, but facilitative implications for second user brands, to the extent that confusion exists. Although the FTDA does not require consumer confusion to establish harm from dilution, it appears that the presence of confusion magnifies the amount of harm likely to be incurred by the first user of the brand name (and provides a greater benefit to be enjoyed by the second user of the brand). Legal practitioners have often tried to demonstrate the presence of confusion, the traditional basis for infringement cases, in dilution cases. This practice has led other legal scholars to suggest that the courts have "muddled" the concepts of dilution and confusion, leading to "erroneous tests and questionable outcomes" (Oswald 1999, p. 282). The results of our analysis indicate that litigants may indeed want to give some weight to confusion factors in dilution cases.

The proposed model does not address the impact of trademark dilution on the strength of associations from the product category to the brand. As research has shown that it is not uncommon to observe asymmetric associative strengths between brand-> category versus category->brand (Farquhar and Herr 1993), additional research is needed to explore this issue. Moreover, this research examined the functionality of brand names as associative cues for category membership, without addressing other important functions of brands, such as their role in helping consumers predict product performance (Janiszewski and Van Osselaer 2000). Broader exploration of the potentially damaging effects of trademark dilution on other brand functions is thus warranted. Replication of these results using controlled strata of respondents is called for. Further, the retrieval measure used in this study is category recall when prompted

with a brand name. Other memory measures may prove more precise, such as reaction times to brand-category pairs presented on a computer screen. Finally, we believe that additional network memory models can be constructed to reflect the retrieval process in different marketing contexts using a Bayesian approach. Future research endeavors in this direction could provide considerable insight to consumer research applications related to branding issues.

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Table 1. CATEGORY RECALL PATTERNS BY CONDITION (Diluted *n* = 159, Undiluted *n* = 53)

Brand	Brand-Exclusive Recall (Recall 1st user but not 2nd user)			Joint Recall (Recall both 1st and 2nd user)		Supplanted Recall (Recall 2nd user but not 1st user)		Null Recall (Recall neither 1st nor 2nd user)	
	Undiluted	Diluted	Percent Difference	Undiluted	Diluted	Undiluted	Diluted	Undiluted	Diluted
Parker	49.1	35.0	-28.7%	0.0%	4.4%	1.9%	43.8%	49.1%	16.9%
Ace	90.6	78.1	-13.8%	0.0%	8.8%	0.0%	6.3%	9.4%	6.9%
Kiwi	60.4	33.1	-45.2%	0.0%	25.6%	3.8%	30.6%	35.8%	10.6%
Bass	77.4	14.4	-81.4%	0.0%	51.3%	11.3%	30.6%	11.3%	3.8%
Gibson	13.2	23.1	+75.0%	0.0%	6.2%	0.0%	10.0%	86.8%	60.6%
Viking	45.3	15.0	-66.9%	0.0%	6.2%	0.0%	21.2%	54.7%	57.5%
Mercury	98.1	80.0	-18.4%	0.0%	12.5%	0.0%	2.5%	1.9%	5.0%
Pioneer	85.8	75.0	-12.6%	0.0%	13.1%	0.0%	3.8%	13.2%	8.1%
Mean	65.1	44.2	-32.1%	0.0%	16.0%	2.1%	18.6%	32.8%	21.24%

Table 2. SUMMARY STATISTICS OF BRAND CHARACTERISTICS (*n* = 212)

Brands	Familiarity with:		Knowledge of:	
	First User	Second User	First User Category	Second User Category
Parker (pens, games)	3.55	7.56	4.63	5.85
Ace (hardware stores, uniforms)	7.61	2.69	4.75	2.78
Kiwi (shoe polish, airlines)	5.98	2.80	3.90	5.49
Bass (ale, shoes)	6.15	7.11	5.64	6.75
Gibson (greeting cards, housewares)	3.57	1.93	4.90	4.08
Viking (computer components, pest control)	1.61	1.29	3.81	2.03
Mercury (automobiles, aircraft)	8.08	1.96	6.34	4.36
Pioneer (audio equipment, chain saws)	7.90	1.83	5.88	2.44
Mean	5.56	3.39	4.98	4.22

	Confusion	Logo Similarity	Category Similarity
Parker	2.90	2.62	2.84
Ace	3.17	4.99	3.61
Kiwi	3.24	4.48	1.25
Bass	3.77	7.45	1.35
Gibson	5.42	8.47	2.70
Viking	3.78	4.24	1.16
Mercury	2.51	2.49	6.00
Pioneer	4.46	6.08	2.42
Mean	3.65	5.11	2.67

Table 3. FIT COMPARISON OF ALTERNATIVE MODELS

Model Specification	Respondent-Level Parameters	Log Marginal Density[d]
Associative Network Model[a]	8	-1195.15
Constrained Network Model[b]	8	-1216.45
Logit Model[c]	8	-1206.71

[a] Associative Network Model specification: $\Pr(y_f = 1) = \dfrac{\exp[(w_f - \theta_f)/\sigma]}{1 + \exp[(w_f - \theta_f)/\sigma]}$ where

$$w_f = \alpha_f (know_f - know_s)$$
$$\theta_f = \beta_{0f} + \beta_1 (fam_f)$$
$$\sigma = \exp[\lambda_1 (confuse) + \lambda_2 (logo) + \lambda_3 (catsim)]$$

[b] Constrained Network Model specification (w_i sum to one):

$$w_f = \frac{\exp[\alpha_f (know_f - know_s)]}{\exp[\alpha_f (know_f - know_s)] + \exp[\alpha_s (know_s - know_f)]}$$

[c] Logit Model specification:

$$\Pr(y_f = 1) = \frac{\exp[\beta_{0f} + \beta_1 (confuse) + \beta_2 (fam_f) + \beta_3 (logo) + \beta_4 (catsim) + \beta_5 (know_f)]}{1 + \exp[\beta_{0f} + \beta_1 (confuse) + \beta_2 (fam_f) + \beta_3 (logo) + \beta_4 (catsim) + \beta_5 (know_f)]}$$

$$\Pr(y_s = 1) = \frac{\exp[\beta_{0s} + \beta_1 (confuse) + \beta_2 (fam_s) + \beta_3 (logo) + \beta_4 (catsim) + \beta_6 (know_s)]}{1 + \exp[\beta_{0s} + \beta_1 (confuse) + \beta_2 (fam_s) + \beta_3 (logo) + \beta_4 (catsim) + \beta_6 (know_s)]}$$

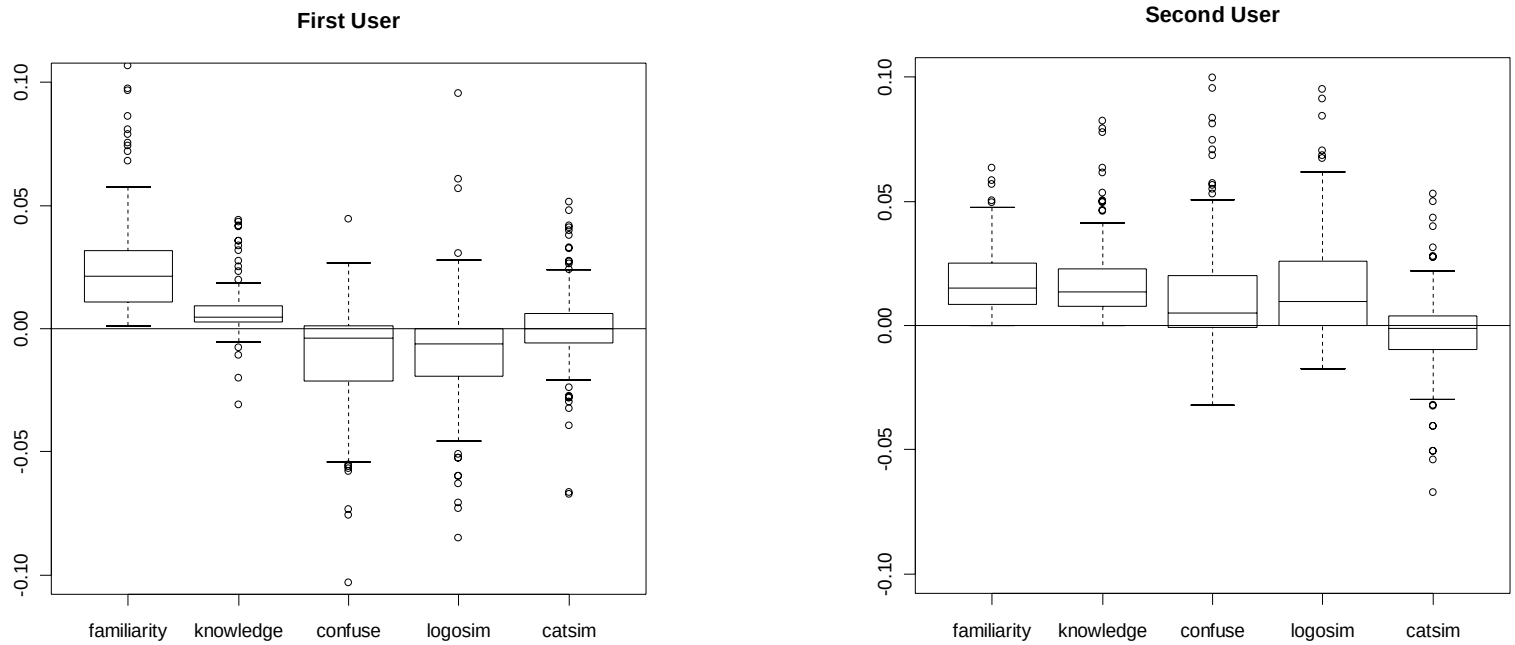
[d] Log marginal density is based on the last 20,000 iterations computed using the importance sampling estimator of Newton and Raftery (1994).

Table 4. POSTERIOR MEAN AND COVARIANCE MATRIX OF HETEROGENEITY FOR THE ASSOCIATIVE NETWORK MODEL

Variable		Mean	Covariance Matrix							
Intercept (1st user)	β_{0f}	6.07	9.67							
		(0.67)	(3.88)							
Intercept (2nd user)	β_{0s}	10.73	-8.65	12.03						
		(0.82)	(3.58)	(7.03)						
Familiarity	β_1	-1.63	-0.75	0.70	0.48					
		(0.12)	(0.50)	(0.41)	(0.12)					
Relative Knowledge	α_f	0.47	0.51	-0.51	-0.01	0.72				
(1st user)		(0.17)	(0.56)	(0.66)	(0.10)	(0.18)				
Relative Knowledge	α_s	1.51	0.24	-0.11	0.07	0.06	1.40			
(2nd user)		(0.30)	(1.37)	(1.34)	(0.18)	(0.20)	(0.49)			
Confusion	γ_1	0.30	0.15	-0.40	-0.15	0.02	-0.02	0.76		
		(0.15)	(0.51)	(0.61)	(0.10)	(0.14)	(0.21)	(0.20)		
Logo Similarity	γ_2	0.39	-0.59	0.74	0.07	0.00	-0.01	-0.26	0.49	
		(0.09)	(0.37)	(0.45)	(0.07)	(0.10)	(0.17)	(0.10)	(0.10)	
Category Similarity	γ_3	0.02	-1.07	-1.07	-0.16	0.02	-0.01	-0.01	-0.14	0.53
		(0.11)	(0.50)	(0.61)	(0.09)	(0.10)	(0.20)	(0.09)	(0.07)	(0.13)

Posterior standard deviations are in parentheses.

Figure 1. BOXPLOTS OF EFFECT SIZES ON BRAND RECALL PROBABILITY



Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

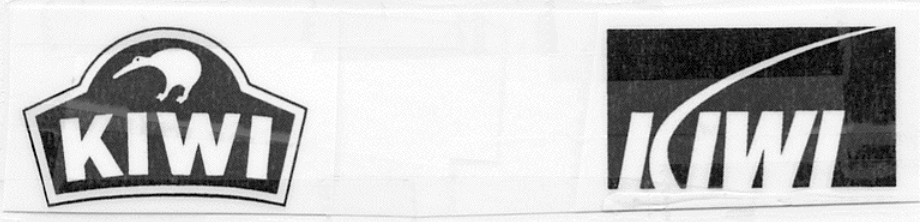
Derivatives of recall probability measure the expected change in recall probability for a unit change in the factor (e.g., familiarity), computed as the posterior mean of the respondent random-effects, and averaged across the observations for each respondent.

APPENDIX 1

In your opinion, how similar in appearance are each of the following pairs of logos?

Not at all Similar								Very Similar
1	2	3	4	5	6	7	8	9

Not at all Similar								Very Similar
1	2	3	4	5	6	7	8	9



Not at all Similar								Very Similar
1	2	3	4	5	6	7	8	9

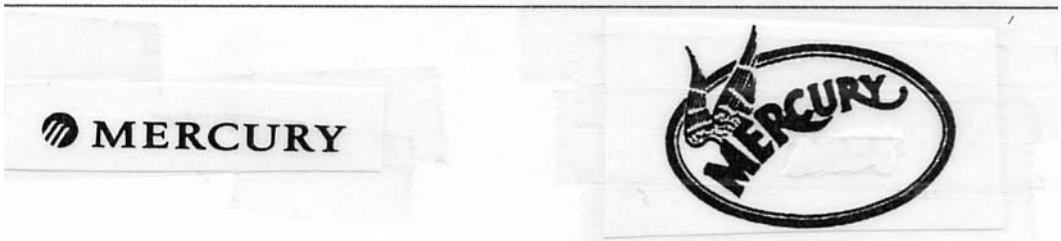
Not at all Similar								Very Similar
1	2	3	4	5	6	7	8	9

Please continue on the next page.

APPENDIX 1 (CONTINUED)

Not at all Similar 1 2 3 4 5 6 7 8 9 Very Similar

Not at all Similar 1 2 3 4 5 6 7 8 9 Very Similar



Not at all Similar 1 2 3 4 5 6 7 8 9 Very Similar

Not at all Similar 1 2 3 4 5 6 7 8 9 Very Similar

Please go to the next page.