

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 effects of dilution 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. Although 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. Frequently cited examples such as Kodak pianos, Dupont shoes, and Buick aspirin might cause confusion among some consumers about product origin, but many would likely correctly infer that 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 that consumers 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., sec. 1125(c)(1), par. 1127 [1995]). 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.*, 123 S. Ct. 1115 [2003]). Although 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. Although brand dilution caused by extensions has received considerable attention from researchers (e.g., Aaker and Keller 1990; Gurhan-Canli and Maheswaran 1998; Loken and John 1993), trademark

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dilution has not (cf. Morrin and Jacoby 2000; Peterson et al. 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 affect 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 consumer 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.*, 191 F.3d [2d Cir. 1999]; *Ringling Bros.-Barnum and Bailey Combined Shows, Inc. v. Utah Div. of Travel Development*, 170 F.3d 449, 463 [4th Cir. 1999]). Although Morrin and Jacoby (2000) showed that brand recognition and recall decline after exposure (vs. no exposure) to trademark diluting advertisements, they did not provide insight regarding the role of consumer confusion. Yet the presence or absence of confusion would appear to have significant implications for how the second user's information is stored in long-term memory and thus should affect the extent of harm from dilution. As described in more detail below, we propose that the presence of consumer confusion will have asymmetric effects on recall probabilities for first and second users.

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, namely, cue-independent models such as ACT-R (Anderson and Lebiere 1998; Anderson et al. 2004), 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 (vs. 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. 2004), simple feed-forward neural networks (McCulloch and 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

$$y_n(t) = I \left(\sum_{m \rightarrow n} w_{m,n} \times y_m(t-1) > \theta_n \right), \quad (1)$$

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 m th brand node, and t denotes time. Indicator function I takes on the value of one 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 . The category threshold level θ_n needs to be surpassed for activation of node n , and the $w_{m,n}$, or activation flows, reflect 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 activations, we operationalize thresholds for consumer i and brand k using consumers' self-reported, preexisting levels of familiarity with the brand names in their respective 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

$$\theta_n^{ik} = \beta_{0i} + \beta_{1i} \times \text{fam}_n^{ik}, \quad (2)$$

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

Activation 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 and direction of activation flow when cued with a brand name. This aspect of the model captures what Anderson et al. (2004) 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 vs. 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:

$$w_f^{ik} = \frac{\exp[\alpha_f(\text{know}_f^{ik} - \text{know}_s^{ik})]}{\exp[\alpha_f(\text{know}_f^{ik} - \text{know}_s^{ik})] + \exp[\alpha_s(\text{know}_s^{ik} - \text{know}_f^{ik})]} \tag{3}$$

and

$$w_f^{ik} = \alpha_f \times (\text{know}_f^{ik} - \text{know}_s^{ik}). \tag{4}$$

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’s 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 product category when prompted with a brand cue is defined as the probability that the activation flow along the association exceeds the category threshold

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

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 and propose that consumer confusion will have asymmetric effects on the retrieval probabilities of first and second users. If a consumer is confused about product origin (i.e., believes the two products come from the same manufacturer), she will integrate the second user’s information into the same brand network as that of the original user. When later cued with the brand name, some activation will be siphoned off to the second user’s category node within the original brand network structure. 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 or more distant from that of the first user, and thus the information will interfere less with activation flow and retrieval for the first user. At the same time, a second user will benefit, in terms of retrieval probability, when confusion exists, with the second user brand benefiting from the activation siphoning-off process. Thus, the presence of confusion will tend to interfere with first user recall but enhance second user recall.

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 sim-

ilarity and category similarity are also 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, logo similarity and category similarity, best belonged in the model as a link to the scale of the error distribution

$$\sigma^{ik} = \exp[\gamma_{i1}(\text{confuse}^{ik}) + \gamma_{i2}(\text{logosim}^{ik}) + \gamma_{i3}(\text{catsim}^{ik})]. \tag{6}$$

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 recall probability associated with equations 5 and 6 is

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

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

$$\Pr(\{y_f\}, \{y_s\} | \{\alpha_i\}, \{\beta_i\}, \{\gamma_i\}) = \prod_{i=1}^N \prod_{k=1}^K [p_f^{y_{ik}} (1 - p_f)^{1-y_{ik}}] \times [p_s^{y_{ik}} (1 - p_s)^{1-y_{ik}}]. \tag{8}$$

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

$$(\alpha'_i, \beta'_i, \gamma'_i)' \sim MVN(\mu, \Omega). \tag{9}$$

Our model generalizes existing specifications in the literature (see, e.g., Anderson et al. 2004, 1042) in that covariates are related to model components (e.g., category thresholds and activation flows) whose associations are heterogeneously estimated. Thus, analysis based on the model does not require prespecification of effect sizes (e.g., the value of the error scale, σ , as in Anderson et al. 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 motivated by the factors considered in prior cases to establish circumstantial proof of dilution (*Mead Data Central, Inc. v. Toyota Motor Sales, U.S.A., Inc.*, 875 F.2d 1026 [2d Cir. 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

Two hundred twelve 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 1 of the booklet at their own pace and stop when they reached part 2. In part 1, participants evaluated a number of real world brand logos, each of which was affiliated with a product category (e.g., Bass ale; see appendix figs. A1 and A2). 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 nine-point scale.

Participants then completed part 2 together with the experimenter. The first phase of part 2 consisted of a 2 min. 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 min. 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 pack-

age (*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 10 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. Summary statistics of brand characteristics are provided in table 1.

Descriptive Statistics

In table 2 we examine what we refer to as brand exclusive recall, which measures 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 2, 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), 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., $n = 159$).

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 that the contextual factors generally have the effects predicted. The threshold (θ) for category activation declines as brand familiarity increases ($\beta = -1.63$), as predicted. We also found the predicted relationship between association strength (w) and relative category knowledge ($\text{know}_f^{ik} - \text{know}_s^{ik}$). The parameter mean (α) for first users is smaller than that for second users (0.47 vs. 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.

Figure 1 presents box plots and means summarizing the

TABLE 1
SUMMARY STATISTICS OF BRAND CHARACTERISTICS ($n = 212$)

Brand	Familiarity		Knowledge		Confusion	Logo similarity	Category similarity
	First user	Second user	First user category	Second user category			
Parker (pens, games)	3.55	7.56	4.63	5.85	2.90	2.62	2.84
Ace (hardware stores, uniforms)	7.61	2.69	4.75	2.78	3.17	4.99	3.61
Kiwi (shoe polish, airlines)	5.98	2.80	3.90	5.49	3.24	4.48	1.25
Bass (ale, shoes)	6.15	7.11	5.64	6.75	3.77	7.45	1.35
Gibson (greeting cards, housewares)	3.57	1.93	4.90	4.08	5.42	8.47	2.70
Viking (computer components, pest control)	1.61	1.29	3.81	2.03	3.78	4.24	1.16
Mercury (automobiles, aircraft)	8.08	1.96	6.34	4.36	2.51	2.49	6.00
Pioneer (audio equipment, chain saws)	7.90	1.83	5.88	2.44	4.46	6.08	2.42
Mean	5.56	3.39	4.98	4.22	3.65	5.11	2.67

distribution of the effect sizes of the contextual factors. The box plots 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 are 0.027 and 0.018, respectively, for first and second user brands in the study. This implies that a four-point increase in brand familiarity is associated with an 8%–10% increase in average category recall probability.

The box plots for source confusion and logo similarity indicate asymmetric effects for the first and second users, as predicted. 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 box plots 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 affect on category recall. It may be that category similarity (i.e., feature overlap) may not be the determining factor affecting perceptions of product origin but, rather, fit based on more conceptual bases (e.g., Broniarczyk and Alba 1994).

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 article we demonstrate how consumer exposure to brand diluting logos tends to reduce brand exclusive recall levels. In this

TABLE 2
CATEGORY RECALL PATTERNS BY CONDITION (DILUTED $n = 159$, UNDILUTED $n = 53$)

Brand	Brand-exclusive recall (Recall first user but not second user)			Joint recall (Recall both first and second user)		Supplanted recall (Recall second user but not first user)		Null recall (Recall neither first nor second user)	
	Undiluted	Diluted	% Difference	Undiluted	Diluted	Undiluted	Diluted	Undiluted	Diluted
Parker	49.1	35.0	-28.7	.0	4.4	1.9	43.8	49.1	16.9
Ace	90.6	78.1	-13.8	.0	8.8	.0	6.3	9.4	6.9
Kiwi	60.4	33.1	-45.2	.0	25.6	3.8	30.6	35.8	10.6
Bass	77.4	14.4	-81.4	.0	51.3	11.3	30.6	11.3	3.8
Gibson	13.2	23.1	75.0	.0	6.2	.0	10.0	86.8	60.6
Viking	45.3	15.0	-66.9	.0	6.2	.0	21.2	54.7	57.5
Mercury	98.1	80.0	-18.4	.0	12.5	.0	2.5	1.9	5.0
Pioneer	85.8	75.0	-12.6	.0	13.1	.0	3.8	13.2	8.1
Mean	65.1	44.2	-32.1	.0	16.0	2.1	18.6	32.8	21.24

TABLE 3
FIT COMPARISON OF ALTERNATIVE MODELS

Model specification	Respondent-level parameters	Log marginal density ^a
Associative network model ^b	8	-1,195.15
Constrained network model ^c	8	-1,216.45
Logit model ^d	8	-1,206.71

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

^bAssociative network model specification:

$$\Pr(y_i = 1) = \frac{\exp[(w_i - \theta_i)/\sigma]}{1 + \exp[(w_i - \theta_i)/\sigma]}$$

where $w_i = \alpha_i(\text{know}_i - \text{know}_s)$, $\theta_i = \beta_{0f} + \beta_1(\text{fam}_i) + \beta_2(\text{fam}_s) + \beta_3(\text{logo}) + \beta_4(\text{catsim}) + \beta_5(\text{know}_i)$.

^cConstrained network model specification (w_i sum to one):

$$w_i = \frac{\exp[\alpha_i(\text{know}_i - \text{know}_s)]}{\exp[\alpha_i(\text{know}_i - \text{know}_s)] + \exp[\alpha_s(\text{know}_s - \text{know}_i)]}$$

^dLogit model specification:

$$\Pr(y_i = 1) = \frac{\exp[\beta_{0f} + \beta_1(\text{confuse}) + \beta_2(\text{fam}_i) + \beta_3(\text{logo}) + \beta_4(\text{catsim}) + \beta_5(\text{know}_i)]}{1 + \exp[\beta_{0f} + \beta_1(\text{confuse}) + \beta_2(\text{fam}_i) + \beta_3(\text{logo}) + \beta_4(\text{catsim}) + \beta_5(\text{know}_i)]}$$

$$\Pr(y_s = 1) = \frac{\exp[\beta_{0s} + \beta_1(\text{confuse}) + \beta_2(\text{fam}_s) + \beta_3(\text{logo}) + \beta_4(\text{catsim}) + \beta_5(\text{know}_s)]}{1 + \exp[\beta_{0s} + \beta_1(\text{confuse}) + \beta_2(\text{fam}_s) + \beta_3(\text{logo}) + \beta_4(\text{catsim}) + \beta_5(\text{know}_s)]}$$

study, a single exposure to diluting brand stimuli is found to have a damaging effect on brands, reducing brand exclusive recall by about a third, on average.

More important, 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

TABLE 4

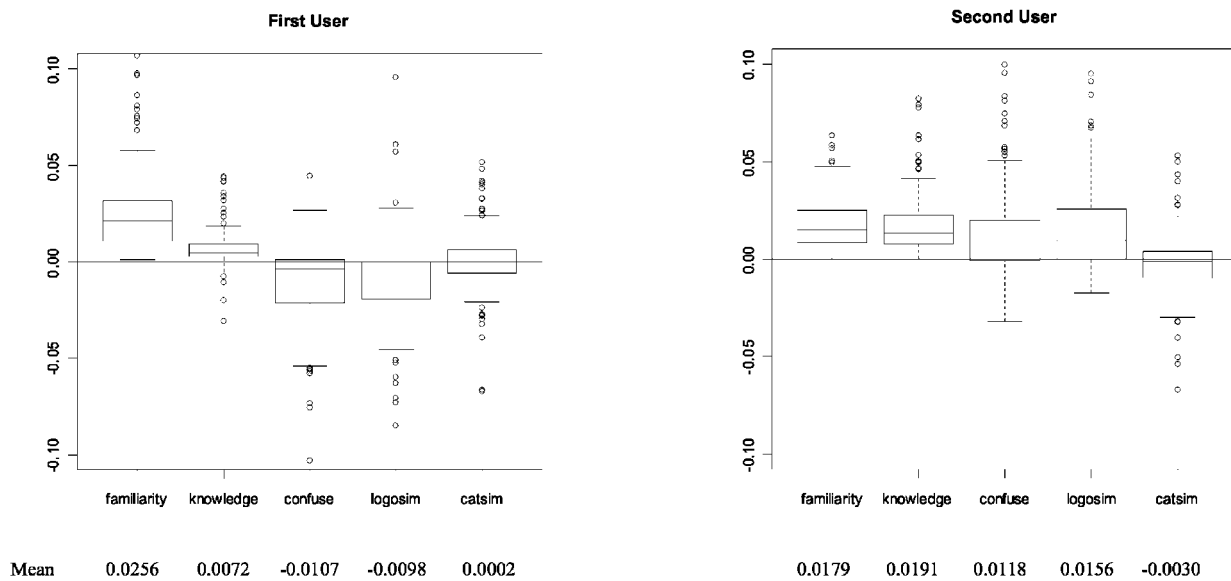
POSTERIOR MEAN AND COVARIANCE MATRIX OF HETEROGENEITY FOR THE ASSOCIATIVE NETWORK MODEL

Variable	Symbol	Mean	Covariance matrix								
Intercept (first user)	β_{0f}	6.07 (.67)	9.67 (3.88)								
Intercept (second user)	β_{0s}	10.73 (.82)	-8.65 (3.58)	12.03 (7.03)							
Familiarity	β_1	-1.63 (.12)	-.75 (.50)	.70 (.41)	.48 (.12)						
Relative knowledge (first user)	α_f	.47 (.17)	.51 (.56)	-.51 (.66)	-.01 (.10)	.72 (.18)					
Relative knowledge (second user)	α_s	1.51 (.30)	.24 (1.37)	-.11 (1.34)	.07 (.18)	.06 (.20)	1.40 (.49)				
Confusion	γ_1	.30 (.15)	.15 (.51)	-.40 (.61)	-.15 (.10)	.02 (.14)	-.02 (.21)	.76 (.20)			
Logo similarity	γ_2	.39 (.09)	-.59 (.37)	.74 (.45)	.07 (.07)	.00 (.10)	-.01 (.17)	-.26 (.10)	.49 (.10)		
Category similarity	γ_3	.02 (.11)	-1.07 (.50)	-1.07 (.61)	-.16 (.09)	.02 (.10)	-.01 (.20)	-.01 (.09)	-.14 (.07)	.53 (.13)	

NOTE.—Posterior standard deviations are in parentheses.

FIGURE 1

BOX PLOTS OF EFFECT SIZES ON BRAND RECALL PROBABILITY



NOTE.—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.

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 stimulus 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 relationship between the products at issue and the sample of respondents chosen for consumer surveys in trademark dilution cases should be accorded considerable thought.

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, although the second user's category is more likely to be recalled. 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, 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 emanating 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. Because the current results are based on a convenience sample of students, replication is called for using probabilistic sampling methods. Further, the retrieval measure used in this study is category recall when prompted with a brand name. Other memory measures may provide additional insight, such as reaction times to brand-category pairs. We do believe, nevertheless, 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.



APPENDIX



FIGURE A1



SIMILARITY OF LOGO APPEARANCE MEASURES

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

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

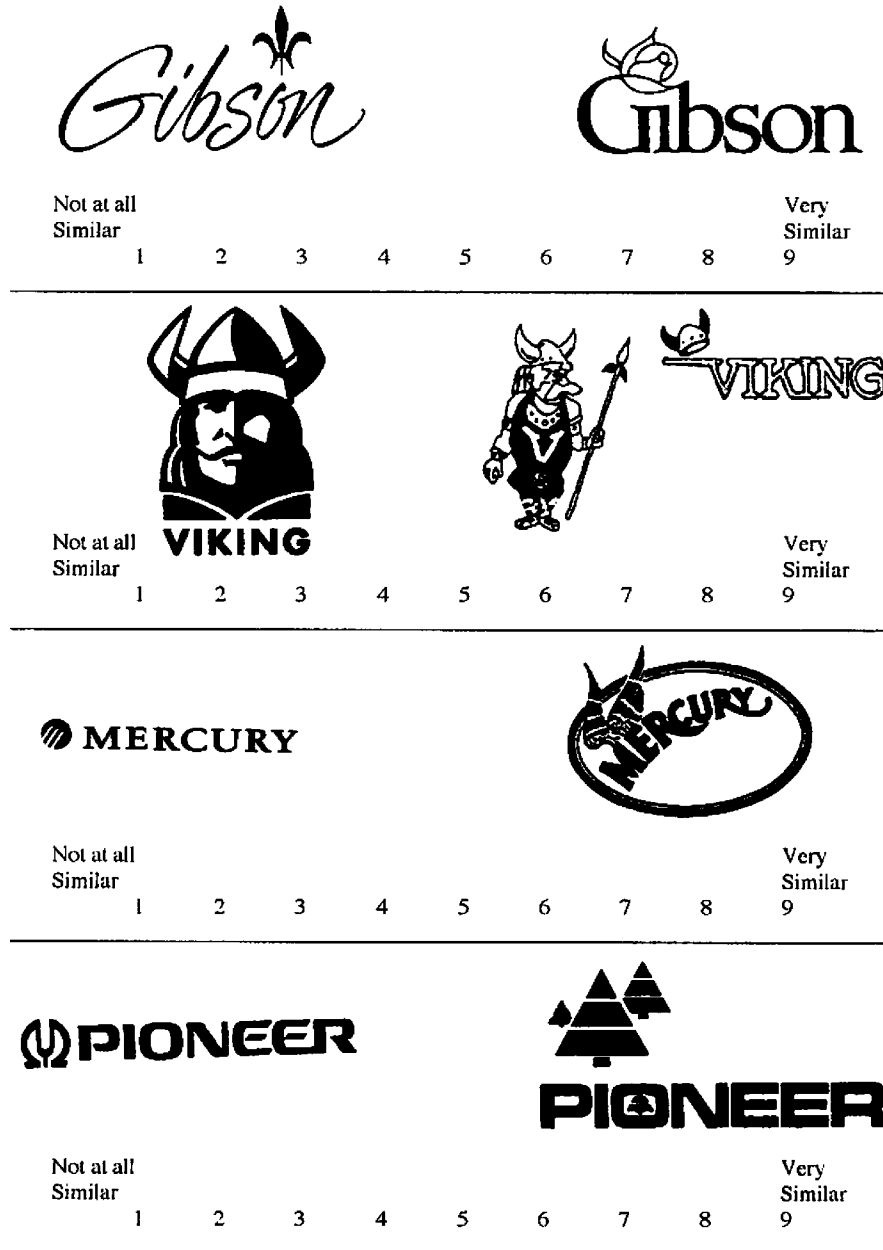
										
Not at all Similar	1	2	3	4	5	6	7	8	9	Very Similar

										
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 continue on the next page.

FIGURE A2
SIMILARITY OF LOGO APPEARANCE MEASURES (CONTINUED)



Please go to the next page.

REFERENCES

Aaker, David A. and Kevin Lane Keller (1990), "Consumer Evaluations of Brand Extensions," *Journal of Marketing Research*, 54 (January), 27-41.
 Anderson, John R., Daniel Bothell, Michael D. Byrne, Scott Doug-

lass, Christian Lebiere, and Yulin Qin (2004), "An Integrated Theory of the Mind," *Psychological Review*, 111 (4), 1036-60.
 Anderson, John R. and Christian Lebiere (1998), *The Atomic Components of Thought*, Mahwah, NJ: Erlbaum.
 Broniarczyk, Susan M. and Joseph W. Alba (1994), "The Importance of the Brand in Brand Extension," *Journal of Marketing Research*, 31 (May), 214-28.

- Farquhar, Peter H. and Paul M. Herr (1993), "The Dual Structure of Brand Associations," in *Brand Equity and Advertising: Advertising's Role in Building Strong Brands*, ed. David A. Aaker and Alexander L. Biel, Hillsdale, NJ: Erlbaum, 263–77.
- Gluck, Mark A. and Gordon H. Bower (1988), "From Conditioning to Category Learning: An Adaptive Network Model," *Journal of Experimental Psychology: General*, 117 (September), 227–47.
- Gurhan-Canli, Zeynep and Durairaj Maheswaran (1998), "The Effects of Extensions on Brand Name Dilution and Enhancement," *Journal of Marketing Research*, 35 (November), 464–73.
- Janiszewski, Chris and Stijn M. J. Van Osselaer (2000), "A Connectionist Model of Brand-Quality Associations," *Journal of Marketing Research*, 37 (August), 331–50.
- Loken, Barbara and Deborah Roedder John (1993), "Diluting Brand Beliefs: When Do Brand Extensions Have a Negative Impact?" *Journal of Marketing*, 57 (July), 71–84.
- Loken, Barbara, Ivan Ross, and Ronald L. Hinkle (1986), "Consumer Confusion of Origin and Brand Similarity Perceptions," *Journal of Public Policy and Marketing*, 5 (1), 195–211.
- Lots O' Logos* (1998), Los Angeles: Typesetting, Ink.
- McCulloch, Warren S. and Walter Pitts (1943), "A Logical Calculus of Ideas Immanent in Neural Activity," *Bulletin of Mathematical Biophysics* 5, 115–33. Reprinted in James A. Anderson and Edward Rosenfeld, eds. (1988), *Neurocomputing: Foundations of Research*, Cambridge, MA: MIT Press, 15–27.
- Morrin, Maureen and Jacob Jacoby (2000), "Trademark Dilution: Empirical Measures for an Elusive Concept," *Journal of Public Policy and Marketing*, 19 (2), 265–76.
- Nedungadi, Prakash (1990), "Recall and Consumer Consideration Sets: Influencing Choice without Altering Brand Evaluations," *Journal of Consumer Research*, 17 (December), 263–76.
- Newton, Michael A. and Adrain E. Raftery (1994), "Approximate Bayesian Inference with the Weighted Likelihood Bootstrap," *Journal of the Royal Statistical Society, Series B*, 56 (1), 3–48.
- Oswald, Lynda J. (1999), "'Tarnishment' and 'Blurring' under the Federal Trademark Dilution Act of 1995," *American Business Law Journal*, 36 (2), 255–300.
- Pearce, John M. (1994), "Similarity and Discrimination: A Selective Review and a Connectionist Model," *Psychological Review*, 101 (October), 587–607.
- Peterson, Robert A., Karen H. Smith, and Philip C. Zerrillo (1999), "Trademark Dilution and the Practice of Marketing," *Journal of the Academy of Marketing Science*, 27 (2), 255–68.
- Ripley, Brian D. (1996), *Pattern Recognition and Neural Networks*, New York: Cambridge University Press.
- Schechter, Frank I. (1927), "The Rational Basis of Trademark Protection," *Harvard Law Review*, 40, 813–31.
- Simonson, Alexander (1993), "How and When Do Trademarks Dilute: A Behavioral Framework to Judge 'Likelihood' of Dilution," *Trademark Reporter*, 83 (2), 149–74.
- Van Osselaer, Stijn M. J. and Chris Janiszewski (2001), "Two Ways of Learning Brand Associations," *Journal of Consumer Research*, 28 (September), 202–23.