

**CROSS-NATIONAL LOGO EVALUATION ANALYSIS:  
AN INDIVIDUAL LEVEL APPROACH**

by

Ralf van der Lans  
Joseph A. Cote  
Catherine A. Cole  
Siew Meng Leong  
Ale Smidts  
Pamela W. Henderson  
Christian Bluemelhuber  
Paul A. Bottomley  
John R Doyle  
Alexander Fedorikhin  
M. Janakiraman  
B. Ramaseshan  
Bernd Schmitt

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Ralf van der Lans is Assistant Professor of Marketing, Rotterdam School of Management, Erasmus University, Rotterdam. Joseph A. Cote is Professor of Marketing, Washington State University. Catherine A. Cole is Professor of Marketing at the Henry B. Tippie College of Business at The University of Iowa. Siew Meng Leong is Professor of Marketing, NUS Business School, National University of Singapore. Ale Smidts is Professor of Marketing Research, Rotterdam School of Management, Erasmus University, Rotterdam. Pam Henderson is owner of New Edge Inc. a marketing consulting firm. Christian Bluemelhuber is Professor of Marketing at the Technical University of Munich. Paul A. Bottomley and John R. Doyle are Distinguished Senior Research Fellow and Professor of Marketing respectively at the Cardiff Business School, Cardiff University, UK. UK. Alexander Fedorikhin is Associate Professor of Marketing at Kelley School of Business, Indiana University, Indianapolis. M. Janakiraman is Associate Professor of Marketing, Indian Institute of Management at Lucknow. B. Ramaseshan is Professor of Marketing and Head, School of Marketing at Curtin University of Technology, Perth, Australia. Bernd H. Schmitt is the Robert F. Calkins Professor of International Business and Director of the Center on Global Brand Leadership at Columbia Business School.

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Please send correspondence regarding this manuscript to Joseph A Cote, Department of Marketing, Washington State University, 14204 NE Salmon Creek Avenue, Vancouver, WA 98686, 360-546-9753, [cote@wsu.edu](mailto:cote@wsu.edu).

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**Abstract**

The universality of design perception and response is tested using logo data collected from ten countries: Argentina, Australia, China, Germany, Great Britain, India, the Netherlands, Russia, Singapore, and the United States. A finite-mixture structural-equation model is developed in a Bayesian framework that identifies latent clusters of logos while accounting for heterogeneity in evaluations. The concomitant variable approach allows cluster probabilities to be country specific. Rather than a priori defined clusters, our procedure provides a posteriori cross-national logo clusters based on consumer response similarity. To compare the a posteriori cross-national logo clusters, our approach is integrated with Steenkamp and Baumgartner's (1998) measurement invariance methodology. Our model reduces the ten countries to three cross-national clusters that respond differently to logo design dimensions: the West, Asia, and Russia. The dimensions underlying design are found to be similar across countries, suggesting that elaborate, natural, and harmony are universal design dimensions. Responses (affect, shared meaning, subjective familiarity, and false and true recognition) to logo design dimensions (elaborate, natural and harmony) and elements (repetition, proportion and parallel) are also relatively consistent, although we find minor differences across clusters. Our results suggest that managers can implement a global logo strategy – but can optimize logos for specific countries if desired.

Keywords: design, logos, international marketing, standardization, adaptation, structural equation models, Gibbs sampling, concomitant variable, Bayesian, mixture models

## 1. Introduction

Design is a language which communicates to consumers and others independently of verbal information. Hence, it is critical that marketing managers and scholars understand its impact on viewers. In general, visual information is processed differently from, faster than, and independent of verbal information (Edell and Staelin, 1983). In addition, visual information can trigger affect prior to cognitive processing (Lutz and Lutz, 1977).

Most marketing research has examined how individual design elements such as color, symmetry, proportion, and angularity affect consumers' reactions (e.g., Pittard et al., 2007). While such research is useful, it is like studying alphabets — critical to understand, but offering limited insight into word or sentence meaning. Henderson and Cote (1998), in an early attempt to understand broader design characteristics, uncovered three basic design dimensions: elaborate, natural, and harmony. Elaborate refers to a design's richness and its ability to use simple lines to capture the essence of something; natural designs depict commonly experienced objects; and harmony refers to how congruently the patterns and parts of a design are arranged. Extending our analogy, these design dimensions act as words instead of letters. Preliminary evidence indicates that these design dimensions are important for understanding reactions to a variety of marketing stimuli such as typeface (Henderson et al., 2004) and wine bottle design (Orth and Malkewitz, 2008).

While the evidence suggests that elaborate, natural, and harmony are “universal words” useful for understanding visual marketing stimuli, we have limited evidence about whether these design dimensions exist across cultures. We also do not know if people from different cultures respond in the same way to these design dimensions. Evolutionary psychology suggests that human response to visual stimuli is genetically programmed and relatively immune from cultural

influence (Adams, 2003). For example, we have an innate capability to determine what stimulus features provide information across several domains including evaluations of landscapes (Orians and Heerwagen, 1992), facial expressions of emotion (Ekman, 1998), and physical attractiveness (Jones, 1996). However, some research on reactions to individual design elements find cultural differences (e.g., Perfetti et al., 2005, Zhang et al., 2006), while others such as Pittard (2007) report similarities across cultures.

Given the conflicting findings in the literature, this study examines whether the design dimensions uncovered by Henderson and her colleagues underlie reactions to logos in ten different countries: Argentina, Australia, China, Germany, Great Britain, India, Netherlands, Russia, Singapore, and the United States. Using consumer and designer ratings of 195 stimuli, we apply a Bayesian finite-mixture structural-equation model employing an MCMC algorithm to uncover any latent differences in cultural perceptions of and responses to designs. This will provide the most comprehensive and rigorous test to date of such cultural variations regarding design dimensions (as opposed to individual design elements<sup>1</sup>). Specifically, we build upon Henderson and Cote (1998) to examine the following research questions:

1. Do the design dimensions of elaborate, natural, and harmony exist cross-nationally?
2. Are consumers' responses to these design dimensions stable cross-nationally?

Beyond studying the theoretical questions of design dimension universality and consumer response stability, our paper also makes a methodological contribution. Research in experimental aesthetics typically analyzes data at the stimulus level by averaging individual judgments for each stimulus (e.g., Henderson and Cote, 1998). However, such an approach does not consider heterogeneity in individual responses, which will mask information contained in individual response variation. This may bias correlations between judgments about different stimuli

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<sup>1</sup> A design element is a single characteristic while a design dimension is a combination of elements.

(DeShon, 1998). Thus, we extend finite-mixture structural-equation models (DeSarbo et al., 2006) to simultaneously analyze responses at the stimuli level while accounting for individual judgment heterogeneity through an additional hierarchical layer. Our model also uses a concomitant variable specification (ter Hofstede et al., 1999) to allow the probabilities of stimuli belonging to specific latent clusters to vary across countries. We then use the country-specific cluster probabilities to interpret the latent clusters. Last, we assess measurement invariance (Steenkamp and Baumgartner, 1998) across clusters rather than across countries. This offers two advantages. First, the number of cross-national clusters is usually smaller than the number of countries if many countries are studied – so fewer computations are required and invariance testing is more tractable (invariance tests grow exponentially with the number of countries). Second, Steenkamp and Baumgartner’s framework usually selects countries *a priori*, while our approach is not restricted to country.<sup>2</sup> *A priori* allocations may not be realistic, because “consumers in different countries often have more in common with one another than with other consumers in the same country” (ter Hofstede, Steenkamp and Wedel, 1999).

We use logos as a context to examine the research questions. As a key component of corporate visual identity, managers employ logos to create positive emotions, convey meaning, or enhance recognition about the company and brand. However, managers have expressed uncertainty about how to manage corporate visual identity systems globally (e.g. see, Alashban et al., 2002). The literature suggests that logos are most often used in an unaltered form when going abroad (Kapferer, 1992). Does using unaltered logos in new markets accomplish their communication goals, or would it be necessary to modify logos for individual countries? Depending on our findings, managers can either feel secure using standardized logos and other

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<sup>2</sup> The constrained finite-mixture does not require that all stimuli within a country be part of the same cluster. Any cluster may contain only a portion of stimuli from a given country.

visual material; or, if cross-cultural differences exist, we can provide guidelines for adapting logos to specific countries or regions.

### **3. Conceptual Framework**

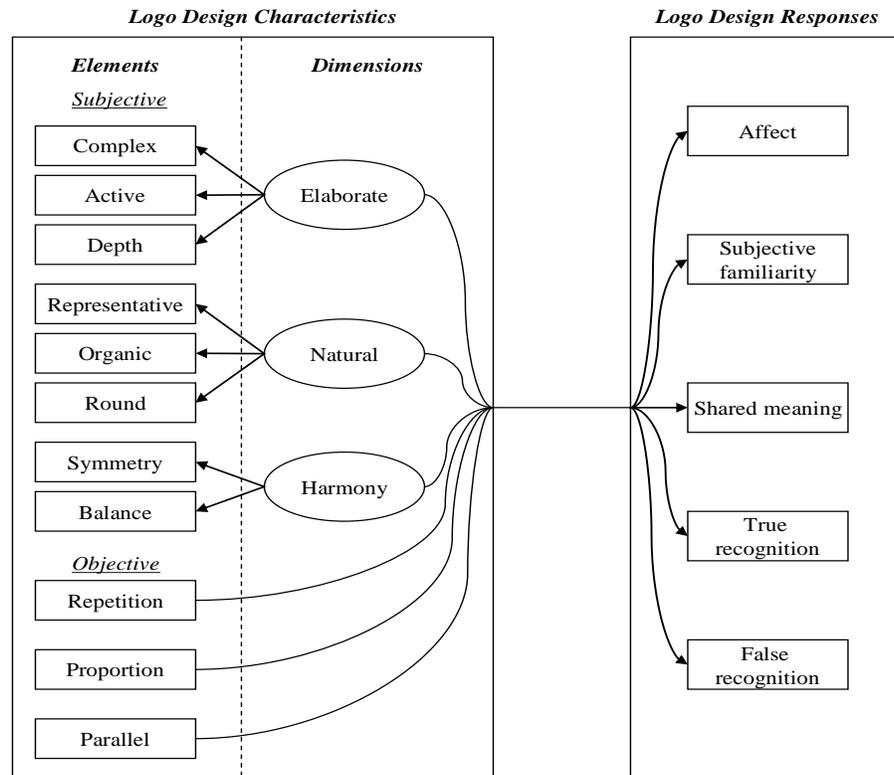
Consistent with Henderson and Cote (1998) our framework is specified at the logo level, and proposes that consumers perceive logo designs along three objective design elements and three design dimensions (see Figure 1). The objective design elements include: repetition (number of times identical shapes are repeated), proportion (the ratio of a logo's width to its height), and parallel (number of parallel lines). As discussed earlier, the design dimensions are elaborate, natural, and harmony. The design dimensions consist of 8 design elements (complex, active, depth, representative, organic, round, symmetric, and balance) measured subjectively by designers (see Appendix A). While these six characteristics do not capture all aspects of design, they appear to represent a fundamental core for logo design.

We use positive affect, shared meaning, subjective familiarity, and true and false recognition to assess responses to logo designs. *Positive affect* is important because feelings can transfer to the product or company, especially in low-involvement decision making where affective reactions can guide choice. Prior work suggests that increasing the harmony, elaborate, and natural dimensions in designs increases positive affect primarily because these design changes facilitate perception (Anand and Sternthal, 1991, Martindale et al., 1988) and stimulate arousal (Raymond et al., 2003). Natural designs may also be more pleasing, because they are more prototypical (Seifert, 1992).

*Shared meaning* exists when there is a consensus among respondents regarding the first meaning or association that comes to mind when they see a logo (Ellis et al., 1974). Logos with high shared meaning are valuable because they are perceived, interpreted, and remembered better

than stimuli with varied meaning (Rodewald and Bosma, 1972). Natural, harmony, and to a lesser extent elaborate, may increase shared meaning because universally experienced objects are more easily interpreted and recognized than abstract objects (Seifert, 1992, Shinar et al., 2003).

**Figure 1**  
**Conceptual Framework of Logo Design Evaluation**



*Note:* Logo design dimensions (consisting of subjective elements) and objective elements are on the left, while consumer responses to logos are depicted on the right.

Previous studies have not examined the relationship between logo design and *subjective familiarity* (feeling of having seen a logo before, regardless of prior exposure). Subjective familiarity can increase positive affect (Zajonc, 1968), and even enhance brand choice (Henderson and Cote, 1998). Since shared meaning and subjective familiarity are closely related, the rationale behind the relationships between the design characteristics and subjective familiarity are similar to those for shared meaning.

Logo *recognition* means consumers remember seeing the logo before. Because consumers recognize pictures more quickly than words, a company can communicate quickly by using a logo in the brand name (Edell and Staelin, 1983). We distinguish between two types of recognition: *true recognition* is the correct assertion that one has seen the logo before; and *false recognition* is the incorrect assertion that one has seen the logo before. False recognition is not necessarily a bad outcome as companies may deliberately create new logos that seem familiar. According to Gestalt, motivational, and cognitive theories, consumers are likely to exhibit true recognition for stimuli that are easy to encode and command attention. Natural logos, which are easy to encode, should increase true recognition and decrease false recognition. However, other design dimensions should have little effect on either type of recognition.

This conceptual framework does not propose any cross-cultural differences. Rather, we expect that the same underlying design structure, and relationships between design characteristics and consumer responses, exist independent of where the consumer lives. In our analysis, we start with the framework in Figure 1 and use a latent class methodology to test whether different logo clusters exist across cultures.

### **3. Method**

#### **3.1 Overview**

To test if perception of and response to design is invariant across cultures, we collected data from consumers and designers in ten countries: Argentina, Australia, China, Germany, Great Britain, India, the Netherlands, Russia, Singapore, and the United States. These countries, on five continents, represent an array of geographic, economic, political, language, and cultural backgrounds (see Table 1), thus rigorous test perceptions of and responses to logo designs. By comparison, recent international marketing research has generally involved two

**Table 1**  
**Characteristics of the Countries Studied**

<b>Nation/ Characteristic</b>	<b>Argentina</b>	<b>Australia</b>	<b>China</b>	<b>Germany</b>	<b>Great Britain</b>	<b>India</b>	<b>The Netherlands</b>	<b>Russia</b>	<b>Singapore</b>	<b>U.S.</b>
Geography	South America	Oceania	East Asia	Western Europe	Western Europe	South Asia	Western Europe	Eastern Europe/Asia	East Asia	North America
Economics: <sup>1</sup>										
Gross National Income/capita	\$5528	\$37,924	\$2,055	\$34,955	\$39,207	\$784	\$40,535	\$6,877	\$30,159	\$43,562
Government <sup>2</sup>	Republic	Common- wealth	Socialist	Federal Republic	Constitutional Monarchy	Federal Republic	Constitutional Monarchy	Federalist	Republic	Federal Republic
Culture: <sup>3</sup>										
Power distance	49	36	80	35	35	77	38	93	74	40
Uncertainty Avoidance	86	51	30	65	35	40	53	95	8	46
Individualism/ Collectivism	46	90	20	67	89	48	80	39	20	91
Masculinity/ Femininity	56	61	66	66	66	56	14	36	48	62
Language/ Writing System <sup>4</sup>	Spanish/ Alphabetic 26+3	English/ Alphabetic 26	Mandarin/ Logographic 47,035	German/ Alphabetic 26+4	English/ Alphabetic 26	English & Hindi/ Alphabetic & Abugida 64	Dutch & Frisian/ Alphabetic 26+1	Cyrillic/ Alphabetic 33	English & Mandarin/ Alphabetic & Logographic	English/ Alphabetic 26

Footnotes:

1. 2006 UN data (<http://unstats.un.org/unsd/demographic/products/socind/inc-eco.htm> - accessed 7-24-2008).
2. Source: CIA (2004), *The World Factbook*.
3. Source: Hofstede (1983) Higher scores reflect greater power distance, uncertainty avoidance, individualism, and masculinity respectively. Statistics for China and Russia were not in the original IBM data set, but collected later and reported in (Hofstede, 2001, Exhibit A5.3, p. 502).
4. The first value is the number of basic symbols in the writing system. The second is the number of diacritics and ligatures.

(e.g., Gurhan-Canli and Maheswaran, 2000) or three countries (e.g., Erdem et al., 2004), or a limited region (Baumgartner and Steenkamp, 2001, ter Hofstede, Steenkamp and Wedel, 1999).

The stimuli, which comprised the 195 unfamiliar logos used by Henderson and Cote (1998), were originally obtained from a book of foreign logos (Kuwayama, 1973) and from yellow pages advertisements. To minimize the effects of past exposure and to prevent confounding of symbolic with verbal processing, the logos contained no verbal material. Standard back translation methods were used on all questionnaires. A bilingual native speaker translated the questionnaires written in English into each country's language. A different bilingual native speaker translated the questionnaires back into English. The 11 design elements used in this research are the same as those in Henderson and Cote (1998). Appendix A defines these design elements and contains examples of logos scoring high and low on them.

### **3.2 Ratings of Logo Design Elements**

Consistent with experimental aesthetics research, data was collected on a large number of stimuli and a large number of variables, across multiple samples. Two or three professional logo designers in each country evaluated the extent to which each logo possessed the design elements of active, balance, depth, organic, representative, round, and symmetric. The designers had formal training and extensive experience with commercial clients and logo design. Before rating the logos, the evaluators received a short description of each characteristic. Consistent with Henderson and Cote (1998), five groups of about 40 undergraduates in each country evaluated the design element of complex for a different subset of 39 logos.<sup>3</sup> Finally, data from Henderson and Cote (1998) provided the three objectively measured logo design elements of parallel, proportion, and repetition.

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<sup>3</sup> This furnishes evaluations for 5 X 39 or 195 logos in total.

In summary, the 11 design elements were each measured with a single indicator. Eight of the design elements (active, balance, depth, organic, representative, round, symmetric, and complex) are country-specific and are measured by different raters (either designers or students) in each country. Repetition, proportion, and parallel are identical across countries.

### **3.3 Responses to Logo Design**

*Affect and Subjective Familiarity.* To minimize fatigue, each respondent rated only 39 logos on the five affective items (like/dislike, good/bad, high/low quality, distinct/not distinct, and interesting/uninteresting), as well as subjective familiarity (familiar/unfamiliar). Each logo appeared on a separate page with the 7-point rating scales and was evaluated by 20-70 respondents (about 40 on average).

*Shared Meaning.* Shared meaning exists when there is a consensus among respondents regarding the first meaning or association that comes to mind when they see a logo (Ellis, Parente and Shumate, 1974). The same respondents for the affect and subjective familiarity questions listed the first meaning or association that came to mind when they looked at each logo (collected in the second half of the booklet). A trained research assistant from each country grouped similar associations. For each logo in each country, we calculated the Hirschman-Herfindahl index score by squaring and then summing across the probabilities of each response (Henderson and Lafontaine 1996)<sup>4</sup>. A high concentration index indicates that a logo evokes shared meaning.

*Recognition.* For each country, five groups of approximately 30 business undergraduates (different from the groups used to collect the affect, familiarity, and meaning ratings) viewed a subset of 39 logos in a slide show, with each logo appearing for two seconds. Respondents next

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<sup>4</sup> For example, if 50% of respondents said a logo reminded them of a sun, 30% said wheel, and 20% said star, the Hirschman-Herfindahl index would be  $.5^2 + .3^2 + .2^2 = .38$ .

participated in a distracter task for about ten minutes. They then viewed a booklet with 78 logos – 39 target logos from the slide presentation and 39 distracter logos that were not presented earlier. The students then indicated whether they had seen the logo in the slide show. True recognition is the percentage of respondents who correctly recognize a target logo, while false recognition is the percentage of respondents who claimed to recognize a distracter logo.

#### **4. The Model**

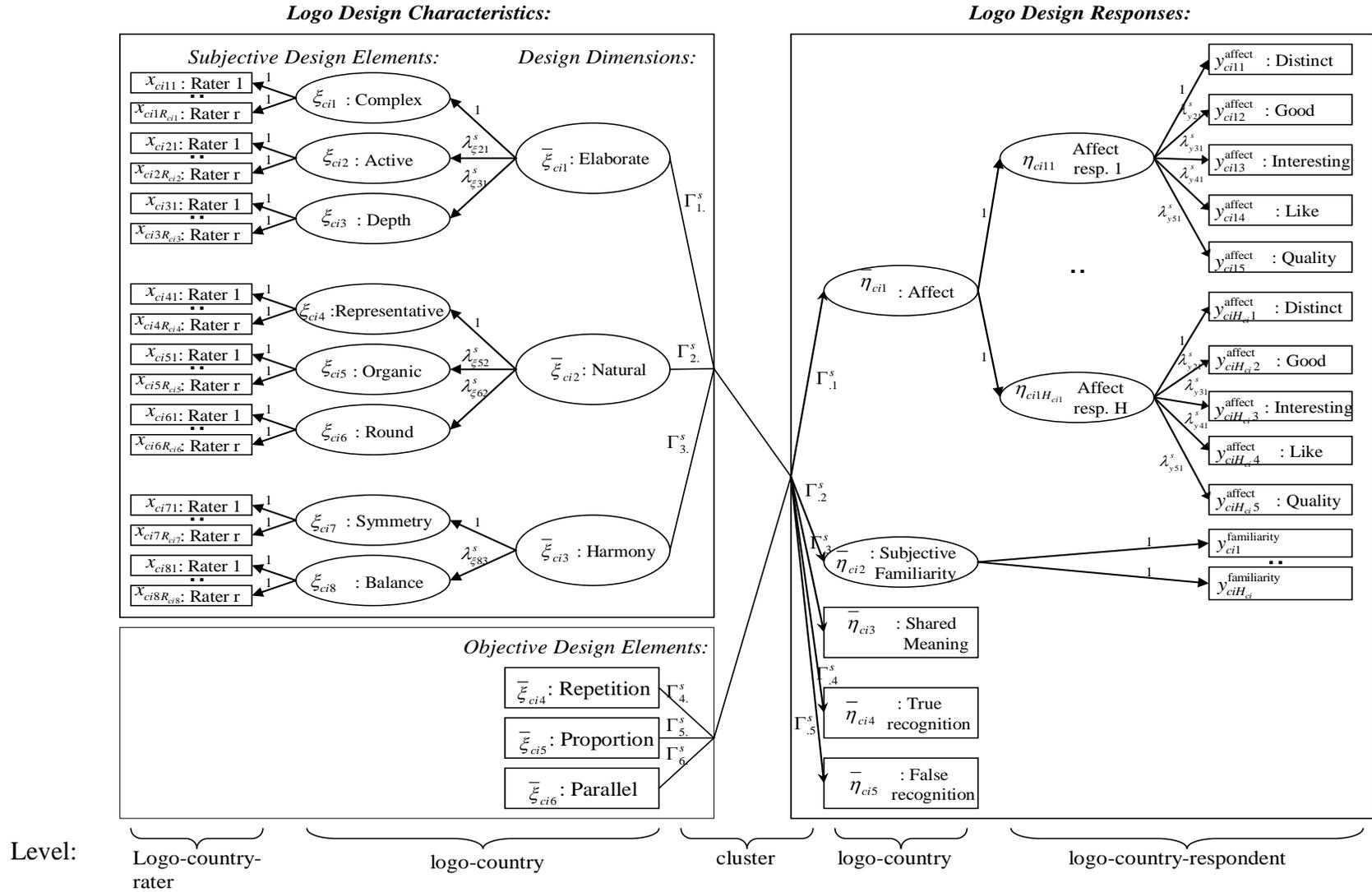
Following previous aesthetics research, our model uses logos as the primary unit of analysis. The structural relationships between logo design characteristics and consumer responses are specified using data collected at the logo level (see Figure 2). Previous research averages individual ratings and responses to compute each logo's design and response scores (e.g., Henderson et al 2003). Our model includes an additional hierarchy to analyze data at the individual level, thus minimizing potential aggregation bias (DeShon, 1998).<sup>5</sup> To test whether perceptions and evaluations of logos are similar cross-nationally, we specify a concomitant variable finite-mixture structural equation model that allocates logos to clusters. With fewer clusters than countries, our approach reduces the number of invariance tests relative to Steenkamp and Baumgartner (1998) who define clusters a priori at the country level.

If logos are evaluated similarly across cultures, we will find a one-cluster solution. We estimate our model in a Bayesian framework using an MCMC algorithm, which has several advantages over traditional methods including no asymptotic assumptions, suitability for smaller sample sizes, incorporation of prior information (Rossi and Allenby, 2003), and avoidance of Heywood cases (negative variances). Most importantly, Bayesian inference estimates individual-specific effects. Thus, we can obtain each individual logo's country-specific posterior

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<sup>5</sup> We estimated a model without taking into account individual response differences and found a significant aggregation bias.

**Figure 2**  
**Model Specification at the Cluster and Individual Response Level**<sup>6</sup>



<sup>6</sup> All intercepts and errors are omitted for clarity

distribution of factor scores and cluster probabilities. Managers can use this information to optimize individual logos on specific dimensions of interest, as shown in Section 6.1.

#### 4.1 Model Specification

Before introducing our model, we present some notation that defines the sets and (latent) variables. Let:

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$i = 1, \dots, I$	denote the set of logos. In this study, $I = 195$ .
$c = 1, \dots, C$	denote the set of countries. In this study, $C = 10$ .
$s = 1, \dots, S$	denote the a priori unknown set of cross-national clusters to be determined empirically.
$q = 1, \dots, Q$	denote the set of logo design elements related to the design dimensions. In this study, $Q = 8$ (i.e., complex, active, depth, representative, organic, round, symmetry, and balance).
$n = 1, \dots, N$	denote the set of logo design characteristics. In this study, $N = 6$ and consists of two subsets: $N_{\text{dimension}} = 3$ design dimensions (i.e. elaborate, natural, and harmony); and $N_{\text{element}} = 3$ objective design elements (i.e., repetition, proportion, and parallel).
$p = 1, \dots, P$	denote the set of affect response items. In this study, $P = 5$ (i.e., distinct, good, interesting, like, and quality).
$m = 1, \dots, M$	denote the set of logo response variables. In this study, $M = 5$ (i.e., affect, subjective familiarity, shared meaning, true recognition, and false recognition).
$r = 1, \dots, R_{ciq}$	denote the raters in country $c$ that evaluated design element $q$ of logo $i$ .
$h = 1, \dots, H_{ci}$	denote the respondents in country $c$ that responded to logo $i$ on affect and subjective familiarity.
$x_{cirq}$	denote the evaluation of design element $q$ , of logo $i$ in country $c$ by rater $r$ .
$\xi_{ciq}$	denote the latent score of design element $q$ of logo $i$ in country $c$ .
$\bar{\xi}_{cin}$	denote the (latent) value of design dimension or objective element $n$ of logo $i$ in country $c$ .
$\mathbf{y}_{cih}^{\text{affect}}$	denote the $(P \times 1)$ -vector containing the value of the affect items of logo $i$ in country $c$ by respondent $h$ .
$y_{cih}^{\text{familiarity}}$	denote the value of the subjective familiarity item of logo $i$ evaluated in country $c$ by respondent $h$ .
$\eta_{cimh}$	denote the latent score on logo variable $m$ by respondent $h$ in country $c$ on logo $i$ . In this study, this score is only computed for affect and subjective familiarity, i.e. $m = 1, 2$ respectively.
$\bar{\eta}_{cim}$	denote the (latent) scores on logo response variable $m$ in country $c$ on logo $i$ .

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Based on our conceptual framework, Figure 2 summarizes our model specification for a given cluster  $s$ , and incorporates both individual and logo level data. The  $Q = 8$  design elements are measured at the individual level and capture the first  $N_{dimension} = 3$  logo design dimensions: elaborate (complex, active, and depth), natural (representative, organic, and round), and harmony (symmetry and balance). The  $N_{element} = 3$  logo objective design elements (repetition, proportion, and parallel) are measured at the logo level and are equal across countries. These  $N = 6$  logo design characteristics influence  $M = 5$  response variables (affect, subjective familiarity, shared meaning, and true and false recognition). Affect is assessed by  $P = 5$  items measured at the individual level. Subjective familiarity is also measured at the individual level by one item for each respondent. Shared meaning, true recognition, and false recognition are measured at the logo level and are an aggregate of the individual level responses as described previously. As these aggregated responses are proportions, we applied a logit transformation to obtain continuous dependent variables.

Previous research on aesthetics assumes that the scores of the subjective logo design elements,  $\xi$ , are observed and therefore computes these values by averaging over the rater scores

$\mathbf{x}$ , i.e.  $\xi_{ciq} = \frac{1}{R_{ciq}} \sum_{r=1}^{R_{ciq}} x_{cirq}$  (Henderson and Cote, 1998). In contrast, our approach recognizes

heterogeneity of individual ratings and directly models these, given cluster membership  $s$ , as follows:

$$x_{cirq} | s = \xi_{ciq} + \delta_{cirq}^s, \quad (1)$$

where  $\delta_{cirq}^s$  is assumed to be normally distributed with mean zero and standard deviation  $\sigma_{sq}^x$ . To

derive the latent scores of the subjective logo design elements,  $\bar{\xi}$ , we assume the following measurement model, given cluster membership  $s$ :

$$\xi_{ci} | s = \tau_{\xi}^s + \Lambda_{\xi}^s \begin{pmatrix} \bar{\xi}_{ci1} & \bar{\xi}_{ci2} & \bar{\xi}_{ci3} \end{pmatrix}' + \epsilon_{\xi_{ci}}^s. \quad (2)$$

In (2),  $\Lambda_{\xi}^s$  ( $Q \times N_{\text{dimension}}$ ) is a factor loading matrix and  $\tau_{\xi}^s$  is a ( $Q \times 1$ ) vector containing measurement intercepts. The ( $Q \times 1$ ) vector of disturbance terms  $\epsilon_{\xi_{ci}}^s$  is multivariate normal distributed with mean vector zero and diagonal covariance matrix  $\Sigma_{\xi}^s$  ( $Q \times Q$ ), given cluster  $s$ .

Note that (2) is the standard measurement model used in a structural equation modeling approach in which  $\xi_{ci}$  is observed, while in our approach it is a vector of latent scores depending on (1). In addition we specify

$$\begin{pmatrix} \bar{\xi}_{ci1} & \bar{\xi}_{ci2} & \bar{\xi}_{ci3} \end{pmatrix}' | s = \mu^s + \psi_{ci}^s, \quad (3)$$

with  $\mu^s$  ( $N_{\text{dimension}} \times 1$ ) containing the intercepts of the design dimensions. The disturbance terms  $\psi_{ci}^s$  are assumed to be normally distributed with mean zero and diagonal covariance matrix  $\Omega_{\xi}^s$  ( $N_{\text{dimension}} \times N_{\text{dimension}}$ ). Note that each country  $c$  has the same scores for the logo objective design elements (i.e.,  $\bar{\xi}_{cin}$  with  $n \in N_{\text{element}}$ ) as these are measured directly (see Section 3.2).

Previous research on aesthetics uses average scores across individuals to measure affect and subjective familiarity; which ignores individual differences. We compute a separate affect and subjective familiarity score for each respondent. Since subjective familiarity is measured with only one item (see Figure 2), its score is equal to the observed item:  $\eta_{ci2h} = y_{cjh}^{\text{familiarity}}$  for all countries  $c$ , logos  $i$ , and individuals  $h$ . For affect, we assume the following measurement model at the respondent level, given that the logo belongs to cluster  $s$  in country  $c$ :

$$\mathbf{y}_{cjh}^{\text{affect}} | s = \tau_y^s + \Lambda_y^s \cdot \eta_{ci1h} + \epsilon_{y_{cjh}}^s. \quad (4)$$

In (4),  $\Lambda_y^s$  is a  $(P \times 1)$  vector containing the factor loadings, and  $\tau_y^s$  is a  $(P \times 1)$  vector containing measurement intercepts. The  $(P \times 1)$  error vector  $\epsilon_{y_{cih}}^s$  is assumed to be normally distributed with mean zero and diagonal covariance matrix  $\Sigma_y^s$  ( $P \times P$ ), given cluster  $s$ . Similar to equation (1), we assume the following measurement model to derive the latent scores of affect and subjective familiarity at the logo level:

$$(\eta_{ci1h} \quad \eta_{ci2h})' | s = (\bar{\eta}_{ci1} \quad \bar{\eta}_{ci2})' + \epsilon_{\eta_{cih}}^s. \quad (5)$$

In (5),  $\epsilon_{\eta_{cih}}^s$  is a  $(2 \times 1)$ -vector that is assumed to be normally distributed with mean zero and  $(2 \times 2)$  diagonal covariance matrix  $\Sigma_\eta^s$ , given cluster  $s$ .

Given the measurement model in (1) to (5), we now specify the structural relationships among the exogenous design characteristics and the responses at the logo level. Henderson and Cote (1998) found the effects of the response variables on each other were nominal. Thus, we did not include any response variables as predictors to avoid multicollinearity problems (Grewal et al., 2004). This leads to the following structural relationships, given cluster  $s$ :

$$\bar{\eta}_{ci} | s = \alpha^s + \Gamma^s \cdot \bar{\xi}_{ci} + \zeta_{ci}^s, \quad (6)$$

In (6), the vector  $\alpha^s$  ( $M \times 1$ ) contains the intercepts for the endogenous logo responses  $\bar{\eta}_{ci}$ . The coefficient matrix  $\Gamma^s$  incorporates the effects of the exogenous logo design dimensions and objective design elements,  $\bar{\xi}_{ci}$ , on the endogenous logo responses  $\bar{\eta}_{ci}$  (see Figure 2). It is assumed that the disturbance term  $\zeta_{ci}^s$  is normally distributed with mean zero and diagonal covariance matrices  $\Omega_{\bar{\eta}}^s$  ( $M \times M$ ).

The model is tested on logos that may belong to an unknown group of cross-national clusters. Thus, we propose a constrained finite-mixture structural-equation approach to allow for

heterogeneity in both measurement and structural relationships (DeSarbo, Benedetto, Jedidi and Song, 2006, Jedidi et al., 1997). Because structural relationships are defined at the logo level, our constrained finite-mixture approach assigns logos to clusters. Logo cluster membership may differ depending on the country in which it is evaluated. However, a concomitant variable specification for cluster membership (ter Hofstede, Steenkamp and Wedel, 1999) allows the mixture probabilities to be country specific. The concomitant variable specification simultaneously derives clusters of logos, and profiles these clusters based on country membership (i.e. the concomitant variable). Similar to DeSarbo et al. (2006), response and structural parameters are flexibly constrained across clusters to test for nested versions of the model. These nested model versions are needed to assess measurement invariance and our two research questions. Using country-specific cluster proportions  $\pi_{cs}$  in combination with the measurement equations (1) to (5), and structural equations (6), we obtain the following model likelihood:

$$\begin{aligned}
L(\mathbf{y}, \mathbf{x}, \mathbf{z}, \boldsymbol{\eta}, \bar{\boldsymbol{\eta}}, \boldsymbol{\xi}, \bar{\boldsymbol{\xi}}; \boldsymbol{\Theta}, \boldsymbol{\pi}) = & \prod_{c=1}^C \prod_{i=1}^{I_c} \sum_{s=1}^S \pi_{cs} \left\{ \left( \prod_{h=1}^{H_{ci}} N_P \left( \mathbf{y}_{cih}^{\text{affect}}; \boldsymbol{\tau}_y^s + \boldsymbol{\Lambda}_y^s \boldsymbol{\eta}_{ci1h}, \boldsymbol{\Sigma}_y^s \right) \right) \cdot \right. \\
& \cdot \left( \prod_{h=1}^{H_{ci}} N_2 \left( \left( \boldsymbol{\eta}_{ci1h} \quad \boldsymbol{\eta}_{ci2h} \right)'; \left( \bar{\boldsymbol{\eta}}_{ci1} \quad \bar{\boldsymbol{\eta}}_{ci2} \right)', \boldsymbol{\Sigma}_{\boldsymbol{\eta}}^s \right) \right) \cdot \left( \prod_{q=1}^Q \prod_{r=1}^{R_{ciq}} N \left( x_{cirq}; \boldsymbol{\xi}_{ciq}^s, \boldsymbol{\Sigma}_{xqq}^s \right) \right) \cdot \\
& \cdot N_Q \left( \boldsymbol{\xi}_{ci}^s; \boldsymbol{\tau}_{\boldsymbol{\xi}}^s + \boldsymbol{\Lambda}_{\boldsymbol{\xi}}^s \left( \bar{\boldsymbol{\xi}}_{ci1} \quad \bar{\boldsymbol{\xi}}_{ci2} \quad \bar{\boldsymbol{\xi}}_{ci3} \right)', \boldsymbol{\Sigma}_{\boldsymbol{\xi}}^s \right) \cdot N_M \left( \bar{\boldsymbol{\eta}}_{ci}; \boldsymbol{\alpha}^s + \boldsymbol{\Gamma}^s \bar{\boldsymbol{\xi}}_{ci}, \boldsymbol{\Omega}_{\bar{\boldsymbol{\eta}}}^s \right) \\
& \cdot N_{N_{\text{Dimension}}} \left( \left( \bar{\boldsymbol{\xi}}_{ci1} \quad \bar{\boldsymbol{\xi}}_{ci2} \quad \bar{\boldsymbol{\xi}}_{ci3} \right)'; \boldsymbol{\mu}^s, \boldsymbol{\Omega}_{\bar{\boldsymbol{\xi}}}^s \right) \left. \right\} \quad (7)
\end{aligned}$$

where  $\boldsymbol{\Theta} = \{\boldsymbol{\Theta}^1, \dots, \boldsymbol{\Theta}^S\}$  contains the set of cluster specific structural equation parameters

$$\boldsymbol{\Theta}^s = \left( \boldsymbol{\alpha}^s, \boldsymbol{\Gamma}^s, \boldsymbol{\tau}_{\boldsymbol{\xi}}^s, \boldsymbol{\tau}_y^s, \boldsymbol{\Lambda}_{\boldsymbol{\xi}}^s, \boldsymbol{\Lambda}_y^s, \boldsymbol{\Sigma}_x^s, \boldsymbol{\Sigma}_y^s, \boldsymbol{\Sigma}_{\boldsymbol{\xi}}^s, \boldsymbol{\Sigma}_{\boldsymbol{\eta}}^s, \boldsymbol{\Omega}_{\bar{\boldsymbol{\xi}}}^s, \boldsymbol{\Omega}_{\bar{\boldsymbol{\eta}}}^s \right).$$

## 4.2 Model Identification and Estimation

To ensure identification, one item's factor loading was set to unity (and intercept to zero) for all cross-national clusters  $s$ . As noted by Jedidi et al. (1997), the finite mixture of a structural

equation model (with unknown groups) is identified when the corresponding multi-group model with known groups is identified and the data is multivariate normal.

Using these identification restrictions, the model was estimated using the Gibbs sampler with auxiliary variables to estimate the clusters (Diebolt and Robert, 1994, Rossi and Allenby, 2003). For the estimation of cross-national cluster membership, an auxiliary variable  $z_{ci} \in \{1, 2, \dots, S\}$  was introduced for each logo  $i$  evaluated in country  $c$ . This indicates which cluster ( $s$ ) logo  $i$  in country  $c$  is allocated (Diebolt and Robert, 1994). After introducing the auxiliary variables ( $z_{ci}$ ), the likelihood (7) can be rewritten as follows:

$$L(\mathbf{y}, \mathbf{x}, \mathbf{z}, \boldsymbol{\eta}, \bar{\boldsymbol{\eta}}, \boldsymbol{\xi}, \bar{\boldsymbol{\xi}}; \boldsymbol{\Theta}, \boldsymbol{\pi}) = \prod_{c=1}^C \prod_{s=1}^S \prod_{i: z_{ci}=s} \left\{ \left( \prod_{h=1}^{H_{ci}} N_P(\mathbf{y}_{cih}^{\text{affect}}; \boldsymbol{\tau}_y^s + \boldsymbol{\Lambda}_y^s \boldsymbol{\eta}_{ci1h}, \boldsymbol{\Sigma}_y^s) \right) \cdot \left( \prod_{h=1}^{H_{ci}} N_2 \left( (\boldsymbol{\eta}_{ci1h} \quad \boldsymbol{\eta}_{ci2h})'; (\bar{\boldsymbol{\eta}}_{ci1} \quad \bar{\boldsymbol{\eta}}_{ci2}), \boldsymbol{\Sigma}_{\boldsymbol{\eta}}^s \right) \right) \cdot \left( \prod_{q=1}^Q \prod_{r=1}^{R_{ciq}} N(x_{cirq}; \boldsymbol{\xi}_{ciq}, \boldsymbol{\Sigma}_{xqq}^s) \right) \right\}, \quad (8)$$

$$\cdot N_Q \left( \boldsymbol{\xi}_{ci}; \boldsymbol{\tau}_{\boldsymbol{\xi}}^s + \boldsymbol{\Lambda}_{\boldsymbol{\xi}}^s \left( \bar{\boldsymbol{\xi}}_{ci1} \quad \bar{\boldsymbol{\xi}}_{ci2} \quad \bar{\boldsymbol{\xi}}_{ci3} \right)', \boldsymbol{\Sigma}_{\boldsymbol{\xi}}^s \right) \cdot N_M \left( \bar{\boldsymbol{\eta}}_{ci}; \boldsymbol{\alpha}^s + \boldsymbol{\Gamma}^s \bar{\boldsymbol{\xi}}_{ci}, \boldsymbol{\Omega}_{\bar{\boldsymbol{\eta}}}^s \right)$$

$$\cdot N_{N_{\text{Dimension}}} \left( \left( \bar{\boldsymbol{\xi}}_{ci1} \quad \bar{\boldsymbol{\xi}}_{ci2} \quad \bar{\boldsymbol{\xi}}_{ci3} \right); \boldsymbol{\mu}^s, \boldsymbol{\Omega}_{\bar{\boldsymbol{\xi}}}^s \right)$$

where  $i : z_{ci} = s$  under the third product indicates that this index runs over all logos  $i$  in country  $c$  that belong to cluster  $s$ . Given the unobserved values for  $z_{ci}$ , specification (8) leads to standard posterior distributions for  $\boldsymbol{\Theta}$ ,  $\boldsymbol{\eta}$ ,  $\bar{\boldsymbol{\eta}}$ ,  $\boldsymbol{\xi}$ ,  $\bar{\boldsymbol{\xi}}$  and  $\boldsymbol{\pi}$ . For model estimation, we use flat prior distributions specified in Web Appendix A in the MCMC algorithm (see Appendix B).

To address possible label switching, a well-known problem during Bayesian inference for mixture models (Frühwirth-Schnatter, 2006, Rossi et al., 2005), we re-labeled cluster memberships by post-processing the posterior draws using Richardson and Green's (1997) approach.<sup>7</sup> In all runs, we used 2,000 draws, thinned 1 in 10, with a burn-in of 100,000 iterations. We examined convergence using diagnostics proposed by Raftery and Lewis (1992) and Geweke

<sup>7</sup> In our analysis, we did not observe label switching in any of the runs, indicating that the clusters are well separated (Rossi et al 2005); see Web Appendix C for some posterior draws.

(1992), and found that all runs converged well before burn-in (see Web Appendix B). Synthetic data analysis revealed that the model recovered all parameter values well within the corresponding 95% confidence intervals.

### 4.3 Model Selection and Investigation of Research Questions

Since the number of cross-national clusters is a priori unknown, we estimated several models with different numbers of clusters and selected the model with largest posterior probability (Lenk and DeSarbo, 2000). We implemented Chib's (1995) procedure to compute the log marginal density (LMD) for each model and obtain the number of cross-national clusters represented in the data a posteriori.

Research Question 1 (i.e., whether logo design characteristics are captured by the same design dimensions across cross-national clusters) corresponds to testing for configural invariance (Steenkamp and Baumgartner, 1998). In the configural model, each cross-national cluster has the same factor structure. Hence, configural invariance is satisfied when the pattern of the unrestricted (nonzero) factor loadings of  $\Lambda_{\xi}^s$  and  $\Lambda_y^s$  is the same across clusters. To test for configural invariance, we investigated whether all factor loadings are significantly and substantially different from zero. In addition, we compared our model with a model without any factor structure (i.e., a simultaneous equation model where  $\Lambda_{\xi}^s$  corresponds to the  $(Q \times Q)$  identity matrix). A more stringent test is the metric model which constrains the factor loadings  $\Lambda_{\xi}^1 = \Lambda_{\xi}^2 = \dots = \Lambda_{\xi}^S$  and  $\Lambda_y^1 = \Lambda_y^2 = \dots = \Lambda_y^S$  to be equal across all  $S$  cross-national clusters. If the metric model provides similar or better fit based on LMD, metric invariance also exists; not only do the clusters have similar factor structures, but the size of the factor loadings are also similar. If the two models are not equivalent, Steenkamp and Baumgartner (1998) suggest relaxing constraints for some factor loadings. If at least two equal factor loadings per factor (including the

marker) are observed, we have partial metric invariance and are allowed to test the second research question (i.e., whether consumers' responses to design dimensions are stable cross-nationally) by testing for invariance of structural relationships across clusters, i.e.

$$\Gamma_1 = \Gamma_2 = \dots = \Gamma_s.$$

## 5. Results

### 5.1 Number of Cross-National Clusters

The Log Marginal Density indicates that a three-cluster model fits best (LMD=-891,508 versus -896,328 for the one-cluster, -891,879 for the two-cluster, and -891,894 for the four-cluster models). The country-specific cluster probabilities displayed in Table 2 indicate that each country (except Argentina) clearly belongs to a single cluster. The clusters are labeled: *West*, which includes Australia, Great Britain, Germany, the Netherlands and the US; *Asia*, which includes China, India, and Singapore; and *Russia*, which includes only Russia. Argentina straddles the West and Asia, which means that logo evaluations in Argentina are somewhat ambiguous.

These three clusters vary by cultural characteristics (except Masculine/Feminine for the West and Asia) and writing systems. The Asian cultures use more complex writing system and have lower individualism scores than either the West or Russia. Interestingly, Argentina shares the simpler writing system with the West and a relatively low individualism score with Asia. Russia has a higher uncertainty avoidance score than the West and Asia. For the remainder of the analysis, we focus on the three-cluster solution.

### 5.2 Similarity of Design Factor Structures across Clusters

Inspection of the factor loadings (see Table 3) reveals that all estimates are significantly and substantially different from zero. The proposed factor structure also strongly outperforms a

simultaneous equation model in which no factor structure is assumed for logo design (LMD=-1,055,170). These results confirm Henderson and Cote's (1998) design factor structure with three dimensions: elaborate (complex, active, and depth), natural (organic, representative, and round), and harmony (symmetry and balance). We tested for metric invariance using the LMD and found the metric invariance model (LMD = -891,403) fits better than the configural model

**Table 2**  
**Median Cluster Probabilities and Summary Characteristics**

Country/Cluster	West	Asia	Russia
<b>Argentina</b>	0.41 (0.31 to 0.51)	0.43 (0.34 to 0.52)	0.16 (0.11 to 0.23)
<b>Australia</b>	<b>0.76</b> (0.67 to 0.84)	0.08 (0.04 to 0.14)	0.15 (0.08 to 0.23)
<b>Great Britain</b>	<b>0.97</b> (0.93 to 0.99)	0.02 (0.00 to 0.06)	0.01 (0.00 to 0.03)
<b>China</b>	0.19 (0.13 to 0.26)	<b>0.76</b> (0.69 to 0.82)	0.04 (0.02 to 0.08)
<b>Germany</b>	<b>0.60</b> (0.51 to 0.69)	0.37 (0.29 to 0.46)	0.02 (0.01 to 0.05)
<b>India</b>	0.30 (0.22 to 0.38)	<b>0.62</b> (0.53 to 0.69)	0.08 (0.04 to 0.14)
<b>Netherlands</b>	<b>0.75</b> (0.66 to 0.82)	0.22 (0.16 to 0.30)	0.03 (0.01 to 0.06)
<b>Russia</b>	0.01 (0.00 to 0.03)	0.01 (0.00 to 0.03)	<b>0.98</b> (0.95 to 1.00)
<b>Singapore</b>	0.08 (0.05 to 0.13)	<b>0.91</b> (0.86 to 0.95)	0.00 (0.00 to 0.02)
<b>USA</b>	<b>0.85</b> (0.77 to 0.91)	0.12 (0.06 to 0.19)	0.03 (0.01 to 0.07)
<b>Characteristic Weighted Averages*</b>			
Income	\$ 25,763	\$ 17,551	\$ 11,136
Power/Distance	42.7	64.3	77.8
Uncertainty Avoidance	49.8	39.2	76.8
Individualism/Collectivism	75.5	41.1	45.4
Masculine/Feminine	54.8	54.8	43.5

95% confidence intervals are between brackets; **Bold** percentages indicate cluster category with the highest value

\* All characteristic values are statistically different, except Masculine/Feminine for the West and Asia

(LMD = -891,508). This indicates that logo design characteristics are captured by the same factor structure and loadings across clusters.

**Table 3**  
**Median Factor Loadings of Design Dimension and Affect\***

Design Dimension	Design Characteristic	Factor Loading
<b>Elaborate:</b>	Complex	1
	Active	1.29 (1.13 to 1.47)
	Depth	1.34 (1.18 to 1.50)
<b>Natural:</b>	Organic	1
	Representative	0.82 (0.74 to 0.91)
	Round	0.76 (0.67 to 0.86)
<b>Harmony:</b>	Symmetry	1
	Balance	0.62 (0.57 to 0.66)
<b>Affect:</b>	Distinct	1
	Good	1.07 (1.06 to 1.08)
	Interest	1.25 (1.24 to 1.26)
	Like	1.23 (1.22 to 1.25)
	Quality	1.08 (1.07 to 1.09)

95% confidence intervals are between parentheses

\*Factor loadings are equal across clusters due to metric invariance

### 5.3 Similarity of Design–Response Relationships across Clusters

Since we found metric invariance, we can now test whether the structural paths are invariant across the three clusters. As indicated by the LMD of structural relationship invariance (LMD = -891,510), this model is rejected. Table 4 presents the results of the metric invariance model where structural paths are different across clusters. As suggested by Gelman and Pardoe (2006), its last column contains the explained variance for each dependent factor. Table 4 shows that the explained variance for each response variable varies substantially across clusters. Although there

is a high degree of similarity to the pattern of relationships between design dimensions and response variables, the structural parameters have slight differences across clusters. We consider reasons for these patterns in the summary at the end of this Section.

*Affect* – Overall, logo design dimensions and objective elements explain 84% of the variance in affect for Asia, 62% for the West, and 28% for Russia. In all clusters, affect increases as the design dimensions (harmony, elaborate, and natural) increase as seen in the positive and significant structural path coefficients. However, the importance of elaborate varies across the three clusters. The Russian cluster puts significantly less emphasis on it (.19) than the Asian (.70) and Western clusters (.54). The effects of parallel, proportion, and repetition on affect are small and statistically equivalent across the three clusters.

*Subjective Familiarity* – Logo design characteristics explain 24% of subjective familiarity for the West, 35% for Russia, and 41% for Asia. The relationships for harmony and natural are positive and statistically significant in all three clusters. Additionally, the effects of parallel, repetition, and proportion are non-significant across the clusters. However, the relationship between elaborate and subjective familiarity varies across clusters; the path for Russia (-0.22) is negative and significant, while the West (.26) and Asia (.41) are positive and significant.

*Shared Meaning* – Logo design characteristics explained about the same amount of variance for all three clusters (22% for the West, 23% for Russia, and 19% for Asia). Natural increases shared meaning, while elaborate reduces shared meaning in all three clusters. Harmony and the objective design elements do not influence shared meaning.

*True Recognition* – Logo design dimensions and objective elements explain 10% of true recognition for Asia, 3% for the West, and 6% for Russia. Natural has a positive influence and is equivalent across the clusters (Asia .10, Russia .06, and the West .07). Harmony, parallel, and

**Table 4**  
**Median Estimates Structural Paths**

<b>Response</b>	<b>Cluster</b>	<b>Elaborate</b>	<b>Natural</b>	<b>Harmony</b>	<b>Parallel</b>	<b>Proportion</b>	<b>Repetition</b>	<b>Intercept</b>	<b>Variance Explained</b>
<b>Affect</b>	West	<b>.54</b> (.41 to .77)	<b>.12</b> (.08 to .17)	<b>.06</b> (.03 to .09)	.00 (-.02 to .03)	-.06 (-.12 to .01)	.01 (-.01 to .04)	<b>1.75</b> (1.01 to 2.22)	.62
	Asia	<b>.70</b> (.59 to .82)	<b>.17</b> (.12 to .24)	<b>.03</b> (.01 to .05)	<b>-.04</b> (-.06 to -.01)	-.02 (-.11 to .07)	.02 (-.01 to .05)	<b>.87</b> (.48 to 1.21)	.84
	Russia	<b>.19</b> (.05 to .34)	<b>.14</b> (.09 to .19)	<b>.09</b> (.04 to .16)	.04 (-.01 to .08)	-.08 (-.25 to .08)	<b>.06</b> (.01 to .12)	<b>2.40</b> (1.69 to 3.05)	.28
<b>Subjective Familiarity</b>	West	<b>.26</b> (.02 to .61)	<b>.22</b> (.13 to .30)	<b>.17</b> (.11 to .23)	.02 (-.03 to .06)	.14 (.00 to .28)	-.01 (-.06 to .04)	.93 (-.13 to 1.71)	.24
	Asia	<b>.41</b> (.21 to .61)	<b>.26</b> (.16 to .38)	<b>.07</b> (.04 to .11)	-.04 (-.08 to -.00)	.04 (-.12 to .21)	.03 (-.01 to .08)	<b>.93</b> (.33 to 1.44)	.41
	Russia	<b>-.22</b> (-.46 to -.02)	<b>.29</b> (.21 to .36)	<b>.12</b> (.03 to .22)	.05 (-.02 to .11)	-.01 (-.25 to .23)	.04 (-.04 to .12)	<b>3.04</b> (2.08 to 4.11)	.35
<b>Shared Meaning</b>	West	<b>-.07</b> (-.10 to -.02)	<b>.08</b> (.06 to .09)	.00 (-.01 to .01)	.00 (-.01 to .01)	.02 (-.01 to .05)	.00 (-.01 to .01)	<b>.18</b> (.03 to .31)	.22
	Asia	<b>-.05</b> (-.08 to -.01)	<b>.06</b> (.04 to .08)	-.00 (-.01 to .00)	.00 (-.01 to .01)	.01 (-.03 to .05)	-.00 (-.02 to .01)	<b>.16</b> (.04 to .27)	.19
	Russia	<b>-.11</b> (-.18 to -.05)	<b>.06</b> (.04 to .08)	-.00 (-.03 to .02)	-.00 (-.02 to .01)	-.00 (-.07 to .07)	-.01 (-.03 to .01)	<b>.67</b> (.40 to .96)	.23
<b>True Recognition</b>	West	-.04 (-.12 to .06)	<b>.07</b> (.03 to .10)	.01 (-.02 to .04)	.02 (.00 to .05)	-.01 (-.08 to .07)	.02 (-.00 to .05)	.27 (-.07 to .59)	.03
	Asia	<b>.07</b> (.00 to .16)	<b>.10</b> (.07 to .14)	.00 (-.02 to .02)	.00 (-.02 to .03)	.03 (-.07 to .13)	.01 (-.02 to .04)	-.13 (.41 to .14)	.10
	Russia	-.02 (-.14 to .09)	<b>.06</b> (.03 to .10)	-.03 (-.07 to .02)	.01 (-.03 to .04)	<b>-.17</b> (-.31 to -.03)	.03 (-.02 to .07)	<b>.75</b> (.24 to 1.28)	.06
<b>False Recognition</b>	West	<b>.15</b> (.05 to .24)	<b>-.06</b> (-.10 to -.02)	<b>.05</b> (.02 to .09)	-.01 (-.04 to .02)	-.08 (-.17 to .00)	.02 (-.01 to .05)	<b>-1.29</b> (-1.66 to -.95)	.07
	Asia	<b>.14</b> (.05 to .23)	<b>-.07</b> (-.12 to -.03)	<b>.03</b> (.00 to .05)	-.01 (-.03 to .02)	-.01 (-.12 to .09)	.01 (-.02 to .04)	<b>-1.21</b> (-1.51 to -.89)	.06
	Russia	<b>.13</b> (.03 to .26)	<b>-.13</b> (-.16 to -.09)	<b>.06</b> (.01 to .11)	-.02 (-.05 to .02)	.03 (-.11 to .17)	.00 (-.04 to .05)	<b>-1.31</b> (-1.86 to -.79)	.23

95% confidence intervals are between brackets

**Bold** values correspond to coefficients with 95% confidence interval not containing zero

repetition have non-significant effects on true recognition in all three clusters. Two cluster differences emerge in the relationships between elaborate, proportion and true recognition. Elaborate has a positive influence in Asia, but no influence in Russia or the West (Asia .07 vs. West -.04 vs. Russia -.02); although this difference is not statistically significant across clusters. The effect of proportion is not statistically different across clusters, but has a negative influence in Russia (-0.17), and is insignificant in Asia (0.04) or the West (-.01).

*False Recognition* – Logo design characteristics explain a small percent of false recognition for Asia (6%) and the West (7%), but a larger percent in Russia (23%). For all clusters, natural decreases false recognition, while elaborate and harmony increase false recognition.

*Summary* - Overall, the results for the cross-national clusters were consistent with prior work (Henderson and Cote, 1998, Henderson et al., 2003). This is especially true for natural and harmony where the patterns of the path estimates are consistent across response variables and clusters. Natural designs universally increase positive affect, shared meaning, subjective familiarity, and true recognition and decrease false recognition. Designs high in harmony universally increase positive affect, subjective familiarity, and false recognition, while not affecting shared meaning or true recognition. However, the effect of harmony on subjective familiarity was higher for the West than Asia.

The largest cluster differences were for elaborate designs. In most cases, elaborate designs increased positive affect, subjective familiarity, true and false recognition, while decreasing shared meaning. However, the Russian cluster differed significantly from the other clusters, where the influence of elaborate designs on affect was much smaller and that on subjective familiarity was actually negative. Arrindell et al (2004) offer a possible explanation for this result. They find that countries with low uncertainty avoidance scores have greater tolerance for

uncertainty and complexity. Since consumers in the Asian and, to a lesser extent, Western clusters have lower uncertainty avoidance scores, they may like and feel more familiar with complex designs than their Russian counterparts.

## **6. Conclusion**

The goals of our study were to: 1) extended finite-mixture structural-equation models to account for individual judgment in stimulus level design responses, 2) assess the cross-cultural universality of design dimensions and the stability of responses to these dimensions, and 3) address managerial concerns about adapting logos for global markets.

### **6.1 Extending Finite-Mixture Structural-Equation Models**

The proposed constrained finite-mixture structural equation modeling approach using concomitant variables proved a valuable tool for identifying latent logo clusters that are evaluated similarly across countries. Our approach does not assume logo evaluations within countries belong, a priori, to the same cluster (although our findings resulted in country based clusters). Due to our concomitant variable formulation, the identified cross-national clusters are easily interpreted. Further, previous experimental research in aesthetics aggregates individual responses for each logo. In contrast, our approach addresses potential aggregation bias by modeling response heterogeneity through a hierarchical structure. More generally, our constrained finite-mixture structural equation modeling procedure can be extended to analyze data sets with many subgroups; aggregating them into larger classes based on response similarity. For example, it can answer such questions as: how would different stakeholders (stockholders, consumers, competitors, public policy makers) respond to different multi-dimensional stimuli such as a company's pricing practices; or how would different industries or markets react to different types of R&D projects. In addition, the proposed approach is suitable

for smaller sample sizes, allows the incorporation of available prior parameter information, and avoids obtaining negative variances or Heywood cases.

The constrained-finite mixture modeling procedure also provides important logo optimization guidelines. For instance, the Western cluster seems to have difficulty recognizing logo 65 , as indicated by an average true-recognition score of .57 (on a 0-1 scale) – compared to .64 in Asia and .73 in Russia. In addition, this logo has a moderate affect score across cultures (average score 3.9 on a 7-point scale). The low natural score (2.3) is probably why this logo performs poorly; since natural has a positive influence on both true recognition and affect. Using posterior draws of the parameters, a designer can determine the minimum required natural score for a given country, such that its expected affect and true-recognition values are higher than a predetermined threshold.<sup>8</sup> For instance, the score of natural should be at least 3.5 in Russia, 3.9 in China, and 5.7 in the U.K. to obtain true-recognition and affect scores of at least .65 and 4.0 respectively. Similarly, the elaborate score of logo 65 in Germany should be between 3.2 and 4.2 (current median score equals 3.0) to reach an expected score of at least 4.0 on affect and .15 on shared meaning (current median scores are 3.9 and .33, respectively). Such optimization is especially important for elaborate since its effects are not positive on all responses for all clusters.

## **6.2 Design Dimension Universality and Stability of Consumer Responses**

Previous research suggests that elaborate, natural, and harmony are design dimensions that exist across stimuli. Even when the design elements are quite different, these three dimensions appear repeatedly. Our results show that these design dimensions also exist across cultures, suggesting

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<sup>8</sup> In the optimization, we determined for each posterior draw what the minimum score of natural should be, given the scores of this logo on the other dimensions, such that prespecified values of affect and true recognition are reached. We chose the posterior median of the minimum expected score as the threshold for natural.

they may be universal. The existence of universal design dimensions has important implications for design research. Currently, when developing a design study, researchers must select which of innumerable elements should be used to describe the design. For example, Orth and Malkewitz (2008) included 62 design elements for wine labels and Henderson, Giese, and Cote (2004) used 24 elements for typeface. Focusing on a reduced set of design dimensions should make design research more tractable.

Our results also support the contention of evolutionary psychology that design perceptions are innate and relatively immune from cultural influence. Not only do different cultures perceive design similarly, but they also appear to respond similarly as well. Of course, culture does have some influence. For example, our results suggest that higher uncertainty avoidance cultures may find elaborate designs less attractive than lower uncertainty avoidance ones.

Future research can extend our findings in several important ways. Most notably, future research should investigate the universality of other possible design dimensions, such as weight, flourish, compression, size, and color. Additionally, consumer responses to brands with established designs/logos may differ from reactions to the unfamiliar logos. Future work might consider how brand familiarity moderates the relationships uncovered in this research. Future research might also study more countries and extend the concomitant variable approach to allow cluster proportions to vary along more dimensions (e.g., writing systems and uncertainty avoidance) than only country evaluations.

### **6.3 Managerial Guidelines for Adapting Global Logos**

For the manager interested in maintaining a consistent brand image worldwide, our results suggest a standardized core logo can work globally. Logo perceptions and responses are similar enough across cultures, that a given logo design will produce similar effects in many parts of the

world. In addition, when evaluating logo designs, managers may want to focus on affective responses for which design dimensions and elements appear to have the strongest influence. Design appears less related to recognition and shared meaning, which are learned responses strongly influenced by other marketing investments. This implies that managers should particularly focus on designing elaborate, natural, and harmonious logos that elicit positive affect; as it may be difficult to rectify design problems by other marketing efforts.

For example, Habitat for Humanity recently created a new logo: . It is more natural and elaborate, but may be slightly less harmonious, than the previous logo: . We predict that this new logo will increase positive affect and, to a lesser extent, shared meaning, worldwide.

Increasing harmony such as  might have been even more effective. Although these guidelines seem intuitive, managers continue to create poor logos (Colman et al., 1995) as the 2012 London Olympics Logo (which cost £400,000 to create) so vividly illustrates (Methven and McGurran, 2007).

Elaborating on the suggestions of Kohli, Suri, and Thakor (2002), we suggest managers do the following when designing or modifying a logo:

1. Choose the core logo image carefully and specify clear response objectives for various regions.
2. Communicate with logo designers using the design dimensions of elaborate, natural, and harmony. Our results suggest they provide a parsimonious vocabulary for design communication.
3. Design something effective before entering new markets. You often cannot change your brand name, but you can change your logo.
4. Don't go with the flavor-of-the-month or "artistically interesting" logos. Stick to logos that simply and richly capture the essence of something (elaborate); depict commonly experienced objects (natural); and represent congruent patterns or arrangements of parts (harmony).
5. Be systematic and objective; allow designers to modify the core logo for individual markets. However, use the results of Table 4 to guide logo selection, rather than rely solely on the opinion of a particular logo designer or committee.

6. Test new alternatives against existing logos since there are multiple ways to create elaborate, natural, and harmonious logos.

As a company builds familiarity with its brand within a country, consumer responses to its logo may depend less on the actual design and more on the associations formed with the brand.

However, there are several cases where our recommended guidelines will be important independent of brand name and reputation. These include:

1. New companies – When you first create a logo and brand, they have no meaning.
2. New consumers – New international markets will interpret a logo design before the brand's verbal information.
3. Changing logos – A product may have a place in the mind, but a new logo triggers new thinking about the brand (which may be inconsistent with original positioning). If a logo is not properly designed, it can interfere with the processing of brand information and interpretation of the new image.
4. Mergers or brand extensions - Acquiring new companies may necessitate modifying a logo to better capture full range of company products.
5. Marketing to children or the illiterate – Children and the illiterate will learn by visuals before any processing of verbal information.

Last, for managers less concerned about having a single global logo, it may be possible to optimize a logo for specific countries or regions, as shown in the previous discussion of logo optimization. Since country differences are mostly in degree, not direction, adding or deleting a design element or dimension should elicit better responses across cultures. If Habitat wanted to optimize their logo for Russia, it could be made less complex by removing the repetitive

elements as in . Tide did something similar with its logo (left below). When the logo was used for packaging in China (right), it was much more elaborate and natural than in the U.S.

(middle). Additional color and visual elements, plus arms added to the traditional circular logo make the image more active and representative – like a cyclone.



There are at least three caveats associated with our recommended approach to logo design in international markets. First, because our research was done in only 10 of 195 possible countries, managers need to be cautious about generalizing results beyond the 10 studied markets. If a manager needs to modify a design for markets not included in our study, we recommend that managers obtain the cultural characteristics of the country from a web site such as:

<http://www.geert-hofstede.com/> and match the new market to the cultural characteristics of the markets described in Table 1. Then select the most similar country and apply the optimization procedure discussed in section 6.2 to obtain dimensional estimates of the optimal logo design.

Second, student subjects were used to test consumer responses to consumer logos. Hence, the observed relationships between logo characteristics and responses may have a different direction and strength in other groups. Our respondent homogeneity may underestimate the cultural effects of logo design characteristics. Third, our recommendations may not apply to brand/logo combinations. Future research could assess consumer familiarity with brands; expose them to different brand/logo combinations; and measure affect, subjective familiarity, shared meaning, and recognition. In a limited experiment with U.S. student subjects, the logo used for the 2012

London Olympics application campaign  generated a more positive attitude towards

the Olympics brand than when using the final official logo  (see Web Appendix D). The alternative logo was rated as more natural, harmonious, and elaborate than the one selected. This result suggests that logos can have an effect even on an established brand. We are thus optimistic that future brand/logo research will replicate our findings.

**Appendix A**  
 Examples and Definitions of Design Elements and Dimensions\*  
 (from Henderson and Cote 1998)

<b>Design Characteristics</b>	<b>High</b>	<b>Low</b>
<b>Elaborate</b> captures the concept of design richness and the ability to use simple lines to capture the essence of something. It comprises the elements of complexity, activeness, and depth.		
<b>Complexity</b> is created by irregularity in the arrangement of elements, increases in the number of elements, heterogeneity in the nature of elements, and how ornate the design is.		
<b>Active</b> designs are those that give the impression of motion or flow.		
<b>Depth</b> gives the appearance of perspective or being 3-dimensional.		
<b>Natural</b> reflects the degree to which the design depicts commonly experienced objects. It comprises the elements of representative and organic.		
<b>Representative</b> the degree of realism in a design. This occurs when the elements of an object are distilled to its most typical features.		
<b>Organic</b> refers to natural shapes as opposed to angular and abstract designs		
<b>Round</b> designs are made of primarily curved lines and circular elements.		
<b>Harmony</b> is a congruent pattern or arrangement of parts which combines the elements of symmetry and balance.		
<b>Symmetric</b> designs appear as reflections along one or more axis.		
<b>Balance</b> captures the notion that there is a center of suspension between two weights or portions of the design.		
<b>Parallel</b> designs contain multiple lines or elements that appear adjacent to each other.		
<b>Repetition</b> is the repeated use of design parts which are similar or identical to each other – unless they are simply part of a larger whole (e.g., branches on a tree).		
<b>Proportion</b> is the relationship between the horizontal and vertical dimensions.		

\* Design dimensions are in **bold**, while design elements are *italic and bold*.

## Appendix B

This Appendix presents the posterior distributions that we used to draw the model parameters in the MCMC sampler. Because we chose conjugate prior distributions,<sup>9</sup> the derivations of these posterior distributions are relatively standard. However, for some of the derivations of conditional posteriors, we use the following well-known result in statistics to derive the conditional distribution of the free parameters in a multivariate normal vector in which some parameters are fixed to a pre-specified number  $\mathbf{a}$ . Let

$$\begin{pmatrix} \mathbf{X}_{\text{free}} \\ \mathbf{X}_{\text{fixed}} \end{pmatrix} \sim N \left( \begin{pmatrix} \boldsymbol{\mu}_{\text{free}} \\ \boldsymbol{\mu}_{\text{fixed}} \end{pmatrix}, \begin{pmatrix} \boldsymbol{\Sigma}_{\text{free,free}} & \boldsymbol{\Sigma}_{\text{fixed,free}} \\ \boldsymbol{\Sigma}_{\text{free,fixed}} & \boldsymbol{\Sigma}_{\text{fixed,fixed}} \end{pmatrix} \right), \text{ then } \mathbf{X}_{\text{free}} \mid \mathbf{X}_{\text{fixed}} = \mathbf{a} \sim N(\bar{\boldsymbol{\mu}}, \bar{\boldsymbol{\Sigma}}), \text{ with}$$

$\bar{\boldsymbol{\mu}} = \boldsymbol{\mu}_{\text{free}} + \boldsymbol{\Sigma}_{\text{free,fixed}} \boldsymbol{\Sigma}_{\text{fixed,fixed}}^{-1} (\mathbf{a} - \boldsymbol{\mu}_{\text{fixed}})$ , and  $\bar{\boldsymbol{\Sigma}} = \boldsymbol{\Sigma}_{\text{free,free}} - \boldsymbol{\Sigma}_{\text{free,fixed}} \boldsymbol{\Sigma}_{\text{fixed,fixed}}^{-1} \boldsymbol{\Sigma}_{\text{fixed,free}}$  (see Arnold, 1990 p. 214). In the derivations, we refer to this result as ‘*partitioning result*’.

For the Gibbs sampler we used cycles sequentially through the following conditional posteriors. In the first two steps, we followed (Diebolt and Robert, 1994) to draw the augmented variables  $z_{ci}$  and the cluster probabilities  $\boldsymbol{\pi}$ .

$$1. z_{ci} \mid \dots \sim MN \left( \frac{L(\mathbf{y}_{ci}, \mathbf{x}_{ci}, \boldsymbol{\eta}_{ci}, \bar{\boldsymbol{\eta}}_{ci}, \boldsymbol{\xi}_{ci}, \bar{\boldsymbol{\xi}}_{ci}; \boldsymbol{\Theta}^{s=1})}{\sum_{s=1}^S L(\mathbf{y}_{ci}, \mathbf{x}_{ci}, \boldsymbol{\eta}_{ci}, \bar{\boldsymbol{\eta}}_{ci}, \boldsymbol{\xi}_{ci}, \bar{\boldsymbol{\xi}}_{ci}; \boldsymbol{\Theta}^s)}, \dots, \frac{L(\mathbf{y}_{ci}, \mathbf{x}_{ci}, \boldsymbol{\eta}_{ci}, \bar{\boldsymbol{\eta}}_{ci}, \boldsymbol{\xi}_{ci}, \bar{\boldsymbol{\xi}}_{ci}; \boldsymbol{\Theta}^{s=S})}{\sum_{s=1}^S L(\mathbf{y}_{ci}, \mathbf{x}_{ci}, \boldsymbol{\eta}_{ci}, \bar{\boldsymbol{\eta}}_{ci}, \boldsymbol{\xi}_{ci}, \bar{\boldsymbol{\xi}}_{ci}; \boldsymbol{\Theta}^s)} \right), \text{ with } MN(\cdot) \text{ the}$$

multinomial distribution, and  $L(\mathbf{y}_{ci}, \mathbf{x}_{ci}, \boldsymbol{\eta}_{ci}, \bar{\boldsymbol{\eta}}_{ci}, \boldsymbol{\xi}_{ci}, \bar{\boldsymbol{\xi}}_{ci}; \boldsymbol{\Theta}^s)$  the likelihood (8) of logo  $i$  in country  $c$  assigned to cluster  $s$ .

$$2. \boldsymbol{\pi}_c \mid \dots \sim D \left( r_{c1} + \sum_{i=2}^{I_c} I\{z_{ci} = 1\} \quad \dots \quad r_{cS} + \sum_{i=2}^{I_c} I\{z_{ci} = S\} \right) \text{ for each country } c = 1, \dots, C, \text{ with } D(\cdot)$$

representing the Dirichlet distribution, and  $I\{\cdot\}$  the indicator function that equals 1 when the expression between brackets holds, and zero otherwise.

$$3. \begin{pmatrix} \boldsymbol{\tau}_{\xi, \text{free}}^s \\ \text{vec}(\boldsymbol{\Lambda}_{\xi, \text{free}}^s) \end{pmatrix} \sim N(\bar{\mathbf{U}}_{\xi}^s, \bar{\mathbf{Q}}_{\xi}^s) \text{ and } \begin{pmatrix} \boldsymbol{\tau}_{y, \text{free}}^s \\ \text{vec}(\boldsymbol{\Lambda}_{y, \text{free}}^s) \end{pmatrix} \sim N(\bar{\mathbf{U}}_y^s, \bar{\mathbf{Q}}_y^s), \text{ where subscripts } \textit{fix} \text{ and } \textit{free} \text{ refer}$$

respectively to the set of fixed and free parameters of the corresponding matrix (Arnold, 1990).

Using the *partitioning results* described earlier, we get for  $\phi \in \{\xi, y\}$ :

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<sup>9</sup> For the specifications of the prior distributions, see Web Appendix A.

$$\overline{\mathbf{U}}_{\phi}^s = \mathbf{U}_{\phi, \text{free}}^s + \mathbf{Q}_{\phi, \text{free}, \text{fix}}^s \left( \mathbf{Q}_{\phi, \text{fix}, \text{fix}}^s \right)^{-1} \left( \begin{pmatrix} \boldsymbol{\tau}_{\phi, \text{fix}}^s \\ \text{vec}(\boldsymbol{\Lambda}_{\phi, \text{fix}}^s) \end{pmatrix} - \mathbf{U}_{\phi, \text{fix}}^s \right), \text{ and } \overline{\mathbf{Q}}_{\phi}^s = \mathbf{Q}_{\phi, \text{free}, \text{free}}^s - \mathbf{Q}_{\phi, \text{free}, \text{fix}}^s \left( \mathbf{Q}_{\phi, \text{fix}, \text{fix}}^s \right)^{-1} \mathbf{Q}_{\phi, \text{fix}, \text{free}}^s,$$

$$\text{with } \mathbf{U}_{\xi}^s = \mathbf{Q}_{\xi}^s \cdot \left( \sum_{c=1}^C \sum_{i:z_{ci}=s} \left\{ \left( \begin{bmatrix} 1 & \bar{\xi}_{ci} \end{bmatrix} \otimes \mathbf{I}_Q \right)' \boldsymbol{\Sigma}_{\xi}^{s-1} \boldsymbol{\xi}_{ci} \right\} + \begin{pmatrix} \mathbf{H}_{\xi}^s & \mathbf{0} \\ \mathbf{0} & \mathbf{V}_{\xi}^s \end{pmatrix}^{-1} \begin{pmatrix} \mathbf{h}_{\xi}^s \\ \mathbf{L}_{\xi}^s \end{pmatrix} \right), \mathbf{U}_y^s = \mathbf{Q}_y^s \cdot \left( \sum_{c=1}^C \sum_{i:z_{ci}=s} \sum_{h=1}^{H_{ci}} \left\{ \left( \begin{bmatrix} 1 & \boldsymbol{\eta}_{cih} \end{bmatrix} \otimes \mathbf{I}_P \right)' \boldsymbol{\Sigma}_y^{s-1} \mathbf{y}_{cih}^{\text{affect}} + \begin{pmatrix} \mathbf{H}_y^s & \mathbf{0} \\ \mathbf{0} & \mathbf{V}_y^s \end{pmatrix}^{-1} \begin{pmatrix} \mathbf{h}_y^s \\ \mathbf{L}_y^s \end{pmatrix} \right\}, \mathbf{Q}_{\xi}^s = \left( \left( \sum_{c=1}^C \sum_{i:z_{ci}=s} \left[ \begin{bmatrix} 1 & \bar{\xi}_{ci} \end{bmatrix} \cdot \begin{bmatrix} 1 & \bar{\xi}_{ci} \end{bmatrix}' \right] \otimes \boldsymbol{\Sigma}_{\xi}^{s-1} + \begin{pmatrix} \mathbf{H}_{\xi}^s & \mathbf{0} \\ \mathbf{0} & \mathbf{V}_{\xi}^s \end{pmatrix}^{-1} \right)^{-1},$$

$$\text{and } \mathbf{Q}_y^s = \left( \left( \sum_{c=1}^C \sum_{i:z_{ci}=s} \sum_{h=1}^{H_{ci}} \left[ \begin{bmatrix} 1 & \boldsymbol{\eta}_{cih} \end{bmatrix} \cdot \begin{bmatrix} 1 & \boldsymbol{\eta}_{cih} \end{bmatrix}' \right] \otimes \boldsymbol{\Sigma}_y^{s-1} + \begin{pmatrix} \mathbf{H}_y^s & \mathbf{0} \\ \mathbf{0} & \mathbf{V}_y^s \end{pmatrix}^{-1} \right)^{-1}.$$

In the following four steps, we sequentially drew respectively 4) the scores on the subjective logo design items, 5) logo design dimensions, 6) affect response items, and 7) affect and subjective familiarity response dimensions. The derivations of these conditional posterior distributions are relatively straightforward using multiplication of normal distributions.

$$4. \xi_{ciq} \sim N \left( \frac{\sum_{\xi qq}^s \sum_{r=1}^{R_{\xi q}} x_{cirq} + \left( \boldsymbol{\tau}_{\xi q}^s + \boldsymbol{\Lambda}_{\xi q}^s \bar{\xi}_{ci} \right) \boldsymbol{\Sigma}_{\xi qq}^s}{R_{ciq} \boldsymbol{\Sigma}_{\xi qq}^s + \boldsymbol{\Sigma}_{\xi qq}^s}, \frac{\boldsymbol{\Sigma}_{\xi qq}^s \boldsymbol{\Sigma}_{\xi qq}^s}{R_{ciq} \boldsymbol{\Sigma}_{\xi qq}^s + \boldsymbol{\Sigma}_{\xi qq}^s} \right).$$

$$5. \bar{\xi}_{ci} \sim N(\mathbf{U}_{\bar{\xi}_{ci}}, \mathbf{Q}_{\bar{\xi}_{ci}}), \text{ with } \mathbf{Q}_{\bar{\xi}_{ci}} = \left( \boldsymbol{\Lambda}_{\xi}^{z_{ci}'} \left( \boldsymbol{\Sigma}_{\xi}^{z_{ci}} \right)^{-1} \boldsymbol{\Lambda}_{\xi}^{z_{ci}} + \boldsymbol{\Gamma}^{z_{ci}'} \left( \boldsymbol{\Omega}_{\bar{\eta}}^{z_{ci}} \right)^{-1} \boldsymbol{\Gamma}^{z_{ci}} + \left( \boldsymbol{\Omega}_{\frac{\xi}{\bar{\eta}}}^{z_{ci}} \right)^{-1} \right)^{-1}, \text{ and}$$

$$\mathbf{U}_{\bar{\xi}_{ci}} = \mathbf{Q}_{\bar{\xi}_{ci}} \left( \boldsymbol{\Lambda}_{\xi}^{z_{ci}'} \left( \boldsymbol{\Sigma}_{\xi}^{z_{ci}} \right)^{-1} \left( \boldsymbol{\xi}_{ci} - \boldsymbol{\tau}_{\xi}^{z_{ci}} \right)' + \boldsymbol{\Gamma}^{z_{ci}'} \left( \boldsymbol{\Omega}_{\bar{\eta}}^{z_{ci}} \right)^{-1} \left( \bar{\boldsymbol{\eta}}_{ci} - \boldsymbol{\alpha}^{z_{ci}} \right)' + \left( \boldsymbol{\Omega}_{\frac{\xi}{\bar{\eta}}}^{z_{ci}} \right)^{-1} \boldsymbol{\mu}^{z_{ci}} \right).$$

$$6. \eta_{cih} \sim N(L_{\eta_{cih}}, \mathbf{Q}_{\eta_{cih}}), \text{ with } \mathbf{Q}_{\eta_{cih}} = \left( \boldsymbol{\Lambda}_y^{z_{ci}'} \left( \boldsymbol{\Sigma}_y^{z_{ci}} \right)^{-1} \boldsymbol{\Lambda}_y^{z_{ci}} + \left( \boldsymbol{\Sigma}_{\eta}^{z_{ci}} \right)^{-1} \right)^{-1}, \text{ and}$$

$$\mathbf{L}_{\eta_{cih}} = \mathbf{Q}_{\eta_{cih}} \left( \boldsymbol{\Lambda}_y^{z_{ci}'} \left( \boldsymbol{\Sigma}_y^{z_{ci}} \right)^{-1} \left( \mathbf{y}_{cih}^{\text{affect}} - \boldsymbol{\tau}_y^{z_{ci}} \right) + \left( \boldsymbol{\Sigma}_{\eta}^{z_{ci}} \right)^{-1} \bar{\boldsymbol{\eta}}_{ci1} \right).$$

$$7. \bar{\boldsymbol{\eta}}_{ci} \sim N(\mathbf{U}_{\bar{\boldsymbol{\eta}}_{ci}}, \mathbf{Q}_{\bar{\boldsymbol{\eta}}_{ci}}), \text{ with } \mathbf{U}_{\bar{\boldsymbol{\eta}}_{ci}} = \mathbf{Q}_{\bar{\boldsymbol{\eta}}_{ci}} \left( \left( \boldsymbol{\Sigma}_{\eta}^{z_{ci}} \right)^{-1} \sum_{h=1}^{H_{ci}} \boldsymbol{\eta}_{cih} + \left( \boldsymbol{\Omega}_{\bar{\eta}}^{z_{ci}} \right)^{-1} \left( \boldsymbol{\alpha}^{z_{ci}} + \boldsymbol{\Gamma}^{z_{ci}'} \bar{\boldsymbol{\xi}}_{ci} \right)' \right), \text{ and}$$

$$\mathbf{Q}_{\bar{\boldsymbol{\eta}}_{ci}} = \left( H_{ci} \left( \boldsymbol{\Sigma}_{\eta}^{z_{ci}} \right)^{-1} + \left( \boldsymbol{\Omega}_{\bar{\eta}}^{z_{ci}} \right)^{-1} \right)^{-1}.$$

In the following Step we draw the means of the subjective logo design dimensions. The derivations are again relatively straightforward using multiplication of normal distributions.

8.  $\boldsymbol{\mu}^s \sim N(\mathbf{U}_\mu^s, \mathbf{Q}_\mu^s)$ , with  $\mathbf{U}_\mu^s = \mathbf{Q}_\mu^s \left( (\boldsymbol{\Omega}_{\xi}^s)^{-1} \left( \sum_{c=1}^C \sum_{i:z_{ci}=s} \bar{\xi}_{ci} \right) + (\mathbf{H}_{\xi}^s)^{-1} \mathbf{h}_{\xi}^s \right)$ , and

$$\mathbf{Q}_\mu^s = \left( \left( \sum_{c=1}^C \sum_{i=1}^{I_c} I\{z_{ci} = s\} \right) (\boldsymbol{\Omega}_{\xi}^s)^{-1} + (\mathbf{H}_{\xi}^s)^{-1} \right)^{-1}.$$

In the following 6 steps, we respectively draw the variances of 9) the rater variance of the subjective logo design items, 10) the item variances of logo response items, 11) the item variances of the subjective logo design characteristics, 12) the variance of the subjective logo design dimensions, and 13) the variances of the logo design responses (affect and subjective familiarity)

$$9. \Sigma_{xqq}^s \sim IG \left( \frac{1}{2} \sum_{c=1}^C \sum_{i=1}^{I_c} I(z_{ci} = s) \cdot R_{ciq} + v_{x0}^s, \frac{1}{2} \sum_{c=1}^C \sum_{i:z_{ci}=s} \sum_{r=1}^{R_{ciq}} (\mathbf{x}_{cirq} - \xi_{ciq})^2 + v_{xp}^s \right).$$

$$10. \Sigma_{ypp}^s \sim IG \left( \frac{1}{2} \sum_{c=1}^C \sum_{i=1}^{I_c} I(z_{ci} = s) \cdot H_{ci} + v_{y0}^s, \frac{1}{2} \sum_{c=1}^C \sum_{i:z_{ci}=s} \sum_{h=1}^{H_{ci}} (\mathbf{y}_{cihp}^{\text{affect}} - \boldsymbol{\tau}_{yp}^s - \boldsymbol{\Lambda}_{yp}^s \cdot \boldsymbol{\eta}_{ci1h})^2 + v_{y,p}^s \right).$$

$$11. \Sigma_{\xi qq}^s \sim IG \left( \frac{1}{2} \sum_{c=1}^C \sum_{i=1}^{I_c} I(z_{ci} = s) + v_{\xi 0}^s, \frac{1}{2} \sum_{c=1}^C \sum_{i:z_{ci}=s} \sum_{r=1}^{R_{ciq}} (\xi_{ciq} - \boldsymbol{\tau}_{\xi q}^s - \boldsymbol{\Lambda}_{\xi q}^s \cdot \bar{\xi}_{ci})^2 + v_{\xi p}^s \right).$$

$$12. \Sigma_{\eta pp}^s \sim IG \left( \frac{1}{2} \sum_{c=1}^C \sum_{i=1}^{I_c} I(z_{ci} = s) \cdot H_{ci} + v_{\eta 0}^s, \frac{1}{2} \sum_{c=1}^C \sum_{i:z_{ci}=s} \sum_{h=1}^{H_{ci}} (\boldsymbol{\eta}_{cihp} - \bar{\boldsymbol{\eta}}_{cip})^2 + v_{\eta p}^s \right), \forall p \in \{1, 2\}.$$

$$13. \boldsymbol{\Omega}_{\xi nm}^s \sim IG \left( \frac{1}{2} \sum_{c=1}^C \sum_{i=1}^{I_c} I(z_{ci} = s) + v_{\xi 0}^s, \frac{1}{2} \sum_{c=1}^C \sum_{i:z_{ci}=s} (\bar{\xi}_{cin} - \boldsymbol{\mu}_n^s)^2 + v_{\xi n}^s \right), \forall n \in \{1, 2, 3\}.$$

$$14. \boldsymbol{\Omega}_{\eta mm}^s \sim IG \left( \frac{1}{2} \sum_{c=1}^C \sum_{i=1}^{I_c} I(z_{ci} = s) + v_{\eta 0}^s, \frac{1}{2} \sum_{c=1}^C \sum_{i:z_{ci}=s} (\bar{\boldsymbol{\eta}}_{cim} - \boldsymbol{\alpha}_m^s - \bar{\xi}_{ci} \boldsymbol{\Gamma}_{.m}^s)^2 + v_{\eta m}^s \right).$$

In the last step, we drew the intercepts and parameters of the structural relationships between the logo design characteristics and responses. The derivations are based on standard derivations for multivariate normal distributions.

$$15. \begin{bmatrix} \text{vec}(\mathbf{a}^s) \\ \text{vec}(\boldsymbol{\Gamma}^s) \end{bmatrix} \sim N(\bar{\mathbf{U}}^s, \bar{\mathbf{Q}}^s), \text{ with } \bar{\mathbf{U}}^s = \bar{\mathbf{Q}}^s \cdot \left( \begin{bmatrix} \mathbf{1} & \bar{\xi}_{ci:z_{ci}=s} \end{bmatrix} \otimes (\boldsymbol{\Omega}_{\eta}^s)^{-1} \right) \text{vec}(\bar{\boldsymbol{\eta}}_{ci:z_{ci}=s}) + \begin{pmatrix} \mathbf{A}^s & \mathbf{0} \\ \mathbf{0} & \mathbf{G}^s \end{pmatrix}^{-1} \begin{pmatrix} \mathbf{a}^s \\ \mathbf{g}^s \end{pmatrix},$$

$$\bar{\mathbf{Q}}^s = \left( \begin{bmatrix} \mathbf{1} & \bar{\xi}_{ci:z_{ci}=s} \end{bmatrix} \begin{bmatrix} \mathbf{1} & \bar{\xi}_{ci:z_{ci}=s} \end{bmatrix} \otimes (\boldsymbol{\Omega}_{\eta}^s)^{-1} + \begin{pmatrix} \mathbf{A}^s & \mathbf{0} \\ \mathbf{0} & \mathbf{G}^s \end{pmatrix}^{-1} \right)^{-1}, \text{ and } i:z_{ci} = s \text{ the logos assigned to cluster } s.$$

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