Cross-National Logo Evaluation Analysis:
An Individual Level Approach

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The universality of design perception and response is tested using data collected from ten countries: Argentina, Australia, China, Germany, Great Britain, India, the Netherlands, Russia, Singapore, and the United States. A Bayesian, finite-mixture, structural-equation model is developed that identifies latent logo clusters 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 elaborateness, naturalness, and harmony are universal design dimensions. Responses (affect, shared meaning, subjective familiarity, and true and false recognition) to logo design dimensions (elaborateness, naturalness, and harmony) and elements (repetition, proportion, and parallelism) are also relatively consistent, although we find minor differences across clusters. Our results suggest that managers can implement a global logo strategy, but they also can optimize logos for specific countries if desired.

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CROSS-NATIONAL LOGO EVALUATION ANALYSIS:
AN INDIVIDUAL LEVEL APPROACH

by

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

The universality of design perception and response is tested using data collected from ten countries: Argentina, Australia, China, Germany, Great Britain, India, the Netherlands, Russia, Singapore, and the United States. A Bayesian, finite-mixture, structural-equation model is developed that identifies latent logo clusters 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 elaborateness, naturalness, and harmony are universal design dimensions. Responses (affect, shared meaning, subjective familiarity, and true and false recognition) to logo design dimensions (elaborateness, naturalness, and harmony) and elements (repetition, proportion, and parallelism) are also relatively consistent, although we find minor differences across clusters. Our results suggest that managers can implement a global logo strategy, but they also 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 that communicates to consumers and others, independent of verbal information. Hence, it is critical that marketing managers and scholars understand design's 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 understanding 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: elaborateness, naturalness, and harmony. Elaborateness refers to a design's richness and its ability to capture the essence of an object; natural designs depict commonly experienced objects; and harmony refers to the congruency of the patterns and parts of a design. 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 elaborateness, naturalness, and harmony are universal words that are 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

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from cultural influence (Adams, 2003). For example, we have an innate ability 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 literature's conflicting findings, our study examines whether the design dimensions uncovered by Henderson and colleagues underlie reactions to logos in ten different countries: Argentina, Australia, China, Germany, Great Britain, India, the 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 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[1]). Specifically, we build upon Henderson and Cote (1998) to examine the following research questions:

1. Do the design dimensions of elaborateness, naturalness, 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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[1] 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's latent clusters membership 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.[2] 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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[2] 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.

2. 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 parallelism (number of parallel lines). As discussed earlier, the design dimensions are elaborateness, naturalness, and harmony. The design dimensions consist of eight design elements (complexity, activeness, depth, representativeness, organicity, roundness, symmetry, and balance) measured subjectively by designers (see Appendix A). While these six characteristics (i.e., three dimensions plus three objective design elements) 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 a design's harmony, elaborateness, and naturalness creates 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). Naturalness, harmony, and to a lesser extent elaborateness, may increase shared meaning because universally experienced objects are more easily interpreted and recognized than abstract objects (Seifert, 1992, Shinar et al., 2003).

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 easily encoded and command attention. Natural logos, are easily encoded and 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. 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

Our conceptual model (Figure 1) is defined at the logo level. We follow previous studies on aesthetics (Berlyne, 1974, Henderson and Cote, 1998) to derive scores for design and responses and asked different designers and consumers to rate subjective logo design elements and responses for each individual logo. In addition, to test if perception of and response to design is invariant across cultures, we collected these 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). This dataset allows a rigorous test of perceptions of and responses to logo designs. By comparison, recent international marketing research has generally involved two (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).

We employed 195 unfamiliar logos used by Henderson and Cote (1998) that were originally obtained from a book of foreign logos (Kuwayama, 1973) and Yellow Page 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, and then a different bilingual native speaker translated the

questionnaires back into English.

3.2 Ratings of Logo Design Elements

Consistent with experimental aesthetics research (Berlyne, 1974), data was collected on a large number of stimuli and variables, across multiple samples. Two or three professional logo designers in each country evaluated the degree of activeness, balance, depth, organicity, representativeness, roundness, and symmetry each logo possessed. 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), for each country, five groups of approximately forty undergraduates evaluated the design element of complexity for a different subset of thirty-nine logos.[3] Finally, data from Henderson and Cote (1998) provided the three objectively measured logo design elements of parallelism, proportion, and repetition.

In summary, the eleven design elements were each measured with a single indicator. Eight of the design elements (activeness, balance, depth, organicity, representativeness, roundness, symmetry, and complexity) are country-specific and measured by different raters (either designers or students) in each country. Repetition, proportion, and parallelism are identical across countries. Appendix A defines these design elements and contains examples of logos scoring high and low on them.

3.3 Responses to Logo Design

Affect and Subjective Familiarity. To minimize fatigue, each respondent rated only thirty-nine logos on the five affective items (like/dislike, good/bad, high/low quality, distinctive/not distinctive, 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

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[3]   This furnishes evaluations for 5 x 39 or 195 logos in total.

twenty to seventy respondents (about forty on average).

Shared Meaning. Shared meaning exists when respondents agree about 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)[4]. A high concentration index indicates that a logo evokes shared meaning.

Recognition. For each country, five groups of approximately thirty 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 participated in a distracter task for about ten minutes. Then they viewed a booklet with seventy-eight logos—(thirty-nine target logos from the slide presentation and thirty-nine 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 logo-level data (see Figures 1 and 2). Previous research averages individual ratings and

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[4]   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 $.5^2 + .3^2 + .2^2 = .38$.

responses to compute each logo's design and response scores (e.g., Henderson et al., 2003). In contrast, our model (Figure 2) includes an additional hierarchy to analyze individual level data, thus minimizing potential aggregation bias (DeShon, 1998).[5] 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 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:

$i = 1,..,I$	denote the set of logos. In this study, $I = 195$.
$c = 1,..,C$	denote the set of countries. In this study, $C = 10$.
$s = 1,..,S$	denote the a priori unknown set of cross-national clusters to be determined empirically.
$q = 1,..,Q$	denote the set of subjective logo design elements related to the design dimensions.

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[5] We estimated a model without taking into account individual response differences and found a significant aggregation bias.

	In this study, $Q = 8$ (i.e., complexity, activeness, depth, representativeness, organicity, roundness, symmetry, and balance).
$n = 1,..,N$	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., elaborateness, naturalness, and harmony); and $N_{\text{element}} = 3$ objective design elements (i.e., repetition, proportion, and parallelism).
$p = 1,..,P$	denote the set of affect response items. In this study, $P = 5$ (i.e., distinctive, good, interesting, like, and quality).
$m = 1,..,M$	denote the set of logo response variables. In this study, $M = 5$ (i.e., affect, subjective familiarity, shared meaning, true recognition, and false recognition).
$r = 1,..,R_{ciq}$	denote the raters in country c that evaluated subjective design element q of logo i.
$h = 1,..,H_{ci}$	denote the respondents in country c that responded to logo i on affect and subjective familiarity.
x_{cirq}	denote the evaluation of subjective design element q of logo i in country c by rater r.
ξ_{ciq}	denote the latent score of subjective design element q of logo i in country c.
$\bar{\bar{\xi}}_{cin}$	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.
η_{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.

Based on our conceptual framework, Figure 2 summarizes our model specification for a given cluster s and incorporates both individual rater 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: elaborateness (complexity, activeness, and depth), naturalness (representativeness, organicity, and roundness), and harmony (symmetry and balance). The $N_{\text{element}} = 3$ logo objective design elements (repetition, proportion, and parallelism) 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 using a single 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 subjective logo design scores, $\boldsymbol{\xi}$, are observed and therefore computes these values by averaging over the rater scores $\mathbf{x}$, i.e.

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

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

$$x_{cirq} \mid s = \xi_{ciq} + \delta_{cirq}^{s} \; , \tag{1}$$

where δ_{cirq}^{s} is assumed to be normally distributed with mean zero and standard deviation σ_{xq}^{s}.

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

$$\boldsymbol{\xi}_{ci} \mid s = \boldsymbol{\tau}_{\xi}^{s} + \boldsymbol{\Lambda}_{\xi}^{s} \left(\overline{\xi}_{ci1} \quad \overline{\xi}_{ci2} \quad \overline{\xi}_{ci3} \right)' + \boldsymbol{\varepsilon}_{\xi ci}^{s} . \tag{2}$$

In (2), $\boldsymbol{\Lambda}_{\xi}^{s}$ $\left(Q \times N_{\text{dimension}} \right)$ is a factor loading matrix and $\boldsymbol{\tau}_{\xi}^{s}$ is a $\left(Q \times 1 \right)$ vector containing measurement intercepts. The $\left(Q \times 1 \right)$ vector of disturbance terms $\boldsymbol{\varepsilon}_{\xi ci}^{s}$ is multivariate normally distributed with mean vector zero and diagonal covariance matrix $\boldsymbol{\Sigma}_{\xi}^{s}$ $\left(Q \times Q \right)$, given cluster s. Note that (2) is the standard measurement model used in a structural-equation modeling approach in which $\boldsymbol{\xi}_{ci}$ is observed, while in our approach it is a vector of latent scores depending on (1).

In addition, we specify

$$\left(\overline{\xi}_{ci1} \quad \overline{\xi}_{ci2} \quad \overline{\xi}_{ci3} \right)' \mid s = \boldsymbol{\mu}^s + \boldsymbol{\psi}_{ci}^s, \tag{3}$$

with $\boldsymbol{\mu}^s$ ($N_{\text{dimension}} \times 1$) containing the design dimension intercepts. The disturbance terms $\boldsymbol{\psi}_{ci}^s$ are

assumed to be normally distributed with mean zero and diagonal covariance matrix $\boldsymbol{\Omega}_{\xi}^s$

$\left(N_{\text{dimension}} \times N_{\text{dimension}} \right)$. Note that each country c has the same scores for the logo objective design

elements (i.e., $\overline{\xi}_{cin}$ with $n \in N_{\text{element}}$) as these are measured directly (see Section 3.2).

Aesthetics research generally 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: $\eta_{ci2h} = y_{cih}^{\text{familiarity}}$ 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:

$$\mathbf{y}_{cih}^{\text{affect}} \mid s = \boldsymbol{\tau}_y^s + \boldsymbol{\Lambda}_y^s \cdot \eta_{ci1h} + \boldsymbol{\varepsilon}_{ycih}^s. \tag{4}$$

In (4), $\boldsymbol{\Lambda}_y^s$ is a $(P \times 1)$ vector containing the factor loadings, and $\boldsymbol{\tau}_y^s$ is a $(P \times 1)$ vector containing

measurement intercepts. The $(P \times 1)$ error vector $\boldsymbol{\varepsilon}_{ycih}^s$ is assumed to be normally distributed with

mean zero and diagonal covariance matrix $\boldsymbol{\Sigma}_s^y$ $(P \times P)$, given cluster s.

Similar to equation (1), we assume the following measurement model to derive the latent

affect and subjective familiarity scores at the logo level:

$$\left(\eta_{ci1h} \quad \eta_{ci2h} \right)' \mid s = \left(\overline{\eta}_{ci1} \quad \overline{\eta}_{ci2} \right)' + \boldsymbol{\varepsilon}_{\eta cih}^s. \tag{5}$$

In (5), $\boldsymbol{\varepsilon}_{\eta cih}^s$ is a (2×1) vector that is assumed to be normally distributed with mean zero and

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(2×2) diagonal covariance matrix Σ_η^s, given cluster s.

Given the measurement model in equations (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:

$$\overline{\boldsymbol{\eta}}_{ci} \mid s = \boldsymbol{\alpha}^s + \boldsymbol{\Gamma}^s \cdot \overline{\boldsymbol{\xi}}_{ci} + \boldsymbol{\zeta}_{ci}^s, \tag{6}$$

In (6), the vector $\boldsymbol{\alpha}^s$ $(M \times 1)$ contains the intercepts for the endogenous logo responses $\overline{\boldsymbol{\eta}}_{ci}$. The

coefficient matrix $\boldsymbol{\Gamma}^s$ incorporates the effects of the exogenous logo design dimensions and

objective design elements, $\overline{\boldsymbol{\xi}}_{ci}$, on the endogenous logo responses $\overline{\boldsymbol{\eta}}_{ci}$ (see Figure 2). It is

assumed that the disturbance term $\boldsymbol{\zeta}_{ci}^s$ is normally distributed with mean zero and diagonal

covariance matrices $\boldsymbol{\Omega}_{\overline{\eta}}^s$ $(M \times M)$.

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 cluster-specific and defined

at the logo level, our constrained finite-mixture approach assigns logos to clusters. Using a

concomitant variable specification (ter Hofstede, Steenkamp and Wedel, 1999) we allow mixture

probabilities for country-specific logo cluster membership. We therefore introduce parameter π_{cs}

that specifies the probability that a logo evaluated in country c is assigned to cluster s. This

concomitant variable specification simultaneously derives clusters of logos and profiles these

clusters based on country membership (i.e., the concomitant variable that indicates in which country a logo is evaluated). 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 the country-specific cluster proportions π_{cs} in combination with the measurement equations (1) to (5), and structural equation (6), we obtain the following model likelihood:

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

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

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

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 multigroup model with known groups is identified and the data is multivariate normal.

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

rewritten as follows:

$$L\left(\mathbf{y},\mathbf{x},\mathbf{z},\boldsymbol{\eta},\overline{\boldsymbol{\eta}},\boldsymbol{\xi},\overline{\boldsymbol{\xi}};\boldsymbol{\Theta},\boldsymbol{\pi}\right)=\prod_{c=1}^{C}\prod_{s=1}^{S}\prod_{i:z_{ci}=s}\left\{\left(\prod_{h=1}^{H_{ci}}N_{P}\left(\mathbf{y}_{cih}^{\text{affect}};\boldsymbol{\tau}_{y}^{s}+\boldsymbol{\Lambda}_{y}^{s}\eta_{ci1h},\boldsymbol{\Sigma}_{y}^{s}\right)\right)\cdot\right.$$
$$\cdot\left(\prod_{h=1}^{H_{ci}}N_{2}\left(\left(\eta_{ci1h}\quad\eta_{ci2h}\right)';\left(\overline{\eta}_{ci1}\quad\overline{\eta}_{ci2}\right),\boldsymbol{\Sigma}_{\eta}^{s}\right)\right)\cdot\left(\prod_{q=1}^{Q}\prod_{r=1}^{R_{ciq}}N\left(x_{cirq};\xi_{ciq},\boldsymbol{\Sigma}_{xqq}^{s}\right)\right),\ (8)$$
$$\cdot N_{Q}\left(\boldsymbol{\xi}_{ci};\boldsymbol{\tau}_{\xi}^{s}+\boldsymbol{\Lambda}_{\xi}^{s}\left(\overline{\xi}_{ci1}\quad\overline{\xi}_{ci2}\quad\overline{\xi}_{ci3}\right)',\boldsymbol{\Sigma}_{\xi}^{s}\right)\cdot N_{M}\left(\overline{\boldsymbol{\eta}}_{ci};\boldsymbol{\alpha}^{s}+\boldsymbol{\Gamma}^{s}\overline{\boldsymbol{\xi}}_{ci},\boldsymbol{\Omega}_{\overline{\eta}}^{s}\right)$$
$$\left.\cdot N_{N_{\text{Dimension}}}\left(\left(\overline{\xi}_{ci1}\quad\overline{\xi}_{ci2}\quad\overline{\xi}_{ci3}\right);\boldsymbol{\mu}^{s},\boldsymbol{\Omega}_{\overline{\xi}}^{s}\right)\right\}$$

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 $\boldsymbol{\Theta}$, $\boldsymbol{\eta}$, $\overline{\boldsymbol{\eta}}$, $\boldsymbol{\xi}$, $\overline{\boldsymbol{\xi}}$ and $\boldsymbol{\pi}$. We used flat prior distributions specified in

Web Appendix A to estimate the model using the MCMC algorithm as specified in 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 relabeled cluster

memberships by post-processing the posterior draws using Richardson and Green's (1997)

approach.[6] 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

(1992) and found that all runs converged well before burn-in (see Web Appendix C). 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 the largest posterior probability

(Lenk and DeSarbo, 2000). We implemented Chib's (1995) procedure to compute the log

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[6] 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 B for some posterior draws.

marginal density (LMD) for each model and obtained 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 $\boldsymbol{\Lambda}_\xi^s$ and $\boldsymbol{\Lambda}_y^s$ 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 $\boldsymbol{\Lambda}_\xi^s$ corresponds to the $(Q \times Q)$ identity matrix). A more stringent test is the metric model which constrains the factor loadings $\boldsymbol{\Lambda}_\xi^1 = \boldsymbol{\Lambda}_\xi^2 = ... = \boldsymbol{\Lambda}_\xi^S$ and $\boldsymbol{\Lambda}_y^1 = \boldsymbol{\Lambda}_y^2 = ... = \boldsymbol{\Lambda}_y^S$ 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., $\Gamma_1 = \Gamma_2 = .. = \Gamma_S$.

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 Masculinty/Femininity for the

West and Asia) and writing systems. The Asian cultures use a 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: elaborateness (complexity, activeness, and depth), naturalness (organicity,

representativeness, and roundness), 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 (LMD = -891,508). This indicates that logo design characteristics are

captured by the same factor structure and loadings across clusters.

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), the 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, elaborateness, and naturalness) increase as seen in the positive and significant structural path coefficients. However, the importance of elaborateness 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 parallelism, 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 naturalness are positive and statistically significant in all three clusters. Additionally, the effects of parallelism, repetition, and proportion are not significant across the clusters. However, the relationship between elaborateness and subjective familiarity varies across clusters—the path for Russia (-0.22) is negative and significant, while those of 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 (19% for Asia, 22% for the West, and 23% for Russia). Naturalness increases shared meaning, while elaborateness 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, 6% for Russia, and 3% for the West. Naturalness has a positive influence and is equivalent across the clusters (Asia .10, the West .07, and Russia .06). Harmony, parallelism, and repetition have nonsignificant effects on true recognition in all three clusters. Two cluster differences emerge in the relationships between elaborateness, proportion, and true recognition. Elaborateness has a positive influence in Asia but no influence in Russia or the West (Asia .07 vs Russia -.02 vs West -.04), 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 percentage of false recognition for Asia (6%) and the West (7%) but a larger percentage in Russia (23%). For all clusters, naturalness decreases false recognition, while elaborateness and harmony increase false recognition.

Summary. Overall, the results for the cross-national clusters were consistent with prior work (Henderson and Cote, 1998, Henderson, Cote, Leong and Schmitt, 2003). This is especially true for naturalness 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

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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 for Asia.

The largest cluster differences were for elaborate designs. In most cases, elaborate designs increased positive affect, subjective familiarity, and 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) extend 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 that logo evaluations within countries belong to the same cluster a priori (although our findings resulted in country-based clusters). Due to our concomitant variable formulation, the identified cross-national clusters are

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easily interpreted. Further, previous experimental research in aesthetics aggregates individual responses for each logo. In contrast, our approach addresses a 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 datasets with many subgroups, aggregating them into larger classes based on response similarity. For example, our procedure can answer such questions as: how would different stakeholders (stockholders, consumers, competitors, public policy makers) respond to different multidimensional stimuli such as a company's pricing practices; or how would different industries or markets react to different types of research and design 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 can also provide 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 naturalness score (2.3) is probably why this logo performs poorly, since naturalness has a positive influence on both true recognition and affect. Using posterior draws of the parameters, a designer can determine the minimum required naturalness score for a given country, such that its expected affect and true recognition values are higher than a predetermined threshold.[7] For instance, the score of naturalness 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

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[7] 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.

least .65 and 4.0 respectively. Similarly, the elaborateness 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 elaborateness 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 elaborateness, naturalness, 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 that 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 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 where 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 because 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 it 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 elaborateness, naturalness, 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 (elaborateness); depict commonly experienced objects (naturalness); and represent congruent patterns or arrangements of parts (harmony).
5. Be systematic and objective and allow designers to modify the core logo for individual markets. However, use the results of Table 4 to guide logo selection rather than to 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 brand familiarity 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 regardless 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 the 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 the 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.

Lastly, 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 toward 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.

Table 1
Characteristics of the Countries Studied

Nation/ Characteristic	Argentina	Australia	China	Germany	Great Britain	India	Netherlands	Russia	Singapore	U.S.
Geography	South America	Oceania	East Asia	Western Europe	Western Europe	South Asia	Western Europe	Eastern Europe/Asia	East Asia	North America
Economics:[1] Gross National Income/capita	$5,528	$37,924	$2,055	$34,955	$39,207	$784	$40,535	$6,877	$30,159	$43,562
Government[2]	Republic	Common-wealth	Socialist	Federal Republic	Constitutional Monarchy	Federal Republic	Constitutional Monarchy	Federalist	Republic	Federal Republic
Culture:[3] 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[4]	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 dataset but were 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.

Table 2
Median Cluster Probabilities and Summary Characteristics

Country/Cluster	West	Asia	Russia
Argentina	0.41 (0.31 to 0.51)	0.43 (0.34 to 0.52)	0.16 (0.11 to 0.23)
Australia	**0.76** (0.67 to 0.84)	0.08 (0.04 to 0.14)	0.15 (0.08 to 0.23)
Great Britain	**0.97** (0.93 to 0.99)	0.02 (0.00 to 0.06)	0.01 (0.00 to 0.03)
China	0.19 (0.13 to 0.26)	**0.76** (0.69 to 0.82)	0.04 (0.02 to 0.08)
Germany	**0.60** (0.51 to 0.69)	0.37 (0.29 to 0.46)	0.02 (0.01 to 0.05)
India	0.30 (0.22 to 0.38)	**0.62** (0.53 to 0.69)	0.08 (0.04 to 0.14)
Netherlands	**0.75** (0.66 to 0.82)	0.22 (0.16 to 0.30)	0.03 (0.01 to 0.06)
Russia	0.01 (0.00 to 0.03)	0.01 (0.00 to 0.03)	**0.98** (0.95 to 1.00)
Singapore	0.08 (0.05 to 0.13)	**0.91** (0.86 to 0.95)	0.00 (0.00 to 0.02)
USA	**0.85** (0.77 to 0.91)	0.12 (0.06 to 0.19)	0.03 (0.01 to 0.07)
Characteristic Weighted Averages*			
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
Masculinity/Femininity	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 Masculinity/Femininity for the West and Asia.

Table 3
Median Factor Loadings of Design Dimension and Affect[*]

Design Dimension	Design Characteristic	Factor Loading
Elaborateness:	Complexity	1
	Activeness	1.29 (1.13 to 1.47)
	Depth	1.34 (1.18 to 1.50)
Naturalness:	Organic	1
	Representativeness	0.82 (0.74 to 0.91)
	Roundness	0.76 (0.67 to 0.86)
Harmony:	Symmetry	1
	Balance	0.62 (0.57 to 0.66)
Affect:	Distinctive	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.

Table 4
Median Estimates: Structural Paths

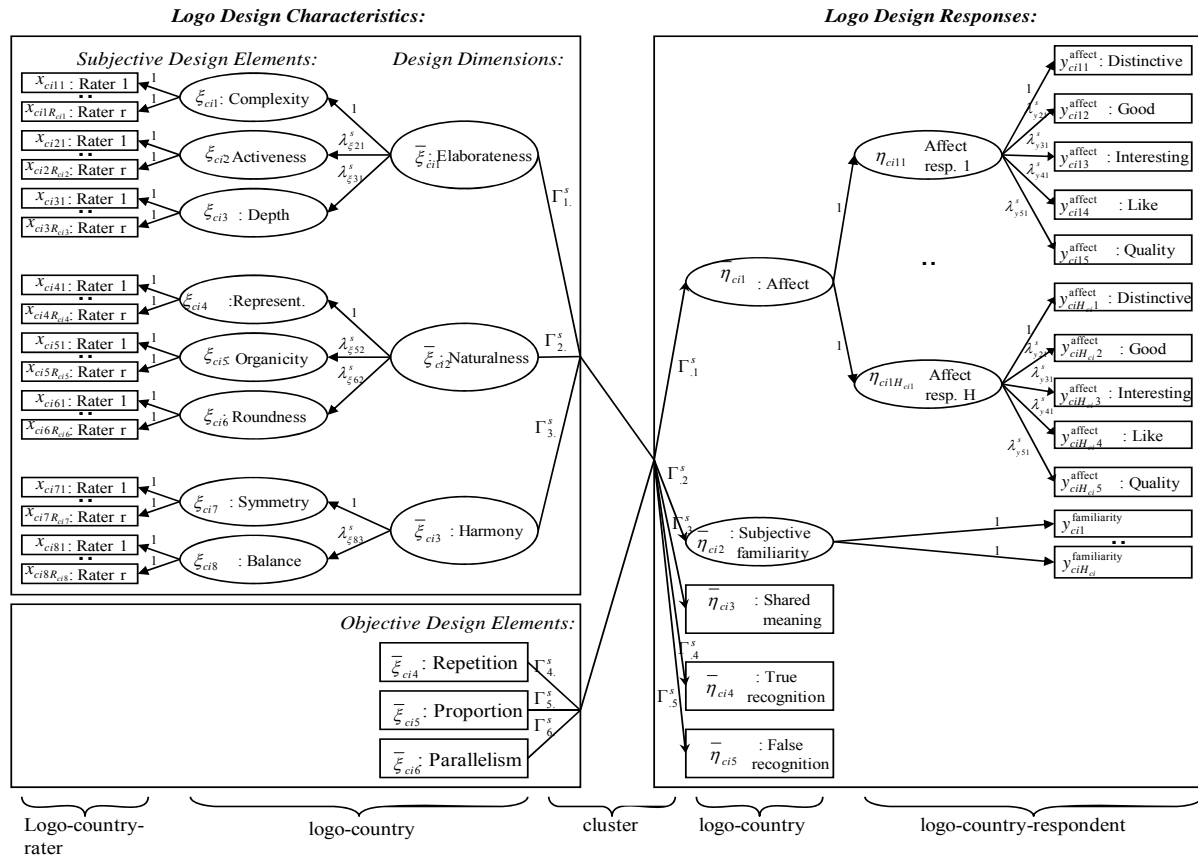| Response	Cluster	Elaborateness	Naturalness	Harmony	Parallelism	Proportion	Repetition	Intercept	Variance Explained
Affect	West	**.54** (.41 to .77)	**.12** (.08 to .17)	**.06** (.03 to .09)	.00 (-.02 to .03)	-.06 (-.12 to .01)	.01 (-.01 to .04)	**1.75** (1.01 to 2.22)	.62
	Asia	**.70** (.59 to .82)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

95% confidence intervals are between brackets.
Bold values correspond to coefficients with a 95% confidence interval not containing zero.

Figure 1
Conceptual Framework of Logo Design Evaluation
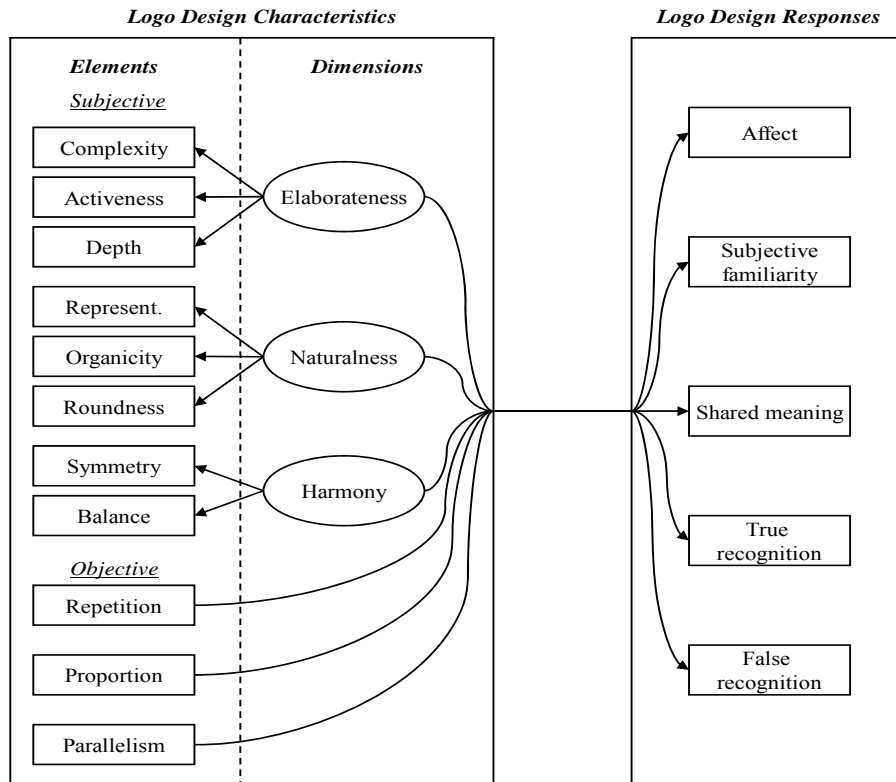
Note: Logo design dimensions (consisting of subjective elements) and objective elements are on the left, while consumer responses to logos are depicted on the right.
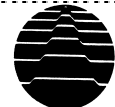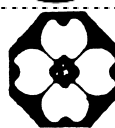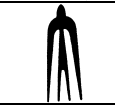
Figure 2
Model Specification at the Cluster and Individual Response Level [8]

Logo Design Characteristics: *Logo Design Responses:*

Level:

Logo-country-rater | logo-country | cluster | logo-country | logo-country-respondent

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

Design Characteristics	High	Low
Elaborateness captures the concept of design richness and the ability to use plain lines to capture the essence of an object. It comprises the elements of complexity, activeness, and depth.		
Complexity is created by irregularity in the arrangement of elements, increases in the number of elements, heterogeneity in the nature of elements, and ornateness of the design.		
Active designs give the impression of motion or flow.		
Depth gives the appearance of perspective or of being three-dimensional.		
Naturalness reflects the degree to which the design depicts commonly experienced objects. It comprises the elements of representativeness and organicity.		
Representativeness **is** the degree of realism in a design. This occurs when the elements of an object are distilled to its most typical features.		
Organicity refers to natural shapes as opposed to angular and abstract designs.		
Round designs are made of primarily curved lines and circular elements.		
Harmony is a congruent pattern or arrangement of parts that combines the elements of symmetry and balance.		
Symmetric designs appear as reflections along one (or more) axis.		
Balance captures the notion that there is a center of suspension between two weights or portions of the design.		
Parallel designs contain multiple lines or elements that appear adjacent to each other.		
Repetition is the iterative use of design parts that are similar or identical to each other— unless they are simply part of a larger whole (e.g., branches on a tree).		
Proportion 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 we used to draw the model parameters in the MCMC sampler. Because we chose conjugate prior distributions,[9] 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 prespecified number $\mathbf{a}$. Let

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

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

For the Gibbs sampler, we use 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. $z_{ci} \mid .. \sim MN\left(\dfrac{L\left(\mathbf{y}_{ci}, \mathbf{x}_{ci}, \boldsymbol{\eta}_{ci}, \overline{\boldsymbol{\eta}}_{ci}, \boldsymbol{\xi}_{ci}, \overline{\boldsymbol{\xi}}_{ci}; \boldsymbol{\Theta}^{s=1} \right)}{\sum\limits_{s=1}^{s} L\left(\mathbf{y}_{ci}, \mathbf{x}_{ci}, \boldsymbol{\eta}_{ci}, \overline{\boldsymbol{\eta}}_{ci}, \boldsymbol{\xi}_{ci}, \overline{\boldsymbol{\xi}}_{ci}; \boldsymbol{\Theta}^{s} \right)}, ..., \dfrac{L\left(\mathbf{y}_{ci}, \mathbf{x}_{ci}, \boldsymbol{\eta}_{ci}, \overline{\boldsymbol{\eta}}_{ci}, \boldsymbol{\xi}_{ci}, \overline{\boldsymbol{\xi}}_{ci}; \boldsymbol{\Theta}^{s=S} \right)}{\sum\limits_{s=1}^{s} L\left(\mathbf{y}_{ci}, \mathbf{x}_{ci}, \boldsymbol{\eta}_{ci}, \overline{\boldsymbol{\eta}}_{ci}, \boldsymbol{\xi}_{ci}, \overline{\boldsymbol{\xi}}_{ci}; \boldsymbol{\Theta}^{s} \right)} \right)$, with $MN(.)$ the

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

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

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

3. $\begin{pmatrix} \boldsymbol{\tau}_{\xi,\text{free}}^{s} \\ vec\left(\boldsymbol{\Lambda}_{\xi,\text{free}}^{s} \right) \end{pmatrix} \sim N\left(\overline{\mathbf{U}_{\xi}^{s}}, \overline{\mathbf{Q}_{\xi}^{s}} \right)$ and $\begin{pmatrix} \boldsymbol{\tau}_{y,\text{free}}^{s} \\ vec\left(\boldsymbol{\Lambda}_{y,\text{free}}^{s} \right) \end{pmatrix} \sim N\left(\overline{\mathbf{U}_{y}^{s}}, \overline{\mathbf{Q}_{y}^{s}} \right)$, where subscripts *fix* and *free* 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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[9] For the specifications of the prior distributions, see Web Appendix A.

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

$$\text{with } \mathbf{U}_{\xi}^{s} = \mathbf{Q}_{\xi}^{s} \cdot \left(\sum_{c=1}^{C} \sum_{i:z_{ci}=s} \left\{ \left(\begin{bmatrix} 1 & \overline{\boldsymbol{\xi}}_{ci} \end{bmatrix} \otimes \mathbf{I}_{Q}\right)' \boldsymbol{\Sigma}_{\xi}^{s-1} \boldsymbol{\xi}_{ci} \right\} + \begin{pmatrix} \mathbf{H}_{\xi}^{s} & \mathbf{0} \\ \mathbf{0} & \mathbf{V}_{\xi}^{s} \end{pmatrix}^{-1} \begin{pmatrix} \mathbf{h}_{\xi}^{s} \\ \mathbf{L}_{\xi}^{s} \end{pmatrix}\right), \quad \mathbf{U}_{y}^{s} = \mathbf{Q}_{y}^{s} \cdot \left(\sum_{c=1}^{C} \sum_{i:z_{ci}=s} \sum_{h=1}^{H_{ci}} \left\{\left(\begin{bmatrix} 1 \end{bmatrix}\right.\right.\right.$$

$$\left.\left.\boldsymbol{\eta}_{cih} \end{bmatrix} \otimes \mathbf{I}_{P}\right)' \boldsymbol{\Sigma}_{y}^{s-1} \mathbf{y}_{cih}^{\text{affect}} + \begin{pmatrix} \mathbf{H}_{y}^{s} & \mathbf{0} \\ \mathbf{0} & \mathbf{V}_{y}^{s} \end{pmatrix}^{-1} \begin{pmatrix} \mathbf{h}_{y}^{s} \\ \mathbf{L}_{y}^{s} \end{pmatrix}\right), \quad \mathbf{Q}_{\xi}^{s} = \left(\left(\sum_{c=1}^{C} \sum_{i:z_{ci}=s} \begin{bmatrix} 1 & \overline{\boldsymbol{\xi}}_{ci} \end{bmatrix} \cdot \begin{bmatrix} 1 & \overline{\boldsymbol{\xi}}_{ci} \end{bmatrix}'\right) \otimes \boldsymbol{\Sigma}_{\xi}^{s-1} + \begin{pmatrix} \mathbf{H}_{\xi}^{s} & \mathbf{0} \\ \mathbf{0} & \mathbf{V}_{\xi}^{s} \end{pmatrix}^{-1}\right)^{-1},$$

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

In the following four steps, we sequentially draw, 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. $\boldsymbol{\xi}_{ciq} \sim N\left(\dfrac{\boldsymbol{\Sigma}_{\xi qq}^{s} \sum_{r=1}^{R_{ciq}} x_{cirq} + \left(\boldsymbol{\tau}_{\xi q}^{s} + \boldsymbol{\Lambda}_{\xi q.}^{s} \overline{\boldsymbol{\xi}}_{ci}\right) \boldsymbol{\Sigma}_{xqq}^{s}}{R_{ciq} \boldsymbol{\Sigma}_{\xi qq}^{s} + \boldsymbol{\Sigma}_{xqq}^{s}}, \dfrac{\boldsymbol{\Sigma}_{xqq}^{s} \boldsymbol{\Sigma}_{\xi qq}^{s}}{R_{ciq} \boldsymbol{\Sigma}_{\xi qq}^{s} + \boldsymbol{\Sigma}_{xqq}^{s}}\right).$

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

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

6. $\eta_{ci1h} \sim N\left(L_{\eta_{cih}}, Q_{\eta_{ci}}\right)$, with $\mathbf{Q}_{\eta_{ci}} = \left(\boldsymbol{\Lambda}_{y}^{z_{ci}'} \left(\boldsymbol{\Sigma}_{y}^{z_{ci}}\right)^{-1} \boldsymbol{\Lambda}_{y}^{z_{ci}} + \left(\boldsymbol{\Sigma}_{\eta}^{z_{ci}}\right)^{-1}\right)^{-1}$, and

$$\mathbf{L}_{\eta_{cih}} = \mathbf{Q}_{\eta_{ci}} \left(\boldsymbol{\Lambda}_{z_{ci}}^{y}{}' \left(\boldsymbol{\Sigma}_{z_{ci}}^{y}\right)^{-1} \left(\mathbf{y}_{cih}^{\text{affect}} - \boldsymbol{\tau}_{y}^{z_{ci}}\right) + \left(\boldsymbol{\Sigma}_{\eta,11}^{z_{ci}}\right)^{-1} \overline{\eta}_{ci1}\right).$$

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

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

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

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

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

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

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

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

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

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

In the last step, we draw 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. $\begin{bmatrix} vec\left(\mathbf{\alpha}^{s}\right) \\ vec\left(\mathbf{\Gamma}^{s}\right) \end{bmatrix} \sim N\left(\overline{\mathbf{U}}^{s}, \overline{\mathbf{Q}}^{s}\right)$, with $\overline{\mathbf{U}}^{s} = \overline{\mathbf{Q}}^{s}\cdot\left(\left(\begin{bmatrix} \mathbf{1} & \bar{\xi}_{i:z_a=s} \end{bmatrix}\otimes\left(\mathbf{\Omega}_{\bar{\eta}}^{s}\right)^{-1}\right)vec\left(\bar{\mathbf{\eta}}_{i:z_a=s}\right)+\begin{pmatrix} \mathbf{A}^{s} & \mathbf{0} \\ \mathbf{0} & \mathbf{G}^{s} \end{pmatrix}^{-1}\begin{pmatrix} \mathbf{a}^{s} \\ \mathbf{g}^{s} \end{pmatrix}\right),$

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

s.

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Web Appendix A
Prior Distributions

In Appendix B, we provide the posterior distributions used to draw the model parameters in the MCMC sampler. To estimate our model we use the following flat conjugate priors:

1. $\boldsymbol{\pi}_{c.} \sim D(\mathbf{r}_{c.})$, for each country $c = 1,..,C$, with $D(.)$ representing the Dirichlet distribution which is the natural conjugate prior for the mixture probabilities. In our analysis we assume $\mathbf{r}_{c.} = [1..1]$, i.e. $(1 \times S)$-vector containing ones.

2. For each cluster $s = 1,..,S$, we define multivariate normal priors for the item intercepts, i.e., $\boldsymbol{\tau}_\xi^s \sim N(\mathbf{h}_\xi^s, \mathbf{H}_\xi^s)$ and $\boldsymbol{\tau}_y^s \sim N(\mathbf{h}_y^s, \mathbf{H}_y^s)$. In our analysis, we assume $\mathbf{h}_\xi^s = \mathbf{0}$, $\mathbf{h}_y^s = \mathbf{0}$, $\mathbf{H}_\xi^s = 10^6 \cdot \mathbf{I}_{(Q \times Q)}$, and $\mathbf{H}_y^s = 10^6 \cdot \mathbf{I}_{(P \times P)}$, with $\mathbf{I}_{(. \times .)}$ representing the $(. \times .)$ identity matrix.

3. For each cluster $s = 1,..,S$, we define multivariate normal priors for the vector containing the parameters of the factor loadings, i.e., $vec(\boldsymbol{\Lambda}_\xi^s) \sim N(\mathbf{L}_\xi^s, \mathbf{V}_\xi^s)$ and $vec(\boldsymbol{\Lambda}_y^s) \sim N(\mathbf{L}_y^s, \mathbf{V}_y^s)$. In our analysis we assume $\mathbf{L}_\xi^s = \mathbf{1}$, $\mathbf{L}_y^s = \mathbf{1}$, $\mathbf{V}_\xi^s = 10^6 \cdot \mathbf{I}_{(QN_{\text{Dimension}} \times QN_{\text{Dimension}})}$, and $\mathbf{V}_y^s = 10^6 \cdot \mathbf{I}_{(P \times P)}$.

4. We assume independent inverted gamma distributions as priors for the rater variances $\boldsymbol{\Sigma}_{xqq}^s \sim IG(v_{x0}^s, v_{xq}^s)$ and $\boldsymbol{\Sigma}_{ypp}^s \sim IG(v_{y0}^s, v_{yp}^s)$. In our analysis we set $v_{x0}^s = 3$, $v_{y0}^s = 3$, $v_{xq}^s = 1$, and $v_{yp}^s = 1$ for all $s = 1,..,S$, $q = 1,..,Q$, and $p = 1,..,P$.

5. For the items of the three logo design dimensions (i.e., elaborateness, naturalness, and harmony), $\boldsymbol{\Sigma}_{\xi qq}^s$, and the affect and subjective familiarity response variances $\boldsymbol{\Sigma}_{\eta mm}^s$, we assume independent inverted gamma distributions as priors. $\boldsymbol{\Sigma}_{\xi qq}^s \sim IG(v_{\xi 0}^s, v_{\xi q}^s)$ and $\boldsymbol{\Sigma}_{\eta mm}^s \sim IG(v_{\eta 0}^s, v_{\eta m}^s)$. In our computations: $v_{\xi 0}^s = 3$, $v_{\eta 0}^s = 3$, $v_{\xi q}^s = 1$, and $v_{\eta m}^s = 1$ for all $s = 1,..,S$, $n = 1,\ldots,N_{dimension}$ and $q = 1,..,Q$.

6. For the structural relationships, we assume multivariate prior distributions for the intercepts $\boldsymbol{\alpha}^s \sim N(\mathbf{a}^s, \mathbf{A}^s)$ and the vector of relationships $vec(\boldsymbol{\Gamma}^s) \sim N(\mathbf{g}^s, \mathbf{G}^s)$. In our analysis: the $(M \times 1)$-vector $\mathbf{a}^s = \mathbf{0}$, the $(MN \times 1)$-vector $\mathbf{g}^s = \mathbf{0}$, $\mathbf{A}^s = 10^6 \cdot \mathbf{I}_{(M \times M)}$, and $\mathbf{G}^s = 10^6 \cdot \mathbf{I}_{(MN \times MN)}$.

7. We assume multivariate prior distributions for the means of the three logo design dimensions (i.e., elaborateness, naturalness, and harmony). $\boldsymbol{\mu}^s \sim N(\mathbf{h}_{\bar{\xi}}^s, \mathbf{H}_{\bar{\xi}}^s)$ for each cluster $s = 1,..,S$. In

our analysis: the ($N_{dimension}$ x 1) - vector $\mathbf{h}_{\bar{\xi}}^{s} = \mathbf{0}$ and $\mathbf{H}_{\bar{\xi}}^{s} = 10^{6}\mathbf{I}_{(N_{\text{Dimension}} \times N_{\text{Dimension}})}$.

8. For the variances of the three logo design dimensions and five logo design responses, we assume independent inverted gamma distributions as priors. $\mathbf{\Omega}_{\bar{\xi}nn}^{s} \sim IG\left(v_{\bar{\xi}0}^{s}, v_{\bar{\xi}n}^{s}\right)$ and $\mathbf{\Omega}_{\bar{\eta}mm}^{s} \sim IG\left(v_{\bar{\eta}0}^{s}, v_{\bar{\eta}m}^{s}\right)$. In our computations: $v_{\bar{\xi}0}^{s} = 3$, $v_{\bar{\eta}0}^{s} = 3$, $v_{\bar{\xi}n}^{s} = 1$, and $v_{\bar{\eta}m}^{s} = 1$ for all $s = 1,..,S$, $n = 1,\ldots, N_{dimension}$, and $m = 1,..,M$.

An important issue that needs to be addressed when estimating mixture models in a Bayesian framework is label switching (Frühwirth-Schnatter 2006; Rossi et al. 2005). Label switching may occur because the mixture likelihood (7 and 8) are invariant under relabeling of the segments, i.e., the likelihood remains the same when the parameter values of $\left\{\mathbf{\Theta}^s, \boldsymbol{\pi}_{.s}\right\}$ and $\left\{\mathbf{\Theta}^{s'}, \boldsymbol{\pi}_{.s'}\right\}$, with $s \neq s'$, are swapped. Label switching can be observed by post-processing the posterior draws of the MCMC sampler. In our empirical setting, label switching does not occur, which becomes clear from the following plot of the posterior draws of the segment probabilities of the Netherlands. The plot clearly illustrates that the segments are well separated for this parameter and that label switching does not occur.
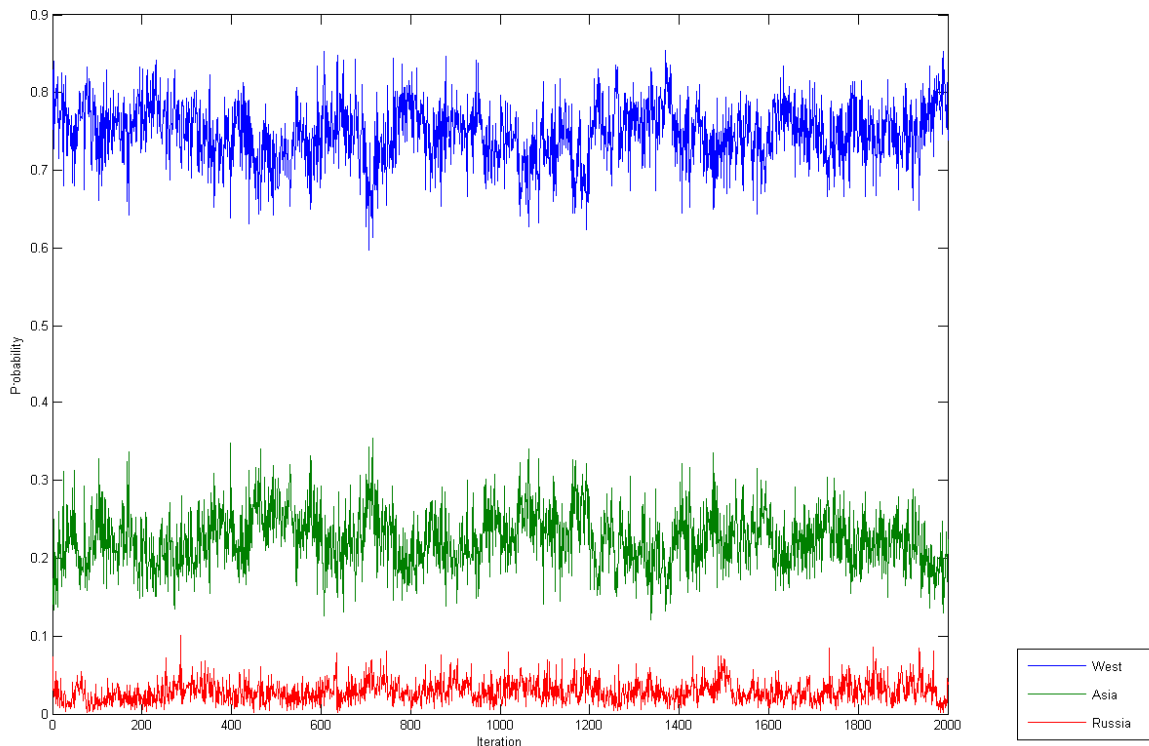
Web Appendix C
Convergence Diagnostics

This Appendix presents convergence diagnostics for the parameter estimates of the final model (i.e., three segments, with metric invariance). For each parameter estimate, we compute three statistics suggested by Raftery and Lewis (1992): *Burn, Total,* and, *I-stat*, and one p-value based on the convergence diagnostic proposed by Geweke (1992). *Burn* indicates the number of draws to use before burn-in. *Total* represents the total number of draws needed to achieve accuracy draws. We follow Raftery and Lewis (1992), such that the estimated .025 and .975 quantiles of the 95% confidence result in an actual posterior interval that lies between .94 and .96. The *I-stat* is a statistic that is based on the autocorrelation of the posterior draws. Raftery and Lewis indicate that values of *I-stat* above 5 are indicative of convergence problems. The p-value (from Geweke) is based on the test that the mean of the first 20 percent of the posterior draws after burn-in is equal to the mean of the last 50 percent of the posterior draws. Nonsignificant differences indicate converged samples.

We estimate the convergence statistics using CODA software (Robert and Casella 2004). Tables C1 to C5 present the convergence diagnostics for each parameter presented in the paper. All 144 parameters have a *Burn* parameter smaller than 15, which means that all parameters converged according to this statistic. This is also confirmed by the p-value of Geweke, which is (for all but three parameters) nonsignificant. In addition, all *I-stats* are smaller than five, indicating that there are no convergence problems.

Table C1
Convergence Diagnostics Segment Probabilities

Cluster	West				Asia				Russia			
Diagnostic	Raftery & Lewis			Geweke	Raftery & Lewis			Geweke	Raftery & Lewis			Geweke
Country	Burn	Total	I-stat	p	Burn	Total	I-stat	p	Burn	Total	I-stat	p
Argentina	7	1,926	2.1	.55	2	969	1.0	.47	2	969	1.0	.79
Australia	4	1,161	1.2	.32	3	1,143	1.2	.23	4	1,243	1.3	.49
Great Britain	2	969	1.0	.61	3	1,143	1.2	.54	2	893	.9	.84
China	4	1,243	1.3	.59	2	893	1.0	.27	3	1,143	1.2	.18
Germany	3	1,053	1.1	.76	4	1,243	1.3	.85	2	969	1.0	.36
India	4	1,243	1.3	.61	2	893	1.0	.74	2	969	1.0	.57
Netherlands	2	969	1.0	.12	3	1,011	1.1	.34	3	1,053	1.1	.05
Russia	2	861	.9	.78	2	893	1.0	.68	3	1,053	1.1	.98
Singapore	3	1,053	1.1	.53	2	969	1.0	.81	2	969	1.0	.57
US	3	1,053	1.1	.14	2	969	1.0	.12	2	969	1.0	.90

Table C2
Convergence Diagnostics: Factor Loadings

Diagnostic Dimension	Design Characteristic	Raftery & Lewis			Geweke
		Burn	Total	I-stat	p
Elaborateness:	Activeness	6	1,608	1.7	.76
	Depth	3	1,143	1.2	.53
Naturalness:	Represent.	4	1,243	1.3	.69
	Roundness	3	1,053	1.1	.18
Harmony:	Balance	4	1,243	1.3	.39
Affect:	Good	2	969	1.0	.27
	Interest	2	893	1.0	.16
	Like	2	893	1.0	.14
	Quality	3	1,053	1.1	.32

Table C3
Convergence Diagnostics: Structural Paths (Subjective Logo Design Dimensions)

| | Design Dimension | Elaborateness | | | | Naturalness | | | | Harmony | | | |
| | Diagnostic | Raftery & Lewis | | | Geweke | Raftery & Lewis | | | Geweke | Raftery & Lewis | | | Geweke |
Response	Cluster	Burn	Total	I-stat	p	Burn	Total	I-stat	p	Burn	Total	I-stat	p
Affect	**West**	9	2,431	2.6	.48	2	969	1.0	.75	4	1,243	1.3	.56
	Asia	4	1,243	1.3	.48	4	1,243	1.3	.82	3	1,143	1.2	.17
	Russia	2	969	1.0	.47	2	893	1.0	.20	2	893	1.0	.29
Shared Meaning	**West**	2	893	1.0	.12	2	969	1.0	.42	2	893	1.0	.87
	Asia	2	969	1.0	.23	2	969	1.0	.18	2	893	1.0	.72
	Russia	3	1,143	1.2	.88	3	1,053	1.1	.11	2	969	1.0	.75
Subjective Familiarity	**West**	3	1,096	1.2	.28	5	1,353	1.4	.16	2	969	1.0	.19
	Asia	3	1,143	1.2	.45	6	1,608	1.7	.11	2	969	1.0	.36
	Russia	3	1,143	1.2	.47	3	1,053	1.1	.36	3	1,053	1.1	.09
True Recognition	**West**	3	1,053	1.1	.25	4	1,243	1.3	.28	2	893	1.0	.20
	Asia	4	1,243	1.3	.86	3	1,011	1.1	.89	2	893	1.0	.16
	Russia	5	1,473	1.6	.28	2	893	1.0	.33	3	1,053	1.1	.11
False Recognition	**West**	2	969	1.0	.95	2	969	1.0	.63	2	893	1.0	.14
	Asia	3	1,053	1.1	.09	2	969	1.0	.16	2	893	1.0	.32
	Russia	2	893	1.0	.35	2	893	1.0	.45	2	969	1.0	.91

Table C4
Convergence Diagnostics: Structural Paths (Objective Logo Design Dimensions)

Response	Design Dimension / Diagnostic Cluster	Parallelism				Proportion				Repetition			
		Raftery & Lewis			Geweke	Raftery & Lewis			Geweke	Raftery & Lewis			Geweke
		Burn	Total	I-stat	p	Burn	Total	I-stat	p	Burn	Total	I-stat	p
Affect	**West**	2	893	1.0	.39	2	893	1.0	.70	3	1,053	1.1	.58
	Asia	3	1,053	1.1	.25	3	1,053	1.1	.16	5	1,473	1.6	.05
	Russia	2	893	1.0	.48	2	893	1.0	.95	2	861	.9	.20
Shared Meaning	**West**	2	969	1.0	.12	2	969	1.0	.21	2	893	1.0	.68
	Asia	2	969	1.0	.36	2	969	1.0	.97	2	969	1.0	.78
	Russia	2	969	1.0	.11	2	969	1.0	.97	2	893	1.0	.97
Subjective Familiarity	**West**	3	1,143	1.2	.38	2	893	1.0	.31	2	969	1.0	.04
	Asia	3	1,143	1.2	.30	2	893	1.0	.27	2	893	1.0	.07
	Russia	2	893	1.0	.96	2	893	1.0	.88	2	969	1.0	.20
True Recognition	**West**	2	893	1.0	.71	3	1,143	1.2	.25	3	1,053	1.1	.29
	Asia	2	969	1.0	.07	3	1,053	1.1	.58	2	893	1.0	.20
	Russia	2	893	1.0	.22	2	969	1.0	.15	3	1,011	1.1	.59
False Recognition	**West**	3	1,143	1.2	.22	2	893	1.0	.77	3	1,053	1.1	.44
	Asia	2	969	1.0	.16	2	893	1.0	.89	2	969	1.0	.75
	Russia	3	1,053	1.1	.76	2	893	1.0	.74	3	1,053	1.1	.61

Table C5
Convergence Diagnostics: Intercepts of Structural Paths

Response	Diagnostic Cluster	Raftery & Lewis			Geweke
		Burn	Total	I-stat	p
Affect	West	14	3,646	3.9	.60
	Asia	3	1,053	1.1	.03
	Russia	2	969	1.0	.14
Shared Meaning	West	3	1,053	1.1	.54
	Asia	2	969	1.0	.11
	Russia	2	893	1.0	.92
Subjective Familiarity	West	9	2,336	2.5	.80
	Asia	2	969	1.0	.04
	Russia	2	969	1.0	.16
True Recognition	West	3	1,053	1.1	.54
	Asia	3	1,053	1.1	.08
	Russia	2	893	1.0	.92
False Recognition	West	3	1,053	1.1	.68
	Asia	3	1,143	1.2	.14
	Russia	2	969	1.0	.20

Web Appendix D
Mini Experiment Comparing Logos of a Known Brand

We conducted a small experiment with twenty-seven undergraduate U.S. students, using a 2 (version of logo) x 2 (two brand/logos) mixed factorial design. The first factor was between subjects and the second factor was within subjects. Participants saw one of two versions of each brand/logo combination displayed in the table below: Korean Air and the 2012 London Olympics. After viewing each logo, subjects rated their affect toward the brand using the same scale we report in the paper. At the end of the experiment, subjects received definitions of elaborateness, harmony, and naturalness and then rated all four logos in these terms.

The results are interesting and consistent with what is reported in the paper. For the Korean Air condition, students rated the first brand/logo combination (with the geese) as significantly more elaborate, significantly more natural, but just as harmonious as the second brand/logo combination with the circle. Respondents reported more positive affect for the brand after exposure to the first logo/brand combination than to the second combination ($p < .09$). For the Olympics condition, the ribbon design was rated as more elaborate, natural, and harmonious (all $p < .05$) than the puzzle design. The difference in affect ratings was even greater, with the ribbon design being strongly preferred ($p < .05$). We report the relevant means in the table below.

The bottom line: logos matter even when a well-known brand name is present. More elaborate, more natural, and more harmonious logos yield more positive attitudes toward the brand than do less elaborate, less natural, and less harmonious logos in a U.S. sample.

Logo/Brand Combination	Elaborateness, Naturalness, and Harmony Ratings	Attitude toward the Brand
Note: The Korean Air brand logo is real, while the Geese and Circle logos are fictitious.		
	Elaborateness rating 3.52 (std .89) Naturalness rating 4.44 (std .85) Harmony rating 3.07 (std 1.43)	2.85 (std .67)
	Elaborateness rating 1.37 (std .834) Naturalness rating 1.52 (std 1.01) Harmony rating 2.96 (std 1.56)	2.37 (std .78)
Note: The ribbon design was created by the London Olympic Committee for the application campaign. The puzzle design was created at a cost of ₤400,000 and is the design the London Olympic Committee selected for use during the Olympic event.		
	Elaborateness rating 4.30 (std 0.82) Naturalness rating 3.00 (std 1.35) Harmony rating 3.78 (std 1.05)	3.75 (1.15)
	Elaborateness rating 3.70 (std 1.03) Naturalness rating 1.93 (std 1.30) Harmony rating 2.37 (1.39)	2.73 (std 1.34)

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