

Web Appendix for:

**Cross-National Logo Evaluation Analysis:
An Individual Level Approach**

by

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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:

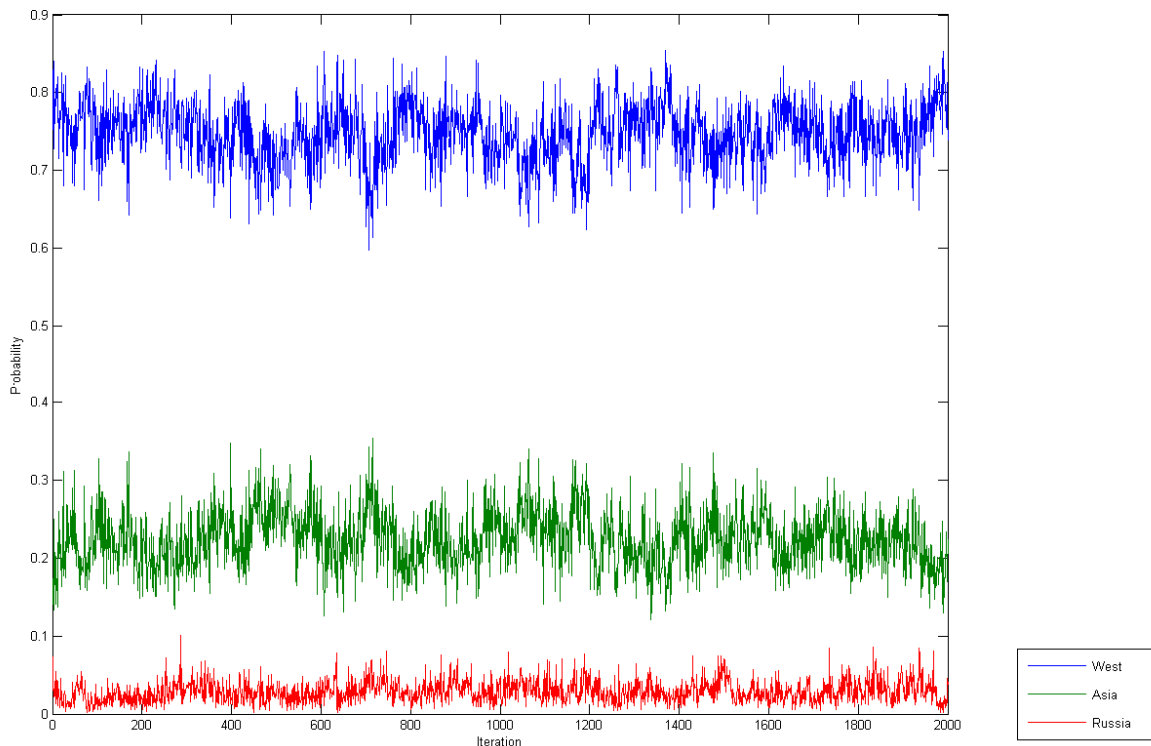
1. $\boldsymbol{\pi}_c \sim D(\mathbf{r}_c)$, for each country $c = 1, \dots, C$, with $D(\cdot)$ representing the Dirichlet distribution which is the natural conjugate prior for the mixture probabilities. In our analysis we assume $\mathbf{r}_c = [1..1]$, i.e. $(1 \times S)$ -vector containing ones.
2. For each cluster $s = 1, \dots, S$, 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 $\mathbf{I}_{(\cdot)}$ representing the (\cdot) identity matrix.
3. For each cluster $s = 1, \dots, S$, we define multivariate normal priors for the vector containing the parameters of the factor loadings, i.e., $\text{vec}(\boldsymbol{\Lambda}_\xi^s) \sim N(\mathbf{L}_\xi^s, \mathbf{V}_\xi^s)$ and $\text{vec}(\boldsymbol{\Lambda}_y^s) \sim N(\mathbf{L}_y^s, \mathbf{V}_y^s)$. 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 $s = 1, \dots, S$, $q = 1, \dots, Q$, and $p = 1, \dots, P$.
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 $s = 1, \dots, S$, $n = 1, \dots, N_{\text{dimension}}$ and $q = 1, \dots, Q$.
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 $\text{vec}(\boldsymbol{\Gamma}^s) \sim N(\mathbf{g}^s, \mathbf{G}^s)$. 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). $\boldsymbol{\mu}^s \sim N(\mathbf{h}_\xi^s, \mathbf{H}_\xi^s)$ for each cluster $s = 1, \dots, S$. In

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

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

Web Appendix B Examples of Posterior Draws

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 $\{\Theta^s, \pi_{\cdot s}\}$ and $\{\Theta^{s'}, \pi_{\cdot s'}\}$, 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 Diagnostic Country	West				Asia				Russia			
	Raftery & Lewis			Geweke	Raftery & Lewis			Geweke	Raftery & Lewis			Geweke
	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		Raftery & Lewis			Geweke
Dimension	Design Characteristic	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)

Response	Design Dimension	Elaborateness				Naturalness				Harmony			
	Diagnostic	Raftery & Lewis			Geweke	Raftery & Lewis			Geweke	Raftery & Lewis			Geweke
	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	Parallelism				Proportion				Repetition			
	Diagnostic	Raftery & Lewis			Geweke	Raftery & Lewis			Geweke	Raftery & Lewis			Geweke
	Cluster	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	Raftery & Lewis			Geweke
	Cluster	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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