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The authors present a Bayesian simultaneous choice factor model that measures consumers' willingness to pay for brand-image associations. Previous research has found that general brand effects influence a brand's scores on specific image dimensions. To investigate the value of general versus specific brand image, the authors specify a higher-order factor model in which a set of correlated factor scores arise from a general brand factor and a set of orthogonal residual scores that measure the specific dimensions of brand image. The general brand factor is consistent with the concept of a halo effect, which theory ascribes to either an overall evaluative effect or errors in cognition. The authors apply the model to stated preference data on branded midsized sedans accompanied by data on consumer brand-image associations. The authors find that there is substantial value for the specific dimensions of brand image, but only after controlling for the general brand effect with the higher-order factor decomposition.

Keywords: choice models, factor models, Bayesian methods

Estimating the Value of Brand-Image Associations: The Role of General and Specific Brand Image

Marketing research studies often collect a variety of attitudinal data from consumers. These data typically contain diagnostic information regarding why a consumer may prefer a particular product or product attribute. Recent academic work in marketing has considered augmenting stated preference and choice data with such attitudinal information (Ben-Akiva et al. 2002). Ashok, Dillon, and Yuan (2002) present a maximum likelihood approach for incorporating intangible attributes that do not vary over conjoint tasks (e.g., extant customer satisfaction) by augmenting the conjoint data with attitudinal survey data. Luo, Kannan, and Ratchford (2008) model the effect of subjective product perceptions that vary as a function of the specific attributes of each task. These studies lay much of the methodological foundation for integrating stated preference and attitudinal data using latent variable models to represent the structure of the attitudinal data but do not consider brand-image associations and the particular challenges presented by brand-image data.

Brand-image associations are key building blocks in customer-based brand equity frameworks (Aaker 1991; Keller 1993; Park and Srinivasan 1994). Several approaches to customer-based brand equity have been proposed in the literature. Kamakura and Russell (1993) decompose brand constants estimated for latent segments into tangible and intangible components; the former component is based on a brand's product attributes, and the latter component is based on a mean brand effect. Park and Srinivasan (1994) conceptualize customer-based brand equity as depending on the subjective perceptions that consumers associate with brands. Swait et al. (1993) develop a choice-based monetary expression for the total utility of a brand that depends on the brand's subjective image attributes. As a whole, these models underscore the importance of brand-image associations. Apart from a customer-based brand equity point of view, consumers may directly value specific types of brand image, benefiting brands that develop an association with such imagery (Sullivan 1998). However, estimating the value of brand-image associations is complicated by issues with brand

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ratings. Although some research suggests that consumers are able to explicate product attribute importance (Gilbride, Yang, and Allenby 2005; Netzer and Srinivasan 2009), consumer beliefs about brand performance on specific attributes may be affected by order, halo, and justification effects (Dillon et al. 2001; Gilbride, Yang, and Allenby 2005).[1]

When consumer associations between brands and specific brand-image items are affected by a general brand effect, interitem correlations are likely to be high (Balzer and Sulsky 1992; Dillon et al. 2001), which can adversely affect estimates of the effect of each specific image association on preference ratings or choice. Furthermore, if a brand's association with an image attribute consists of a general effect common to all attributes and effects unique to each specific attribute, it is interesting to consider the value that consumers place on the general versus the specific. A common explanation attached to the presence of high interitem correlations and a general brand effect is that an overall affective impression seeps into ratings on specific dimensions (Dillon et al. 2001). Recent work in the choice literature demonstrates that consumer-level information about brand preferences adds explanatory power to a choice model specified with heterogeneous brand constants (Horsky, Misra, and Nelson 2006), which raises the question of what, if any, information is left in a specific brand-image score after controlling for the general brand effect. Any consumer value for the specific image may be due in large part or in whole to an overall affective impression.

The main contribution of this research is to demonstrate the substantial value of specific brand-image associations. We show that this value is revealed only after controlling for general brand effects. To estimate the value of the brand-image associations, we use a Bayesian simultaneous factor choice model that uses choice-based conjoint (CBC) data and attitudinal pick-any data on consumer associations between brands and brand-image attributes. Consistent with previous research, we find that a general brand factor permeates the brand-image factor scores (Dillon et al. 2001; Gilbride, Yang, and Allenby 2005). We model this general factor with a higher-order factor model that decomposes correlated brand-image factors into a general brand factor common to each of the specific image factors and orthogonal residual terms associated with each specific image factor. We demonstrate that ignoring the general factor leads to erroneous conclusions about the value of the specific brand-image factors. After controlling for the general brand factor, we find substantial willingness to pay (WTP) for the specific brand-image factors in our study. Note that we find that removing the general brand factor altogether from the choice model yields the best model fit. To better understand the role of general brand factor in the choice model, we offer some possible theoretical explanations for its presence.

A high correlation between factors and the presence of a general brand factor are consistent with operational definitions of "halo" in the applied psychology literature. The psychology literature describes two different theories of halo effects in ratings data that lead to high interdimensional correlations. As we discussed previously, one type of halo stems from an overall affective evaluation that spills over into ratings on specific dimensions and results in ratings that covary across dimensions. This type of halo has been referred to as a "general-impression" halo, a "true" halo, and a "valid" halo. A second type of halo also results in rating covariance across specific dimensions, but the tendency to render consistent cross-dimension ratings is attributed to various cognitive errors rather than affect. This type of halo has been referred to as a "dimensional similarity" halo, an "illusory" halo, and an "invalid" halo. Thus, theory suggests that high interfactor correlation and the presence of a general brand factor may be results of either spillover of an overall affective evaluation or errors in cognition.

Cooper (1981) discusses possible sources of cognitive error that may lead to interdimensional correlation. According to the representativeness heuristic, the dimensions may cue associations in respondents' minds, causing them to mistake the perception of resemblance for true covariance. That is, correlation may be a result of respondents' perceived coherence of the dimensions regardless of the brand or brands being rated. However, other potential sources of cognitive error suggest a more brand-specific process. The availability of plausible associative connections between brands and dimensions (the availability heuristic) may infect respondents' ratings. In associating brands with image attributes, consumers may overemphasize similarities between available conceptual schema for the brand and the image items (Krueger 1978; Tversky 1977). Furthermore, consumers may be prone to confirmatory bias when testing their hypotheses about brand-image associations (Tversky and Kahneman 1971). Seizing on a minimal reason to expect associations, consumers may simply seek and find confirming evidence while either failing to seek impression-inconsistent information or simply discounting any such information (Snyder 1981). Brand knowledge may also play a role; lower levels of knowledge may lead to a greater reliance on the aforementioned heuristics in the image-association task.

Note that each type of halo results in high interdimensional correlation that can be modeled with a general brand factor.[2] Our primary goal is to control for this general brand factor in measuring the value of the specific brand imagery. However, it is of interest to consider adding the general brand-factor score to the choice model. The general factor will either add incremental information to the model or not. Consumer-level information about brand preferences has been shown to add explanatory power to a choice model specified with heterogeneous brand constants (Horsky, Misra, and Nelson 2006). Heterogeneous brand constants reflect individual-level preferences for the brands and are typically specified with shrinkage toward the "average"

[1]Suggesting that consumers may not be able to self-explicate product valuations, Jedidi, Jagpal, and Manchanda (2003) show that self-explicated reservation prices do not predict choice as well as reservation prices estimated from choice-based conjoint data.

[2]In some cases, the factor structure may be able to distinguish between different explanations for the general brand factor. For example, a model that restricts the general brand factor to be equivalent across brands would be consistent with the explanation of perceived similarity across the dimensions, regardless of the brands, driving the interdimensional correlation. However, testing such a restriction is not tantamount to a test of the affect versus cognitive error explanations, because the latter is not a priori inconsistent with an unrestricted general brand factor.

customer. Shrinkage toward the average customer is especially useful with sparse choice observations at the individual level. Especially in the case of sparse data, consumer-level information about brand preferences should add incremental information to the model.

In the case of scanner-panel data, in which it is not uncommon to observe many households only once or twice, Horsky, Misra, and Nelson (2006) demonstrate the value of additional preference information. In contrast with scanner-panel data, CBC data such as ours typically have relatively more individual-level information. In such studies, each respondent usually completes between 10 and 15 choice tasks, which may be enough information to enable the brand constants to approximate unobserved preference heterogeneity and render any preference information contained in the general brand factor redundant. Furthermore, if the general brand factor is due to errors in cognition, it may not contain any information dispositive with respect to choice. In either case, the general brand factor would not seem to influence choice. In summary, a positive and significant effect of the general brand factor in the choice model would seem to indicate that the general factor is consistent with the affect explanation. Conversely, if we find no effect of the factor on choice, it is difficult, if not impossible, to discern the psychological content of the general brand factor.

Our empirical application considers the effect of existing parent brand–image associations on preferences for umbrella-branded goods. For example, automotive products typically carry both a parent brand name (e.g., Toyota or Ford) and a subbrand name (e.g., Camry or Taurus). The image attributes are designed to measure two latent brand-image factors consistent with parent brand slogans used in automotive industry advertising, labeled "dependable" and "exciting."[3] Using stated-choice data from conjoint experiments on midsized sedans and pick-any data on the associations between the sedan parent brands and the brand-image attributes (collected before the conjoint experiments), we estimate various specifications of our simultaneous factor choice model, which yields estimates of the WTP for the brand-image factors. Simultaneous estimation of the factor and choice models avoids attenuation bias arising from treating the factor scores as error-free dependent variables in the choice model (Ashok, Dillon, and Yuan 2002; Greene 2000). Simultaneous estimation also improves the efficiency of estimates for parameters common to both models (Gilbride, Yang, and Allenby 2005).

To accommodate the multivariate binomial data resulting from the pick-any format, we specify a confirmatory factor model based on the multivariate binomial probit model (Ansari and Jedidi 2000). A standard confirmatory factor model yields a high correlation between the dependable and exciting factors, which hampers estimation of the WTP for the factors. Analogous to factor models of intelligence with a general intelligence factor (i.e., the g factor), we model this correlation with a higher-order factor model. The upper-level factor scores are decomposed into a single general brand factor common to both the dependable and exciting factors and orthogonal residual scores specific to the dependable and exciting factors. This decomposition enables us to better understand and compare consumer valuations for general and specific brand image. Controlling for the general brand factor results in improved model fit and improved estimates of WTP for the dependable and exciting brand-image factors. The model indicates that dependable and exciting brand-image associations have considerable value, from \$3,800 to \$4,800 on average, for a standard deviation improvement in the residual scores. Compared with a model that uses only the orthogonal residual scores, adding the general brand-factor score to the choice model does not improve model fit.

The remainder of the article proceeds as follows: We first introduce a higher-order confirmatory factor model for multivariate binomial data linked to a choice model via the latent factor. Then, we discuss the conjoint and attitudinal data used in the empirical application of the proposed model. The penultimate section presents our results. Finally, we summarize and conclude.

MODELS

A Higher-Order Confirmatory Factor Model for Multivariate Binomial Data

We now introduce a higher-order confirmatory factor analytic model suited for multivariate binomial brand-image association data. We observe i = 1, ..., N individual consumers rating j = 1, ..., J brands on a Z-dimensional vector of image attributes. The consumers offer binary ratings of the association (applies/does not apply) between the brands and each attribute. Let u^*_{ij} be a Z-dimensional vector of latent responses from individual i rating item j. The observed set of binomial responses is related to the latent variable as follows:

$$u_{ijz} = \begin{cases} 1 \text{ if } u^*_{ijz} > 0 \\ 0 \text{ otherwise} \end{cases} \quad \text{for } z = 1, ..., Z. \tag{1}$$

The variation in the latent responses is modeled as arising from a higher-order factor structure (Yung, Thissen, and McLeod 1999):

$$\begin{aligned} u^*_{ij} &= \alpha_j + \tau_i + \Lambda^1_j \xi^1_{ij} + \eta^1_{ij} \\ \xi^1_{ij} &= \Lambda^2_j \xi^2_{ij} + \eta^2_{ij} \\ \tau_i &\sim MVN(0, \Sigma^\tau) \\ \xi^2_{ij} &\sim MVN(0, 1) \\ \eta^1_{ij} &\sim MVN(0, \Theta^1_j) \\ \eta^2_{ij} &\sim MVN(0, \Theta^2_j), \end{aligned} \tag{2}$$

where α_j is a brand-specific mean vector and τ_i is an individual-specific mean vector that allows for heterogeneity in response patterns regardless of the brands being rated (e.g., some respondents may be more or less prone to checking items or prone to checking items appearing on the left, middle, or right). The upper-level factor-loading matrix Λ^1_j is a patterned Z × L matrix (where L is the number of latent

[3]Recent exciting slogans used by automotive brands include "Driving Excitement" (Pontiac) and "Drivers Wanted" (Volkswagen); recent dependable slogans include "Everyday People" (Toyota) and "Always There for You" (Hyundai).

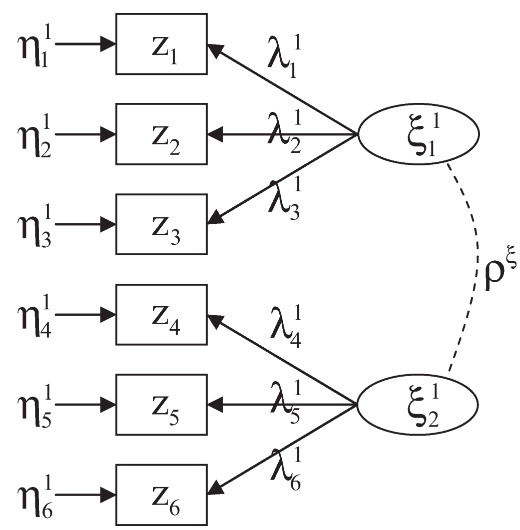
factors) with certain elements restricted to zero.[4] The upper-level factor score ξ^1_{ij} is an $L \times 1$ vector, and η^1_{ij} is a vector of normally distributed errors with mean zero and a diagonal covariance matrix Θ^1_j. The vector ξ^1_{ij} is modeled as arising from a lower-level factor structure where the loading Λ^2_j is an $L \times 1$ vector, ξ^2_{ij} is a scalar factor score, and η^2_{ij} is a residual term with diagonal covariance matrix Θ^2_j. Consistent with the notion of a general brand effect, we constrain the L elements of the loading vector Λ^2_j to be equal.[5]

The covariance matrix of ξ^1_{ij} is $[\Lambda^2_j\Lambda^{2'}_j + \Theta^2_j]$. For identification, the diagonal elements of this covariance matrix are set to 1, which implies the constraint $\Theta^2_j = I_L - \text{diag}[\Lambda^2_j\Lambda^{2'}_j]$, where I_L is an L-dimensional identity matrix. The covariance matrix of the latent u^*_{ij} values is $\Lambda^1_j[\Lambda^2_j\Lambda^{2'}_j + \Theta^2_j]\Lambda^{1'}_j + \Theta^1_j$. For identification, the diagonal elements of this covariance matrix are also set to 1, which implies the constraint $\Theta^1_j = I_Z - \text{diag}[\Lambda^1_j\Lambda^{1'}_j]$. The sign of either the factor loadings or the factor scores must also be fixed because the likelihood has the same value for $\Lambda^1_j\xi^1_{ij}$ and $(-\Lambda^1_j)(-\xi^1_{ij})$ (and similarly for the lower-level loadings and scores). We fix the factor loadings to be positive; in total, the constraints of the model imply that the elements of Λ^1_j and Λ^2_j lie on the unit interval and that the elements of the latter are constrained to be equal.

In a pioneering article on measuring general brand effects, Dillon et al. (2001) present a constrained-components model that decomposes observed brand ratings into a global brand impression and brand-specific associations. As Dillon et al. (2001) discuss, their constrained-components model can be written as a hierarchical confirmatory factor model in which observed brand ratings are an additive function of latent global brand impression and brand-specific association factors (Yung, Thissen, and McLeod 1999). However, a variety of estimation problems arise in frequentist estimation of confirmatory factor models, including Heywood cases (negative variances), problems with optimizing the likelihood function, and the need to estimate the factor scores with one of several available methods. Bayesian inference addresses all three of these issues. Appropriate priors on variance parameters avoid Heywood cases, Markov chain Monte Carlo (MCMC) simulation methods avoid problems with maximization, and the factor scores are treated as any unknown quantity in Bayesian estimation. They are assigned a prior distribution, and we sample from their full conditional distribution. Our Bayesian confirmatory factor analytic approach also easily accommodates binary brand-image ratings data affected by a general or global brand effect.

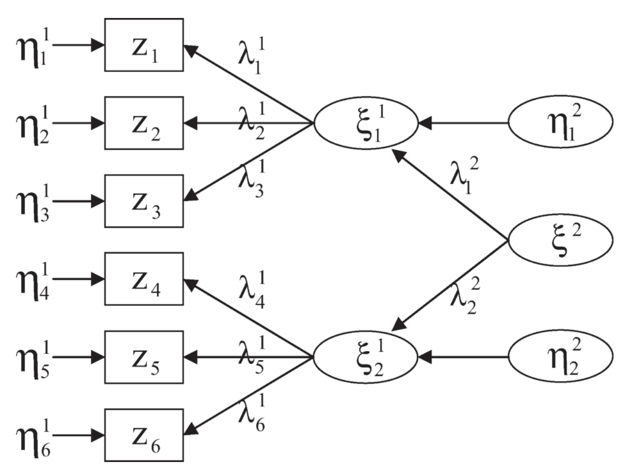
To better understand the structure of the higher-order factor model presented here, it is useful to first consider the standard confirmatory factor model. Figure 1 illustrates such a model for L = 2. The correlation between factors is described by the parameter ρ^ξ. A high correlation suggests that the factors are affected by a common factor (Ansari and Jedidi 2000). For example, a general intelligence factor is often cited as influencing specific factors of cognitive ability (Spearman 1904). In our case, a high correlation suggests that a general brand factor is possibly at work. Furthermore, a high correlation may hamper efforts to estimate the value of each factor in the choice model. Figure 2 illustrates our higher-order confirmatory factor model. This model treats the correlated upper-level factor scores as arising from a general single-dimension lower-level factor, ξ^2, that is common

Figure 1
ILLUSTRATION OF A STANDARD CONFIRMATORY FACTOR MODEL



Notes: For binary z, the factor loadings are constrained to lie on the unit interval.

Figure 2
ILLUSTRATION OF A HIGHER-ORDER CONFIRMATORY FACTOR MODEL



Notes: For binary z, the upper- and lower-level loadings are constrained to lie on the unit interval. For our general brand-factor model, we also impose the constraint $\lambda^2_1 = \lambda^2_2$.

[4]Half of the attributes were related to aspects of exciting and half to dependable. We fixed all exciting loadings to 0 for the dependable factor, and vice versa. We list the attributes in Table 2.

[5]Our higher-order confirmatory factor model could be construed as similar in spirit to a multitrait–multimethod (MTMM) approach. The binary manifest items could be construed as analogous to the traits, whereas the different brands could be analogous to the methods. The lower-level factor structure would be similar to what is referred to as a "methods" factor in the MTMM approach. We thank an anonymous reviewer for bringing this to our attention.

to the upper-level factors and a vector of orthogonal residual scores, η^2, unique to the upper-level factors.

From Equation 2, we observe that without the general brand factor, the upper-level score $\xi^1_{ij} = \eta^1_{ij}$ and the model can be written as a standard confirmatory factor model with orthogonal factors. Therefore, the general brand factor can be interpreted as shifting the scores on the specific brand-image factors and inducing correlation across the upper-level factors. The higher-order representation in Figure 2 clarifies that ξ^2_{ij} and η^2_{ij} arise from the decomposition of the correlated upper-level factor scores (ξ^1_{ij}) into a unidimensional general score (ξ^2_{ij}) and orthogonal residual scores specific to the upper-level factors (η^2_{ij}). Because factor analysis is often used to reduce the dimensionality of multivariate data, typically with the goal of using the lower dimensional factors in analysis, the higher-order representation of the model is well suited to assess what, if any, information is left in a brand-image factor score after the general brand factor is removed. Related to this question, we try to understand how consumers value the general brand factor versus specific brand-image factors. To address these questions, we next turn our attention to integrating the higher-order factor model with our choice model.

An Integrated Factor Choice Model

The N consumers choose among m = 1, ..., M alternatives on each of t = 1, ..., T CBC experiments. The choice alternatives contain a brand (from the set of J possible brands), a set of product attributes, and a price. At experiment t, alternative m for consumer i is then described by a J-dimensional brand indicator vector, b_{imt}, a K_a-dimensional product attribute vector, a_{imt}, and a price, p_{imt}.

For each choice occasion, we observe the indicator vector I_{it}, which indexes the choice that maximizes the consumer's indirect utility at experiment t. We model the consumer's indirect utility as composed of a deterministic and random component, $U^*_{imt} = V^*_{imt} + \varepsilon^*_{imt}$. The deterministic component is expressed as a linear function of brand and product attributes, collected into a single vector, x_{imt}, the latent brand-image factors, income (denoted y_i), and price: $V^*_{imt} = x'_{imt}\phi^*_i + \xi^2_{imt}\delta^*_i + \tilde{\eta}^{2\prime}_{imt}\upsilon^*_i + \gamma^*_i(y_i - p_{imt})$. The term $\xi^2_{imt} = \Sigma^J_{j=1}\xi^2_{ij}\,I(b_{ijmt} = 1)$ and the lth element of the L × 1 vector $\tilde{\eta}^2_{limt}$ is $\Sigma^J_{j=1}(\eta^2_{lij}/\sqrt{\pi^2_{lj}})I(b_{ijmt} = 1)$, where π^2_{lj} is the lth diagonal element of Θ^2_j and $\eta^2_{lij} = \xi^1_{lij} - \lambda^2_{lj}\xi^2_{ij}$. Normalization of the residual factor scores ensures that ξ^2 and $\tilde{\eta}^2$ both are mean zero with unit variance, which aids in interpretation. The error term is assumed to be distributed $\varepsilon^*_{imt} \sim EV(0, \mu^*_i)$, which leads to multinomial logit choice probabilities:

$$(3)\quad \Pr(I_{imt} = 1) = \left[\frac{\exp\left(\dfrac{x'_{imt}\phi^*_i + \xi^2_{imt}\delta^*_i + \tilde{\eta}^{2\prime}_{imt}\upsilon^*_i + \gamma^*_i p_{imt}}{\mu^*_i}\right)}{\sum_{k=1}^{M}\exp\left(\dfrac{x'_{ikt}\phi^*_i + \xi^2_{ikt}\delta^*_i + \tilde{\eta}^{2\prime}_{ikt}\upsilon^*_i + \gamma^*_i p_{ikt}}{\mu^*_i}\right)}\right].$$

Note that income is constant across choice alternatives and, thus, drops out of the choice probability.

As is well known, the parameters $[\phi^*_i\ \delta^*_i\ \upsilon^*_i\ \gamma^*_i]$ are not identified separately from the scale parameter of the error distribution, μ^*_i (Swait and Louviere 1993). In estimation, this is typically dealt with by reparameterizing the choice probabilities in Equation 3 to be

$$(4)\quad \Pr[I_{imt} = 1] = \left[\frac{\exp\left(x'_{imt}\phi_i + \xi^2_{imt}\delta_i + \tilde{\eta}^{2\prime}_{imt}\upsilon_i + \gamma_i p_{imt}\right)}{\sum_{k=1}^{M}\exp\left(x'_{ikt}\phi_i + \xi^2_{ikt}\delta_i + \tilde{\eta}^{2\prime}_{ikt}\upsilon_i + \gamma_i p_{ikt}\right)}\right],$$

where $\phi_i = [\phi^*/\mu^*]_i$, $\delta_i = [\delta^*/\mu^*]_i$, $\upsilon_i = (\upsilon^*_i/\mu^*_i)$, and $\gamma_i = [\gamma^*/\mu^*]_i$ are the parameters to be estimated.

An alternative way to achieve identification is to parameterize the model to directly identify WTP:

$$(5)\quad \Pr[I_{imt} = 1] = \left[\frac{\exp\left(\dfrac{x'_{imt}\varphi_i + \xi^{2\prime}_{imt}\beta_i + \tilde{\eta}^{2\prime}_{imt}\kappa_i - p_{imt}}{\mu_i}\right)}{\sum_{k=1}^{M}\exp\left(\dfrac{x'_{ikt}\varphi_i + \xi^{2\prime}_{ikt}\beta_i + \tilde{\eta}^{2\prime}_{ikt}\kappa_i - p_{ikt}}{\mu_i}\right)}\right],$$

where $\varphi_i = [\phi/\gamma]_i = [\phi^*/\gamma^*]_i$, $\beta_i = [\delta/\gamma]_i = [\delta^*/\gamma^*]_i$, $\kappa_i = [\upsilon/\gamma]_i = [\upsilon^*/\gamma^*]_i$, and $\mu_i = [\mu^*/\gamma^*]_i$. The coefficient φ measures the incremental amount the consumer would be willing to p ay for a unit change in the attributes. Because the factor scores are standardized, β and κ measure the WTP per standard deviation change in the factor scores; thus, we can directly compare estimates of β and κ across the factors. Note that $\mu_i \neq \mu^*_i$ is an estimate of the effect of uncertainty relative to the effect of price and allows for heterogeneity in response to price changes (Allenby and Ginter 1993). The choice probabilities in Equations 4 and 5 are equivalent, but the priors will be equivalent only in special cases. For example, a normal prior on $[\phi\ \delta\ \upsilon\ \gamma]$ implies that the prior on $[\varphi\ \beta\ \kappa]$ is a ratio of normals. Differences in priors for heterogeneous models can have a substantial impact on WTP estimates (Sonnier, Ainslie, and Otter 2007). Since our goal is to estimate WTP for the brand-image factors, we work with the model that directly identifies WTP as it allows for heterogeneity distributions and/or hierarchical regressions to be specified directly on the WTP values. We specify WTP for product attributes and brand-image factors to be normally distributed such that $\theta_i \sim MVN(\bar{\theta}, \Sigma^\theta)$, where $\theta_i = [\varphi'_i\ \beta_i\ \kappa'_i\ \ln(\mu_i)]'$. For identification, we set WTP of one of the J brands to 0, which implies that WTP for the remaining brands is measured relative to the identifying brand.[6]

Regardless of how one parameterizes the choice probabilities, the models for the brand-image association data and the choice data share common parameters. Consider the model hierarchy in Equation 6:

$$(6)\quad \begin{array}{l} u_{ijz} | u^*_{ijz}, \alpha_z, \tau_i, \Lambda^1_{jp}, \xi^1_{ij}, \Theta^1_{z,z} \\ I_{imt} | x_{imt}, b_{imt}, p_{imt}, \xi^1_{ij}, \xi^2_{ij}, \Lambda^2_j, \Theta^2_{z,z}, \theta_i \\ \tau_i | \Sigma^\tau \\ \xi^1_{ij} | \Lambda^2_j, \xi^2_{ij}, \Theta^2 \\ \theta_i | \bar{\theta}, \Sigma^\theta \end{array} .$$

[6]If the "none" option is included in the CBC experiments, it can be used as the identifying "brand." The brand WTP values would then be interpreted as reservation prices for the brands, ceteris paribus. The interpretation of the remaining coefficients, including the WTP for the brand-image factors, is unaffected (for details, see Sonnier, Ainslie, and Otter 2007).

The full conditional distributions for ξ^1_{ij} will depend on both the logit choice data likelihood and the normal data likelihood from the factor model. The full conditional distributions for ξ^2_{ij}, and Λ^2_j will depend on the logit choice data likelihood and the normal likelihood for ξ^1_{ij}. Sequential estimation of the factor and choice models ignores information in the choice data likelihood, resulting in inefficiency in estimates of the posterior distribution of the factor scores and loadings. Furthermore, if the posterior means of the estimated scores and loadings are plugged into the choice model, measurement error may bias estimates of the posterior distribution of β_i and κ_i. The model is completed with proper but diffuse priors for $\{\alpha, \Sigma^\tau, \Lambda^1, \Lambda^2, \bar{\theta}, \Sigma^\theta\}$. Recall that Θ^1_j and Θ^2_j are not estimated but rather computed from the identification constraint on the diagonal elements of the covariance matrices for the latent utility and the higher-level factor scores, respectively. We derive the prior specification, the joint distribution, and the full conditional distributions of model parameters in the Appendix.

THE VALUE OF BRAND-IMAGE ASSOCIATIONS

Data

We obtained the data used to estimate the model from a market research study conducted by a major automotive manufacturer. Respondents qualified for participation in the study on the basis of the vehicle they currently own, their intention to purchase a midsized sedan in the next six months, and other socioeconomic information. In all, 333 respondents from a large Midwest city completed the study. The respondents are representative of a target market, not the general market of midsized sedan buyers. The set of clinic vehicles consists of the manufacturer's offering plus four competitive offerings. Only one offering per manufacturer is in the competitive set. As part of the study, respondents completed a CBC task designed to assess the sensitivity of choice to a variety of attributes and levels. Table 1 presents the attributes and levels involved in the design of the study. Each respondent completed 15 choice tasks, with each task consisting of three sedans, and a holdout task with all five sedans.

Among the information collected in the study are respondents' associations of six image attributes with each of the parent brands of the sedans in the study. These data are collected before the respondents' evaluation of the vehicles and are not manipulated as part of the CBC exercise. The attributes are intended to represent two dimensions of parent brand imagery of interest to the manufacturer: dependable and exciting. For each item, the respondent provides a yes or no response as to whether the item in question definitely applies to the parent brand, or make, of the sedans. Respondents may check all items that they believe to apply. Table 2 contains a list of the image attributes in the battery and the percentage of respondents who associate the attributes with each of the brands. The first three items measure dependable image associations, and the last three items measure exciting image associations.

Before presenting the estimation results for the integrated factor choice models, we conduct a simple exploratory factor analysis of the brand-image association data. Because our manifest items are binary, we first compute the tetrachoric correlation matrix of the data pooled across brands and then factor-analyze the tetrachoric correlation matrix. This analysis results in a single factor that accounts for 62% of variance.

Table 1

ATTRIBUTES AND LEVELS

Attribute	*Levels*
Make and model	Toyota Camry Honda Accord Ford Taurus Volkswagen Passat Nissan Maxima
Engine	4 cylinder, 1.8 L, 150 HP 4 cylinder, 2.4 L, 160 HP 6 cylinder, 3.0 L, 155 HP 6 cylinder, 3.0 L, 222 HP
Audio and navigation	Standard audio Premium audio Premium audio with navigation
Antilock brakes	No Yes
Side door/window curtain airbags	No Yes
Vehicle skid control	No Yes
Price	\$17,400 \$18,900 \$20,400 \$21,900 \$23,400 \$24,900 \$26,400

We found similar results when analyzing the data separately for each brand; a single factor accounts for 55%–63% of variance. The prevalence of a single-factor solution indicates that a single-factor model may be sufficient to describe the attitudinal data. Thus, we consider various specifications of the confirmatory factor model in our empirical application, including a single-factor model, a confirmatory factor model with two correlated factors (dependable and exciting), and our higher-order confirmatory factor model.

Results

We estimate a total of five models: a baseline choice model and four integrated factor choice models. Model M1 is a baseline choice model that does not incorporate the attitudinal data. Model M2 is an integrated model with a single-dimension confirmatory factor model. Model M3 is an integrated model in which the factor model is a standard confirmatory factor model with correlated dependable and exciting factors. Model M4 is an integrated model in which the factor model is a higher-order confirmatory factor model and the choice model includes only the orthogonal residual dependable and exciting scores from the factor model. Model M5 is also an integrated model. The factor model is the same as Model M4, but the choice model includes both the residual scores and the general brand-factor score from the factor model. For identification in the choice model, the make/model "Volkswagen Passat" is dropped, as is the lowest level of each of the remaining nonprice attributes. We use the negative of price (in \$1,000s) in the likelihood. For each model, we run the chain for 50,000 iterations, keeping the last 25,000 for inference. Visual inspection of time-series plots along with tests of mean differences in model log-likelihoods across different subchains indicate that convergence was achieved (Geweke 1992).

Table 3 presents descriptive information about each model as well as in-sample and out-of-sample fit statistics. To assess in-sample fit, we use Newton and Raftery's (1994) harmonic mean estimator of the log-marginal density (LMD). Although popular and easy to compute with standard MCMC output, the Newton–Raftery estimator can be unstable. Thus, we also compute the deviance information criterion (DIC) to assess in-sample model fit (Spiegelhalter et al. 2004). To assess out-of-sample fit of the choice model, we compute the mean deviation between 1 and the choice probability of the chosen alternative in the holdout choice task, where the mean is taken across respondents on each iteration of the sampler. For the integrated Models M2–M5, we compute the in-sample fit statistics with likelihood of both the factor and choice data.

The best-fitting model is M4. The improvement in fit from Model M3 to M4 demonstrates the benefit of removing

Table 2

BRAND-IMAGE ATTRIBUTES

Factor	*Item*	*Ford (%)*	*Toyota (%)*	*Nissan (%)*	*Honda (%)*	*Volkswagen (%)*
Dependable	Reflects sensibility	43	62	31	55	32
	Makes life easy	17	52	23	44	18
	Delivers the essentials	43	60	43	58	39
Exciting	Expresses my status	20	56	29	41	32
	Gives me a sense of excitement	13	35	26	27	38
	Reflects my individuality	12	32	18	25	38

Table 3

MODEL DESCRIPTIONS AND FIT STATISTICS

Model[a]	*Factor Model Includes General Brand Factor*	*Choice Model Includes General Brand Factor*	*Dimension of Latent Factor Space: Upper Level*	*Dimension of Latent Factor Space: Lower Level*	*Equations*	*LMD*[b]	*DIC*	*Out-of-Sample Fit: Choice Model*[c]
M1	—	—	—	—	$V_{imt} = x'_{imt}\varphi_i - p_{imt}$	—	—	.570
M2	No	No	1	—	$V_{imt} = x'_{imt}\varphi_i + \xi^{1\prime}_{imt}\beta_i - p_{imt}$ $u^*_{ij} = \alpha_j + \tau_i + \Lambda^1_j\xi^1_{ij} + \eta^1_{ij}$ $\xi^1_{ij} \sim N(0,1)$	–6288	14,733	.549
M3	No	No	2	—	$V_{imt} = x'_{imt}\varphi_i + \xi^{1\prime}_{imt}\beta_i - p_{imt}$ $u^*_{ij} = \alpha_j + \tau_i + \Lambda^1_j\xi^1_{ij} + \eta^1_{ij}$ $\xi^1_{ij} \sim N(0,\Sigma\xi)$	–5700	13,092	.538
M4[d]	Yes	No	2	1	$V_{imt} = x'_{imt}\varphi_i + \tilde{\eta}^{2\prime}_{imt}\kappa_i - p_{imt}$ $u^*_{ij} = \alpha_j + \tau_i + \Lambda^1_j\xi^1_{ij} + \eta^1_{ij}$ $\xi^1_{ij} = \Lambda^2_j\xi^2_{ij} + \eta^2_{ij}$	–5435	13,057	.529
M5	Yes	Yes	2	1	$V_{imt} = x'_{imt}\varphi_i + \xi^{2\prime}_{imt}\beta_i$ $+ \tilde{\eta}^{2\prime}_{imt}\kappa_i - p_{imt}$ $u^*_{ij} = \alpha_j + \tau_i + \Lambda^1_j\xi^1_{ij} + \eta^1_{ij}$ $\xi^1_{ij} = \Lambda^2_j\xi^2_{ij} + \eta^2_{ij}$ $\xi^2_{ij} \sim N(0,1)$	–5518	13,116	.530

[a]Model M1 is a standalone choice model that does not include factor scores. Models M2–M5 are the integrated factor choice models.
[b]Computed as harmonic mean estimator (Newton and Raftery 1994).
[c]Posterior mean of average deviation between one and probability of chosen alternative. The holdout task has five choice alternatives; thus, random choice would result in an average deviation of .8.
[d]The $\tilde{\eta}$ is the normalized residual from the lower-level factor model.

the general brand factor from the upper-level brand-image factor scores. Model M4 does not include the general brand-factor score in the choice model. Model M5 adds the general brand-factor score to the choice model. However, there is no improvement in fit from the added model complexity. In fact, the in-sample fit measured by LMD and DIC is slightly degraded relative to M4. For the sake of completeness, we computed a restricted version of model M4 with the κ_i values restricted to 0; thus, the factor and choice models are not linked. The LMD and DIC for this restricted model are –5726 and 14,133, respectively, considerably worse than the unrestricted version of M4. In summary, we find that the correlated two-factor models all outperform the single-factor model. Furthermore, after decomposing the correlated upper-level factor scores, we find that the information being added to the model resides in the specific brand-image factor scores rather than the general brand score.

We now discuss the WTP estimates for the brand-image factors implied by the different models. We report the posterior mean and posterior standard deviation of the WTP estimates from the models in Tables 4 and 5. Table 4 presents the estimates for the baseline model, M1, and the single-factor model, M2. Table 5 presents the estimates for the standard confirmatory factor model, M3, and the higher-order factor models, M4 and M5. We calculated the standard deviations as the posterior means of the square root of the diagonal elements of Σ_θ. We find little change in the mean and standard deviation of WTP for engine, audio, and safety features across all five models. Comparing the make/model WTP values across the baseline model, M1, and the integrated factor choice models, we find that the brand-image factor scores reduce the amount of unobserved heterogeneity. This result is similar to those of studies in the brand choice literature that show that observed brand loyalty or preferences reduces the unobserved heterogeneity in brand intercepts (Guadagni and Little 1983; Horsky, Misra, and Nelson 2006). In our CBC analysis, the make/model WTP values capture relative preferences for the parent brand name, the specific model name, and any idiosyncratic product features that are not manipulated in the conjoint, such as trunk space. Our results suggest that including information about parent brand–image associations significantly reduces (i.e., explains) the unobserved heterogeneity in the make/model WTP values.

Models M3–M5 all specify a correlated two-dimensional latent factor structure at the upper level, and Models M4 and M5 model the correlated upper-level factors with a lower-level factor structure. Each of the Models M3–M5 has superior fit compared with Model M2, which describes the attitudinal data with a single factor. However, examining the estimates of the distribution of WTP for the factors, we find pronounced differences between Model M3, the standard confirmatory model, and Models M4 and M5, the higher-order models. For Model M3, the posterior mean estimate of the WTP for the dependable factor has a relatively high standard error, and the 95% coverage interval for the estimate spans zero. The posterior mean estimate of the WTP for the exciting factor is positive, with a small standard error. Furthermore, the posterior mean estimates of the standard deviations are high relative to the estimates of the mean. Figure 3 presents histograms of the posterior means of the individual-level WTP estimates for the dependable and exciting factors from M3, which show the highly dispersed distribution of WTP.

The posterior mean estimate of the factor-score correlation coefficient in Model M3 is .63 with a 95% coverage interval spanning [.56, .70]. As the factor-score correlation approaches 1, the individual-factor WTP values become less well identified. Perfect collinearity (i.e., a correlation coefficient of 1) implies that the two-factor model is indistinguishable from the single-factor model. In addition, with perfectly collinear

Table 4

MEAN AND STANDARD DEVIATION WTP ESTIMATES ($1,000s) OF MODELS M1 AND M2

		Model M1: Baseline		*Model M2: Factor Choice Model with Single Factor*	
		WTP		*WTP*	
Attribute	*Level*	*M*	*SD*	*M*	*SD*
Make and model	Ford Taurus	–2.96 (.84)	11.75 (.86)	–2.65 (.81)	8.19 (.99)
	Toyota Camry	7.17 (.75)	10.58 (.84)	7.44 (.78)	7.93 (.71)
	Nissan Maxima	5.34 (.75)	10.80 (.77)	5.63 (.79)	8.18 (.76)
	Honda Accord	4.16 (.73)	9.91 (.73)	4.54 (.69)	6.82 (.65)
Engine	4 cylinder, 2.4 L, 160 HP	2.19 (.27)	1.88 (.25)	2.26 (.32)	1.93 (.30)
	6 cylinder, 3.0 L, 155 HP	3.83 (.34)	3.25 (.45)	4.01 (.35)	3.39 (.47)
	6 cylinder, 3.0 L, 222 HP	5.07 (.37)	3.91 (.46)	5.18 (.40)	4.14 (.46)
Audio	Premium audio	1.22 (.22)	1.40 (.22)	1.31 (.29)	1.65 (.28)
	Premium audio with navigation	1.60 (.24)	1.97 (.27)	1.59 (.34)	2.14 (.30)
Safety features	Antilock brakes	2.22 (.24)	2.33 (.30)	2.13 (.26)	2.28 (.27)
	Side curtain airbags	1.47 (.24)	1.93 (.29)	1.49 (.23)	2.01 (.29)
	Vehicle skid control	1.40 (.23)	1.59 (.23)	1.46 (.24)	1.57 (.24)
Brand-image factors	Single factor	—	—	4.18 (.42)	3.20 (.49)
		ln (μ)		*ln (μ)*	
		M	*SD*	*M*	*SD*
Price	–Price ($1,000s)	1.12 (.06)	.82 (.07)	1.13 (.07)	.87 (.08)

Notes: Cell entries are posterior mean and posterior standard errors (in parentheses).

Table 5

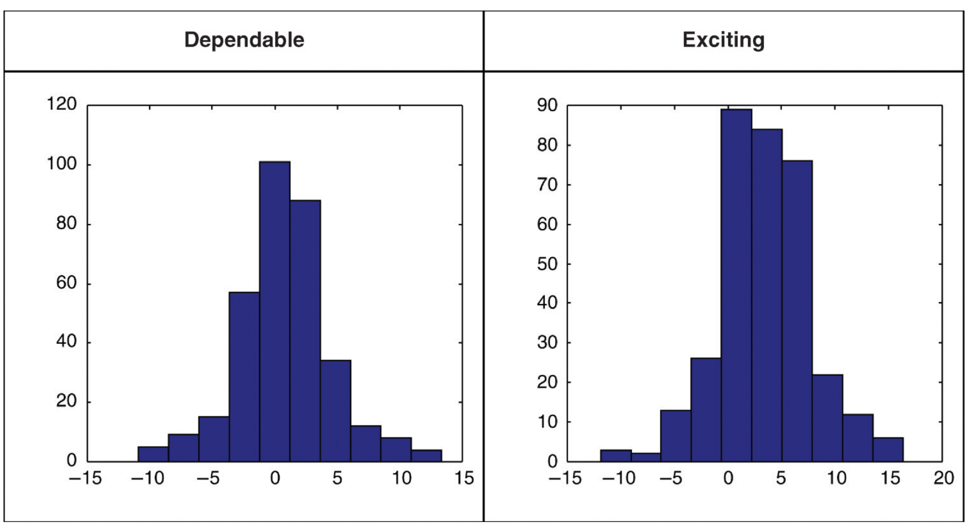
MEAN AND STANDARD DEVIATION WTP ESTIMATES ($1,000s) OF MODELS M3–M5

		Model M3: Factor Choice Model with Two Correlated Factors		*Model M4: Factor Choice Model with General Brand Factor (Not Included in Choice Model)*		*Model M5: Factor Choice Model with General Brand Factor (Included in Choice Model)*	
		WTP		*WTP*		*WTP*	
Attribute	*Level*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Make and model	Ford Taurus	–2.57 (.67)	2.44 (.47)	–3.94 (.64)	2.92 (.65)	–2.42 (.64)	3.27 (.75)
	Toyota Camry	6.73 (.67)	4.01 (1.04)	6.46 (.67)	2.65 (.55)	7.63 (.83)	5.23 (.78)
	Nissan Maxima	5.31 (.70)	4.70 (.87)	4.48 (.46)	2.29 (.53)	5.56 (.81)	4.88 (.82)
	Honda Accord	4.17 (.67)	3.62 (1.01)	3.45 (.60)	2.09 (.45)	4.31 (.68)	4.13 (1.01)
Engine	4 cylinder, 2.4 L, 160 HP	2.35 (.30)	1.96 (.40)	2.45 (.36)	2.03 (.29)	2.35 (.28)	1.96 (.31)
	6 cylinder, 3.0 L, 155 HP	4.20 (.43)	3.60 (.37)	4.29 (.47)	3.51 (.33)	4.16 (.41)	3.49 (.40)
	6 cylinder, 3.0 L, 222 HP	5.24 (.46)	4.24 (.37)	5.58 (.52)	4.27 (.40)	5.31 (.43)	4.04 (.46)
Audio	Premium audio	1.13 (.29)	1.60 (.25)	1.00 (.25)	1.42 (.21)	1.21 (.27)	1.55 (.22)
	Premium audio with navigation	1.48 (.32)	2.00 (.32)	1.55 (.36)	2.13 (.24)	1.75 (.27)	2.09 (.29)
Safety features	Antilock brakes	2.21 (.28)	2.38 (.31)	2.35 (.30)	2.39 (.26)	2.33 (.35)	2.42 (.29)
	Side curtain airbags	1.53 (.29)	2.00 (.28)	1.54 (.27)	1.98 (.25)	1.56 (.25)	2.04 (.24)
	Vehicle skid control	1.49 (.23)	1.63 (.21)	1.57 (.24)	1.55 (.22)	1.54 (.24)	1.63 (.24)
Brand-image factors	General	—	—	—	—	.92 (.46)	1.59 (.39)
	Dependable	.81 (.90)	6.46 (.73)	4.30 (.44)	2.88 (.51)	3.76 (.54)	2.97 (.53)
	Exciting	3.49 (.87)	7.19 (.93)	5.39 (.56)	3.44 (.47)	4.86 (.49)	3.71 (.60)
		ln (μ)		*ln (μ)*		*ln (μ)*	
		M	*SD*	*M*	*SD*	*M*	*SD*
Price	–Price ($1,000s)	1.08 (.08)	.94 (.08)	1.08 (.08)	.98 (.09)	1.07 (.08)	.99 (.08)

Notes: Cell entries are posterior mean and posterior standard errors (in parentheses).

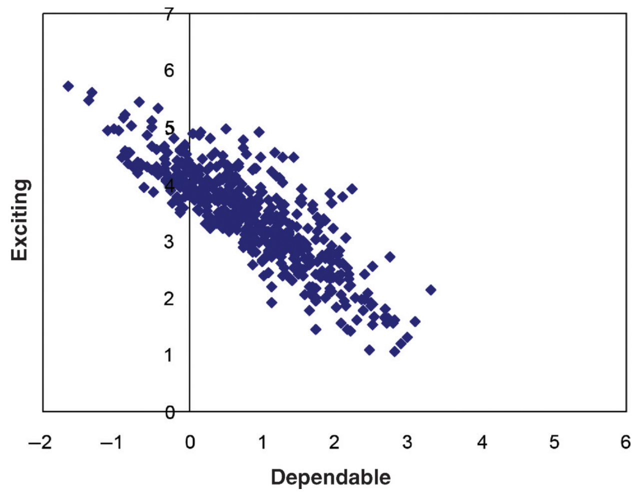
Figure 3

HISTOGRAM OF POSTERIOR MEAN OF INDIVIDUAL-LEVEL WTP ($1,000s) FOR DEPENDABLE AND EXCITING BRAND-IMAGE FACTORS, MODEL M3



factor scores, only the sum of the WTP coefficients for the two factors is identified (Edwards and Allenby 2003). To investigate whether multicollinearity is affecting the WTP estimates, we first examine the draws of the population means of dependable and exciting WTP. Figure 4 presents a scatterplot of a random sample of 500 draws of the population means from M3, which exhibit a strong negative correlation. The empirical correlation of draws over iterations of the sampler is –.87. Second, we compute the sum of the individual-level draws of dependable and exciting WTP on each iteration of the sampler by taking the mean and standard deviation of the sum on each iteration. The posterior mean estimate of the mean and standard deviation of the sum are 4.31 and 2.79, respectively, which are close to the posterior mean estimate of the mean and standard deviation of the WTP from the single-factor model (M2): 4.18 and 3.20, respectively. Thus, the large standard deviations for dependable and exciting WTP seem to be a function of poor identification due to correlation in the factor scores.

Figure 4
DRAWS OF POPULATION MEANS FOR DEPENDABLE AND EXCITING WTP ($1,000s), MODEL M3



Although results of the analysis strongly suggest that the factor-score correlation is hampering estimation of WTP for dependable and exciting brand imagery, the correlated two-factor model (M3) outperforms the single-factor model (M2) on fit, indicating that the two-factor specification adds more incremental information to the model. Models M4 and M5 both decompose the scores for dependable and exciting into a general brand factor and orthogonal residual scores unique to the dependable and exciting factors. This decomposition enables us to empirically assess the relative value of the general and specific factors. Model M4 presents the results of using the residual scores for dependable and exciting in the choice model. A significantly different picture of the value of specific brand imagery emerges from this model.

Unlike Model M3, the posterior mean estimates of WTP for both dependable and exciting in Model M4 are positive; both are estimated with a small standard error. On average, the WTP for the exciting factor is slightly higher than that for the dependable factor. In addition, the posterior mean estimates of the standard deviations are much smaller for Model M4 than for Model M3. Figure 5 presents the histograms of the individual-level WTP estimates for Model M4. The dependable estimates range from approximately $800 to $7,500. The exciting estimates range from approximately $1,200 to $9,500. Compared with the estimates from Model M3, these are much narrower ranges and lie strictly in the positive domain. The WTP estimates from Model M3 range from approximately –$11,000 to $13,000 for the dependable factor and approximately –$12,000 to $16,000 for the exciting factor. Figure 6 presents a scatterplot of a random sample of 500 draws of the population means, which exhibit little correlation. The empirical correlation of draws over iterations of the sampler is .25, indicating much better identification. These results demonstrate that decomposing the upper-level dependable and exciting factor scores with the higher-order factor model effectively isolates the information about specific brand-image associations and that consumers have significant value for these associations.

Model M5 adds the general brand-factor score to the choice model. As we discussed previously, psychology theory suggests that high interfactor correlation may be a result of spillover of an overall affective evaluation or errors in cognition. If the general brand factor is a result of overall preference for the brand, then including this preference information in the choice model may improve model fit (Horsky, Misra, and Nelson 2006). Although the choice model contains heterogeneous make/model intercepts that approximate any unobserved parent-brand (i.e., make) preferences, the quality of the approximation depends on how well the heterogeneity distribution captures unobserved preferences. Information on respondent

Figure 5
HISTOGRAM OF POSTERIOR MEAN OF INDIVIDUAL-LEVEL WTP ($1,000s) FOR DEPENDABLE AND EXCITING BRAND-IMAGE FACTORS, MODEL M4

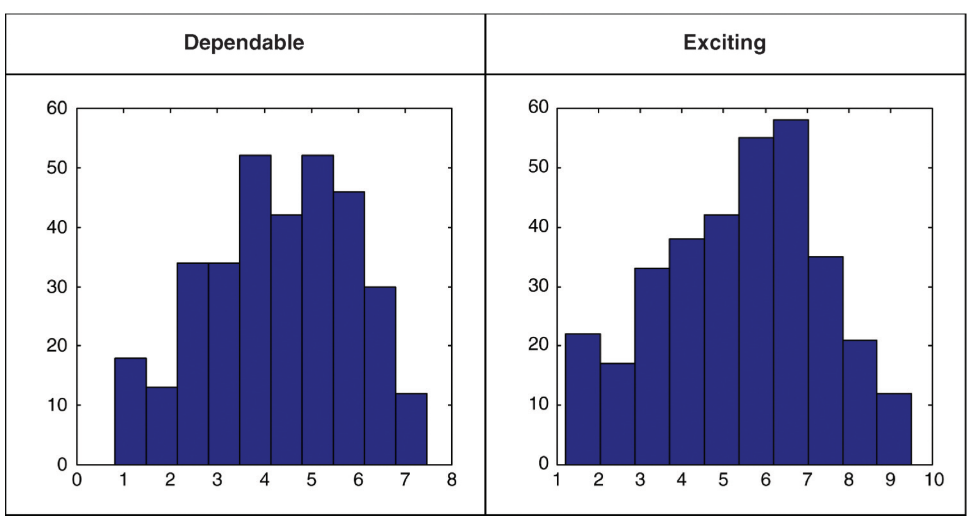
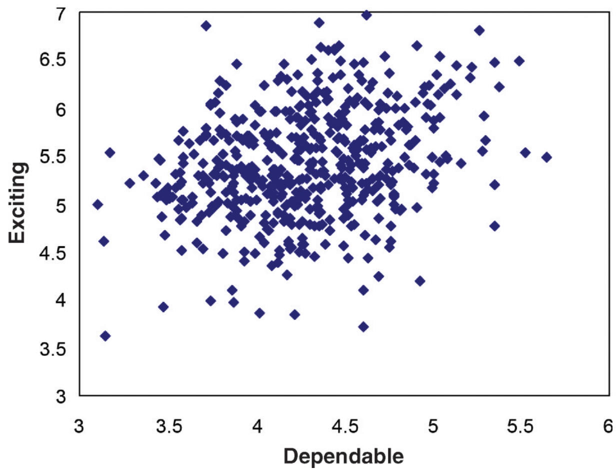


Figure 6
DRAWS OF POPULATION MEANS FOR DEPENDABLE AND EXCITING WTP ($1,000s), MODEL M4



preferences for the parent brand may add incremental information because the heterogeneity distribution is unlikely to perfectly approximate these preferences. If the model is not improved, then we conclude that the general brand factor, at minimum, adds no preference information beyond that which is captured by the heterogeneous intercept and may be a result of cognitive error as opposed to an overall affective evaluation. As we previously demonstrated, relative to Model M4, the out-of-sample fit for Model M5 is unimproved, whereas the in-sample fit is slightly degraded by the addition of the general brand factor to the choice model. Furthermore, the posterior mean estimate of the standard error of the average WTP is relatively large, and the 99% coverage interval for the posterior mean estimate of the average WTP spans zero.

We present the posterior mean estimates of the factor loadings on dependable and exciting for each brand, Λ_j^1, and the general brand-factor loading, Λ_j^2, in Table 6, Panels A and B. The reported estimates are from the best-fitting model (Model M4). We note that the estimates of the general brand-factor loadings exhibit cross-brand differences that are proportional to the posterior mean make/model WTP values. Makes/models with higher mean WTP values also have larger general brand effects as measured by the factor loadings. However, we find no significant correlation between the individual-level make/model WTP values and general brand-factor scores. This result suggests that the scores are capturing additional information apart from that which is captured by the make/model parameters, but this information does not seem helpful in explaining choice.

We also note that some of the cognitive errors hypothesized to result in a halo effect may occur regardless of the brand being rated, which implies that a significant portion of the variance in the general brand-factor score, ξ_{ij}^2, may be a result of variation across people.[7] If this is the case, the general brand-factor score would not contain much information useful in explaining choice, because individual-specific information (e.g., demographic variables) does not vary across choice alternatives. Using 500 randomly selected draws of the general brand-factor score, we test for an individual variance component by estimating $\xi_{ij}^2, = \upsilon_i + \nu_{ij}$, with $\upsilon_i \sim N(0, \sigma_\upsilon^2)$ and $\nu_{ij} \sim N(0, \sigma_\nu^2)$ for each draw. The individual variance component, σ_υ^2, accounted for between 7% and 9% of the total variance. Thus, the variation in the general brand-factor score does not seem to be due in large part to individual variation regardless of the brand. Taken as a whole, the results of the analysis strongly suggest that a two-factor correlated model best explains the data, the correlated factors can be modeled by a higher-order structure, and, in terms of explaining choice, the incremental information in the factor scores resides in the factor-specific residual scores rather than the general brand-factor score.

SUMMARY AND CONCLUSIONS

We investigate the value of brand-image associations, which are key building blocks in customer-based brand equity frameworks. Previous research on brand ratings suggests that a general or global brand effect may permeate consumer ratings on specific image dimensions (Dillon et al. 2001; Gilbride, Yang, and Allenby 2005). When brand-image data are affected by a general brand effect, correlations across specific dimensions are likely to be high, which can hamper any analysis that makes use of the ratings or scores on these dimensions. Furthermore, if a brand's rating

[7]We thank an anonymous reviewer for bringing this to our attention.

Table 6
HIGHER-ORDER FACTOR MODEL

A: Upper-Level Factor Loadings (Λ_j^1)						
Upper-Level Factor	*Item*	*Ford*	*Toyota*	*Nissan*	*Honda*	*Volkswagen*
Dependable	Reflects sensibility	.71 (.08)	.67 (.09)	.63 (.09)	.64 (.10)	.60 (.09)
	Makes life easy	.65 (.09)	.92 (.08)	.93 (.08)	.88 (.11)	.84 (.11)
	Delivers the essentials	.93 (.08)	.82 (.07)	.92 (.06)	.81 (.12)	.81 (.12)
Exciting	Expresses my status	.74 (.12)	.98 (.03)	.84 (.07)	.81 (.06)	.95 (.06)
	Gives me a sense of excitement	.74 (.09)	.60 (.07)	.86 (.06)	.75 (.06)	.74 (.07)
	Reflects my individuality	.77 (.11)	.78 (.07)	.92 (.06)	.99 (.02)	.70 (.07)
B: Higher-Order Factor Model, General Brand-Factor Loadings (Λ_j^2)						
Lower-Level Factor	*Upper-Level Factor*	*Ford*	*Toyota*	*Nissan*	*Honda*	*Volkswagen*
General brand	Dependable, exciting[a]	.65 (.06)	.81 (.04)	.79 (.04)	.73 (.04)	.68 (.05)

Notes: General brand-factor loadings restricted to be equal across both upper-level factors of dependable and exciting.

or score on a specific dimension of brand image is a function of a general brand effect, it is of interest to consider the value of general versus specific brand imagery. General brand effects are sometimes ascribed to an overall affective evaluation of the brand spilling over into ratings on specific items or dimensions. Thus, the value of a brand-image association may be due in large part or in whole to the general effect.

Using CBC data on midsized sedans and pick-any data on the imagery associated with the parent brands of the sedans, we estimate various specifications of a simultaneous factor choice model. The brand-image items are designed to measure two latent dimensions of brand image: dependable and exciting. The models are linked by the factor scores on each dimension, which enter directly into the consumer choice model. The choice model is parameterized to directly measure consumer WTP for the conjoint product attributes and the brand-image factors. We find that a two-factor solution fits the data better than a single-factor model but with a high correlation between the latent factor scores. This correlation causes identification problems in estimation of the factor-score parameters in the choice model. The distribution of WTP for both factors exhibits excessive dispersion, and the coverage interval for the estimate of the mean WTP for the dependable image factor spans zero.

The correlated factor scores can be modeled by introducing a higher-order factor. The higher-order factor model treats the correlated dependable and exciting factor scores at the upper level as arising from a lower-level structure composed of a unidimensional general brand factor common to the dependable and exciting factors and orthogonal residual scores unique to each factor. The residual factor scores are whatever remains of the upper-level dependable and exciting scores after removing the general brand factor. Controlling for the general effect, we find that consumers have substantial value for both dependable and exciting brand imagery. Compared with the estimates that do not control for the general brand factor, the WTP estimates are much less dispersed and in the positive range for each consumer. The posterior mean estimates WTP for a standard deviation change in the residual dependable and exciting factors are \$3,800 to \$4,800, respectively.

High correlation in factor scores and the presence of a general brand factor is symptomatic of data affected by halo. The psychology literature has described two types of halo effects. The first type occurs when an overall affective evaluation seeps into evaluations on specific dimensions. The second type occurs when task or cognitive errors result in similar ratings for an object across different dimensions. Observationally, types of halo result in correlated ratings or scores and a general brand effect, which makes distinguishing one from the other a difficult proposition. A more precise delineation of the affect versus error theories of halo formation could be a fruitful area for further research. Understanding the dynamic properties of general versus specific brand-image associations is also a worthwhile topic.

In terms of practice, attitudinal data that measure brand-image associations are quick and easy to collect, especially with a pick-any format. Using the calibration from the model and integrating over the consumers' heterogeneity distribution, brand managers can monitor the value of shifts in consumer image associations after any new brand campaigns or promotions. This provides a useful tool to help measure brand advertising campaigns. However, our results reinforce previous research that finds brand ratings on specific items are influenced by general brand effects. Failure to properly account for these effects yields misleading results about the value of associating a brand with specific image attributes. Collecting attitudinal and choice data simultaneously, and modeling them appropriately, gives the researcher a far deeper understanding of what drives consumers' preferences for products and helps inform brand-building activities over time.

APPENDIX

We detail the MCMC sampler for Model M5. Let the λ^1_{zlj} denote the nonzero entries of the patterned matrix Λ^1 and λ^2_{lj} the entries of Λ^2. The priors for $\{\alpha, \Sigma^\tau, \Lambda^1, \Lambda^2, \bar{\theta}, \Sigma^\theta\}$ are as follows:

$$\alpha_j \sim \text{MVN}\left(\bar{\alpha}_0, \Sigma^{\alpha_0}\right)$$

$$\Sigma^\tau \sim \text{IW}\left(v_0^\tau, V_0^\tau\right)$$

$$\lambda^1_{zlj} = \frac{\exp\left(\lambda^{1*}_{zlj}\right)}{1+\exp\left(\lambda^{1*}_{zlj}\right)}, \text{ where } \left(\lambda^{1*}_{zlj}\right) \sim N\left(\bar{\lambda}^1_0, \sigma^2_{\lambda^1_0}\right)$$

$$\lambda^2_l = \frac{\exp\left(\lambda^{2*}_{lj}\right)}{1+\exp\left(\lambda^{2*}_{lj}\right)}, \text{ where } \left(\lambda^{2*}_{lj}\right) \sim N\left(\bar{\lambda}^2_0, \sigma^2_{\lambda^2_0}\right)$$

$$\bar{\theta} \sim N\left(\bar{\theta}_0, \Sigma^{\theta_0}\right)$$

$$\Sigma^\theta \sim \text{IW}\left(v_0^\theta, V_0^\theta\right).$$

The joint posterior is

$$L \propto \prod_{i=1}^{N}\left(\begin{array}{l}\left\{\begin{array}{l}\prod_{t=1}^{T}\left[\prod_{m=1}^{M} f\left(I_{imt}|x_{imt}, b_{imt}, p_{imt}, \xi^1_{ij}, \Lambda^2_j, \xi^2_{ij}, \Theta^2_j, \theta_i\right)\right] \\ \times\prod_{j=1}^{J}\left[\prod_{z=1}^{Z} f\left(u^*_{ijz}|u_{ijz}, \alpha_{jz}, \tau_{iz}, \Lambda^1_{jz}, \xi^1_{ij}, \pi^1_{jz}\right)\right]\end{array}\right\} \\ \times\prod_{j=1}^{J}\left[f\left(\xi^1_{ij}|\Lambda^2_j, \xi^2_{ij}, \Theta^2_j\right)\right]\times\prod_{j=1}^{J}\left[f\left(\xi^2_{ij}|0,1\right)\right] \\ \times f\left(\tau_i|0, \Sigma^\tau\right)\times f\left(\theta_i|\bar{\theta}, \Sigma^\theta\right)\end{array}\right)$$

$$\times\prod_{j=1}^{J}\left[f\left(\alpha_j\right)\right]\times\prod_{z=1}^{Z}\prod_{l=1}^{L}\prod_{j=1}^{J} f\left(\lambda^{1*}_{zlj}\right)\times\prod_{l=1}^{L}\prod_{j=1}^{J} f\left(\lambda^{2*}_{lj}\right)$$

$$\times f\left(\bar{\theta}\right)\times f\left(\Sigma^\theta\right)\times f\left(\Sigma^\tau\right).$$

We take advantage of conditional independence in two places. First, the choice-data likelihood is independent of the factor model data likelihood, conditional on the factor scores and halo (Ashok, Dillon, and Yuan 2002). Second, the factor model data likelihood is a product over each of the z binary indicators, which are independent conditional on $\{\alpha_{jz}, \tau_{iz}, \Lambda^1_{jz}, \xi^1_{ij}\}$(Ansari and Jedidi 2000). This enables us to compute the likelihood of the factor model, which will be required to take draws from the nonconjugate conditional posterior of ξ^1_{ij}. Recall that $\tilde{\eta}^2_{lij} = (\xi^1_{lij} - \lambda^2_{lj}\xi^2_{lij})/\sqrt{\pi^2_{jl}}$ where π^2_{jl} is the lth diagonal element of Θ^2_j. The full expression for the joint posterior is as follows:

$$
\begin{aligned}
L \propto \prod_{i=1}^{N} \Bigg[& \left(\prod_{t=1}^{T} \left\{ \prod_{m=1}^{M} \left[\frac{\exp\left(\frac{x'_{imt}\varphi_i + \xi^{2'}_{imt}\beta_i + \tilde{\eta}^{2'}_{imt}\kappa_i - p_{imt}}{\mu_i} \right)}{\sum_{k=1}^{M} \exp\left(\frac{x'_{ikt}\varphi_i + \xi^{2'}_{ikt}\beta_i + \tilde{\eta}^{2'}_{ikt}\kappa_i - p_{ikt}}{\mu_i} \right)} \right] \right\} \right. \\
& \left. \times \prod_{j=1}^{J} \left\{ \prod_{z=1}^{Z} \Phi\left(\frac{\alpha_{jz} + \tau_{iz} + \Lambda^{1'}_{jz}\xi^1_{ij}}{\sqrt{\pi^1_{z,z}}} \right)^{u_{ijz}} \times \left[1 - \Phi\left(\frac{\alpha_{jz} + \tau_{iz} + \Lambda^{1'}_{jz}\xi^1_{ij}}{\sqrt{\pi^1_{z,z}}} \right) \right]^{1-u_{ijz}} \right\} \right) \\
& \times \prod_{j=1}^{J} |\Theta^2|^{-1/2} \exp\left[-\frac{1}{2}\left(\xi^1_{ij} - \Lambda^2_j \xi^2_{ij} \right)' [\Theta^2]^{-1} \left(\xi^1_{ij} - \Lambda^2_j \xi^2_{ij} \right) \right] \\
& \times \prod_{j=1}^{J} \exp\left[-\frac{1}{2}\left(\xi^2_{ij} \right)' \left(\xi^2_{ij} \right) \right] \times |\Sigma^{\tau}|^{-1/2} \exp\left[-\frac{1}{2}(\tau_i)' \Sigma^{\tau^{-1}} (\tau_i) \right] \\
& \times |\Sigma^{\theta}|^{-1/2} \exp\left[-\frac{1}{2}(\theta_i - \bar{\theta})' \Sigma^{\theta^{-1}} (\theta_i - \bar{\theta}) \right] \Bigg] \\
& \times \prod_{j=1}^{J} |\Sigma^{\alpha_0}|^{-1/2} \exp\left[-\frac{1}{2}(\alpha_j - \bar{\alpha}_0)' \Sigma^{\alpha_0^{-1}} (\alpha_j - \bar{\alpha}_0) \right] \\
& \times |\Sigma^{\theta_0}|^{-1/2} \exp\left[-\frac{1}{2}(\bar{\theta} - \bar{\theta}_0)' [\Sigma^{\theta_0}]^{-1} (\bar{\theta} - \bar{\theta}_0) \right] \\
& \times \prod_{z=1}^{Z} \prod_{l=1}^{L} \prod_{j=1}^{J} \frac{1}{\sigma_{\lambda^1_0}} \phi\left(\frac{\lambda^{1'}_{zlj} - \bar{\lambda}^1_0}{\sigma_{\lambda^1_0}} \right) \times \prod_{l=1}^{L} \prod_{j=1}^{J} \frac{1}{\sigma_{\lambda^2_0}} \phi\left(\frac{\lambda^{2'}_{lj} - \bar{\lambda}^2_0}{\sigma_{\lambda^2_0}} \right) \\
& \times \left| V^{\theta}_0 \right|^{v^{\theta}_0/2} |\Sigma^{\theta}|^{-(v^{\theta}_0 + K + 1)/2} \exp\left[-\frac{1}{2} \mathrm{tr}\left(V^{\theta}_0 \Sigma^{\theta^{-1}} \right) \right] \\
& \times \left| V^{\tau}_0 \right|^{v^{\tau}_0/2} |\Sigma^{\tau}|^{-(v^{\tau}_0 + P + 1)/2} \exp\left[-\frac{1}{2} \mathrm{tr}\left(V^{\tau}_0 \Sigma^{\tau^{-1}} \right) \right].
\end{aligned}
$$

From this joint posterior, we derive the full conditional distribution of all model parameters. For parameters with nonconjugate conditional posteriors, we use Metropolis–Hastings algorithms to draw from the full conditional.

1. Conditional on the means, loading, and factor scores, the Z latent response variables for individual i rating brand j are independent. Thus, we can draw the vector of latent responses by drawing each element from a univariate truncated normal $u^*_{ijz} \mid u_{ijz}, \alpha_{jz}, \tau_{iz}, \Lambda^1_{zj}, \xi^1_{ij}, \pi^1_{jz} \sim TN(\alpha_{jz} + \tau_{jz} + \Lambda^{1'}_{zj}\xi^1_{ij}, \pi^1_{jz})$ with truncation such that $u^*_{ijz} > 0$ for $u_{ijz} = 1$. The vector ofdiagonal terms in Θ^1_j, $[\pi^1_{j1}, ..., \pi^1_{jZ}]'$, are computed with the constraint $\Theta^1 = I_Z - \mathrm{diag}\,[\Lambda^1_j \Lambda^{1'}_j]$.
2. The full conditional distribution for the brand-specific means of the latent variable in the factor model is $\alpha_j | u^*_{ij}, \tau_i, \Lambda^1_j, \xi^1_{ij}, \bar{\alpha}_0, \Sigma^{\alpha_0}, \Theta^1_j \sim N\{(\Sigma^{\alpha_0^{-1}} + (N)(\Theta^1_j)^{-1})^{-1} [\Sigma^{\alpha_0^{-1}}\bar{\alpha}_0 + (\Theta^1_j)^{-1}\Sigma^N_{i=1}\tilde{u}^*_{ij}], [\Sigma^{\alpha_0^{-1}} + (N)(\Theta^1_j)^{-1}]^{-1}\}$, where $\tilde{u}^*_{ij} = u^*_{ij} - (\tau_i + \Lambda^1_j \xi^1_{ij})$. We set $\bar{\alpha}_0 = 0_{p \times 1}$ and $\Sigma_{\alpha_0} = 10^6 I_p$. These are proper but diffuse priors.
3. The full conditional distribution for the individual-specific means of the latent variable in the factor model is $\tau_i | u^*_{ij}, \alpha_j, \Lambda^1_j, \xi^1_{ij}, \Sigma^{\tau}, \Theta^1_j \sim N\{[\Sigma^{\tau^{-1}} + (J)(\Theta^1_j)^{-1}]^{-1} [(\Theta^1_j)^{-1}\Sigma^N_{i=1}\tilde{u}^*_{ij}], [\Sigma^{\tau^{-1}} + (J)(\Theta^1_j)^{-1}]^{-1}\}$, where $\tilde{u}^*_{ij} = u^*_{ij} - [\alpha_i + \Lambda^1_j \xi^1_{ij}]$. For identification, the prior mean is fixed to 0.
4. The full conditional distribution for the nonzero elements of the upper-level factor loadings, λ^1_{zlj}, mixes the data likelihood for u* with the normal prior for λ^{1*}_{zli}. We use a random-walk Metropolis–Hastings algorithm to take draws from this distribution.
5. The full conditional distribution for the upper-level factor scores, ξ^1_{ij}, mixes the data likelihoods for I and u* with the normal prior for ξ^1_{ij} We use a random-walk Metropolis–Hastings algorithm to take draws from this distribution.
6. The full conditional distribution for the elements of the lower-level factor loadings, λ^2_{lj}, mixes the data likelihood for I and ξ^1_{ij} with the normal prior for λ^{2*}_{lj}. We use a random-walk Metropolis–Hastings algorithm to take draws from this distribution.
7. The full conditional distribution for the lower-level factor scores, ξ^2_{ij}, mixes the data likelihoods for I and ξ^1_{ij} with the normal prior for ξ^2_{ij}. We use a random-walk Metropolis–Hastings algorithm to take draws from this distribution.
8. The full conditional distribution for the variances of the individual-level means, Σ^{τ}, is $\Sigma^{\tau} \mid \theta_i, v^{\tau}_0, V^{\tau}_0 \sim IW\{v^{\tau}_0 + N, [v^{\tau}_0 V^{\tau}_0 + \Sigma^N_{i=1}(\tau_i)(\tau_i)'](v^{\tau}_0 + N)^{-1}\}$. We set $v_0 = 2 + Z$ and $v_0 = I_K$. These are proper but diffuse priors.
9. The full conditional distribution for the means of the individual-level choice-model coefficients, $\bar{\theta}$, is $\bar{\theta} | \theta_i, \Sigma^{\theta}, \bar{\theta}_0, \Sigma^{\theta_0} \sim N\{[(\Sigma^{\theta_0})^{-1} + N(\Sigma^{\theta_0})^{-1}]^{-1} [(\Sigma^{\theta_0})^{-1}\bar{\theta}_0 + N(\Sigma^{\theta})^{-1}(1/N\Sigma^N_{i=1}\theta_i)] [(\Sigma^{\theta_0})^{-1} + N(\Sigma^{\theta})^{-1}]^{-1}$. We set $\bar{\theta}_0 = 0_{K \times 1}$ and $\Sigma^{\theta_0} = 10^6 I_K$. These are proper but diffuse priors.
10. The full conditional distribution for the variances of the individual-level choice-model coefficients, Σ^{θ}, is $\Sigma^{\theta} | \theta_i, \bar{\theta}, v^{\theta}_0, V^{\theta}_0, \sim IW\{v^{\theta}_0 + N, [v^{\theta}_0 V^{\theta}_0 + \Sigma^N_{i=1}(\theta_i - \bar{\theta})(\theta_i - \bar{\theta})'](v^{\theta}_0 + N)^{-1}\}$. We set $v_0 = 2 + K$ and $V_0 = I_K$. These are proper but diffuse priors.
11. The full conditional distribution for the individual-level choice parameters θ_i mixes the data likelihoods for I with the normal prior for θ_i. We use a random-walk Metropolis–Hastings algorithm to take draws from this distribution.

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