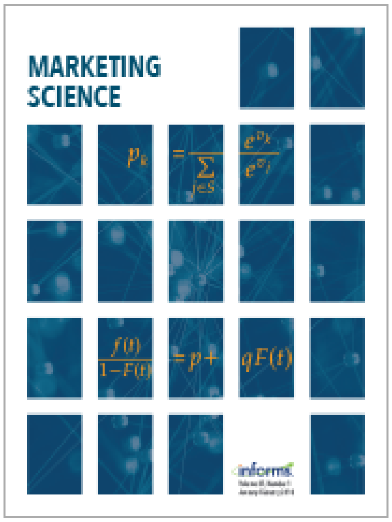

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Brand Effects on Choice and Choice Set Formation Under Uncertainty

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This paper examines the effects of brand credibility, a central concept in information economics–based approaches to brand effects and brand equity, on consumer choice and choice set formation. We investigate the mechanisms through which credibility effects materialize, namely, through perceived quality, perceived risk, and information costs saved. The credibility of a brand as a signal is defined as the believability of the product position information contained in a brand, which depends on consumer perceptions of the willingness and ability of firms to deliver what they have promised. The choice set is defined as the collection of brands that have a nonzero probability of being chosen among those actually available for choice in a given context.

Furthermore, we study the impact of brand credibility on the variance of the stochastic component of utility. Not only do choice model parameters capture the impact of systematic utility differences on choice probabilities, but also the magnitude of this systematic impact is moderated by the relative importance of the stochastic utility component in preference. We term this moderation phenomenon *preference discrimination*, which we conceptualize as the decision makers' capacity to effectively discriminate between products' utilities in choice situations.

We estimate a discrete choice model of brand choice set formation and preference discrimination on experimental data in two categories—juice and personal computers—and find strong evidence for brand credibility effects and differential mechanisms through which brand credibility's impact materializes on brand choice conditional on choice set, choice set formation, and preference discrimination.

Key words: information economics; perceived quality; perceived risk; brand preference; branding; brand choice; choice models; personal computers; juice
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1. Introduction

As "a name, term, sign, symbol or design, or a combination of them which is intended to identify the goods and services of one seller or a group of sellers and to differentiate them from those of competitors" (Kotler 1997, p. 443), the *brand* plays multiple roles in consumer choice. These roles may include brands' effects on consumer preferences; on brand and quantity choice; and on consideration, to name a few. Additionally, these effects may materialize through various mechanisms such as psychological (e.g., associative network memory), sociological (such as brand communities), and economic processes (brands as signals under uncertainty) (Keller 2002).

In this paper, we investigate the impact of brand credibility, a central concept in economics-based approaches to brand effects and brand equity, on consumer choice set formation and preference discrimination, the latter a concept on which we will subsequently elaborate. *Brand credibility* (the credibility of a brand as a signal) is defined as the believability of the product position information contained in a brand. This information depends on consumers' perceptions of the willingness and ability of firms to deliver what they have promised. This perceived willingness and ability to deliver constitute the two components of brand credibility: trustworthiness and expertise. When asymmetric information characterizes a market, economic agents (i.e., consumers and firms) may use signals (i.e., manipulable attributes or activities) to convey information about their characteristics (Spence 1974). To be effective, such signals must be credible (Tirole 1990). Previous literature has studied the credibility of a brand as a signal of quality or product positioning (Wernerfelt 1988, Rao and Ruekkert 1994, Erdem and Swait 1998).

We define the *choice set* as the brands that have a nonzero probability of being chosen among those actually available for choice in a given context, at the time of choice. We should note that in the literature some researchers used the terms consideration set and choice set interchangeably (for a review, see Roberts and Nedungadi 1995), while others have drawn a distinction. Following Shocker et al. (1991), we make such a distinction: although these are closely related constructs, *consideration sets* refer to long-term, dynamic sets that vary within and across usage and purchase occasions, whereas *choice sets* are conceptualized as the set of alternatives considered immediately prior to choice, and are thus more instantaneous in nature. (Of course, the choice set could itself be the end result of a dynamic process.) This paper proposes and shows that brand credibility not only affects choice set formation and conditional brand choice, but it also argues and tests for the differential mechanisms through which credibility operates at each stage.

Besides the impact of brand credibility on choice set formation, we also explore the effect of brand credibility on what we term preference discrimination. It is well known that in discrete choice models, many of which possess a characteristically sigmoidal shape (e.g., multinomial logit, nested logit, and probit), the more the slope coefficient grows in magnitude, the steeper the sigmoidal shape becomes. In fact, at one of its limits the sigmoidal shape will arbitrarily closely emulate a step function (see, e.g., Ben-Akiva and Lerman 1985, pp. 70–72). A behavioral interpretation of this phenomenon is that decision makers' capacity to discriminate between alternatives may be higher in certain contexts. This discrimination can be conceptualized as preference discrimination, that is, a given consumer's choice probabilities will be consistently low or high for certain brands since the consumer can discriminate better among such alternatives. We conjecture that brand credibility will affect preference discrimination thus defined.

While previous research has explored the impact of credibility on product utility in adopting a structural equation modeling framework (Erdem and Swait 1998) and separately on brand consideration and choice (Erdem and Swait 2004), we investigate brand credibility's effect on choice set formation and brand choice, conditional on choice set in an integrated framework. For example, Erdem and Swait (2004) estimated simple binary logistic models on self-reported consideration data from several product categories and found evidence for brand credibility effects. These results call for further research since (a) one needs to test whether such effects are robust (for example, one needs to link brand choice to formation of subsets from the universal set in a unified framework, control for unobserved heterogeneity, and incorporate price in the model to explore the effect of brand credibility, none of which steps were taken in Erdem and Swait 2004); (b) it is of interest in itself to research the mechanisms through which brand credibility operates in brand choice conditional on choice set versus the choice set formation stage; (c) it is necessary to determine whether brand credibility also affects choice set formation, in addition to consideration (Erdem and Swait 2004). We tackle all three issues in this paper. Furthermore, in this paper we also investigate the impact of brand credibility (and the mechanisms through which these effects materialize) on preference discrimination. We conduct our analysis on experimental data collected through one study involving both the juice and personal computer (PC) product categories, and a second study involving only PCs.[1]

We review relevant literature and define the conceptual framework guiding our testing in §2; we discuss our modeling approach and data in §3 and our results in §4. We conclude the paper with a discussion of managerial implications and future research.

2. Related Work and Conceptual Framework

2.1. Choice Set Formation and Brand Choice Conditional on Choice Set

Previous empirical work on how consumers may narrow attention to a subset of brands out of a bigger set has focused on modeling choices as the outcome of a two-stage process of consideration set or choice set formation and conditional brand choice (e.g., Swait and Ben-Akiva 1987a, b; Roberts and Lattin 1991; Andrews and Srinivasan 1995; Chiang et al. 1999).

However, there has been no published empirical model of consideration or choice set formation in the context of brand choice that explicitly captures the explanations offered for brands' effects on consideration or choice set formation. This is not to say that the wider literature has not considered appropriate theoretical bases for specifying consideration or choice set formation models. For example, Meyer (1979) formulated a theory of destination choice set formation, incorporating information availability and constraints; in the transportation demand area, Swait and Ben-Akiva (1987a, b) modeled the impact of different constraints on choice.

While empirical work tried to link choice or consideration set formation stages to the brand choice stage,

[1] We should note that Erdem and Swait (1998, 2004) have not used any experimental data and conducted their analysis on consumer self-reports on several items.

the main approach in the literature to conceptualizing the formation of subsets from universal sets of alternatives has been the cost-benefit approach (Hauser and Wernerfelt 1990). This approach employs the expected utility maximization framework to advance the notion that consumers weigh the cost of brand evaluation for membership in this subset against the benefits of adding or dropping the brand. This approach based on expected utility maximization implies consumer uncertainty about brands, since consumers are unsure about the utility they would get from each available brand and, hence, need to make expected utility-expected cost calculations in forming their consideration or choice sets.

2.2. Brand Credibility

The importance of credibility under uncertainty has been established in several contexts (e.g., Xie and Shugan 2001, Godes and Mayzlin 2004). There is also a growing literature on the importance of brand credibility under consumer uncertainty. When consumers are uncertain about brands and the market is characterized by asymmetric information (i.e., firms know more than consumers do about their products), brands can serve as signals of product positions (Wernerfelt 1988). As a signal of product positioning, the most important characteristic of a brand is its credibility. A firm can use various marketing mix elements in addition to the brand to signal product quality: for example, charging a high price, offering a certain warranty, or distributing via certain channels. Each of these actions may or may not be credible depending on market conditions, including competitive and consumer behavior. However, credible signals that set brands apart from the individual marketing mix elements is that the former embody the cumulative effect of past marketing mix strategies and activities, as well as consumer interactions with the firm. This historical notion that credibility is based on the sum of past behaviors has been referred to as reputation in the information economics literature (see Herbig and Milewicz 1995).

Credibility is broadly defined as the believability of an entity's intentions at a particular time. It is posited to have two main components: trustworthiness and expertise. Thus, brand credibility is defined as the believability of the product information contained in a brand, which requires that consumers perceive that the brand have the ability (i.e., expertise) and willingness (i.e., trustworthiness) to continuously deliver what has been promised (if and when brands do not deliver what is promised, their brand equity will erode).[2]

Brand credibility, in turn, may (a) increase consumer expected attribute (e.g., quality) levels (Aaker 1991), (b) decrease the variance of consumer attribute beliefs, i.e., consumer perceived risk[3] (Srinivasan and Ratchford 1991), and (c) decrease information costs (Shugan 1980) by credibly signaling product positions when there is consumer uncertainty about brands (Erdem and Swait 1998, Montgomery and Wernerfelt 1992, Wernerfelt 1988).

2.3. Brand Credibility, Choice Set Formation, and Conditional Brand Choice

Such a signaling framework of brand effects on consumer brand utility and choice also implies that when there is consumer uncertainty about brands and information is costly to obtain or process, the credibility of a brand may be an important factor underlying the formation of choice sets (as well as consideration sets; see Erdem and Swait 2004). The higher perceived value and lower perceived risk associated with a higher-credibility brand are anticipated to increase expected benefits (Hauser and Wernerfelt 1990). Additionally, the lower information costs associated with credible brands are likely to decrease expected costs, while the credibility of a brand decreases perceived risk because it increases consumers' confidence in a firm's product claims. Credibility also decreases information costs since consumers may use credible brands as a source of knowledge to economize on information gathering and processing costs (e.g., reading *Consumer Reports* or doing online searches for product reviews).

In the context of brand choice, the cost-benefit approach implies consumer uncertainty about the attributes (i.e., quality) of brands. Although not explicitly included in models of consideration or choice set formation and brand choice, models of Bayesian learning (Roberts and Urban 1988, Erdem and Keane 1996) are consistent with a cost-benefit approach based on expected utility maximization to model brand evaluations. Erdem and Keane (1996) model consumers'

[2] The credibility of a brand has been shown to be higher for brands with higher marketing mix consistency over time and higher brand investments, ceteris paribus (Erdem and Swait 1998). Consistency refers to the degree of harmony and convergence among the marketing mix elements and the stability of marketing mix strategies and attribute levels over time. Brand investments, on the other hand, are resources that firms spend on brands to (a) assure consumers that brand promises will be kept and (b) demonstrate longer-term commitment to brands (Klein and Leffler 1981). Furthermore, it has also been shown that the clarity (i.e., lack of ambiguity) of the product information contained in a brand is an antecedent to brand credibility (Erdem and Swait 1998).

[3] Consumer uncertainty about product attributes generates consumer perceived risk (which can be conceptualized as the variance of consumer attribute beliefs) because "any action of a consumer will produce consequences which he cannot anticipate with anything approximating certainty, and some of which at least are likely to be unpleasant" (Robertson et al. 1984, p. 184).

learning about imperfectly known product attributes through advertising and experience, which alters consumers' mean attribute evaluations (expected quality) and their variance (perceived risk). Their model is consistent with Howard and Sheth's (1969) theory of formation of subsets from universal sets of alternatives, which posits that consumers will try different brands to learn about them and then buy from among only a small subset of available brands. Mehta et al. (2003) estimated such an explicit model on scanner panel data; in their model, experience provides information about brands and reduces consumer uncertainty.

We postulate that the more credible the brand, the greater the likelihood of a consumer including it in his choice set due to its possible impact on perceived quality, perceived risk, and information costs. While this notion follows directly from the cost-benefit approach (Hauser and Wernerfelt 1990), the magnitude of credibility's impact on choice set formation versus its impact on the conditional brand choice stage, and the differential mechanisms through which brand credibility may operate at these two stages, have not been tested explicitly.

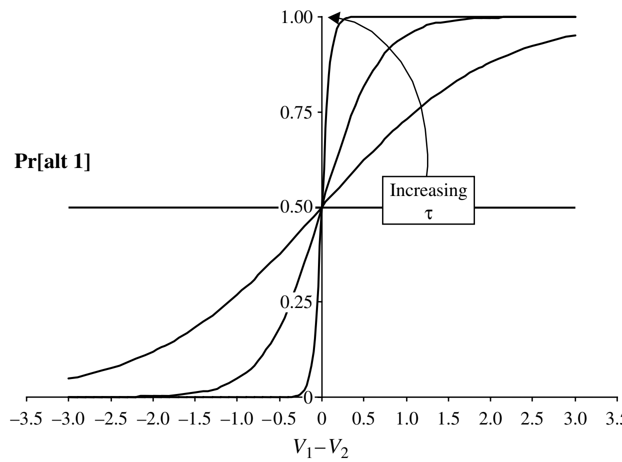
2.4. Brand Credibility and Preference Discrimination

Choice models are used to predict behavior as a function of attribute-based utility differences. To elaborate and set the stage for subsequent explanations, we remind the reader that in these latent variable choice models the total utility of a product is generally decomposed into a systematic component V and a stochastic component ε (also commonly termed the error, in analogy to linear models). Substantive theoretical developments in the area of choice modeling have concentrated almost exclusively on the systematic component, but the realization that the stochastic component of utility also influences a model's ability to predict choice behavior is gradually growing among researchers (e.g., Swait and Louviere 1993, Louviere et al. 2000).

Choice models exhibit an interesting property with respect to the size of these systematic utility differences: in different contexts and for different decision makers, the same systematic utility difference can result in more-extreme choice probabilities, depending on the relative sizes (or scales) of the stochastic utility components. To illustrate, consider a binary logit probability model between Brands 1 and 2 that is a function of the systematic utility difference between the brands, $V_1 - V_2$, as well as an effect size parameter $\tau \geq 0$, thus

$$\mathrm{Pr}_1 = \{1 + \exp(-\tau(V_1 - V_2))\}^{-1}, \quad \tau \geq 0. \tag{1}$$

Figure 1 **The Impact of Effect Size on Binary Logit Choice Probabilities**



This effect-size parameter τ is directly related to the relative importance of the stochastic utility difference $(\varepsilon_1 - \varepsilon_2)$ compared to the systematic utility difference $(\mathrm{V}_1 - \mathrm{V}_2)$; precisely, τ is inversely related to the variance of this stochastic difference. Figure 1 maps out the choice probability of Brand 1 as a function of the systematic utility difference and the effect-size parameter τ. As $\tau \to 0$ (i.e., the variance of $(\varepsilon_1 - \varepsilon_2)$ approaches infinity), the probability of Brand 1 approaches 1/2 everywhere, which is to say, choice is random. On the other hand, as $\tau \to \infty$ (i.e., the variance of $(\varepsilon_1 - \varepsilon_2) \to 0$), the probability of Brand 1 being chosen approaches a step function that transitions abruptly at $V_1 - V_2$ close to zero, which is to say, in the limit choice is deterministic with respect to the systematic utility difference between the brands: if $V_1 - V_2 < 0$, Brand 2 certainly will be chosen, if $V_1 - V_2 > 0$ then Brand 1 certainly will be chosen, and if the difference is zero, choice will be random. This effect is discussed in Ben-Akiva and Lerman (1985, pp. 70–72) and Louviere et al. (2000, p. 236), and is known to hold for multinomial logit and probit, nested logit, and other choice model forms.

In effect, not only do choice model parameters capture the impact of systematic utility differences on choice probabilities, but the magnitude of this systematic impact is moderated by the relative importance of the stochastic utility. We term this moderation phenomenon *preference discrimination*. As Figure 1 clearly illustrates, for the same systematic utility difference, a larger effect size will translate into more-extreme probabilities (i.e., closer to zero or one). As an effect size grows (i.e., stochastic utility decreases in importance with respect to total product utility), systematic preferences become more and more able to discriminate between alternatives, with the choice process tending toward the step-function limiting condition; this is nothing more than the model's attribution of perfect discrimination between the products or brands to the decision maker on the basis of known attributes.

A recent stream of literature in the discrete choice area has studied the impact of error heteroscedasticity on choice model parameter inferences (see, among others, Swait and Louviere 1993, Allenby and Ginter 1995, Dellaert et al. 1999, Louviere et al. 2000). In that literature, heteroscedasticity plays the same role that effect size has played above. However, the effect-size phenomenon we have discussed above is more general because the heteroscedasticity explanation can only be used in the context of random utility models, whereas the effect-size explanation can apply for any probabilistic choice model (PCM).

Erdem and Swait (1998) found that credibility affects product evaluation by causing utility (i.e., product attractiveness) to increase with increasing quality, decreasing risk perceptions and increasing information costs saved. The effect-size phenomenon we are postulating to be a function of brand credibility is over and above the wholesale differences Erdem and Swait (1998) found in their structural equation models. Referring to Figure 1, Erdem and Swait's results would suggest that credibility causes vertical shifts in the sigmoidal shape; preference discrimination or effect size, on the other hand, refers to the steepness or sharpness of the sigmoidal shape around its point of balance (here, where utility differences are zero).

This steepening or flattening of the sigmoidal shape is meaningful only to the analyst, of course, and not to the consumer. Theoretically, the consumer is assumed to be aware of a product's full utility attribution (systematic and stochastic). What the effect size is describing is simply the relative reliance of the consumer on known (to the analyst) sources versus unknown (again, to the analyst) sources of utility when making a choice. The steepening of the sigmoidal shape indicates a sharper (i.e., steeper) sensitivity with respect to all the variables included in the systematic utility specification—thus, the consumer will be relying more strongly on the systematic component of utility than on the stochastic component. This greater consumer reliance on the systematic component would be reflected in more-discriminating (i.e., more-extreme) behavior in regard to the choice alternatives on the part of consumers. Our expectation is that brand credibility may affect the degree of this discriminating behavior. For example, if high (low) credibility serves as a quick heuristic for consumers to discriminate among brands, to the analyst such reliance by consumers on brand credibility would reflect itself in a conditional choice model through increased (decreased) parameter magnitudes, that is, increased (decreased) effect size. Thus, it is possible that the net impact of credibility on impact size can be either positive or negative, depending on the role that credibility plays in choice heuristics. Since the choice heuristics consumers apply under uncertainty (and, hence, the impact of credibility on choice) may vary across different decision contexts, we test the net impact of credibility on impact size in two specific decision contexts, characterized by the variability (fixed versus variable) and size of the choice set (small versus large).

3. Empirical Tests

We have conducted two separate studies to test the concepts discussed above. In the first, more-comprehensive study, we investigate the impacts of brand credibility on choice set formation, preference discrimination, and conditional choice in two product categories (juices and PCs) for which we expect differential brand impacts. This first study involves an experimental choice task, designed with fixed-size sets using five brands. Having found strong support for the hypothesized impacts of brand credibility, it was decided to conduct a second study on the PC product category only, but substantially increase the number of brands and make the size of choice sets vary considerably. The purposes of the second study are twofold: (a) to lend face validity to the structural choice set formation model by eliciting choice set membership information, in addition to choice data; and (b) to investigate the robustness of the results of the first study when the complexity of the choice context is increased by using varying set sizes and nine different brands (almost double the number of brands used in the first study). The second study results are found to strongly support the first study results.

3.1. Study 1

3.1.1. Model Description. We have formulated a PCM that structurally includes choice set formation and also allows for capturing preference discrimination effects due to brand credibility. Our specification is an elaboration on Swait's (1984) independent availability multinomial logit (IA-MNL) model (see also Swait and Ben-Akiva 1987a, Andrews and Srinivasan 1995, Ben-Akiva and Boccara 1995). The two-stage model we use in our research adds two features to the IA-MNL model:

1. Preference discrimination, parametrized as a function of brand credibility, which allows us to characterize how consumers continue to rely on brand credibility as a decision aid during the second stage of choice. We accomplish this by defining and estimating an effect-size function τ, which is parametrized in terms of brand credibility, among other factors.

2. Random parameters, to capture individual-specific heterogeneity in product evaluations. As

shown by Heckman (1981), among others, if unobserved heterogeneity is unaccounted for, biased parameter estimates can result. We therefore include person-specific random effects.

The derivation of the basic probabilistic choice model we employ is available from the authors upon request.

We now describe in detail the econometric specification we use, beginning with P_{in}, the unconditional probability that individual n chooses alternative i

$$P_{in} = \int_{\beta} \sum_{C \in \Delta_M} P_{in|C}(X_n, Z_n \mid \beta, \theta) \cdot Q_n(C, W_n \mid \delta) \phi(\beta \mid \bar{\beta}, \Sigma_\beta)\, d\beta, \quad \forall i \in M, \tag{2a}$$

where C is a choice set in Δ_M, which is the set of all possible choice sets derived from the universal (or available) set M of brands eligible for choice at the time of decision, $P_{in|C}$ is the conditional probability of choosing i from set C, and $Q_n(C)$ is the likelihood of C being the choice set from which i is chosen. The conditional choice probability is defined by the multinomial logit (MNL) model with effect-size function τ:[4]

$$\begin{aligned} P_{in|C}(X_n, Z_n \mid \beta, \theta) &= \frac{\exp[\tau_{in}(Z_{in} \mid \theta) \cdot V_{in}(X_{in} \mid \beta_n)]}{\sum_{j \in C} \exp[\tau_{jn}(Z_{jn} \mid \theta), \ldots, V_{jn}(X_{jn} \mid \beta_n)]}, \quad \forall i \in C \subseteq M, \\ &= 0, \quad \forall i \notin C, \end{aligned} \tag{2b}$$

where V_{in} is the deterministic utility, defined subsequently as a function of product attributes and personal characteristics, as well as person-specific taste weights β_n, which are distributed according to the multivariate density function $\phi(\beta \mid \bar{\beta}, \Sigma_\beta)$ (see Expression (2a)), where $\bar{\beta}$ is the population mean and Σ_β is the variance-covariance matrix. The vector Z_{in} of product- and person-specific characteristics is used to parametrize the effect-size function

$$\tau_{in}(Z_{in} \mid \theta) = \exp(\theta Z_{in}), \quad \forall i \in M, \tag{2c}$$

where θ is a conformable parameter vector; the exponentiation operator is used to constrain effect-size τ_{in} to be nonnegative. The probability of a choice set C is given by (2d) and (2e):[5]

$$Q_n(C, W_n \mid \delta) = \frac{(\prod_{j \in C} A_{jn}(W_{jn} \mid \delta))(\prod_{k \in M-C}[1 - A_{kn}(W_{kn} \mid \delta)])}{1 - (\prod_{k \in M}[1 - A_{kn}(W_{kn} \mid \delta)])}, \quad C \in \Delta_M. \tag{2d}$$

$$A_{in}(W_{in} \mid \delta) = [1 + \exp(-\delta W_{in})]^{-1}, \quad \forall i \in M, \tag{2e}$$

where A_{in} is the probability alternative, i is included in the choice set, W_{in} is a vector of product- and person-specific characteristics, and δ is a conformable parameter vector. The normalization constant in the denominator of (2d) excludes the possibility of a null choice set, a logical impossibility when choice is actually observed, as it will be in the data we collected.

Thus, Model (2a–2e) details a conditional MNL choice model with random coefficients (mean $\bar{\beta}$ and variance-covariance matrix Σ_β) and parametrized effect-size function, plus an independent availability choice set formation model in which the individual probabilities of brand inclusion in the choice set are given by a logistic CDF, which is a function of covariates. Despite the fact that this model is more complex than standard choice models, particularly due to the explicit formulation of a two-stage decision process, it is not our intent to claim that decision makers actually employ such a two-stage approach to choice. Instead, we put this model forward as an improved paramorphic representation of observed choice behavior.

The three parametrized functions in the model above are detailed below:

$$V_{in} = \alpha_{in} + \beta_1 \ln(p_i) + \beta_2 C_{in} \quad i \in M, \tag{3a}$$

$$\tau_{in} = \exp(\theta_{i1} + \theta_1 C_{in} + \theta_2 C_{in}^2), \quad i \in M, \tag{3b}$$

$$A_{in} = [1 + \exp(-(\delta_{i1} + \delta_2 p_i + \delta_3 C_{in}))]^{-1}, \quad i \in M, \tag{3c}$$

where

C_{in} = brand credibility construct for brand i, person n;

p_i = price of brand i; and

α, β, δ, θ = parameter vectors to be estimated.

[4] Independence of irrelevant alternatives (IIA) is a well-known characteristic of the basic MNL model, as well as this variant of it. However, even though the conditional choice model of our proposed model system displays IIA, the overall choice probability model (Expression (2a)) does not share this property. Intuitively, because there is explicit consideration of choice set formation, and choice sets are essentially an expression of specific market structures, the overall choice model does not have the IIA property. Furthermore, we estimate a random effects specification and allow for a continuous distribution in tastes, which implies that the brand choice model we estimate is not subject to IIA at the aggregate level (that is, IIA holds only for each individual separately).

[5] As pointed out by Swait (1984), the IA-MNL model (and, consequently, our extension of it) has the characteristic that the inclusion of any one alternative in the consideration set is probabilistically independent of the inclusion of any other alternative from M. This assumption is made principally for tractability. Without this simplification, the probability of each consideration set must be estimated separately. For a set with J alternatives, there are $(2^J - 1)$ subsets whose probabilities must be estimated, which is in practice intractable for even small J (say, $J \geq 5$). This assumption of independent availability precludes the possibility that brands may share unobserved attributes and characteristics that cause brand groups to jointly have greater or smaller probabilities of joint occurrence in the choice set than would be predicted by independence.

Price is included in systematic utility Function (3a) in logarithmic form to capture a decreasing marginal impact on utility; price is also included in the availability Function (3c) to capture price threshold effects in choice set formation, which might otherwise be confounded with brand credibility. In the latter function, price is included linearly because the logistic function lends itself to capturing a threshold effect for variables included in a linear fashion in its argument. It will also be noted that (3b) includes both linear and quadratic credibility terms. We have argued before that high or low levels of brand credibility might lead to increased preference discrimination. However, it is possible that the marginal impact of credibility on preference discrimination will decrease at extreme credibility levels due to a threshold effect: at very high or very low credibility levels, the marginal impact of credibility on preference discrimination is likely to diminish because some residual level of uncertainty will persist. This same kind of argument can be made in terms of the impact of credibility on choice set formation; Expression (3c) allows this kind of threshold effect of choice set formation directly through the logistic CDF functional form (see subsequent discussion of results). However, in the case of (3b), the possibility of a threshold effect must be allowed for explicitly through the quadratic term since the exponentiation operator is strictly monotonic in its argument. These three functions should be understood simply as flexible forms that will be determined by the data; there is no a priori theory to guide their specifications, though we've tried above to justify to some extent the specific forms shown.

It will be noted in (3a–3c) that brand credibility enters the model in three ways: First, it affects choice set formation via the brand inclusion probability Model (3c)—increasing brand credibility is expected to increase a brand's likelihood of being in the latent choice set. Second, conditional on the brand being in the choice set, brand credibility is expected to affect utility by shifting utility upward, as in Expression (3a), in which β_2 is expected to be positive. Third, it is hypothesized that the effect-size function τ will reflect greater preference discrimination (perhaps with diminishing marginal impact) at the extremes of credibility since that construct may be used by consumers to define credibility thresholds, below or above which preferences are better discriminated by known attribute or variable impacts (i.e., attributes or variables included in the systematic utility).

One of our goals is to understand the mechanisms whereby brand credibility affects the different stages of choice behavior. Previous research (Erdem and Swait 1998, 2004) strongly suggests that (a) perceived quality (PQ), perceived risk (PR), and information costs saved (ICS) are constructs that share brand credibility as a common antecedent; and (b) that the impacts of credibility on utility are entirely mediated by these three constructs. Accordingly, we also estimate variant models of (3a–3c) that substitute these end constructs in the place of brand credibility:

$$V_{in} = \alpha_{in} + \beta_1 \ln(p_i) + \gamma_1 \mathrm{PQ}_{in} + \gamma_2 \mathrm{PR}_{in} + \gamma_3 \mathrm{ICS}_{in}, \quad i \in M, \quad (4a)$$

$$\tau_{in} = \exp(\theta_{i1} + \kappa_1 \mathrm{PQ}_{in} + \kappa_2 \mathrm{PQ}_{in}^2 + \kappa_3 \mathrm{PR}_{in} + \kappa_4 \mathrm{PR}_{in}^2 + \kappa_5 \mathrm{ICS}_{in} + \kappa_6 \mathrm{ICS}_{in}^2), \quad i \in M, \quad (4b)$$

$$A_{in} = [1 + \exp(-(\delta_{i1} + \delta_2 p_i + \pi_1 \mathrm{PQ}_{in} + \pi_2 \mathrm{PR}_{in} + \pi_3 \mathrm{ICS}_{in}))]^{-1}, \quad i \in M. \quad (4c)$$

Vectors γ, κ, and π are additional parameters to be estimated, along with or instead of previously defined parameters. Working our way through the implicit hypotheses in (4a–4c), it is our expectation that in the choice set formation stage all three end constructs are likely to affect brand inclusion in Model (4c): (a) employment of a quality threshold should lead to a significant and positive π_1; (b) the desire to exclude high PR brands should lead to a significantly negative π_2 effect; and (c) economies with respect to decision-making costs should be indicated by a statistically and substantively positive π_3. In the utility Function (4a), which is of course estimated conditional on brand inclusion in the choice set, (a) it seems to us that relative quality differences among brands in the choice set should play a role, leading to a discernible positive effect for γ_1; (b) with respect to risk and information costs, it is not so clear from a priori considerations that these variables should continue to play a role in determining product attractiveness or utility, once their impact has been controlled for in the choice set formation stage. Whether or not they do must be determined empirically. However, this is not to say that systematic utility is wholly unaffected by PR and ICS: we expect these and PQ to display significant impacts on the effect-size Function (4b) if preference discrimination is operative within the conditional brand evaluation stage of choice.

3.1.2. Data Collection and Calculation of Indices. Data were collected through paper-and-pencil surveys, the subjects of which were undergraduate students at two major North American universities who received course credit for participation. The final sample sizes were 391 respondents for juice and 366 for PCs.

Construct value estimates for brand credibility, PQ, PR, and ICS were obtained in a straightforward fashion. Based on the structural equation model reported in Erdem and Swait (1998), as well as on subsequent studies that have used the scales there developed

Table 1 **Brand Credibility and Related Construct Items and Reliability Measures**

Construct	Item	Cronbach's α
Credibility	This brand reminds me of someone who's competent and knows what he/she is doing. (+)	0.85
	This brand has the ability to deliver what it promises. (+)	
	This brand delivers what it promises. (+)	
	This brand's product claims are believable. (+)	
	This brand has a name you can trust. (+)	
	This brand doesn't pretend to be something it isn't. (+)	
PQ	The quality of this brand is very high. (+)	0.77
	In terms of overall quality, I'd rate this brand as a … (+)	
PR	I'd have to try it several times to figure out what this brand is like. (+)	0.64
	I never know how good this brand will be before I buy it. (+)	
ICS	I need lots more information about this brand before I'd buy it. (−)	0.75
	I know what I'm going to get from this brand, which saves time shopping around. (+)	
	I know I can count on this brand being there in the future. (+)	
	This brand gives me what I want, which saves me time and effort trying to do better. (+)	

Notes. (a) All scales formed as simple averages of component items, reverse scored for negative items. (b) All items measured on nine-point agree-disagree scale except for second PQ item, which was measured on nine-point scale with 1 = low quality, 9 = high quality. (c) (+/−) signs indicate a priori sign expectation.

(Erdem and Swait 2004), we employed the first six items presented in Table 1 to measure brand credibility. The two components of the brand credibility construct, namely expertise (first two items in Table 1) and trustworthiness (next four items in Table 1), are both included in credibility. These items were measured on nine-point agree-disagree scales; credibility for a person and brand combination was calculated as the simple average of all six items. There is the possibility, however, that such measures might simply reflect individual differences (i.e., an individual rates all brands better or worse than other individuals); thus, the final construct estimate was defined for brand i, person n, as the mean-centered value $C_{in} = \tilde{C}_{in} - \bar{C}_n$, where

$$\tilde{C}_{in} = \sum_{j=1,\ldots,6} x_{ijn} \Big/ 6$$

is the simple average of the six items x_{ijn}, and $\bar{C}_n = \sum_i \tilde{C}_{in}/K$ is the person-specific average of $\tilde{C}_{in}$ over the K brands.

Table 1 also shows measurement scales for three other constructs: PQ, PR, and ICS. Recall that Erdem and Swait (1998) showed that brand credibility is an antecedent to these three constructs, which are the mediating mechanisms whereby credibility affects product evaluation and utility.

We defined person- and brand-specific PQ, PR, and ICS measures by averaging the respective items given in Table 1, then centering each construct within person, analogously to the procedure used for credibility. These measures permit examination of how credibility affects choice set formation and preference discrimination. To ascertain that these indices of credibility, quality, risk, and information costs maintain the expected interrelationships between them, as specified by Erdem and Swait (1998), we estimated simultaneous equation models involving only observables (i.e., the calculated indices) by product class, and confirmed that the credibility index, decomposed into trustworthiness and expertise, is an antecedent of the other three construct indices. These results, not presented here, are available from the authors.

In addition to rating each of five brands[6] in terms of the items in Table 1 (as well as providing certain other brand-level information), respondents also completed a simple pricing choice experiment involving 17 choice sets or scenarios for both product categories that they rated on the aforementioned items. An orthogonal main effects design from the 4^{5-3} factorial was used to construct 16 choice sets. This design yields one choice set with all brands priced at their lowest levels, so a 17th set with all brands priced at their highest levels was added to capture a pure category demand effect; we also included a "none of these" option in each set to allow respondents to opt out of the category entirely if they didn't like the brands, the prices, or both. Subjects could thus choose one of the five brands at the prices offered, or select "none of these."

We placed another question between the two main tasks of interest that asked respondents (a) to evaluate the degree of confidence they felt in assessing a new product in each of 21 product categories (including frozen orange juice concentrate and PCs) before trial, after one trial and after one year of use, by means of seven-point agree-disagree scales; and (b) to associate statements with each of the same 21 categories

[6] The brands used in Study 1 were, for juices, Dole, Minute Maid, Sunkist, Tropicana, Welch's; for PCs, Apple, Compaq, Dell, Gateway, IBM.

Table 2 Estimation Results for Juices (Study 1)

	(Asymptotic t-statistics)				
	(a) MNL brand het.	(b) MNL credibility and brand het.	(c) MNL PQ, PR, ICS	(d) IAL credibility & brand het.	(e) IAL PQ, PR, ICS and brand het.
Utility function (V_{in})					
Brand 1	3.713 (12.4)	3.087 (29.1)	3.174 (29.8)	2.378 (6.1)	3.936 (4.4)
Brand 2	4.523 (11.4)	3.651 (34.5)	3.643 (34.3)	2.845 (7.3)	3.613 (4.6)
Brand 3	2.957 (13.3)	2.837 (26.3)	2.918 (26.6)	2.254 (6.4)	3.661 (4.5)
Brand 4	4.325 (11.6)	3.554 (33.4)	3.514 (33.2)	2.534 (6.3)	4.210 (4.8)
Brand 5	3.058 (12.9)	2.884 (26.2)	2.991 (27.3)	2.285 (5.4)	2.810 (4.8)
ln(Price)	−7.429 (−7.9)	−5.931 (−39.7)	−6.129 (−38.8)	−6.206 (−10.1)	−10.523 (−5.0)
Credibility	0	0.893 (38.3)		1.802 (8.1)	
PQ			0.213 (10.3)		2.286 (4.9)
PR			−0.338 (−11.8)		
ICS			0.459 (13.7)		
σ^2_{brand}	2.352 (2.0)	3.76E–10 (—)	0	3.76E–10 (—)	0.810 (1.1)
Effect-size function ($\ln \tau_{in}$)					
Brand 1				0.072 (0.8)	−0.593 (−3.6)
Brand 2				0.12 (1.3)	−0.454 (−3.2)
Brand 3				0.25 (2.3)	−0.254 (−1.4)
Brand 4				0.011 (0.1)	−0.415 (−3.1)
Brand 5				0	0
Credibility				0.366 (5.3)	
Credibility**2				−0.051 (−1.7)	
PQ					0.295 (4.0)
PQ**2					0.037 (1.5)
PR					0.004 (0.1)
PR**2					−0.352 (−5.7)
ICS					0.241 (2.4)
ICS**2					0.258 (3.9)
Brand inclusion functions					
Brand 1				4.267 (9.5)	4.867 (14.2)
Brand 2				4.638 (10.6)	5.723 (16.3)
Brand 3				3.838 (8.9)	4.597 (14.2)
Brand 4				4.965 (10.6)	5.179 (15.6)
Brand 5				4.024 (8.4)	5.116 (14.3)
None				−0.458 (−1.4)	−1.148 (−7.4)
Price				−2.339 (−8.1)	−3.421 (−16.7)
Credibility				−0.132 (−1.1)	0
PQ					−0.043 (−1.2)
PR					−0.382 (−11.0)
ICS					0.376 (9.2)
LL(convergence)	−4,036.67	−3,538.66	−3,425.49	−3,417.74	−3,235.02
Rho-squared Akaike	0.2164	0.3129	0.3344	0.3336	0.3677
Number of parameters	7	7	9	21	28

Notes. (a) All SML estimates based on $R = 150$ Halton replicates. (b) All construct indices are mean-centered for each individual respondent. (c) Number of observations: 6,632 choices from 391 respondents. (d) Stochastic brand effect estimated from IID normal variates.

that describe their familiarity with it, potential risks involved in a purchase, the type of benefits offered, their level of involvement, hedonistic aspects of purchasing in the category, and so forth (these measurement items are detailed in Erdem et al. 2002, Table 2). This information was considered useful as a means of supporting interpretation of results about the two product classes.

The two product categories investigated in our empirical research (frozen orange juice concentrate and PCs) were chosen to cover a wide enough range of potential uncertainty and sensitivity to uncertainty. We wanted to use two product categories that would vary widely with respect to level of involvement, degree of potential PR, and information costs. One factor that affects potential information costs and PR is the imperfect observability of attributes, a concept describing the extent to which consumers can evaluate perfectly the product attributes just by search, through just one or perhaps a few consumption experiences, or through a long consumption history (Nelson 1970, 1974). Indeed, certain attributes may never be perfectly observable (i.e., credence attributes; Darby and Karni 1974). The intervening task mentioned above clearly showed that these subjects, as a group, viewed orange juice concentrate as a search or short-term experience good and the PC as a much-longer-term experience or credence good. The subjects also viewed PCs to be a more complex and higher-involvement category. Considering also that PCs are several orders of magnitude more expensive than orange juice, potential information costs and PR are expected to be higher in PCs. Studying the impacts of brand credibility on choice in such widely differing product classes permits us to examine whether credibility may have different impacts on choice across differing levels of potential information costs and PR.

One would expect, for example, the effect of credibility on choice set formation to be larger in PCs than in juice, given that potential uncertainty and risk are higher for PCs; the data collected through the intervening task described above confirmed this perception on the part of respondents. In regard to the differential mechanisms through which credibility may operate in PC versus juice, in low involvement categories, for example, consumers may have high sensitivity to information costs (they are not willing to bear information costs, even though the potential costs may be low), hence ICS due to credibility may be a more important factor in the choice set generation stage for juice than for PCs (in which consumers are willing to bear some information costs). There is ample empirical evidence, for example, that consumers are very sensitive to information costs in low involvement product categories. For example, Internet shopping agents provide a great deal of information about different retailers even in the case of rather homogeneous products (e.g., books and CDs), but consumers are willing to pay price premiums for credible retailers since they do not want to invest in comparing different online retailers (see, e.g., Iyer and Pazgal 2003).

3.1.3. Model Estimation Results. Tables 2 and 3 present parameter estimation results[7] for five choice models for juice and PCs, respectively. The first three models for each product category are intended (a) to provide baseline comparisons, (b) to make a specific point about brand-level stochastic heterogeneity, and (c) to show that one has a better and more accurate understanding of the mechanisms through which brand credibility operates in models that incorporate both choice set and conditional brand choice stage. We shall concentrate our presentation on the last two models for each product class. In the paragraphs that follow, we will discuss the results for the two product classes in parallel.

Model (1) is a simple MNL model that has only brand constants, price and brand heterogeneity. The latter is specified as independent and identically distributed (IID) normal variates across brands. (The assumption of identical distribution across brands is made for parsimony, based on empirical findings.) From Tables 2 and 3 it is apparent that there is significant brand-level heterogeneity, since the variance of the normally distributed stochastic brand effect is statistically different from zero at the 95% confidence level, in both product classes. However, Model (2) adds the credibility construct to the MNL utility function in Model (1); the log likelihood increases significantly, and most interestingly, the stochastic brand effect (the variance of taste distribution that had been set to be the same for all brands) goes to zero (in juice) or becomes nonsignificant (in PCs). For these data, at least, it seems that the inclusion of the brand-level credibility construct not only accounts for all the variability captured by the unobserved heterogeneity in tastes, but also considerably improves goodness-of-fit.[8] The credibility impact on the estimated utility function, confirming prior results from Erdem and Swait (1998), is strong and positive.

Model (3) is the final baseline model: we substitute the component credibility constructs (PQ, PR, and ICS) into the utility function in place of their common antecedent. All three constructs are found to have strong and statistically significant impacts in the expected directions. To contrast Models (2) and (3), note that in both product categories the latter model has a much better log likelihood value than the former, at an additional cost of only one parameter. This suggests that the simple use of the brand credibility construct to explore how brand effects are actually operationalized for consumers is less insightful than using its succeeding constructs, PQ, PR, and ICS. However, Model (3) also highlights the reduced form nature of the baseline models: although all three succeeding constructs are statistically significant in both

[7] Parameter estimation was done by simulated maximum likelihood (SML), with 150 quasirandom Halton replications used throughout. We refer the reader to Keane (1993) for an overview of SML estimation methods. Note that the log likelihood function considered each choice replication of the individual to be independent, something necessary by the very structure of the choice set formation models, which permit the choice set to vary from one replication to the next.

[8] It should be noted that, while the literature on brand choice models estimated on scanner panel data shows significant unobserved heterogeneity in tastes, those models typically do not incorporate behavioral or attitudinal observables that vary across consumers, thus leading to unobserved heterogeneity. A complementary explanation for this result is that our subjects are quite homogeneous in age and other sociodemographic characteristics, which would not be the case in a scanner panel.

product classes, these models in essence say nothing more than that the utility of a product rises in quality, drops in risk, and rises in saved decision costs. Model (3) simply confirms the structural equation models of Erdem and Swait (1998), without any further explanation of how brand credibility works its impacts. Since the purpose of our paper is to explore the impact of brand credibility on choice set formation and preference discrimination, Models (1)–(3) of Tables 2 and 3 cannot help us in this regard.

Instead, we must look to Model (4) in these tables, which implements the IAL model specified in Expressions (2a–2e) and (3a–3c). This model includes brand credibility in the choice set formation availability functions, in the effect-size function, and in the utility function. Note that, consistent with models discussed earlier, no statistically significant stochastic brand heterogeneity is found in either product category. Somewhat unexpectedly, brand credibility is found to have a nonsignificant impact in choice set formation; this result could be explained in juices by the fact that because this is a low-involvement product category about which these respondents may feel they're not well informed, brand credibility does not serve as the basis for an early brand triage; however, the result is also found in PCs, so we must look for an explanation elsewhere (we will elaborate on this later in this section). Note, however, that in the utility function of Model (4), in both products credibility is found to have the expected strong and positive effect on utility; in addition, the effect-size function τ shows that preferences are better discriminated among brands that have high credibility, and that this effect has a somewhat marginally diminishing impact as credibility grows.

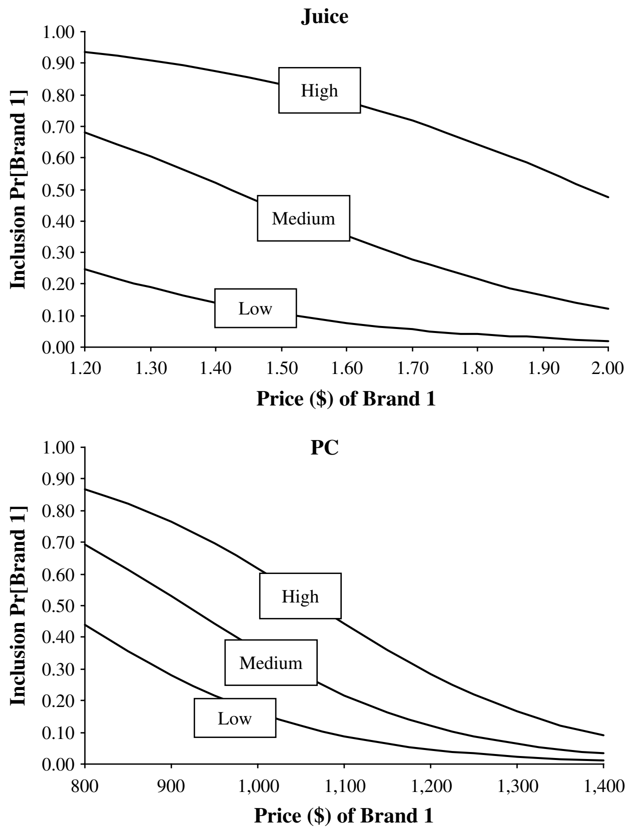
Model (5) substitutes the successors of credibility, PQ, PR, and ICS, into the two-stage choice model system (Expressions (2a)–(2e) and (4a)–(4c). This model allows us to explore the mechanisms whereby brand credibility differences are translated into impacts in the different choice stages. In the brand choice set inclusion functions, Model (5) shows that PQ has a statistically negligible impact on brand inclusion in the choice set for the juice category, but an important role in the PC class; in both product categories, increasing PR decreases the probability of brand inclusion, although the impact is more pronounced in juice than in PCs; finally, increasing ICS increases the likelihood of inclusion of the brand in the individual's juice choice set, but the corresponding impact in PCs is not statistically significant at the 95% level. Thus, in the juice category, quality seems not to have been employed by these respondents in their screening of alternatives, but PR and information processing costs were used as screening criteria. In the PC class, however, quality was a screening criterion, as was risk reduction; ICS seems not to have played a statistically significant role in screening PC brands or products. Note that the nonsignificance of brand credibility in choice set formation in Model (4) may well have to do with the opposite valences of PR and ICS in juice (or PR and PQ in PCs) in Model (5), a consistent effect in both product classes.

Turning our attention to the utility function in Model (5), it will be noted that only PQ is included in this model component. In both product classes, the inclusion of PR and ICS in the utility function, over and above their inclusion in other model components, did not result in statistically improved models; hence, we decided to present only these simpler versions with PQ. It is possible that this result is due to multicollinearity between these three constructs; Study 2, because of a different experimental design, will be useful in clarifying this issue. Quality, as expected, is found in the present data to have a strong positive impact on brand comparisons within the individual's choice set. Note also the maintained support for stochastic brand homogeneity with the inclusion of perceived quality in the utility functions. Again, it is notable that the explanatory power of Model (5) is significantly superior to that of Model (4), suggesting the usefulness of decomposing the impact of brand credibility into that of its successor constructs.

With respect to preference discrimination, the effect-size functions τ of both product categories show themselves to increase significantly with increasing PQ, decreasing PR (for juices, but not PCs), and increasing ICS. Both PQ and ICS display a strong increasing effect through the tested range of these constructs in the juice category, without any amelioration of the impact at higher construct levels; PR has the same type of impact for juices, but in the opposite direction, as expected. These opposite effects may well account for the overall diminishing marginal impact of brand credibility on preference discrimination, as found in the effect-size function of Model (4). For PCs, preference discrimination is also found to be strongly affected by credibility (Model 4), with a diminishing marginal impact. Model (5) indicates that PQ and ICS are the likely means whereby preference discrimination is actually accomplished in PCs; PR seems to have played its important role in the choice set formation process.

It is helpful to visualize the different impacts captured in Model (5) through some simple graphs. In Figure 2, we present the estimated brand inclusion probabilities for Brand 1, both for juice and for PCs. (Brand 1 was arbitrarily selected for this illustration among the five presented, and it represents a different brand in each product category.) The probabilities of inclusion in the latent choice set are presented as a function of price and credibility (set at low, medium,

Figure 2 **Choice Set Formation as a Function of Price and Brand Credibility**



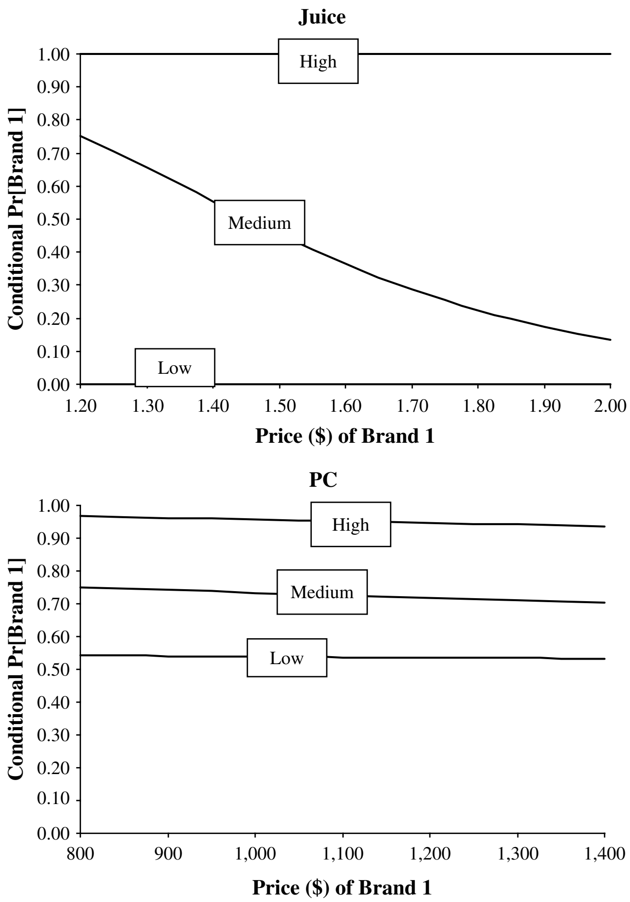
Note. High, medium, low are brand credibility levels.

and high levels). For a given level of credibility, PQ, PR, and ICS are estimated according to the simultaneous equation models (a different one for each product category) alluded to before. In both product categories, inclusion of Brand 1 in the subject's choice set is predicted to become less likely as price is increased and as credibility decreases. While a cursory glance at Figure 2 might suggest that the overall impact of credibility on brand inclusion in the choice set is greater in the juice category than in the PC category, closer examination will find that to be a misapprehension. Specifically, for these two brands calculation of the odds of inclusion in the choice set for medium- and high-credibility perceptions of the brands, compared to low-credibility perception of the brands, varies as follows: (a) for juices, medium-credibility perception makes it 1.6 to 2.7 times more likely that the brand is included over the price range shown than is the case for a low perception of credibility, while the odds vary from 2 to 6.4 times for a high-credibility perception of Brand 1 compared to a low-credibility perception; (b) in PCs, medium-credibility odds vary from 6.5 to 18.5 times greater likelihood, while high-credibility odds vary from 9 to 220. Thus, the overall impact of credibility on choice set formation is estimated to be quite a bit larger in the PC category than in the juice category.

While detailed comparison of the two charts in Figure 2 leads to the conclusion of the greater relative overall importance of brand credibility for choice set formation in the PC category compared to the juice category, the simultaneous use of the coefficients of Model (5) will suggest how these impacts are created via PQ, PR, and ICS. In PCs (see Table 3), for example, we have already noted that brand inclusion probabilities are mainly affected by PQ and PR, and only marginally by ICS. Furthermore, between quality and risk, quality is by far the greater determinant of brand inclusion. This suggests that the role of brand credibility in this first stage of choice in this high-involvement, high-price product category is to permit a quality-based screening of alternatives to occur; PR, on the other hand, has only something like one-third the impact of PQ in this stage. In juices, by contrast, brand inclusion is strongly and about equally determined by PR and ICS, while PQ has no impact to speak of. This suggests that for choice set formation in the juice category, brand credibility is the basis for economizing on information costs, as well as risk minimization; quality will play a role subsequently during the comparative evaluation of brands within the choice set.

Figure 3 is shown to describe how choice probabilities, conditional on choice set formation, are affected by credibility. Note that the conditional choice probabilities that we have estimated are not only a function of brand utility, but also of effect size, which in turn are affected by PQ, PR, and ICS. The preference discrimination effect we hypothesized and illustrated in Figure 1 is quite evident in Figure 3, where we show for both product categories the conditional choice probability for Brand 1 (again arbitrarily chosen) as a function of price and credibility (varying from low to high). (We once more use the simultaneous equation model to cascade the effects of credibility via the PQ, PR, and ICS constructs.) These choice probabilities are calculated using the estimated utility and effect size functions for Brand 1, assuming a binary choice against an aggregate good with zero utility. The impact of credibility is clearly discernible in both product categories, but is quite dramatic in the juice category. The greater sensitivity of Brand 1's conditional choice probability in juices, compared to PCs, is in large part due to the effect-size function in the former product category: in the juice category, credibility has strong discernible impacts via all three credibility successor constructs, whereas in the PC category, credibility's impact is mostly restricted to information costs. This may reflect the possibility that once the choice set is formed, brand credibility actually plays a more determinant role in juices

Figure 3 Brand Credibility, Preference Discrimination and Conditional Choice Probability



Note. High, medium, low are brand credibility levels.

than in PCs, aiding the consumer more in making the final decision among the reduced set of brands. In PCs, however, brand credibility seems to have been stronger in determining the choice set itself, and then its role in the second-stage evaluative and comparative process is basically limited to the impact of quality differences.

Finally, it is worth noting the relative importance of the subconstructs of brand credibility, trustworthiness (Tr), and expertise (Ex) in the two categories we analyze. An analysis of the simultaneous equation system involving the indices for Tr, Ex, PQ, PR, and ICS (model available upon request) indicates that the major impact of credibility on the latter three constructs is via expertise in the juice category (this is not to say that trustworthiness does not play some role), but is balanced between trustworthiness and expertise in the PC category.

3.2. Study 2

As indicated before, Study 1 focused on exploring the validity of certain brand impacts on different components of the choice process across two widely varying product categories. Study 2 was conducted to confirm these results in the PC category, where one expects the more substantive brand impacts to be present; it was also conducted to test their robustness to certain challenging conditions: choice contexts with more brands than used in Study 1, and with choice set sizes varying from scenario to scenario. In addition, Study 2 also has the objective of collecting information to support analyses of choice set formation versus choice behavior in a manner independent of the IAL model, thus permitting a check on the validity of the latent choice set formation model as a means to exploring the impact of brand on different stages of choice. As will be subsequently seen, this design change proved quite useful in elucidating certain effects that remained somewhat ambiguous in Study 1.

3.2.1. Data Collection. Using a survey instrument very similar to that of Study 1 (with certain notable differences to be discussed), 287 undergraduate business students at two North American universities were used as sources of data for Study 2.

The main differences between the two instruments are as follows: (a) Study 2 involved only PCs, whereas Study 1 also had juices. (b) The experimental choice task for Study 2 used eight national brands plus a local computer store generic brand (or a total of nine brands), while Study 1 had only five brand. (c) Whereas Study 1 had fixed choice sets of six alternatives (always showing the same five brands plus the "None" alternative), Study 2 used choice sets with as few as two and as many as nine brands, in addition to the "None" alternative.[9] (d) Whereas Study 1 elicited only the single final choice from respondents, in Study 2 they were requested to provide the single final choice alternative as well as all other alternatives seriously considered for choice.

Subjects in Study 2 also provided responses to the same items as shown in Table 1. Construct estimates were calculated in an identical fashion to calculations in Study 1.

3.2.2. Modeling Results. Only three models were estimated from the data of Study 2, and these are presented in Table 4. The first two models are straightforward: the first model is a binary logit model estimated on the elicited consideration data, and confirms that the PQ, PR, and ICS constructs have a statistically important impact on consideration, in the expected directions; the second model is a simple conditional MNL model with effect-size function, based on the

[9] The experimental design for Study 2 involved 52 different runs. These were initially generated randomly, then an exchange algorithm was used to improve design characteristics. The design was blocked into four groups of 13 runs. The brands used in Study 2 were Apple, Compaq, Dell, Gateway, HP, IBM, Sony, Toshiba, plus the generic moniker "local computer store."

Table 3 Estimation Results for PCs (Study 1)

	(Asymptotic t-statistics)				
	(a) MNL brand het.	(b) MNL credibility and brand het.	(c) MNL PQ, PR, ICS	(d) IAL credibility and brand het.	(e) IAL PQ, PR, ICS and brand het.
Utility function (V_{in})					
Brand 1	50.063 (7.7)	38.603 (14.1)	36.078 (37.6)	40.325 (11.0)	26.779 (3.0)
Brand 2	49.92 (7.7)	39.136 (14.1)	37.034 (38.3)	40.748 (11.2)	21.299 (6.0)
Brand 3	52.457 (7.7)	40.256 (14.1)	37.68 (38.6)	40.765 (11.1)	20.983 (6.1)
Brand 4	50.077 (7.7)	39.105 (14.1)	36.901 (38.1)	40.395 (11.1)	21.498 (6.0)
Brand 5	51.603 (7.7)	39.698 (14.1)	37.188 (38.3)	40.826 (11.5)	21.081 (6.2)
ln(Price)	−7.224 (−7.5)	−5.554 (−13.5)	−5.208 (−37.2)	−5.589 (−11.0)	−2.898 (−6.2)
Credibility	0	0.798 (14.2)		0.99 (7.0)	
PQ			0.486 (15.4)		0.142 (2.3)
PR			−0.061 (−2.6)		
ICS			0.407 (11.3)		
σ^2_{brand}	4.065 (2.4)	0.625 (1.5)	0	0	0.007 (0.1)
Effect-size function ($\ln \tau_{in}$)					
Brand 1				−0.295 (−2.7)	−1.9 (−1.8)
Brand 2				0.246 (2.1)	−0.051 (−0.2)
Brand 3				0.06 (0.8)	0.319 (2.7)
Brand 4				0.035 (0.3)	−0.283 (−0.9)
Brand 5				0	0
Credibility				0.236 (4.3)	
Credibility**2				−0.02 (−1.5)	
PQ					0.103 (2.0)
PQ**2					0.013 (1.0)
PR					−0.017 (−0.9)
PR**2					0.003 (1.0)
ICS					0.416 (4.3)
ICS**2					−0.085 (−3.5)
Brand inclusion functions					
Brand 1				3.279 (6.4)	6.417 (6.8)
Brand 2				2.656 (6.6)	7.805 (7.7)
Brand 3				4.748 (9.4)	9.883 (7.7)
Brand 4				3.284 (6.4)	7.837 (7.4)
Brand 5				3.664 (8.5)	8.833 (7.7)
None				∞^c	0.170 (0.2)
Price				−2.623 (−6.4)	−0.007 (−10.2)
Credibility				−0.101 (−1.5)	0
PQ					0.637 (6.3)
PR					−0.188 (−2.9)
ICS					0.212 (1.6)
LL(convergence)	−3,771.08	−3,294.8	−3,089.92	−3,152.50	−3,034.50
Rho-squared Akaike	0.2575	0.3509	0.391	0.3764	0.3982
Number of parameters	7	8	9	20	28

Notes. (a) All SML estimates based on $R = 150$ Halton replicates. (b) All construct indices are mean centered for each individual respondent. (c) Infinity in the availability function indicates that alternative is always present. This constraint was imposed during estimation. (d) Stochastic brand effect estimated from IID normal variates. (e) Number of observations: 6,194 choices from 366 respondents.

stated choice sets, again confirming that these constructs (and, hence, brand credibility) have a substantive impact on utility, conditional on stated choice set. The only statistically significant effect among the constructs of interest in the effect size is PR (see §4).

The binary consideration model in Table 4 differs from the models in Tables 2 and 3 from Study 1: it includes several choice set size effects that are of interest. The reason they can be identified in Study 2 is due to the explicit variation in brands and number of brands present from one scenario to another, whereas in Study 1 the number of brands and the set of brands shown were held constant across scenarios. (The conditional MNL model does not include size effects in the utility function due to our expectation that product utility should not be a function of number of brands.) Of interest here is that the likelihood of the brand being considered or included in the choice set decreases with number of brands, suggesting that context complexity leads to choice set size reduction, ceteris paribus. In addition, it is found that the impact of PQ as a screening mechanism for brand inclusion in the stated choice set increases with the number of brands, whereas the impacts of PR and ICS are not sensitive to this context variable. Turning our attention to the MNL model conditional on stated choice, we find that number of brands affects the PR construct negatively: as the number of brands increases, the effect size function decreases in PR. This suggests that as risk perceptions increase in the presence of more brands, preference discrimination decreases. Hence, this model suggests that it is possible that as the number of brands presented increases, respondents behave as if nonsystematic factors play a greater role in defining product utility.

The third model in Table 4 is analogous to the specification of Model (5) in Table 3: it is a full IAL model with person-brand heterogeneity. However, it differs from Model (5) in Table 3 due to the inclusion of a number of brand effects in the brand inclusion and effect-size functions. This choice set formation and choice specification on Study 2's data basically confirms the effects previously observed in Study 1: brand credibility has a discernible, substantive impact on all three components of the model (choice set formation, effect size, and choice), in expected directions. The number-of-brands context variable shows that as this increases, ceteris paribus, (a) any brand is less likely to be considered; (b) the "None" alternative is more likely to be considered (another response to context complexity); (c) the PR construct plays an increasingly stronger role as a screening mechanism, while the impact of PQ and ICS is not sensitive to these increases in contextual complexity; and (d) preference discrimination is less negatively affected, suggesting that this construct is correlated with a lower reliance on systematic utility sources when more brands are being presented.

It is informative to examine whether using the full-information structural choice set formation Model (3) of Table 4 is superior to the use of the separate consideration and conditional choice Models (1) and (2) of the same table. It is not possible to directly compare log likelihoods or perform nested statistical tests because the data structures utilized for the models differ: Model (1) uses every alternative presented, but in a yes or no format; Model (2) is restricted to the use of the one choice set composed only of those alternatives indicated to have been seriously considered; and Model (3) uses all alternatives presented, in a choose-one-from-many format, but with explicit structural (and latent) consideration of every possible choice set that can be formed from the alternatives presented in the scenario. However, one means of comparing these models is to apply the estimated coefficients from the nonstructural Models (1) and (2) in the IAL framework of Model (3), and see how well this combination predicts the unconditional data used to estimate Model (3). The rationale for doing this is that the coefficients of Model (1) are analogous to those of the brand inclusion function of Model (3), while those of Model (2) correspond to the utility and effect-size functions of Model (3). From Table 4, it can be seen that the log likelihood at convergence of Model (3) is $-4{,}174.75$, which is the global optimal value achieved by the maximum likelihood estimator; the application of the coefficients of Models (1) and (2) in the IAL model is necessarily worse, at $-4{,}314.76$. The Pearson chi-squared statistic, a measure of asymptotic normalized residuals behavior that converges to unity in a well-specified model, is 1.12 for Model (3) and a somewhat higher 1.27 for the application of Models (1) and (2) coefficients. These results show that the structural model using latent choice sets has better performance on the common data, suggesting that the IAL model better captures the underlying behavior than do the two partial models. Overall, the differences in performance are not overwhelming, but they are substantively significant. In addition, it will be noted that particular parameters are sometimes markedly different between the model systems: e.g., in the brand inclusion function of Model (3), the impact of ICS is estimated to be negligible, whereas in Model (1) there is a statistically significant effect estimated for this construct: the structural choice set formation model results suggest that ICS plays no role in brand inclusion, but the more limited brand consideration model suggests the contrary. We believe that the former results are more credible due to explicit modeling of the choice set formation in the IAL model.

There are some noteworthy comparisons that can be made between the two PC IAL models of Studies 1 and 2. In making these comparisons, it is important to keep in mind that the essential design differences between the studies is that the latter has significantly more brands and the number of brands shown in a scenario is variable. In the brand inclusion function, Model (3) of Table 4 indicates that PQ and PR have significant roles in determining choice set membership; this is essentially the same result shown in Model (5) of Table 3, where ICS is not statistically significant at the 95% confidence level. In the utility function of Model (5) in Table 3, PQ is statistically significant but the other constructs are not (as mentioned before, this result may have been caused by multicollinearity between the three constructs, leading us to present the best model with a single construct); all three constructs are cleanly identified in Study 2, showing that PQ and ICS continue to play significant roles in brand comparisons, conditional on choice set. This improvement in the estimability of

Table 4 Estimation Results for PCs (Study 2)

	(Asymptotic t-statistics)		
	(a) Binary logit consideration model	(b) MNL choice model conditional on stated consideration set	(c) IAL with brand heterogeneity
Utility function (V_{in})			
Brand 1		17.351 (5.26)	14.195 (2.39)
Brand 2		17.959 (5.35)	14.715 (2.39)
Brand 3		18.459 (5.27)	14.809 (2.40)
Brand 4		17.354 (5.28)	14.513 (2.39)
Brand 5		17.68 (5.29)	14.091 (2.39)
Brand 6		17.868 (5.25)	14.473 (2.39)
Brand 7		18.316 (5.25)	15.398 (2.39)
Brand 8		18.447 (5.27)	15.320 (2.39)
Brand 9		17.877 (5.63)	17.257 (2.41)
ln(Price)		−2.493 (−5.30)	−2.043 (−2.39)
PQ		0.396 (4.24)	0.647 (2.36)
PR		−0.132 (−1.82)	−0.096 (−1.55)
ICS		0.126 (0.91)	0.640 (2.30)
Var(brand constants)			0 (0)
Effect size function ($\ln \tau_{in}$)			
Brand 1		0.114 (0.37)	0.754 (4.02)
Brand 2		0.097 (0.55)	0.664 (5.71)
Brand 3		0.158 (0.87)	0.615 (5.38)
Brand 4		0.216 (1.03)	0.752 (4.90)
Brand 5		0.199 (1.13)	0.703 (6.14)
Brand 6		0.161 (0.85)	0.668 (5.74)
Brand 7		−0.045 (−0.24)	0.374 (3.10)
Brand 8		−0.161 (−0.83)	0.384 (3.25)
Brand 9		0	0
PQ		0.131 (1.87)	−0.01 (−0.13)
PQ^2		−0.016 (−1.65)	0.033 (5.26)
PR		0.187 (3.36)	0.087 (1.81)
PR^2		0.006 (1.06)	0.005 (1.81)
ICS		−0.046 (−0.46)	−0.158 (−1.74)
ICS^2		0.015 (1.35)	0.030 (3.08)
Size		−0.021 (−1.15)	0.114 (2.24)
Size ∗ PQ		0.005 (0.61)	−0.018 (−2.24)
Size ∗ PR		−0.021 (−3.89)	−0.005 (−0.94)
Size ∗ ICS		0.004 (0.44)	−0.004 (−0.40)
Brand inclusion functions			
Brand 1	1.041 (9.00)		0.470 (0.96)
Brand 2	2.204 (22.4)		1.039 (3.36)
Brand 3	2.909 (28.06)		2.281 (7.42)
Brand 4	1.597 (15.56)		0.503 (1.46)
Brand 5	2.003 (20.73)		1.762 (5.51)
Brand 6	1.946 (18.80)		1.402 (4.78)
Brand 7	2.167 (20.36)		1.112 (3.87)
Brand 8	1.696 (16.36)		0.779 (2.54)
Brand 9	1.307 (12.64)		−0.451 (−1.73)
None	0		−2.258 (−3.61)
Price/1,000	−1.401 (−19.02)		−1.051 (−6.2)
PQ	0.470 (7.15)		0.388 (3.21)
PR	−0.038 (−0.69)		0.111 (1.09)
ICS	0.254 (2.57)		0.016 (0.09)
Size[Brands 1–9]	−0.138 (−16.3)		−0.141 (−4.46)
Size[None]	0		0.567 (3.56)
Size[1–9] ∗ PQ	0.032 (3.80)		0.007 (0.43)
Size[1–9] ∗ PR	−0.01 (−1.37)		−0.039 (−2.79)
Size[1–9] ∗ ICS	0.013 (1.03)		0.016 (0.68)
LL(convergence)	−10,053.6	−3,019.63	−4,174.75
Rho-squared Akaike	0.3071	0.3116	0.3788
Number of parameters	17	31	51

Notes. (a) All SML estimates based on $R = 150$ Halton replicates. (b) Log likelihoods are not comparable across models since data structures are unique to each model. (c) All construct indices are mean centered for each individual respondent. (d) Stochastic brand effect estimated from IID normal variates. (e) Number of observations: 24,700 choices from 287 respondents.

these parameters is due to the explicit variation of presence or absence of brands by the experimental design used in Study 2. Finally, in terms of the effect-size functions, the two studies indicate that PQ and ICS affect preference discrimination in the expected directions (and that the impact of PQ decreases somewhat with number of brands presented), while the impact of PR is not statistically significant at the 95% level.

Overall, Study 2 has confirmed all the important results of Study 1, while extending the latter's findings by showing that they are robust to significant changes in decision context complexity (number of brands and changing available set composition).

4. Discussion, Conclusions, and Future Research

We have proposed that brand credibility will affect the formation of choice sets, consumer preferences, and preference discrimination. We have also investigated the mechanisms through which credibility effects materialize, namely through PQ, PR, and ICS. We have found strong evidence for brand credibility effects and differential mechanisms through which brand credibility's impact materializes on choice set formation, brand utility, and preference discrimination.

In both the juice and PC categories we found that PQ continued to play a significant role in defining the utility of brands, even after credibility effects are captured at the choice set formation stage. In addition, Study 2 (because of its different and more-flexible study design) results suggest that in the PC category, ICS has just as important a role in defining utility as quality. Risk perceptions, however, have negligible impact at this evaluative stage, conditional on choice set formation. Comparing these findings with those of a simple MNL model with no explicit choice set formation process modeled, which suggest that all three constructs play a role in determining product utility (see Models (3) in Tables 2 and 3), highlights the need for an explicit, structural choice set formation model to understand the mechanisms whereby credibility affects brand choice.

In both categories, we found that credibility affects preference discrimination. We found that choice set size moderates the effect of brand credibility on preference discrimination: higher brand credibility is associated with higher preference discrimination when choice set sizes are constant or the universal brand set remains unchanged across choice instances (as in Study 1). When choice set size varies greatly (as in Study 2), lower brand credibility (through lower perceived quality) is associated with higher preference discrimination, suggesting that decision makers place greater weight on quality differences among lower-quality brands than among higher-quality brands. This could well be because in a changing, dynamic environment that inhibits the development of rule-based choice set formation, and in which high-quality brands may not be included, preference discrimination (i.e., sharper tastes) will be discernible at low quality levels, as opposed to high quality levels.

Our empirical results revealed statistically nonsignificant credibility construct effects at the choice set formation stage. However, we believe this finding to be an outcome of the offsetting effects of brand credibility on choice sets through PQ and PR in PCs, and ICS and PR in juice. Models containing only the end constructs (PQ, PR, and ICS) show that, indeed, PQ and PR in PCs, and PR and ICS in juice have statistically significant effects on choice set formation. (Higher PQ, lower PR, and higher ICS increase the probability of a brand being included in a choice set, ceteris paribus.)

Noteworthy also are the differential mechanisms through which credibility operates at the choice set formation stage in juice versus PCs. ICS is (not) significant in juice (PCs), whereas PQ is (not) significant in PCs (juice). This is an interesting result, which can be explained by the differential involvement and levels of uncertainty and sensitivity to such uncertainty in these two categories: in juice, consumers are not willing to accrue information costs (sensitivity to information costs is high) even though potential information costs are likely low, whereas in PCs, consumers are likely to be willing to bear higher information costs. Furthermore, in the juice category, PQ differences among brands may not be large enough for PQ to determine the likelihood of a brand to be included in the choice set, whereas in the PC category, consumers may perceive larger differences across brands. Our results also indicate that credibility's impact on consumer choice processes through PR, PQ, and ICS are mainly due to the expertise dimension of brand credibility in juice, whereas both subcomponents of brand credibility (expertise and trustworthiness) are affecting consumer choice processes in the PC category.

These results appear reasonable, given that respondents rated PCs to be a more complex and higher-involvement category with more imperfectly observable attributes than juice. The respondents also indicated that they are likely (a) to know less about PCs than about juices, but (b) to be more willing to gather information to make a decision about PCs than about juices.

Our overall results suggest that management of credibility is a key issue in brand management. This is, of course, not a new insight: others had previously pointed out the importance of credibility (e.g., Aaker

1991). However, our results also show the mechanisms through which credibility operates in different contexts. For example, to encourage a brand to be included in the choice set in a low PR–low involvement category such as juice would require focusing on encouraging the brand to be used as a choice heuristic, principally by decreasing consumer information costs, whereas in a high involvement–high PR category such as PCs, marketing efforts would need to be geared mainly toward increasing mean quality expectations, and to some extent decreasing the variance of such expectations.

In regard to the relative importance of trustworthiness versus expertise in juice versus PC, the results obtained from the simultaneous equation system involving the indices for Tr, Ex, PQ, PR, and ICS, along with the results from Tables 2 and 3, suggest certain directions for marketing efforts that differ by product category. In juice, for instance, consumer communications should emphasize quality control to increase brand credibility. According to the results of Table 2, this should (a) enhance the use of the brand as a choice set formation heuristic, leading to greater likelihood of brand inclusion in the choice set; and (b) improve quality perceptions vis-à-vis other brands in the choice set, leading to greater odds of being chosen.

On the other hand, in a high-involvement, high-price category such as PCs, these results suggest that advertising and other marketing actions should build up perceptions of both expertise and trustworthiness. Thus, the message to consumers has to be broader and deeper than in the case of juices: to be sure, the manufacturer's expertise needs to be transmitted, but it is just as necessary to communicate with consumers about such topics as the firm's longevity in the market, the firm's likelihood of future existence, customer satisfaction with prior purchases, customer support after purchase, etc.

We wish to note here an important assumption in our model development that may impose limitations on our conclusions. Specifically, the choice set formation stage in the statistical model (Expression (2d)) assumes that the inclusion or exclusion of an alternative from the choice set is completely uninformative about the inclusion or exclusion of another alternative. This assumption was made to maintain model tractability and make estimation of the statistical model feasible. However, in reality, brands may share unobserved characteristics that cause inclusion probabilities to decrease or increase together. In our models, inclusion probabilities are parametrized by a number of observed brand characteristics, but potentially unobserved characteristics are omitted due to the independence assumption. To the extent that the unobserved characteristics are orthogonal to brand characteristics in the brand inclusion probabilities, our results will be unaffected by the omitted correlations, but if the unobserved characteristics are also correlated with the brand characteristics that parametrize the inclusion probabilities, our estimated effects in those probabilities could be either under- or overstated. In addition, our modeling assumes that the MNL model (and consequently, IIA) holds whatever the structure of the choice set. In reality, correlations between the error terms of different alternatives in a choice would lead to more-complex models of choice conditional on choice set. Future research can profitably investigate whether less-restrictive assumptions in the conditional choice model are warranted.

Another limitation imposed on both our studies has to do with the measurement of credibility and its use in conjunction with the choice experiments. In our method, we measured credibility of each brand prior to observing choices made in designed choice sets. During the choice experiment, however, respondents may have been exposed to brand and price combinations that were, to them, incompatible—e.g., a high credibility brand at a very low price, which might be interpreted by respondents as inconsistent with the perceived credibility of the brand, hence leading to a revision of their credibility perceptions. To the extent that such revisions might occur within the context of a 20-minute paper-and-pencil survey, it seems to us that the major impact would be on the effect-size function, which captures the relative role of unobserved characteristics on utility. Further research on the occurrence and magnitude of such an effect is needed.

There are several other avenues for future research. Our analysis can be extended to include dynamics to explore issues such as choice set formation over time and the dynamics of credibility formation. A larger number of product categories can also be studied to draw more extensive empirical generalizations, as well as to explore factors that may moderate brand credibility effects. Finally, our study is one of the first attempts to link behavioral processes to the measurement of the stochastic component of utility. Further study of such behavioral mechanisms would be fruitful.

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