Mapping the bounds of incoherence: How far can you go and how does it affect your brand?

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Abstract

Consumers form expectations of typical configurations of attributes in a product, based on beliefs of how attributes covary in the product category. Using these beliefs of covariation between attributes (called ‘inter-attribute covariation beliefs’ hereafter), consumers may infer likely levels of one attribute based on the observed levels of the other attributes. In this paper, we examine the case where the proclaimed level of a product attribute is very different from what the consumer would infer, given the level of another product attribute. We are interested in the effect of such an unexpected combination of attributes on perceptions, uncertainty, preference, and ultimately purchase.

We call the presence of such combinations of attributes in a product ‘incoherence’, where a consumer must integrate discrepant information from a number of sources. We show that incoherence occurs frequently in different forms. We develop a formal model of the effect of one particular form of incoherence, unusual or unlikely attribute combinations, on the consumer’s perception of attribute levels, uncertainty, and preference. Our model implies that a product that combines positively valued attributes might increase some elements of preference for the product, but if those attributes occur in unexpected combinations, incoherence will also increase uncertainty, and potentially lower other elements of preference. The net risk-adjusted preference for a product in our model accommodates both the benefit from the expected attribute levels and the multi-dimensional uncertainty associated with incoherence. We derive implications of the model and provide an empirical test that supports those implications. We discuss how the model can be used for product repositioning and new product development.

Key Words: Product Positioning, Product Management, New Products, Brand Management
1.0 Introduction

We examine the situation in which a consumer gains discrepant information about a product’s attribute performance from a number of sources, in particular from other correlated attributes. A product with a combination of attributes that is improbable or unlikely according to the consumer’s beliefs and experience provides that consumer with internally discrepant information. Such a situation occurs frequently in product evaluations, where the consumer receives information about two attributes whose levels are expected to be correlated but where the level of one attribute is far from what the consumer would expect, given the level of the other. As an example, consider the new 2005 Honda Accord hybrid which claims to be a “surprisingly fuel efficient 255 horsepower” car (Newsweek, Nov 22, 2004 p 54). A car with high fuel efficiency and power is deemed surprising because the commonly-observed negative correlation between fuel efficiency and power makes this new combination unexpected. Specifically, the consumer must reconcile the car’s claim of good fuel efficiency with an inference of low fuel efficiency, based on the commonly-observed negative correlation of fuel efficiency and power. Thus, the claim of high fuel efficiency and high power might result in discrepant or unlikely information about the car’s fuel efficiency (and power as well). We call this phenomenon incoherence, where the consumer receives internally discrepant information about attribute performance. The research question that arises here is how the consumer assimilates such discrepant information and what the net effect on product preference will be.

There are many cases that result in incoherence other than those involving unlikely attribute combinations. Consider when a brand name usually associated with the absence of a negative attribute is used for a product that has the attribute (e.g., a caffeinated 7UP as discussed in McGill 1989), or the converse. Other cases of unlikely combinations include brands entering
categories where consumers doubt their appropriateness (e.g., Aaker and Keller’s (1990) Heineken pop corn example), using marketing mix elements that are not a good fit with the brand positioning (e.g., a cheap Porsche, a Rolex watch in K Mart, or American Express Centurion Black cards advertised in *USA Today*) and inconsistent co-branding projects (e.g., Starbucks coffee in McDonalds as discussed in Kachra 1998).

In this paper, we only study the inter-attribute covariation case of incoherence, and model how that incoherence affects the perception of attribute levels, uncertainty, and preference. Incoherence may occur when, in its pursuit of differentiation, a firm tries to position a product to occupy an unoccupied market position, by offering a configuration of attributes that is at once unique and unexpected from the consumer’s perspective. Sujan (1985) suggests that consumers develop a pattern of expectations about a product category – “... a set of hypotheses about what attributes go together, what constitutes typical configurations of attributes ...” (pg. 32). For example, powerful cars are typically believed to be fuel guzzlers (and vice versa), safe cars are typically believed to be boring (i.e., not stylish), and carbonated colas are typically believed to be brown. So when Honda claims that its Accord hybrid is a “fuel efficient 255 horsepower” car, or Volvo claims its 2004 V70 to be “stylish and safe” (http://volvocars-pr.com), or Pepsi launches a blue colored cola called Pepsi-Blue (http://www.spudart.org/pepsiblue/), how will consumers react? In each of these cases, the product has been positioned to occupy a gap in the market, but the important question is whether the consumer will permit the product to first position in, and secondly succeed, in that gap. Products that claim to be “powerful and fuel efficient” (the Honda Accord hybrid), “safe and stylish” (the Volvo V70), and “a cola and blue” (Pepsi Blue) each have an inter-attribute configuration that is inconsistent with typical consumer expectations. The important managerial issue then is how such incoherence affects the consumer’s preference for
and eventual acceptance of the product. Anecdotal evidence suggests that excessive incoherence is likely to hurt the brand. For example, Pepsi has failed twice with non-brown colas: it tried a clear cola, Crystal Pepsi, in 1992 ([http://crystalpepsi.captainmike.org/](http://crystalpepsi.captainmike.org/)) and launched Pepsi Blue in 2002, only to withdraw it in early 2004 as a failure. When the Hong Kong and Shanghai Banking Corporation advertised as “Huge”, but “Personal”, the combination of attributes was not seen as credible or likely by consumers. And in a bridge to our empirical study – if students believe that courses which are interesting also tend to be important for them to take (implying a belief of positive correlation between the importance of the course and how interesting the course is), how easily can a professor with a well-established reputation of teaching uninteresting courses lay claim to teaching important material?

We build a formal model of how a consumer assimilates incoherent information into his or her preference function. Our central thesis is that while combining positively valued attributes may increase expected preference for the product even if those attributes occur in unexpected or incoherent combinations, incoherence will increase uncertainty about the product’s attributes because of the inherent conflict with the consumer’s beliefs about inter-attribute covariation. The consumer’s net preference for a product must then accommodate both the expected benefit of what is being offered and the increased uncertainty associated with “going against the grain.” If the cost of uncertainty (adjusted to reflect the consumer’s risk aversion) is greater than the benefits offered, the consumer’s preference for a product suffers. Our model integrates four factors: (1) the consumer’s beliefs of inter-attribute covariation, (2) the consumer’s perceptions of attributes, (3) the uncertainty of those perceptions, and (4) the consumer’s risk aversion, leading to an expression for the overall risk-adjusted preference for the product.
A better understanding of incoherence can inform several important marketing problems, including (1) improving product design and selection of attribute combinations, (2) choosing a credible, defensible position for a new product launch into an existing market structure, and (3) developing effective communication strategies that emphasize internally consistent (coherent) attributes. Our work suggests that a marketing manager who attempts to differentiate his or her product so that it occupies a gap in the market should understand the consumer belief structures associated with that gap, and the degree to which it is an accessible position from the perspective of those structures. In this paper, we show that inconsistent or unlikely combinations run the risk of the product being viewed as incoherent, affecting the product’s credibility and consumer preferences, thereby influencing the product’s market acceptance.

We proceed as follows. In the next section, we present a conceptual framework of perception and preference formation and suggest how incoherence might affect the magnitude and uncertainty of each. This framework has its roots in the literature on covariation beliefs, consumer inference-making, uncertainty, and preference formation. Next, we present a formal model of the effect of incoherence on preference. We use comparative static analysis based on the model to derive implications and predictions about how the incoherence of a product relates to preference uncertainty and risk adjusted preference. We describe an experimental setting to test key model predictions and then find results that support our model structure. We conclude with an assessment of the theoretical and managerial implications (and limitations) of our work, as well as an agenda for future research.

2.0 A Conceptual Model of the Effect of Incoherence on Preference

To derive our formal individual-level model, we first present a conceptual framework of consumer perception and preference formation (see Figure 1). For simplicity, we discuss the
framework as well as the subsequent formal model in terms of two attributes and symmetric effects of attributes on each other. We address the extension to multiple attributes and asymmetric effects in section 5. To make the exposition simpler, we divide the conceptual framework into five parts, each of which we now describe in turn.

(Insert Figure 1 about here)

2.1 Prior Information. We assume that the consumer has prior information about the product category, based commonly on experience with products in the category. We indicate this prior information with dotted lines in Figure 1. We classify this information into two types: (i) information external to the product configuration (e.g., beliefs of typical attribute performance levels in the category, brand knowledge from other products, etc.), and (ii) information internal to the product configuration (i.e., inter-attribute covariation beliefs in the category). Our interest is primarily in the latter internal information, but we must incorporate the former (external information) to provide a complete representation of the consumer’s evaluation process.

Researchers in psychology and consumer behavior have extensively studied the nature of covariation beliefs held by consumers. Consumers develop these beliefs based on empirical observation of covariation (Pechmann and Ratneshwar 1992, Broniarzcyk and Alba 1994) and/or a conceptual theory of how the attributes are related (Broniarzcyk and Alba 1994, Fugelsang and Thompson 2003). Covariation beliefs are known to be sticky and difficult to change (Pechmann and Ratneshwar 1992). Covariation-based information has also been found to become so embedded within the individual’s cognitive belief structure that it may even induce a classical conditioning type response, without recourse to cognitive effort (Alloy and Tabachnik 1984). As a result, we should expect that consumers will bring these covariation beliefs to bear upon the
process of forming perceptions, which we describe over the next three sections (Sections 2.2-2.4).

2.2 Product Claims about Attribute Performance. The consumer’s process of perception formation is triggered by claims made by a manufacturer about the performance of its product on two attributes that matter to consumers. For example, a car manufacturer might claim that its car has a 255 horsepower engine and a fuel efficiency of 25 miles per gallon. We further assume that the consumer has some uncertainty about the veracity of the manufacturer’s claim.

2.3 Consumers Form Inferences Based on Covariation Beliefs. We assume that the consumer accesses beliefs about covariation, described in Section 2.1, between the two product attributes to infer the information that each attribute provides about the other. Researchers have shown that consumers commonly use their beliefs of inter-attribute covariation to make inferences (see Dick, Chakravarti, and Beihal 1990). Rao and Monroe (1988) and Lichtenstein and Burton (1989) show that consumers make inferences about “experience” attributes based on their beliefs of covariation of such attributes with tangible search attributes that are observed prior to purchase. Ordonez (1998) showed that such inference-making occurs even when information is presented on all attributes – thus suggesting that consumers modify the information provided to them, based on prior inter-attribute covariation beliefs. In line with Feldman and Lynch’s (1988) paper on implicit theories, Broniarzcyk and Alba (1994a) demonstrate that consumers’ implicit theories of inter-attribute relationships are the most important determinants of inference-making. The authors stress that those theories reflect consumers’ understanding of inter-attribute relationships and “need not be logically correct, empirically accurate, or even the result of direct experience” (pg. 395).
In summary, the literature review in Sections 2.1 and 2.3 suggests that (i) covariation beliefs are formed by consumers using empirical observation or implicit theories of how the attributes in the category are related, (ii) those beliefs are likely to be sticky and difficult to change, and (iii) those beliefs are used by consumers to make inferences about attributes, even when contrary information is presented about those attributes. In Figure 1, we use dotted lines to indicate that the consumer’s prior information (external and internal) is used to form inferences.

Going back to the car example, suppose a car claims exceptional driving performance and superior fuel efficiency. A consumer would then make an inference about fuel efficiency based on the claim of exceptional driving performance, combined with the belief about how closely the two attributes are related (in this case, negatively related). Similarly, the consumer makes an inference about driving performance based on the claim of superior fuel efficiency. In both cases, we further assume that the consumer is uncertain about these inferences. This uncertainty could depend on the extent of category experience of the consumer, the variation in the attribute performance across products in the category, and consumer-specific characteristics such as the extent to which the consumer is dogmatic (Meyers-Levy and Tybout 1989), and his or her involvement with the product category.

**2.4 Consumers Form Perceptions Based on Claims and Inferences.** The consumer in our example now has two sources of information about the fuel efficiency of the car in question – first, the product manufacturer claims a level of fuel efficiency and, second, the consumer makes an inference about fuel efficiency by combining the driving performance claim made by the car manufacturer with his or her beliefs about the covariation of fuel efficiency and driving performance. The consumer has some uncertainty associated with each source of information. We propose that the consumer’s perception of fuel efficiency is formed by putting together
information from these two sources, with the relative influence of each source being inversely related to the consumer’s uncertainty about information from that source. Returning to our example, if a car claims exceptional driving performance and superior fuel efficiency, the claim of superior fuel efficiency will be far from the inference of low fuel efficiency based on the exceptional driving performance claim. This conflict, which we call attribute incoherence (defined more formally later in equation 10), results in increased uncertainty about the perception of fuel efficiency, because discrepant information leads to increased uncertainty (Einhorn and Hogarth 1985). The same will hold for the perception of driving performance.

2.5 Consumers Translate Perceptions into Preference (and Utility). While there are several ways by which consumers can form preferences and assign utility to the product, we assume a standard multi-attribute compensatory model (see, for example, the belief-importance model described in Beckwith and Lehmann 1975). The consumer weights each attribute in terms of its importance, determines the value of each product in the choice set, and chooses the product that maximizes utility. Note that we are dealing with uncertain perceptions here, which implies that the consumer accounts for that uncertainty by maximizing expected utility (Roberts and Urban 1988, Keeney and Raiffa 1976). Following Roberts and Urban (1988) and their concept of risk-adjusted preference, we assume that consumers discount mean preference by the uncertainty of that preference. In contrast to Roberts and Urban, however, uncertainty will arise not just from the uncertainty of individual attribute claims, but also because of the beliefs derived from covariation between attributes. We next present a formal, mathematical representation of the phenomena described by this process.

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1 If utility is measured with error, we may employ a suitable discrete choice model to represent the probability that the consumer will choose the product with the highest measured expected risk adjusted utility.
3.0 Mathematical Model of the Effect of Incoherence on Preference

Our mathematical development parallels the conceptual model, outlined in Figure 1 and developed in Section 2. As noted previously, our model development is limited to two attributes, 1 and 2. We discuss the multivariate analog to this formulation later in the paper. Our model is individual and product-specific. For simplicity, we suppress individual and product subscripts. We denote the consumer’s perceptions of products in the category on each attribute as \( x_1 \) and \( x_2 \) respectively, the consumer’s perceptions of the focal product on each attribute as \( X_1 \) and \( X_2 \) respectively, the focal product’s claims of performance on each attribute as \( X_{c1} \) and \( X_{c2} \) respectively, and the consumer’s inferences of performance of the focal product on each attribute as \( X_{i1} \) and \( X_{i2} \) respectively. Uncertainty in each of these terms is conceptualized as the variance of mean beliefs, and is denoted with the same subscripts.

3.1 Representing Prior Information. In the conceptual model, we suggested that the consumer forms a belief of inter-attribute covariation on the basis of category experience or using some other criteria (for example, the relationship of attributes in categories perceived to be related, word of mouth, perceived physical or design constraints, etc.). We assume that this covariation can be represented as a partial regression coefficient (Belsley, Kuh and Welsch 1980), which indicates the correlation between perceptions of performance of products (in the category) on attributes 1 and 2:

\[
x_{1/2} = \tau_1 + \beta_{12} \cdot x_2 + \epsilon_{12},
\]

where \( x_{1/2} \) is the level of performance on attribute 1 given the level of attribute 2, \( \tau_1 \) is the intercept term, \( \beta_{12} \) is the partial regression coefficient, and \( \epsilon_{12} \) is an error term representing the fact that the attributes are not perfectly correlated. The intercept term \( \tau_1 \) represents the summary of indirect information about \( x_1 \) that does not come from the level of the other attribute, \( x_2 \). In this
sense, \( \tau \) represents the consumer's external information about the performance of a product on attribute 1. We assume that the consumer knows \( \beta_{12}, \varepsilon_{12} \) is ~ \( N(0, \sigma_{\varepsilon_{12}}^2) \), and \( \tau \) is ~ \( N(\mu, \sigma_{\tau}^2) \).

### 3.2 Modeling Product Claims about Attribute Performance.

We assume that a manufacturer makes claims of product performance on the two attributes, 1 and 2, and that the consumer has some uncertainty about these product claims, denoted by \( \sigma_{c1}^2 \) and \( \sigma_{c2}^2 \) respectively. We further assume that the consumers’ prior distribution of beliefs about the claim on each attribute is normally distributed with a mean of \( X_{c1} \) and \( X_{c2} \) respectively.

### 3.3 Modeling Formation of Inferences Based on Covariation Beliefs.

We examine the consumer’s inference of the product’s performance on attribute 1 (\( X_{f1} \)), based on (i) the consumer’s external information about attribute performance in the category (manifested in \( \tau \) from equation 1), (ii) the product’s claimed performance on attribute 2 (\( X_{c2} \)), and (iii) the consumer’s belief about the covariation between the two attributes (manifested in \( \beta_{12} \) from equation 1). Using equation (1), and the fact that \( E(\varepsilon_{12}) = 0 \), we assume that the consumer takes the maximum likelihood value of inferences about the mean level of \( X_{f1} \), embodied in the level of \( X_{c2} \). Thus, \( X_{f1} \), given \( X_{c2} \), is:

\[
X_{f1} = \mu_{f1} + \beta_{12} \cdot X_{c2}.
\]

We now assume that the internal information (as manifested in \( \beta_{12} \cdot X_{c2} \)) and external information (as manifested in \( \tau \)) are independent. Putting this assumption together with the one that the consumer knows \( \beta_{12} \), the variance of \( X_{f1} \) is given by,

\[
\sigma_{f1}^2 = \sigma_{\tau}^2 + \sigma_{\varepsilon_{12}}^2 + \beta_{12}^2 \cdot \sigma_{c2}^2,
\]

Similarly, the inferred level of performance of the product on attribute 2, \( X_{f2} \), is given by,
\[
\bar{X}_{t2} = \mu_{t} + \beta_{2t} \cdot \bar{X}_{c1}.
\]

Finally, the assumption of normality for the distributions of \( \tau_1, \tau_2, X_{c1} \) and \( X_{c2} \) implies that the distributions of \( X_{t1} \) and \( X_{t2} \) are also normal.

### 3.4 Modeling Formation of Perceptions Based on Claims and Inferences.

We now model the formation of \( X_1 \) (and \( X_2 \)), the consumer’s perception of performance of the product on attribute 1 (and attribute 2). The consumer must reconcile information about the performance of the product on attribute 1 that comes from the distribution of the claim, denoted by \( \phi_{c1}(x) \), and the distribution of the inference, denoted by \( \phi_{i1}(x) \), to form perceptions (with associated uncertainty) of each attribute. To build our model of this process, we assume that the consumer uses \( X_{c1} \) with probability \( p_1 \) and \( X_{i1} \) with probability \((1 - p_1)\). Given this assumption, the resulting distribution of perceptions, \( \phi(x) \), is a mixture of the distribution of claims and inferences (see Appendix 1 for the proof), as follows:

\[
\phi(x) = p_1 \cdot \phi_{c1}(x) + (1 - p_1) \cdot \phi_{i1}(x),
\]

where \( 0 \leq p_1 \leq 1 \). The expected value and variance of \( X_1 \) are given by (see Appendix 1),

\[
E[X_1] = \bar{X}_i = p_1 \cdot \bar{X}_{c1} + (1 - p_1) \cdot \bar{X}_{i1}, \quad \text{and}
\]

\[
\text{var}(X_1) = \sigma^2_1 = p_1 \cdot (1 - p_1) \cdot (\bar{X}_{c1} - \bar{X}_{i1})^2 + p_1 \cdot \sigma^2_{c1} + (1 - p_1) \cdot \sigma^2_{i1}.
\]

We seek weights \( p_1 \) and \((1 - p_1)\) that make the expected value of \( X_1 \) tend towards "accept the claim" as the variance of the inference (\( \sigma^2_{i1} \)) becomes relatively large (i.e., the consumer places little weight on the distribution of inferences), and "accept the inference" as the variance of the claim (\( \sigma^2_{c1} \)) increases. Bayesian updating would suggest \( p_1 \) and \((1 - p_1)\) as proportional to the precision (inverse of variance), which would satisfy the criterion for selection of weights.
However, we adopt a somewhat more general form. Following Bell, Keeney, and Little (1975), we propose an US/(US + THEM) formulation for \( p_1 \). Specifically,

\[
(8) \quad p_1 = \frac{(\sigma_{II}^2)^\alpha}{(\sigma_{CI}^2)^\alpha + (\sigma_{CI}^2)^\alpha},
\]

where \( \alpha \) is a parameter to be estimated, reflecting the consumer’s uncertainty intolerance (i.e., the greater \( \alpha \) is, the more weight the consumer places on a more certain estimate). There are several attractive features of this formulation. First, \( p_1 \) approaches 1 as \( \sigma_{CI}^2 \) becomes smaller relative to \( \sigma_{II}^2 \), and 0 as \( \sigma_{CI}^2 \) becomes larger (relative to \( \sigma_{II}^2 \)). By symmetry, \( p_1 \) is 0.5 when those variances are equal. Therefore, the weight associated with each distribution (claim or inference) varies inversely with the variance (uncertainty) of that distribution. Second, if \( \alpha \) is equal to 0, each component has an equal influence on the consumer, irrespective of the uncertainty differences between the two components. If \( \alpha \) is equal to 1, each component has an influence inversely proportional to its degree of uncertainty, corresponding to the weight that a standard Bayesian analysis would suggest (Gatignon 1984). If \( \alpha \) is very large, the consumer discounts uncertain information more severely than would be suggested by Bayes rule. For simplicity and tractability, we specify \( p_1 \) as proportional to the square of precision (i.e., \( \alpha = 2 \)), and discuss the more general formulation in the concluding section of the paper. Note that we can obtain analogous expressions for the consumer’s expected level of attribute 2, \( E[X_2] \), its variance, \( \sigma_{E2}^2 \), and the relative weight given to claimed and inferred information, \( p_2 \), (equations 6-8) by symmetry. We can also derive the covariance between \( X_1 \) and \( X_2 \), \( \sigma_{12} \), given by (see Appendix 1 for the derivation),

\[
(9) \quad \sigma_{12} = \{ p_1 \cdot p_2 + (1 - p_1) \cdot (1 - p_2) \cdot \beta_{12} \beta_{21} \} \cdot \sigma_{CI,C2} \\
+ (1 - p_2) \cdot p_1 \cdot \beta_{21} \cdot \sigma_{CI}^2 + (1 - p_1) \cdot p_2 \cdot \beta_{12} \cdot \sigma_{CI}^2,
\]
where $\sigma_{c_1,c_2}$ is the covariance between the claims, $X_{c_1}$ and $X_{c_2}$. This covariance can be expressed in terms of the correlation between the claims and the square roots of the uncertainties (variances) of each claim, but this is not central to our model.

Equations (6) through (8) have some appealing properties. In equation (6), the consumer’s mean perception is a weighted sum of the means of the distribution of the two components (the claim and the inference), with the weights dependent on the variances, consistent with Gatignon’s (1984) advertising information model. The variance in the consumer’s perception, $\sigma_i^2$, depends on the distance between the two components. The greater the distance between the claimed and inferred components, the more uncertain will be the perception. Note that the more unexpected the inter-attribute configuration, the greater is the distance between claimed and inferred components. Thus, an increase in the difference between claimed and inferred attribute levels leads to an increase in preference uncertainty in contrast to Bayesian updating models such as Gatignon’s (1984), which only admit variance reduction when adding new information.

Equation (7) shows that the consumer’s uncertainty about the true level of attribute $i$ increases as the claimed and inferred attribute levels diverge. $\sigma_i^2$ is linear in $\left\{X_{c_1} - X_{i_1}\right\}^2$, which is the squared difference between the expected claim and inference. This squared difference, which we call attribute incoherence, is a measure of the discrepancy in the information about attribute $i$. More formally, in the two attribute case we define the attribute incoherence of attribute 1, $AI_1$ as,

$$\begin{align*}
AI_1 &= \left\{X_{c_1} - X_{i_1}\right\}^2.
\end{align*}$$

In the multi-attribute case, the inference on attribute 1 will be made based on information on all of the attributes (i.e., equation 2 will have a multivariate form). The attribute incoherence
of attribute 2 follows by analogy. We now discuss the translation of the consumer’s uncertain perceptions into preference.

3.5 Modeling the Translation of Perceptions into Preference and Utility. Following Keeney and Raiffa (1976), we specify that a consumer displaying constant risk aversion has a utility for the product that can be specified as:

\[
U = a - b \cdot e^{-r(w_1x_1 + w_2x_2)},
\]

where \(a\) and \(b\) are scaling constants, \(w_1\) and \(w_2\) are relative importance weights of attributes 1 and 2, and \(r\) is the risk-aversion parameter. Keeney and Raiffa derive the consumer’s expected utility for the case of a single normally distributed variable, used subsequently by Chatterjee et al. (1986) and Roberts and Urban (1988). In our case, we need to obtain an expression for expected utility when the consumer has information on two correlated variables. We seek an expression for expected utility that is easily interpretable and managerially useful. In Appendix 2, we show the derivation of such an expression for expected utility.

Assuming that we can approximate the joint distribution of \(X_1\) and \(X_2\) with a bivariate normal density function (see Appendix 3 for a discussion of the reasonableness of this assumption), we take the expectation of \(U\) from equation (11), integrating across the bivariate normal distribution, to obtain the expression for the consumer’s expected utility in the two attribute case as:

\[
E(U) = a - b \cdot e^{-r(\mu_1x_1 + \mu_2x_2 - \frac{1}{2}(\sigma_1^2 + \sigma_2^2 + 2\mu_1\sigma_1\sigma_2 + 2\mu_2\sigma_1\sigma_2))},
\]

where the essential difference from Keeney and Raiffa is that we relax their assumption of preference independence by allowing the two attributes to covary.

The expression for expected utility in equation (12) is interpretable and managerially useful. The first two terms in the exponent of equation (12) comprise the mean value for a
product with two attributes, which may, in turn be expressed in terms of the claimed and inferred mean attribute levels using equation (6) and its attribute 2 analog. The following terms represent the effect of variance or uncertainty in value on expected utility. These terms are shown in expanded form in equation (7), its attribute 2 analog, and equation (9). We denote the mean value and uncertainty in value by $\mu_r$ and $\sigma_r^2$ respectively. Following Roberts and Urban (1988), we note that expected utility in equation (12) is linear in the exponent term, which we define as the risk-adjusted preference, $Z$, for the product:

$$Z = \left\{ w_1 \cdot \bar{X}_1 + w_2 \cdot \bar{X}_2 \right\} - \left\{ \frac{R}{2} \cdot \left( w_1^2 \cdot \sigma_1^2 + w_2^2 \cdot \sigma_2^2 + 2w_1 \cdot w_2 \cdot \sigma_{12} \right) \right\} = \mu_r - \frac{R}{2} \cdot \sigma_r^2$$

For simplicity of exposition, we hereafter call $\mu_r$ “mean preference” and $\sigma_r^2$ “preference uncertainty”. Moreover, under suitable assumptions about measurement error, the risk-adjusted preference function can now be converted into a model of choice using the familiar logit formulation as follows,

$$\text{Prob} = \frac{e^Z}{\sum_{m=1}^{M} e^{Z_m}},$$

where $M$ is the number of products in the consumer’s choice set and Prob is the consumer’s probability of choosing the product under investigation.

3.6 Implications of the model. We analyze the implications of the model in two steps. In section 3.6.1, we investigate how preference uncertainty varies with incoherence, as implied by the conceptual model, while in section 3.6.2, we study the effect of increasing the level of one correlated attribute, in isolation, on risk-adjusted preference.
3.6.1 The effect of incoherence on preference uncertainty. To examine the impact of attribute incoherence on preference uncertainty, we substitute the variance in attribute perceptions (equation 7) into the preference uncertainty term in equation (13) to obtain:

\[
\sigma^2_i = \left\{ w_1^2 \cdot \sigma^2_1 + w_2^2 \cdot \sigma^2_2 + 2w_1 \cdot w_2 \cdot \sigma_{12} \right\} \\
= \left\{ w_1^2 p_1 \cdot (1 - p_1) \cdot (X_{c1} - X_{f1})^2 + w_2^2 p_2 \cdot (1 - p_2) \cdot (X_{c2} - X_{f2})^2 + g \left[ \sigma^2_{c1}, \sigma^2_{c2}, \sigma_{c1,c2} \right] \right\} \\
= \left\{ w_1^2 p_1 \cdot (1 - p_1) \cdot AI_1 + w_2^2 p_2 \cdot (1 - p_2) \cdot AI_2 + g \left[ \sigma^2_{c1}, \sigma^2_{c2}, \sigma_{c1,c2} \right] \right\}
\]

For products with high levels of attribute incoherence, we expect to find the consumer’s inference of performance on the attribute to be very different from the claim. In other words, attribute incoherence \((X_{c1} - X_{f1})^2\) and/or \((X_{c2} - X_{f2})^2\) in equation (15) will increase as the attributes become more incoherent. Therefore, an increase in attribute incoherence increases preference uncertainty, and thus decreases preference.

In general, these results imply that incoherence increases preference uncertainty. However, there are at least two circumstances where attribute incoherence will have a much smaller impact on preference uncertainty. First, if the claim dominates the inference (or vice versa) in determining the consumer’s perception of performance (i.e., if \(p_1\) or \((1 - p_1)\) is small), then the difference between the claim and the inference, i.e., attribute incoherence, will have little effect on preference uncertainty. Our model captures these effects in equation (15) because the terms \((X_{c1} - X_{f1})^2\) and \((X_{c2} - X_{f2})^2\) are weighted by \(p_1 \cdot (1 - p_1)\) and \(p_2 \cdot (1 - p_2)\) respectively. The claim would dominate the inference (or vice versa) when the consumer is very

---

2 We specify the total effect of uncertainty of claims and covariance between claims by a function ‘\(g\)’ because these effects are not central to this paper (we are interested in the effect of incoherence, not claim uncertainty) and, since \(p_1\) and \(p_2\) are functions of claim uncertainty, preference uncertainty is a non-linear and complex function of claim uncertainty, diverting the focus of our work here. We also note that the mean levels of the attribute claims and incoherence are independent of the function \(g\), which contains only variance and covariance terms. Therefore, the effect of attribute incoherence (a function of mean levels of claims and inferences) on preference can be estimated independently of the effect of the terms in the function \(g\) on preference.
certain about the claim relative to the inference, which in turn can result from the inter-attribute correlation being low. In other words, incoherence will have a much smaller, even negligible, effect on preference when the inter-attribute correlation is low. Second, if the attribute only has a small effect on preference, i.e., if \( w \) is small, then even high levels of attribute incoherence should have a very small effect on preference uncertainty\(^3\). This effect is also captured in equation (15) because the terms \( (\bar{X}_{c1} - \bar{X}_{t1})^2 \) and \( (\bar{X}_{c2} - \bar{X}_{t2})^2 \) are weighted by \( w_1 \) and \( w_2 \) respectively.

To help clarify our discussion and provide a useful managerial diagnostic, we create an overall index or measure of product incoherence. We define product incoherence, \( PI \), as,

\[
PI = \left[ w_1 \cdot p_1 \cdot (1 - p_1) \cdot (\bar{X}_{c1} - \bar{X}_{t1})^2 + w_2 \cdot p_2 \cdot (1 - p_2) \cdot (\bar{X}_{c2} - \bar{X}_{t2})^2 \right],
\]

which is now expressed as a weighted sum of the incoherence of each individual attribute. We can now rewrite equation (15), as:

\[
\sigma^2_P = PI + g \left[ \sigma^2_{c1}, \sigma^2_{c2}, \sigma_{c1,c2} \right].
\]

Equation (17) shows that preference uncertainty increases with this measure of product incoherence (\( PI \)).

3.6.2 Effect of improvement of a correlated attribute on risk-adjusted preference.

Given a positive correlation between two attributes, incoherence will increase after a certain level when one attribute increases while holding the other attribute constant\(^4\), after it passes the level inferred from the other attribute. Assuming that both attributes are positively valued, an

\(^3\) If attribute \( l \) were not important in equation (15), i.e., \( w_1 \) was small, attribute \( l \) incoherence \( (\bar{X}_{c1} - \bar{X}_{t1})^2 \) would not affect preference uncertainty, and thus preference. However, the claim on attribute \( l \), \( \bar{X}_{c1} \), may still have a substantial effect on preference through attribute 2 incoherence \( (\bar{X}_{c2} - \bar{X}_{t2})^2 \) because \( \bar{X}_{t2} \) is a function of \( \bar{X}_{c1} \) (see equation 4). This is consistent with an extensive literature on inferencing and the impact of irrelevant attributes on preference (Carpenter, Glazer, and Nakamoto 1994).

\(^4\) This fixedness in an attribute can occur when the variance of a product on that attribute is very low (for e.g., a down-market jewellery store, whose clientele know that it is not prestigious, might have difficulty in trying to persuade its clientele that the store stocks high quality merchandise).
increase in the level of one attribute also increases the mean preference for the product.

Therefore, there is a dual impact of an increase of one attribute, holding the other attribute constant, on risk-adjusted preference – a positive effect because of the impact on mean preference, but a second effect, which could be positive or negative depending on whether the change moves the attribute towards or away from the level inferred from the other, fixed attribute. We now examine the net effect. We first substitute the terms for inference-making from equations (2)-(4) into the terms for attribute perceptions and uncertainty in equations (6) and (7). We then substitute the resulting expressions for attribute perceptions and uncertainty into equation (13) to obtain the following expression for risk-adjusted preference as a function of exogenous claims.

\[
(18) \quad Z = \gamma_0 + \gamma_1 \bar{X}_{C_1} + \gamma_2 \bar{X}_{C_2} + \frac{-r}{2} \left\{ \gamma_3 \cdot \bar{X}_{C_1}^2 + \gamma_4 \cdot \bar{X}_{C_2}^2 - \gamma_5 \cdot \bar{X}_{C_1} \cdot \bar{X}_{C_2} + \gamma_6 \cdot \bar{X}_{C_1} + \gamma_7 \cdot \bar{X}_{C_2} + g(\sigma_{C_1}^2, \sigma_{C_2}^2, \sigma_{C_{1,2}}) \right\},
\]

where,

\[
(19) \quad \gamma_1 = \left\{ w_1 \cdot p_1 + w_2 \cdot (1 - p_2) \beta_{21} \right\}, \\
\gamma_2 = \left\{ w_2 \cdot p_2 + w_1 \cdot (1 - p_1) \beta_{12} \right\}, \\
\gamma_3 = \left\{ w_1^2 \cdot p_1 \cdot (1 - p_1) + w_2^2 \cdot p_2 \cdot (1 - p_2) \cdot \beta_{21}^2 \right\}, \\
\gamma_4 = \left\{ w_2^2 \cdot p_2 \cdot (1 - p_2) + w_1^2 \cdot p_1 \cdot (1 - p_1) \cdot \beta_{12}^2 \right\}, \\
\gamma_5 = \left\{ 2 \cdot w_1^2 \cdot p_1 \cdot (1 - p_1) \beta_{12} + 2 \cdot w_2^2 \cdot p_2 \cdot (1 - p_2) \beta_{21} \right\}, \\
\gamma_6 = \left\{ -2w_1^2 \cdot p_1 \cdot (1 - p_1) \cdot \mu_{\beta_1} + 2w_2^2 \cdot p_2 \cdot (1 - p_2) \cdot \mu_{\beta_2} \beta_{21} \right\}, \text{ and} \\
\gamma_7 = \left\{ -2w_2^2 \cdot p_2 \cdot (1 - p_2) \cdot \mu_{\beta_2} + 2w_1^2 \cdot p_1 \cdot (1 - p_1) \cdot \mu_{\beta_1} \beta_{12} \right\}.
\]

Equation (18) is now completely specified by the exogenous claims of expected performance (\( \bar{X}_{C_1} \) and \( \bar{X}_{C_2} \)). One way of examining the effect of incoherence on risk-adjusted preference is to investigate the impact of increasing the mean level of one attribute, while keeping the other attribute constant. To find the optimal level of attribute 1’s claim, given a level of attribute 2, we take the first derivative of the risk adjusted preference function in equation (18)
with respect to $X_{c1}$ and set it to 0. We then obtain the following expression for $X_{c1}^*$, the preference maximizing performance level of $X_{c1}$ for a given $X_{c2}$,

$$X_{c1}^* = \frac{Y_1}{r \cdot \gamma_3} - \frac{Y_5}{2 \cdot \gamma_3} \cdot X_{c2},$$

where $\gamma_1, \gamma_3, \gamma_5$, and $\gamma_6$ are given in equations (18) and (19).

The second derivative of equation (18) with respect to $X_{c1}$ is negative, implying that $X_{c1}^*$ is a preference maximizing performance level (note in equation 19 that $\gamma_3$ is strictly positive, therefore the second derivative will be negative). Note that from equations (18) and (19), $\gamma_1, \gamma_3, \gamma_5$, and $\gamma_6$ are non-zero for positively correlated attributes ($\beta_{12}, \beta_{21} > 0$), as long as the consumer places a non-zero weight on the claim and/or inference ($0 < p_1$ or $p_2 < 1$) and that attribute has a non-zero importance weight. The main analytical finding is that, for a given $X_{c2}$, preference increases as $X_{c1}$ increases, but only up to a performance level $X_{c1}^*$, after which preference decreases with further increases in $X_{c1}$. This implies an inverted U-shape relationship between preference and $X_{c1}$, for a given value of $X_{c2}$. Note that product incoherence ($PI$) also increases as $X_{c1}$ increases (after it exceeds $X_{l1}$), holding $X_{c2}$ constant (see equation 16).

Therefore, as incoherence increases, risk-adjusted preference first increases until it reaches a maximum and then decreases.

Two important substantive implications of these analytical results are shown in Figure 2. First, the result usually translates into an inverted U-shaped curve (Case 1) for the relationship between incoherence from equation (16) and preference. Note that if a consumer is highly risk averse, where anything new or surprising is deemed negative (dealing with financial or health-related products, for example), the curve would be close to strictly downward sloping (Case 1a).
Second, as the consumer approaches risk neutrality for the product category, the curve moves in the limit to being strictly upward-sloping (Case 2).

(Insert Figure 2 about here)

For the most common case, Case 1, we see that some incoherence is good, but too much incoherence hurts preference. This appealing result is consistent with a main finding in the schema incongruity literature (Meyers-Levy and Tybout 1989), which shows that moderate incongruity is preferred over both congruity and extreme incongruity, but that finding comes with a different explanation than ours. Their explanation is based on the stimulation provided by the newness of a moderately incongruent product (Raju 1980), while ours emerges from incoherence having a positive impact on mean preference, a negative impact on variance of preference, with the net effect being a simple mean-variance trade-off. This result is also consistent with Keller and Aaker’s (1992) findings on the risks of “overextending” a brand.

To summarize the key model predictions, if the inter-attribute correlation is high, incoherence will have a significant negative effect on preference, while, if the correlation is low, incoherence will have a much smaller, even negligible, effect on preference. Our empirical study, described next, tests these predictions.

4.0 Empirical Assessment of Model Predictions

4.1 Empirical design and measures. The sequence of steps we followed to test the predictions of our model is presented in Table 1.

(Insert Table 1 about here)

4.1.1 Experimental Design. Our core thesis is that a product that is inconsistent with covariation belief structures will be viewed with a greater level of uncertainty than a product that is highly consistent, thereby affecting risk-adjusted preference for the discrepant product. Our
model also implies that weak inter-attribute covariation belief structures lessen the effect of incoherence on preference relative to stronger ones. Hence, an empirical assessment of those predictions of our model requires a context where: (i) there are multiple salient attributes that determine, to different degrees, preference for a product, (ii) consumers encounter relatively homogenous service levels from which inter-attribute covariances can be elicited, and (iii) realistic product concepts can be constructed, with attribute levels manipulated in such a way that incoherence can be varied. In addition, respondents must be chosen so that the preference and choice task is both important and salient to them. These requirements are described as Step D1 in Table 1.

A context that meets the requirements set out above is the selection of elective courses by second year students in a major MBA program, a context we used here. In the MBA program under study, at the end of each course, students are asked to respond to a battery of 24 teaching effectiveness items. The scale used by the School at the time of the experiment is shown in Table 2. Students are given access to a summary of past ratings for a course on each attribute in the School library; which students use to select future electives. We define the 24 items as attributes of a course.

(Insert Table 2 about here)

To obtain a measure of expected relationships (Step D2), we obtained permission from the School to analyze historical, individual-level teaching effectiveness data from five large classes in order to estimate the past, aggregate correlation between the 24 attributes.

To test our model’s prediction that the effect of incoherence on preference depends on inter-attribute correlation, we used two pairs of attributes – one pair with a relatively high inter-attribute correlation and another with a relatively low inter-attribute correlation. We also
required the chosen attributes to be important to respondents, i.e., these attributes had to have a clear relationship with course satisfaction. There was no requirement for the attributes to be equally important. Based on the inter-attribute correlation and a regression of attributes in the 24 item scale on overall assessment (Q24 of the scale), we selected the following two pairs of attributes (Step D3):

**Condition 1: High correlation case** Q11 (“the importance of the course to MBA graduates”) and Q12 (“the extent to which the course was interesting”).

**Condition 2: Low correlation case** Q3 (“the preparedness of the lecturer”) and Q12 (“the extent to which the course was interesting”).

The average ecological correlation between “important” and “interesting” was 0.79 (p<0.001) in the historical teaching effectiveness data, while that between “preparedness” and “interesting” was 0.39 (p<0.001), providing sufficient variation in inter-attribute covariation. Each of the attributes was a significant driver of overall assessment, with the “importance of the course” being the most important driver, followed by the “extent to which the course was interesting”, and finally the “preparedness of the lecturer.” Each respondent was randomly assigned to one of these attribute pairs (conditions) and the data from each condition were analyzed separately.

We then constructed a hypothetical product (course in this case) by describing a prospective second year elective, providing only the attribute ratings given by students in the previous year. These ratings were declared to be hypothetical – no course or lecturer names were given to control for any potentially confounding brand-name effects. We presented the ratings for each course in the same summary format that was made publicly available in the School library. The average ratings for the course on each attribute provide an indication of the mean
performance claim made by the product (course). Along with average ratings for each attribute, the summary format provides the percentage of responses for each scale point of the Likert five-point scale. This information provides a measure of the variance in perceived performance on the attribute, which, in our framework, translates into the respondent’s uncertainty about the claim.

In Step D4 we constructed hypothetical products that varied in terms of mean performance and uncertainty of performance on each attribute. Varying the mean attribute performance of the two attributes also allowed for a variation in incoherence across products. Because the attributes were positively correlated, incoherence will be high when one attribute is high and the other is low relative to when a course is good on both attributes or bad on both. We varied the mean of both attributes at two levels (3.0 and 4.5). This implies that a course with mean ratings at a similar level (3 and 3 or 4.5 and 4.5) would be viewed as relatively more coherent than a course with mean ratings at a dissimilar level (3 and 4.5 or 4.5 and 3), given that the mean level of attributes across all courses is close. This 2 (attribute 1 mean) × 2 (attribute 2 mean) implied that each respondent would rate only four hypothetical courses. To obtain more data from each individual respondent, we constructed four additional products by varying the distribution of past student responses for each scale point on the five point scale for attribute 1, without changing the mean attribute performance level. For example, instead of the “0-20-60-20-0” % responses for each of the five scale points of attribute 1 shown in the first table in Figure 3, we changed this to “10-20-40-20-10” % responses for each scale point of attribute 1, thus keeping the mean performance constant while changing the variance in the claim. Each respondent was thus shown eight hypothetical products with a 2 (attribute 1 mean) × 2 (attribute 2 mean) × 2 (attribute 1 variance) within-respondents full factorial design. The two different pairs of attributes were separately administered as a between-respondents condition.
4.1.2 Measurement procedures. We recruited 77 respondents for the experiment, all of whom were second-year MBA students. They had completed essentially the same set of first year courses and, at the time of the experiment, were making choices of elective courses for the first term of the second year. We first randomly assigned respondents to a between-respondents condition. The between-respondents groups were homogenous in terms of demographic characteristics (age, gender, and whether they were domestic or international students).

In the first part of the experiment (Step E1 in Table 1, hereafter called Part 1 of the study), we obtained information from each respondent about the courses they took in the first year of the program. We then asked them to rate each course on the attribute pair provided to them, allowing us to estimate individual-level inter-attribute correlations. Each respondent provided data on eight to ten courses taken by them in the first year.

In the second part of the experiment (Steps E2-E4, hereafter called Part 2 of the study) we showed the respondent the summary ratings for a course on two attributes relevant to the respondent’s condition (see the first table in Figure 3). We then asked respondents to estimate the chances out of 100 that their preference for the course would correspond with each of the five scale points for each attribute if they were presented with such a course in practice (see Task 3A in Figure 3). Their responses were constrained to add up to 100 across the five scale points, thus giving an estimate of the mean and variance of their perceptions of the hypothetical course on both attributes. Next, respondents were asked for their preferences on a sliding scale anchored by “not at all preferred” and “highly preferred” (Step E3). These data were converted to a 0-100 preference scale. Finally, respondents were asked to indicate how confident they felt in their judgments of the course on a sliding scale anchored by “not at all confident” and “extremely
confident” (the final section of Figure 3). We repeated Steps E2 and E3 for each of seven remaining hypothetical courses, for a total of eight within-respondent cells (Step E4). We dropped data for four students from the analysis as their responses had close to zero variance, leaving 73 respondents for analysis.

4.2 Analysis. We first used the data from Part 1 of the study to obtain individual-level estimates of the inter-attribute relationship expected by students. In other words, we fit equations (2) and (4), estimating $\beta$ for each respondent (denoted by $i$). We obtained individual-level estimates of the inferences by substituting the estimates of $\mu$ and $\beta$ in the following equations:

\begin{align}
\hat{X}_{i1,j} &= \hat{\mu}_1 + \hat{\beta}_{12} \cdot X_{i2}\quad \text{and} \\
\hat{X}_{i2,j} &= \hat{\mu}_2 + \hat{\beta}_{21} \cdot X_{i1}\,
\end{align}

We then constructed individual-level measures of attribute incoherence by substituting inferences from (21) and (22) into equation (10), the expression for attribute incoherence, and its analogue for attribute 2, as follows,

\begin{align}
\hat{AI}_{i1,i} &= \left(X_{c1} - \hat{X}_{i1,j}\right)^2, \quad \text{and} \\
\hat{AI}_{i2,i} &= \left(X_{c2} - \hat{X}_{i2,j}\right)^2.
\end{align}

We rewrite equation (13) in terms of perceptions of the two attributes and attribute incoherence, as follows,

\begin{align}
Z_i &= \eta_0 + \eta_1 \cdot \bar{X}_{i1,j} + \eta_2 \cdot \bar{X}_{i2,j} + \eta_3 \cdot \hat{AI}_{i1,i} + \eta_4 \cdot \hat{AI}_{i2,i},
\end{align}

where,

\begin{align}
\eta_1 &= w_1, \\
\eta_2 &= w_2, \\
\eta_3 &= -\frac{r}{2} \cdot \left\{w_1^2 \cdot p_1 \cdot (1 - p_1)\right\}, \\
\eta_4 &= -\frac{r}{2} \cdot \left\{w_2^2 \cdot p_2 \cdot (1 - p_2)\right\}
\end{align}
We can now directly test the predictions of our model by fitting the preference model in (25) to the data collected in the experiment. The attributes in our study were positively valued, so we expect perceptions of these attributes to be positively related to preference implying that $\eta_1$ and $\eta_2$ be positive. The most direct test of the predictions of our model is the sign of the coefficients $\eta_3$ and $\eta_4$, which were expected to be negative as per the theory in section 3.6.1. Also, we expected these coefficients to become less significant as the believed relationship between the attributed becomes weaker. Therefore, in the context of our study, we expected the coefficients to be more significant in the high correlation condition than in the low correlation condition.

In estimating the model in equation (25), we mean-centered the variables and corrected for heteroscedasticity to obtain more efficient estimates (Greene 1997).

4.3 Results. The results of estimating equation (25) are shown in Table 3. The results for the high correlation case ($\rho = 0.79$) show that importance of the course for MBAs is a slightly more significant driver of preference than the course being interesting. The key finding relates to the sign and significance of the measures of attribute incoherence. As expected, $\eta_3$ and $\eta_4$ are negative and significant, which implies that the two attributes interact in determining uncertainty and overall preference. These results show that students will discount their overall preference for a course that is very important, but not interesting (and vice versa), as well as be more uncertain about it. In this case, the importance of a course and how interesting it is are believed to be highly positively correlated and a substantial departure from this positive relationship produces uncertainty and lowers overall preference. These results are all consistent with the predictions from our formal model.

---

5 We also controlled for the variance in attribute 1 claim, which was one of the manipulated variables. The results of interest are substantively the same with and without this variable in the model.
The results for the low correlation case ($\rho = 0.39$) show that being well prepared as a lecturer is less important than the course being interesting. The interesting finding here is the lack of statistical significance of $\eta_3$ and $\eta_4$. This result suggests that, in the range we tested, the correspondence between the level of interest of a course and lecturer preparation does not significantly influence either uncertainty or overall preference. Given the relatively weak correlation between the two variables, this result with the predicted sign but a lack of significance also appears consistent with our theory.

(Insert Table 3 about here)

In addition to testing the predictions of the model, we also assessed the fit of a null model and compared it to the fit of our model. The most common approach to estimating multivariate models is to ignore incoherence. Therefore, to test what incoherence buys us, we estimated equation (25) without attribute incoherence as a null model, and compared our model to the null on the basis of fit and out-of-sample prediction. Given the results on the statistical significance of the $\eta_3$ and $\eta_4$ coefficients that we removed to construct the null model, it is not surprising that the AIC (Akaike’s Information Criterion) for our model was smaller than that for the null model (2488 v 2503) in the high correlation condition but just slightly smaller than that for the null model (2067 v 2075) in the low correlation condition.

We also tested the predictive ability of our model against the null model for each condition via a jackknife prediction task. We dropped one observation at a time, estimated each model, used the estimates to predict preference for the dropped observation, and repeated this procedure for all observations\(^6\). In the high correlation condition, our model predicted better than the null model by 10.08%, as measured by the median absolute error. In the low correlation

\(^6\) We used two other methods of re-sampling -- a jackknife method by dropping one respondent, rather than one observation at a time, and a split-sample method, using 20% of the sample as holdout -- and achieved very similar results.
condition, our model predicted better than the null model by 4.22%. Given this rather conservative test of our model--the experiment was designed to be within the range of the past experience of the respondents and, hence, not overtly incoherent---we find this level of predictive validation supportive of our model.

5.0 Discussion, Conclusions, and Future Research

Incoherence presents a risk that marketers often fail to recognize when launching new products, brand extensions, or product repositionings. To address this issue, we provided a conceptual framework to characterize the phenomenon and developed a mathematical model of the consumer preference formation process based on that framework. The conceptual model in Figure 1 has its roots in a well-established literature in consumer behavior, psychology, and marketing models.

We suggest that incoherence is activated by a product’s configuration being different from what is expected by a consumer on the basis of his or her beliefs of inter-attribute correlations. The extent of incoherence depends on the distance between the product’s attribute performance claims and the consumer’s inferences of performance, based on perceived inter-attribute covariation structures.

Using a mathematical model, we developed predictions of our model and then conducted an empirical assessment of these predictions. The initial empirical study provides evidence to support our theoretical model. If the inter-attribute correlation is weak, the inter-attribute configuration has little or no impact on preference. If the inter-attribute correlation is very strong, the attributes constrain each other, in the sense of increasing uncertainty and reducing overall preference. The consumer doubts an attribute which claims to be improved without an
improvement in the other attribute, thus constraining the appeal of a range of product
configurations.

This paper offers two theoretical contributions. First, we have developed a formal,
mathematical model of the effect of incoherence on preference. We have defined attribute and
product incoherence and have shown how it can be integrated into preference and choice models.
The second contribution is that we have relaxed the standard assumption of preference
independence frequently made in the modeling literature (for example, see Roberts and Urban
1988 and Erdem and Swait 2004). This second contribution is of note because ignoring attribute
inter-dependence can be argued to have been at least partly responsible for some of the brand
extension failures that we cited earlier: many attribute beliefs are truly correlated with each
other. We show that consumers may reduce their preference as a result of incoherence.

Our paper has some significant managerial implications. First, it provides a framework to
show that some forms of differentiation may be risky: some consumers might find the
differentiation to be incoherent and show low brand preference. While some incoherence might
be tolerable for the product, too much can induce high uncertainty that makes a risk-averse
consumer have lower preference for the product. Consumer beliefs about inter-attribute
correlation have an impact on preference and therefore must be taken into account while
designing and positioning products. In other words, there really can be too much of a good thing.
Alternatively, a manufacturer may purposely accept a lower position on a less important attribute
to gain a strong inference on a more important one. For example, consider the design of
Eveready flashlights (Australian Financial Review Magazine, October 29, 2004), purposely
designed to look ugly because the company found that sturdy and robust products in this
category were usually ugly. A product that is not ugly might be inferred to be less sturdy and
robust and therefore less preferred by consumers. In contrast, Body Smarts, a healthy candy line launched by Pfizer in the US with much fanfare, died a quick death because “healthy and candy” was considered incoherent and the company made no attempt to deal with the possible effects of that incoherence (http://static.highbeam.com/c/candyindustry/january012002/).

In modeling incoherence between the attributes of a product, our model has the potential to be incorporated in other models and methodologies (such as discrete choice models in McFadden 1974 and pretest marketing simulators like ASSESSOR Silk and Urban 1975). Such approaches can be directly applied to the product repositioning, new product introduction and brand extension issues addressed here. Hence, the results can provide both quantitative value, as well as qualitative managerial insights.

While we have made a first step toward developing a framework and a model of incoherence, there are various limitations of the approach, many of which provide opportunities for further research. We have only calibrated a situation involving two attributes, and although the approach can be extended to more than two attributes, both the conceptualization and mathematics becomes much more complex, requiring assessment of both individual and joint effects of attribute claims on attribute perceptions. Appendix 2 (equation A2.3) provides the utility transformation for the multidimensional case, which can be used as a foundation for the development of the multivariate case. It should be noted however, that in practice, two dimensions often can describe the principal components of a set of attributes (e.g., Hauser and Shugan’s Defender model, 1983) and our model allows these factors to be oblique. A particularly important example of the two dimensional case is that of price-quality inferencing (Ordonez 1998).
We also assumed the uncertainty intolerance parameter \( \alpha \) in equation (8) to be equal to 2. It would be interesting to understand the drivers of variation in this parameter because that would help managers influence the relative uncertainty of the claims they make.

Another limitation of our model is that it is static and does not address either market dynamics or consumer learning. A dynamic model could involve formal updating of attitudes, beliefs, and preferences, perhaps in a Bayesian framework. It could also relax the assumption that inter-attribute correlations are fixed. It would be more realistic if consumers are assumed to learn about attribute covariances as well as attribute levels. If a new attribute is introduced (for example, Polaroid introduces "instant" as a camera/photography attribute), how does that affect coherence or incoherence structures in the marketplace? The example of an advertisement for the Honda Accord (it is a hybrid car--so you can have power plus fuel economy) is an attempt to change the inter-attribute correlation structures in the marketplace. Addressing that phenomenon would be a valuable model extension as well.

We assume symmetric effects of attributes on each other. If the consumer believes that changes in one attribute's level causes changes in the other but not conversely, the inference may be stronger from this attribute to the other than in the opposite direction. For example, Moreau, Lehmann and Markman (2001, p.18) look at the inter-dependence of camera product features on each other, allowing asymmetric dependency between the features. It would be useful to relax our model to allow for such unequal effects.

In addition to the inter-attribute extensions described above, the concept of incoherence has applicability to a wide range of other marketing problems. It would be useful to generalize the inter-attribute incoherence model to situations where incoherence arises from a wide variety of other sources of correlated information. These include information from the following
combination of sources; brand-brand (co-branding), brand-category (product line extensions),
brand-attribute (new product development), category-attributes (market development), and
brand-marketing mix (positioning and brand support), and others.

While this paper is a first attempt to model and measure incoherence with many
outstanding issues remaining unresolved, we hope this approach and framework can motivate a
platform for further analytical developments and practical applications.
Appendix 1

Derivation of the model of formation of perceptions (equations 6, 7, and 9)

In section 3, we proposed that consumers form the distribution of perceptions for each attribute \(X_1\) and \(X_2\) by using the information in the distributions of the associated claims and inferences.

We first assume that, for each attribute \(k\) \((k=1, 2)\), the consumer uses \(X_{ck}\) with probability \(p_k\) and \(X_{ik}\) with probability \((1-p_k)\). Let \(Y_k\) be a dummy variable with

\[
Pr(Y_k = 1) = p_k = 1 - Pr(Y_k = 0).
\]

We assume \(Y_1\) and \(Y_2\) to be independent. Then we have,

\[
(X_k \mid Y_k = 1) = X_{ck} \quad \text{and} \quad (X_k \mid Y_k = 0) = X_{ik}, \quad k=1, 2.
\]

With this formulation of the process, we find that:

\[
Pr(X_k \leq x) = Pr(X_k \leq x, Y_k = 1) + Pr(X_k \leq x, Y_k = 0)
\]

\[
= Pr(X_k \leq x \mid Y_k = 1) Pr(Y_k = 1) + Pr(X_k \leq x, Y_k = 0) Pr(Y_k = 0)
\]

\[
= p_k \cdot Pr(X_{ck} \leq x) + (1 - p_k) \cdot Pr(X_{ik} \leq x).
\]

Let the densities of \(X_{ck}\) and \(X_{ik}\) be denoted as \(\phi_{ck}\) and \(\phi_{ik}\), respectively. Since \(X_{ck}\) and \(X_{ik}\) are normally distributed, the density of \(X_k\), \(\phi_k\), is a mixture of two normal densities, as follows,

\[
\phi_k(x) = p_k \cdot \phi_{ck}(x) + (1 - p_k) \cdot \phi_{ik}(x).
\]

The mean of \(X_k\) is derived as follows,

\[
\bar{X}_k = E(X_k) = E_{y_k} E(X_k \mid Y_k) = p_k E(X_{ck}) + (1 - p_k) E(X_{ik})
\]

\[
= p_k \cdot \bar{X}_{ck} + (1 - p_k) \cdot \bar{X}_{ik}.
\]

The variance is given by,

\[
\text{var}(X_k) = E \left[ \left( X_k - E(X_k) \right)^2 \right]
\]

\[
= p_k \cdot E \left[ X_k^2 - 2 X_k \bar{X}_k + \bar{X}_k^2 \right] + (1 - p_k) \cdot E \left[ X_k^2 - 2 X_k \bar{X}_k + \bar{X}_k^2 \right].
\]
We now note that $E \left[ X_k^2 \right] = \left( \sigma_{ck}^2 + \bar{X}_{ck}^2 \right), E \left[ X_k^2 \right] = \left( \sigma_{rk}^2 + \bar{X}_{rk}^2 \right), E \left[ X_k \right] = \bar{X}_{ck},$ and $E \left[ X_k \right] = \bar{X}_{rk}$.

Substituting these terms into equation (A1.5), we obtain,

(A1.6) \[ \text{var}(X_k) = \sigma_k^2 = p_k \cdot (1 - p_k) \cdot \{\bar{X}_{ck} - \bar{X}_{rk}\}^2 + p_k \cdot \sigma_{ck}^2 + (1 - p_k) \cdot \sigma_{rk}^2. \]

We derive the covariance of $X_1$ and $X_2$ as follows:

(A1.7) \[ \sigma_{12} = E(X_1X_2) - \bar{X}_1 \bar{X}_2 \]
\[ = E_{Y_1,Y_2}(X_1X_2 | Y_1,Y_2) - \bar{X}_1 \bar{X}_2 \]
\[ = \left\{ p_1p_2E(X_{c1}X_{c2}) + p_1(1 - p_2)E(X_{c1}X_{12}) \right\} \]
\[ + p_2(1 - p_1)E(X_{11}X_{c2}) + (1 - p_1)(1 - p_2)E(X_{11}X_{12}) \}
\[ = \left\{ p_1p_2 \bar{X}_{c1} \bar{X}_{c2} + p_1(1 - p_2) \bar{X}_{c1} \bar{X}_{12} \right\} \]
\[ + p_2(1 - p_1)\bar{X}_{11} \bar{X}_{c2} + (1 - p_1)(1 - p_2)\bar{X}_{11} \bar{X}_{12} \}
\[ = \left\{ (1 - p_1) \beta_{c1,c2} \cdot \sigma_{c1,c2} \right\} \]
\[ + \left\{ (1 - p_2) \beta_{21,c2} \cdot \sigma_{c1,c2} \right\} \]
Appendix 2

Derivation of expected utility (equation 12)

**Multivariate case**

Let $X$ be the vector of attribute perceptions of the focal product. $X$ is assumed multivariate normal $\sim N_p(\mathbf{\mu}, \Sigma)$. Let $w$ be the vector of weights placed by the consumer on each attribute. The moment generating function for $w'X$ is given by (Rencher 2000),

$$M(t) = E\left[e^{t w'X}\right] = e^{(w'\mu)t + (w'\Sigma w)t^2/2}.$$  

Utility is defined in equation (11) as (for simplicity, we drop the scaling constants $a$ and $b$),

$$U = -e^{-r(w'X)},$$

where $t = -r$, where $r$ is the risk aversion parameter.

Then, using (A2.1), we obtain,

$$E[U] = E\left[-e^{-r(w'X)}\right] = -e^{-r\{(w'\mu) - \frac{r}{2}(w'\Sigma w)\}}.$$

**Bivariate case**

For the bivariate case, we define $\mu = [\bar{X}_1, \bar{X}_2]$, $w' = [w_1, w_2]$, and $\Sigma = \begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{bmatrix}$.

Substituting this notation in equation A2.2, we obtain utility $U$ as:

$$U = -e^{-r(w'X)} = -e^{-r(w_1X_1 + w_2X_2)}.$$

Expected utility from equation A2.3 is obtained by taking the expectation of $U$ in A2.4, integrating over the bivariate normal distribution of $X_1$ and $X_2$:

$$E(U) = -e^{-r\left(\frac{1}{2}w_1^2\sigma_1^2 + w_2^2\sigma_2^2 + 2w_1w_2\sigma_{12}\right)}.$$
Appendix 3

In Section 3.5, we seek a model to represent the consumer’s process of translating uncertain perceptions into preference. Given our assumptions of the utility function in equation (11) and the underlying perception formation process (see Appendix 1), we can derive an expression for expected utility as follows:

\[ E(U) = a - b \cdot E_{Y_1,Y_2} \left[ \exp \left\{ -r \cdot (w_1 X_1 + w_2 X_2) \right\} \right] \]

\[ = a - b \cdot \left\{ p_1 p_2 \exp \left\{ -r \cdot \left[ w_1 \bar{X}_{c1} + w_2 \bar{X}_{c2} - (r/2) \cdot (w_1^2 \sigma_{c1}^2 + w_2^2 \sigma_{c2}^2 + 2w_1w_2 \sigma_{c1c2}) \right] \right\} \right. 
\[ \left. + p_1(1-p_2) \exp \left\{ -r \cdot \left[ w_1 \bar{X}_{i1} + w_2 \bar{X}_{i2} - (r/2) \cdot (w_1^2 \sigma_{i1}^2 + w_2^2 \sigma_{i2}^2 + 2w_1w_2 \beta_{i1} \sigma_{c1}^2) \right] \right\} \right\} 
\[ \left. + p_2(1-p_1) \exp \left\{ -r \cdot \left[ w_1 \bar{X}_{j1} + w_2 \bar{X}_{j2} - (r/2) \cdot (w_1^2 \sigma_{j1}^2 + w_2^2 \sigma_{j2}^2 + 2w_1w_2 \beta_{j1} \sigma_{c1c2}) \right] \right\} \right\} 
\[ \left. + (1-p_1)(1-p_2) \exp \left\{ -r \cdot \left[ w_1 \bar{X}_{k1} + w_2 \bar{X}_{k2} - (r/2) \cdot (w_1^2 \sigma_{k1}^2 + w_2^2 \sigma_{k2}^2 + 2w_1w_2 \beta_{k1} \sigma_{c1c2}) \right] \right\} \right\} \].

While the above expression is an exact representation of expected utility, its properties are not readily apparent. However, if (i) the joint distribution of \( X_1 \) and \( X_2 \) is unimodal and (ii) its skewness and kurtosis are not too different from zero, the joint distribution can be well approximated by a bivariate normal, an assumption we made to derive the easily interpretable expression for expected utility in equation (12). We demonstrate that these two conditions are consistent with our formulation next.

For \( k=1, 2 \), the density of \( X_k \) is a mixture of two normal densities, \( N(\bar{X}_{ck}, \sigma_{ck}^2) \) and \( N(\bar{X}_{rk}, \sigma_{rk}^2) \).

Let \( d_k = (\sigma_{ck}^2 / \sigma_{rk}^2) \) and \( T(d_k) = \sqrt{-2 + 3d + 3d^2 - 2d^3 + 2(1-d-d^2)^{3/2} / (\sqrt{d} \cdot (1+\sqrt{d}))} \). Using a result in Schilling, Watkins, and Watkins (2002), we note that the density of \( X_k \) is unimodal if and only if \( |\bar{X}_{ck} - \bar{X}_{rk}| \leq T(d_k) \cdot (\sigma_{ck} + \sigma_{rk}) \). Note that \( T(1)=1 \) and the function is decreasing slowly for \( d_k > 1 \). This requirement for unimodality is likely to be met for most cases within the normal range of attribute levels.
Second, we can show that the third and fourth central moments of $X_k$ are,

\begin{align*}
(A3.2) \quad V_{3k} &= p_k (1-p_k) \left( \overline{X}_{ck} - \overline{X}_{rk} \right) \left[ 3\sigma_{ck}^2 + (1-p_k)^2 \left( \overline{X}_{ck} - \overline{X}_{rk} \right)^2 \right] \\
&\quad + p_k (1-p_k) \left( \overline{X}_{rk} - \overline{X}_{ck} \right) \left[ 3\sigma_{rk}^2 + p_k^2 \left( \overline{X}_{rk} - \overline{X}_{ck} \right)^2 \right] \\
(A3.3) \quad V_{4k} &= p_k \left[ 3\sigma_{ck}^4 + 6 \cdot (1-p_k)^2 \left( \overline{X}_{ck} - \overline{X}_{rk} \right)^2 \sigma_{ck}^2 + (1-p_k)^4 \left( \overline{X}_{ck} - \overline{X}_{rk} \right)^4 \right] \\
&\quad + (1-p_k) \left[ 3\sigma_{rk}^4 + 6 \cdot p_k^2 \left( \overline{X}_{rk} - \overline{X}_{ck} \right)^2 \sigma_{rk}^2 + p_k^4 \left( \overline{X}_{rk} - \overline{X}_{ck} \right)^4 \right]
\end{align*}

Skewness and kurtosis are defined as $S_k = \left( V_{3k} / \sigma_k^3 \right)$ and $K_k = \left( V_{4k} / \sigma_k^4 \right) - 3$ respectively.

If $S_k$ and $K_k$ are not too different from zero, then the unimodal density of $X_k$ may be well approximated by a normal distribution. For example, when $\sigma_{ck}^2 = \sigma_{rk}^2$, $S_k = 0$. Also if $\left| \overline{X}_{ck} - \overline{X}_{rk} \right|$ is small relative to $(\sigma_{ck} + \sigma_{rk})$, $K_k \approx 0$. Thus, under such conditions, the density of $X_k$ can be well approximated by a normal distribution.
Figure 1: Conceptual model of perception and preference formation for a new product

Notes:
1. Dotted lines indicate prior information that the consumer brings to the inferencing process.
2. The boxes in bold indicate the processes that we model.
Figure 2: Risk adjusted preference as a function of incoherence under different conditions

**Notes:**

Case 1: When the consumer is moderately risk averse, some incoherence is good, but too much is viewed as being “too good to be true” and discounted by the consumer. Therefore, the net result is an inverted U-shape curve.

Case 1a: When the consumer is extremely risk averse, very little incoherence is tolerated.

Case 2: When the consumer approaches risk-neutrality, incoherence does not, in the limit, have a negative effect on preference.
PART 2: USING PAST INFORMATION

Given below is a summary table of hypothetical evaluations obtained for an MBA subject last year. This table is similar to the way information is presented to you in the library, except that we are presenting you with evaluations for two questions only. Please note that these are hypothetical evaluations provided by 50 students. All numbers are expressed in percentages. After you look through this evaluation, please complete Tasks 3A, 3B, and 3C below. You will be asked to complete these tasks for 8 subjects.

<table>
<thead>
<tr>
<th>Subject # 1</th>
<th>50 respondents</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Scale Values</td>
</tr>
<tr>
<td></td>
<td>5 4 3 2 1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>SA</th>
<th>A</th>
<th>NAND</th>
<th>D</th>
<th>SD</th>
<th>NA</th>
<th>Mean Rating</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q. 1 The lecturer in this subject is always prepared for class</td>
<td>0</td>
<td>0</td>
<td>20</td>
<td>60</td>
<td>20</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Q. 2 Overall, I think this is an interesting subject</td>
<td>0</td>
<td>0</td>
<td>20</td>
<td>60</td>
<td>20</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Task 3A: Given the limited amount that you know about this subject, clearly you can’t be sure of how you will find it. What do you think are the chances out of 100 of you giving each of the following answers to the questions? Once again, please remember that the chances across the 5 scale points should add to 100. If the total does not add to a 100, you will be asked if you want the computer to prorate your chances such that the total is 100. You can also change your responses yourself, if you so wish.

Task 3B: Now please indicate, by clicking on the preference scale below, your preference for this subject with the above ratings from past students. Preference represents the value you place on the subject relative to other subjects on offer.

Task 3C: Please rate your confidence in your judgments of this subject by clicking on the scale below.

OK, let’s go to the next task!
<table>
<thead>
<tr>
<th>STEP</th>
<th>EXPERIMENTAL DESIGN</th>
<th>PURPOSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>D1.</td>
<td>Select context for study</td>
<td>Satisfy the following requirements: (i) multiple salient attributes that determine, to different degrees, preference, (ii) consumers with relatively homogenous experiences from which inter-attribute covariances can be elicited, and (iii) realistic product concepts possible, with attribute levels manipulated so that incoherence varies.</td>
</tr>
<tr>
<td>D2.</td>
<td>Obtain past ratings on actual products/services experienced</td>
<td>Estimate correlation of attributes in a non-intrusive field setting to select attributes for study and determine belief structures.</td>
</tr>
<tr>
<td>D3.</td>
<td>Construct two conditions – one with high correlation between attributes and the other with low correlation between attributes.</td>
<td>Between-respondents conditions to test whether different levels of inter-attribute covariation influence inferencing and the incoherence - preference relationship.</td>
</tr>
<tr>
<td>D4.</td>
<td>Construct product concepts by varying the performance of each product on the two selected attributes within a correlation condition.</td>
<td>Variation of product performance across attributes implies variation in incoherence. Used to estimate effect of mean attribute levels and incoherence on preference.</td>
</tr>
</tbody>
</table>

**MEASUREMENT PROCEDURES**

<table>
<thead>
<tr>
<th>STEP</th>
<th>EXPERIMENTAL DESIGN</th>
<th>PURPOSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>E1.</td>
<td>Consumers rate all products on attributes 1 and 2 on Likert scale on each of the selected attributes.</td>
<td>Obtain expected performance (perceptions) on each attribute based on actual category experience.</td>
</tr>
<tr>
<td>E2.</td>
<td>Present hypothetical product described by ratings on attributes 1 and 2.</td>
<td>Manipulate incoherence in product concepts.</td>
</tr>
<tr>
<td>E3.</td>
<td>Measure attribute perceptions, confidence in choice, and preference for the product.</td>
<td>Obtain perceptions, uncertainty, and preference measure.</td>
</tr>
<tr>
<td>E4.</td>
<td>Repeat for each of the remaining seven hypothetical products in the orthogonal design.</td>
<td>Vary incoherence to understand its effect on preference.</td>
</tr>
</tbody>
</table>
Table 2: The 24 item teaching effectiveness scale used to rate MBA courses/subjects
(items in bold were used in our study)

<p>| | | | | | | | | | | | | | | | | | | | | | | | | | |
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |</p>
<table>
<thead>
<tr>
<th></th>
<th>SA</th>
<th>A</th>
<th>U</th>
<th>D</th>
<th>SD</th>
<th>NA</th>
</tr>
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<tbody>
<tr>
<td>THIS LECTURER</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>1. Provides clear explanations of materials</td>
<td>SA</td>
<td>A</td>
<td>U</td>
<td>D</td>
<td>SD</td>
<td>NA</td>
</tr>
<tr>
<td>2. Gives well organized lectures</td>
<td>SA</td>
<td>A</td>
<td>U</td>
<td>D</td>
<td>SD</td>
<td>NA</td>
</tr>
<tr>
<td>3. Is always prepared for class</td>
<td>SA</td>
<td>A</td>
<td>U</td>
<td>D</td>
<td>SD</td>
<td>NA</td>
</tr>
<tr>
<td>4. Provides good examples or applications</td>
<td>SA</td>
<td>A</td>
<td>U</td>
<td>D</td>
<td>SD</td>
<td>NA</td>
</tr>
<tr>
<td>5. Has good knowledge of the subject</td>
<td>SA</td>
<td>A</td>
<td>U</td>
<td>D</td>
<td>SD</td>
<td>NA</td>
</tr>
<tr>
<td>6. Appears to enjoy teaching</td>
<td>SA</td>
<td>A</td>
<td>U</td>
<td>D</td>
<td>SD</td>
<td>NA</td>
</tr>
<tr>
<td>7. Does not allow student participation to take too much class time</td>
<td>SA</td>
<td>A</td>
<td>U</td>
<td>D</td>
<td>SD</td>
<td>NA</td>
</tr>
<tr>
<td>8. Does not demand too heavy a workload</td>
<td>SA</td>
<td>A</td>
<td>U</td>
<td>D</td>
<td>SD</td>
<td>NA</td>
</tr>
<tr>
<td>9. Assigns readings which are relevant to papers and exams</td>
<td>SA</td>
<td>A</td>
<td>U</td>
<td>D</td>
<td>SD</td>
<td>NA</td>
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<td>THIS SUBJECT</td>
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<tr>
<td>10. Does not unnecessarily repeat material from other subjects</td>
<td>SA</td>
<td>A</td>
<td>U</td>
<td>D</td>
<td>SD</td>
<td>NA</td>
</tr>
<tr>
<td>11. Is important for MBA graduates to understand</td>
<td>SA</td>
<td>A</td>
<td>U</td>
<td>D</td>
<td>SD</td>
<td>NA</td>
</tr>
<tr>
<td>12. Overall, I think this is an interesting subject</td>
<td>SA</td>
<td>A</td>
<td>U</td>
<td>D</td>
<td>SD</td>
<td>NA</td>
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<td>13. In this subject helped me understand the material</td>
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<td>A</td>
<td>U</td>
<td>D</td>
<td>SD</td>
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<tr>
<td>14. Was given appropriate weight in assessment</td>
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<td>A</td>
<td>U</td>
<td>D</td>
<td>SD</td>
<td>NA</td>
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<td>TUTORIALS</td>
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<tr>
<td>15. Were a considerable help to me</td>
<td>SA</td>
<td>A</td>
<td>U</td>
<td>D</td>
<td>SD</td>
<td>NA</td>
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<tr>
<td>16. Had a clear supportive relationship with the lectures</td>
<td>SA</td>
<td>A</td>
<td>U</td>
<td>D</td>
<td>SD</td>
<td>NA</td>
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<tr>
<td>GUEST LECTURERS</td>
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<tr>
<td>17. Were an effective part of the subject</td>
<td>SA</td>
<td>A</td>
<td>U</td>
<td>D</td>
<td>SD</td>
<td>NA</td>
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<tr>
<td>18. The collection of books relevant to this subject was sufficient</td>
<td>SA</td>
<td>A</td>
<td>U</td>
<td>D</td>
<td>SD</td>
<td>NA</td>
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<tr>
<td>19. The collection of serials provided good coverage for the subject</td>
<td>SA</td>
<td>A</td>
<td>U</td>
<td>D</td>
<td>SD</td>
<td>NA</td>
</tr>
<tr>
<td>20. The librarians helped me located relevant information quickly</td>
<td>SA</td>
<td>A</td>
<td>U</td>
<td>D</td>
<td>SD</td>
<td>NA</td>
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<td>ASSESSMENT</td>
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<td>21. The lecturer provides useful feedback on assignments</td>
<td>SA</td>
<td>A</td>
<td>U</td>
<td>D</td>
<td>SD</td>
<td>NA</td>
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<tr>
<td>22. The lecturer gives assignments back in reasonable time</td>
<td>SA</td>
<td>A</td>
<td>U</td>
<td>D</td>
<td>SD</td>
<td>NA</td>
</tr>
<tr>
<td>23. The assessment system was suitable</td>
<td>SA</td>
<td>A</td>
<td>U</td>
<td>D</td>
<td>SD</td>
<td>NA</td>
</tr>
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<td>OVERALL ASSESSMENT</td>
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<tr>
<td>24. I recommend this subject as taught by this lecturer</td>
<td>SA</td>
<td>A</td>
<td>U</td>
<td>D</td>
<td>SD</td>
<td>NA</td>
</tr>
</tbody>
</table>

SA = Strongly agree; A = Agree; U = Undecided; D = disagree; SD = Strongly disagree; NA = not applicable
### Table 3: Empirical model estimates

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Variable</th>
<th>High Correlation Condition</th>
<th>Low Correlation Condition</th>
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</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Estimate</td>
<td>t-stat</td>
</tr>
<tr>
<td>$\eta_0$</td>
<td>Intercept</td>
<td>3.55</td>
<td>3.87$^a$</td>
</tr>
<tr>
<td>$\eta_1$</td>
<td>$\bar{X}_1$</td>
<td>5.93</td>
<td>3.64$^a$</td>
</tr>
<tr>
<td>$\eta_2$</td>
<td>$\bar{X}_2$</td>
<td>6.60</td>
<td>4.75$^a$</td>
</tr>
</tbody>
</table>

#### Preference Uncertainty

| $\eta_3$ | $AI_1$ | -3.49 | -3.15$^a$ | -0.57 | -0.64 |
| $\eta_4$ | $AI_2$ | -1.34 | -1.98$^b$ | -1.04 | -1.03 |

$^a p<0.01$, $^b p<0.05$

Notes:

1. In the high correlation condition, attributes were “course is important”, and “course is interesting”.
2. In the low correlation condition, attributes were “lecturer is well-prepared”, and “course is interesting”.
3. $\eta_1$ and $\eta_2$ are significant and positive in each correlation condition.
4. $\eta_3$ and $\eta_4$ were expected to be significant in the high correlation case, but not in the low correlation case, confirmed.
5. $\eta_3$ and $\eta_4$ were expected to be negative in both cases, directionally confirmed in both cases.
References


Alloy, Lauren and Naomi Tabachnik (1984), “Assessment of Covariation by Humans and
Animals: The Joint Influence of Prior Expectations and Current Situational Information,”

*Psychological Review*, 91, 112-149.

Beckwith, Neil E. and Donald R. Lehmann (1975) “The Importance of Halo Effects in Multi-
Attribute Models”, *Journal of Marketing Research*, 12, No. 3; pp. 265-75

Bell, David E., Ralph L. Keeney and John D. C. Little (1975) “A Market Share Theorem,”


Influential Data and Sources of Collinearity*, John Wiley, New York.

Correlation Tasks,” *Organizational Behavior and Human Decision Processes*, 57
(January), 117-137.


Meaningless Differentiation: The Dependence on Irrelevant Attributes,” *Journal of
Marketing Research*, 31 (August), 339-350.

Chatterjee, Rabikar, Jehoshua Eliashberg, Hubert Gatignon, and Leonard Lodish (1986), “A
Practical Bayesian Approach to Selection of Optimal Marketing Testing Strategies,”


