The Use of Indicators for Unobservable Product Qualities: Inferences Based on Consumer Sorting

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Abstract We propose a method for measuring the conjectural errors that inexpert consumers make relative to experts in using observable product characteristics as surrogate indicators of a valued unobservable characteristic. Observations on the unobservable characteristic, available to the researcher but not consumers, are used to divide the data into high- and low-quality subsamples. Separate hedonic estimation on the subsamples enables measurement of the relative valuations and conjectures of experts and non-experts with respect to indicators under the assumption that consumers sort across quality grades based on their appraisal expertise. The method is demonstrated using a small sample of SKU-level data on the dietary supplement black cohosh. Our exploratory findings on this sample suggest that, relative to experts, inexpert consumers underestimate the value of most observable characteristics as indicators of black cohosh chemical authenticity; however they overweight therapeutic claims on the product label as a negative indicator of authenticity.

Keywords Consumer behavior, Expertise, Surrogate indicators, Missing information, Credence goods, Hedonic analysis

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Prices indicate the product characteristics that consumers value, but they do not tell us why consumers value them. While in some cases consumers might value a characteristic intrinsically, in other cases characteristics are valued as a signal, or surrogate indicator, of the level of some quality that is not directly observable. For example, a knowledgeable owner of a porcelain vase may find its shape and painted decoration aesthetically pleasing; meanwhile, she may value the vase's thickness as an indicator of its authenticity as an artifact of the Ming Dynasty, rather than, say, because it makes the vase more durable or beautiful (Brook 1998, p. 225-6). Traditional hedonic analysis, which deals in the valuation of observable qualities, would tell us only that consumers value thickness in a vase. Moreover, additional questions relevant to marketing arise in the context of unobservable qualities that the standard hedonic approach does not answer. Do consumers accord full value to a characteristic as an indicator of an unobserved quality, or do they undervalue it as such because they are unaware or tentative with respect to the characteristic's indicator capabilities? Do consumers, on the other hand, accord *too much* value to the characteristic as an indicator and rely too heavily on it? Do different consumers make different conjectures in this regard? If so, how does one identify the different consumers? To answer these questions, it is necessary, inter alia, to measure the quality unobservable to consumers – in the Ming vase example, authenticity – something that is not an element of traditional hedonic analysis.

This paper demonstrates a method for extracting information on consumers' use of observable product characteristics as surrogate indicators. It makes use of data measuring authenticity (i.e., whether the product contains the key ingredients claimed on the label) for a sample of brands of black cohosh, a dietary supplement believed to help with menopause symptoms. Black cohosh is properly characterized as a credence good, or product for which key

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quality-related characteristics (such as botanical authenticity) are not observable even after purchase and use (Darby and Karni 1973; Dulleck and Kerschbamer 2006). We obtain data on authenticity in the laboratory through a standard analytical method called high-performance liquid chromatography. Thus we observe a critical quality-related product characteristic that consumers have not. While this may appear at first blush to present a unique situation, data on consumer-unobservable characteristics are similarly available to researchers in many typical marketing contexts. As experts on their categories, product manufacturers often have superior information on the quality of competing products relative to consumers. Sophisticated quality measurement techniques, such as those used by *Consumer Reports* and other independent testers, while infeasible for most consumers, may be feasible for researchers.

Two problems complicate the process of empirical inference in this context. The first is, as suggested by the above discussion, that consumers are not generally expert appraisers of key unobservable qualities.[1] Consumers may be unaware of the need to appraise a certain unobservable quality, or unaware that information at their disposal from observable characteristics could provide insight into it.[2] Or, they may be aware that an observable characteristic can help in appraisal of an unobservable quality, but they may not know in what way or to what extent. If this last holds true, then the econometric relationship between the indicators and the unobserved quality is not the one consumers conjecture, hence that

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[1] The marketing literature on expertise provides a useful background on this decision-maker trait and its relevance. Alba and Hutchinson (1987) define five dimensions of consumer expertise that are influenced by product familiarity. Mitchell and Dacin (1996) offer experimental evidence of the effect of expertise on consumers' performance at predictive tasks. They also provide an excellent review (p. 219) of the psychological literature relating expertise to performance levels in various cognitive functional areas. For additional evidence, see also Chiou (2003), Maheswaran (1994), and Maheswaran et al. (1996).

[2] Unawareness may be described by subjective state spaces that may contain full *factual* information but lack *awareness* information necessary for reasoning with respect to relevant uncertainties. Thus, the agent possesses facts, but they do not "ring a bell" in a way needed to make a relevant inference. Put another way, the possibility of the inference does not "occur" to the agent. For discussions, see Heifetz et al. (2006), Li (2009), and Liu (2008).

relationship does not provide an accurate basis for determining how the indicator variables are being valued by the market.

We classify inexpert appraisal using surrogate indicators into three cases. A consumer might *overshoot*, overestimating the power of the surrogate indicator to predict the unobservable characteristic. Or she might *undershoot,* underestimating its power of prediction. Or she might entertain a *fallacy*, reversing in her prediction the true sign of the relationship between surrogate indicator and unobservable characteristic. Expert appraisal is nested in this structure as a boundary sub-case between "overshoot" and "undershoot," while unawareness is a boundary sub-case between "undershoot" and "fallacy."

The second problem is that consumers are not all the same. Some are more expert than others. This means hedonic analysis, which relies on the assumption that consumers express homogenous preferences, is inappropriate when applied indiscriminately to the mass of consumers.[3] Moreover, the problem of inferring consumers' conjectures becomes complex, since those conjectures vary across consumers.

We extract information about different consumers' use of surrogate indicators by inferring consumers' expertise levels from their choices. Consumers with greater appraisal expertise are better at discerning quality, and so sort disproportionately to higher quality products. This enables the researcher to measure the surrogate indicator valuations and conjectural errors of inexpert consumers relative to experts by separately performing hedonic analysis on high- and low-quality product pools. Importantly, this process constitutes a justifiable use of the hedonic model assuming consumers' effective preferences *within* quality

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[3] We emphasize "express" here because, even though consumers may all have the same preferences over characteristics, differences in expertise will cause consumers to act as if their preferences differ. This would violate the requirements of the hedonic model. See "Model and approach" section below.

pool are sufficiently homogeneous. We demonstrate the method using separate estimation on authentic and non-authentic black cohosh subsamples.

The idea that consumers sort across quality grades based on differences in ability is not new. A number of theoretical analyses have considered market outcomes in situations in which some consumers are inattentive, unskilled, or otherwise experience higher costs to evaluating market information than others (Armstrong and Chen 2009; Gabaix and Laibson 2006; Nagler 1993; Salop and Stiglitz 1977). One consistent finding across this literature is that people with different abilities select different products (or, more generally, product choice strategies), such that more skilled, less cost-encumbered individuals get better deals than those less skilled and more cost-encumbered. The present paper's innovation is to advance an empirical methodology that uses sorting as a tool to extract information relevant to managerial decision-making. One may apply the methods developed in this study to create targeted pricing, product and promotion strategies based on consumer expertise levels. The methods may also be used to develop and evaluate public policies, particularly policies related to marketing practices and consumer outcomes (see Conclusion).

A number of researchers have studied the processes by which consumers infer product attributes for which information is missing (e.g., Broniarczyk and Alba 1994; Dick et al. 1990; Johnson and Levin 1985; Ross and Creyer 1992; Sanbonmatsu et al. 1991, 2003). A literature specifically devoted indicators of product quality focuses largely on how different surrogate indicators, such as country-of-origin and perceived difficulty of manufacture, influence consumers' perceptions of unobservable quality (e.g., Jo 2005; Johnson and Folkes 2007; Quester et al. 2000; West et al. 2002). Much of the research emphasis has been on the role of price as an indicator of quality; analyses have included experimental studies (e.g., Brucks et al.

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2000; West et al. 2002) and some meta-analytic reviews (Rao and Monroe 1989; Völckner and Hofmann 2007). By and large, the studies in these categories are descriptive: none provides a methodology for using data on consumer-unobservable qualities as a tool for making inferences about consumers' valuations and quality judgments.

Another strand of work, related to the literature on the role of indicators, looks at the accuracy of consumer perceptions. In a set of analyses involving both durable and non-durable goods, Burton and Lichtenstein (1989, 1990) considered how consumers' perceptions of the price-quality relationship contrast with actual price-quality. Mason et al. (2001) examined the determinants of consumers' accuracy at judging brand performance on various attributes. One thing these studies have in common is that they ascertain consumer accuracy using as benchmarks for "objective" quality measures that are publicly available to consumers – for example, ratings in *Consumer Reports*. The present paper is unique in that its measure of objective quality is one that consumers could not possibly have observed themselves; thus we eliminate the possibility that consumers may have improved their accuracy by "peeking" at the objective measures.

The rest of the paper is structured as follows. We begin by laying out a model of unobservable characteristics and surrogate indicators. In the context of the model, we examine the empirical problem posed by inexpert consumer appraisal, and we consider how a hedonic approach predicated on consumer sorting addresses the problem. We then apply of our approach to the market for black cohosh. We conclude by discussing managerial implications, limitations of the current study, and possible objectives for future research.

Model and approach

Unobservable product qualities

The standard hedonic approach posits a continuum of differentiated products, perfect competition, complete information, and consumers with homogeneous preferences who value a product as a bundle of characteristics (Rosen 1974). Let us stipulate to these assumptions for the moment, and specifically let us consider a differentiated product space consisting of K observable characteristics, X_k, $k=1,\ldots,K$, and one unobservable characteristic, z. Thus the utility the representative consumer obtains from consuming the product is given by

$$U = U\left(X_1,\ldots,X_K,z\right) \tag{1}$$

Maximization of (1) subject to a budget constraint produces a hedonic price function, for brand i,

$$p_i = f\left(X_{1i},\ldots,X_{Ki},z\right) \tag{2}$$

where X_{ki} is the value of the kth characteristic for brand i and p_i the price level for i (Huang and Lin 2007). The corresponding hedonic log regression equation specifies

$$P_i = \alpha + \beta_1 X_{1i} + \ldots + \beta_K X_{Ki} + \xi_i \tag{3}$$

where $P_i \equiv \log p_i$ and ξ is a stochastic disturbance term. Note that z does not enter this regression because it is not observable. Estimation of the equation in (3) allows measurement of the extent to which the consumer values increments in each of the observable variables, that is, $\beta_k \equiv \partial P / \partial X_k$. But, as discussed in the introduction, it does not provide information on the extent to which observables are valued as indicators of z. Nor does one get any sense as to how much the consumer values increments in z.

In general, the value of each observable characteristic X_k provides information about the value of z, following from some functional relationship

$$z = z(X_1,...,X_K) \qquad (4)$$

Assuming $\partial z/\partial X_k$ is nonzero, X_k is said to be a surrogate indicator of z. If $\partial z/\partial X_k > 0$, then we say that X_k is a positive indicator of z. If $\partial z/\partial X_k < 0$, X_k is a negative indicator of z. We may therefore decompose the partial derivative of P with respect to the X_k in (3) as

$$\partial P/\partial X_k = \partial P/\partial X_k\big|_D + \partial P/\partial z \cdot \partial z/\partial X_k \qquad (5)$$

That is, the effect of each observable characteristic on the log price of the product is equal to the sum of its direct effect as a quality with intrinsic value to the consumer and its indirect effect as a surrogate indicator to the consumer of the valued unobservable characteristic.[4]

Now suppose we are able to privately observe z, so that z may be included along with the observable variables. Then (3) becomes

$$P_i = \alpha_D + \lambda z_i + \beta_{1D} X_{1i} + ... + \beta_{KD} X_{Ki} + \eta_i \qquad (6)$$

where η is the stochastic disturbance term for the augmented equation. Also, approximating (4) with a linear relationship, we may write a regression equation that determines the value of z,

$$z_i = a + b_1 X_{1i} + ... + b_K X_{Ki} + \varepsilon_i \qquad (7)$$

where ε is a stochastic disturbance. In (6), the effect of the X_k on log price through z is controlled for, so a decomposition has been effected. The coefficients on the X_k represent the

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[4] People obtain indications about unobservable product qualities from a number of sources, including advertising content and intensity, consumption experiences, and prices (e.g., Erdem et al. 2008); as well as word-of-mouth communication by other consumers, including online product reviews (Godes and Mayzlin 2004). Such sources of product indication may be viewed, in the context of our model, as augmenting Lancaster's (1966) model of "proper" product characteristics and extending the corresponding basis for hedonic estimation.

direct effect of the X_k on log price, $\partial P/\partial X_k\big|_D$, purged of the effect that the X_k have as indicators of the value of z. Since the coefficient on z is $\partial P/\partial z$, it appears that by estimating (3) and (6), we would obtain each component in (5).

Inexpert appraisal

The above estimation procedure makes a critical assumption that all consumers incorporate the *full* $\partial z/\partial X_k$ in their valuation of the X_k. This is because including $\hat{z}$ in (6) controls for the $\partial z/\partial X_k$ based on the actual empirical relationship of z to the X_k. Thus it assumes that consumers are aware of all the information each observable characteristic provides about the value of z. This is true if consumers are expert appraisers of z, but it is not true if they are not.

Let us continue to maintain the assumption of a single representative consumer, but allow that the consumer might not be an expert appraiser of z. In light of this, it is necessary to be more precise about what we mean by $\partial z/\partial X_k$. Let us define $\partial z/\partial X_k\big|_T$ as the *total* information content that X_k provides on z, which in turn may be thought of as the sum of two components: $\partial z/\partial X_k\big|_A$, the component the consumer is aware of or presumes in her appraisal of z; and $\partial z/\partial X_k\big|_U$, the component the consumer is unaware of (i.e., the gap between the actual $\partial z/\partial X_k\big|_T$ and what the consumer presumes). With this newly defined structure, the decomposition in (5) is re-written as

$$\partial P/\partial X_k = \partial P/\partial X_k\big|_D + \partial P/\partial z \cdot \partial z/\partial X_k\big|_A \qquad (8)$$

reflecting that the surrogate indicator influence of the X_k on log prices occurs only through that portion of the X_k's explaining power that the consumer presumes.

Now it may be seen that estimation of (6) actually yields $\partial P/\partial X_k \big|_D - \partial P/\partial z \cdot \partial z/\partial X_k \big|_U$ as the coefficients on the X_k, *not* the $\partial P/\partial X_k \big|_D$; the latter are unrecoverable without knowing the extent and nature of the consumer's inexpert use of each surrogate indicator X_k. Put another way, estimation of (6) provides biased estimates of the $\partial P/\partial X_k \big|_D$, where the bias is given by $-\partial P/\partial z \cdot \partial z/\partial X_k \big|_U$. The sign of the bias for each X_k depends on three things: whether the unobservable characteristic z is valued positively or negatively by the market (i.e., the sign of $\partial P/\partial z$), whether X_k is a positive or negative surrogate indicator of z (i.e., the sign of $\partial z/\partial X_k \big|_T$), and the nature of consumers' inexpertise in using X_k to appraise z (i.e., the relationship of $\partial z/\partial X_k \big|_A$ to $\partial z/\partial X_k \big|_T$).

Delving into this last item in greater detail, let us assume that consumers exhibit a consistent form of inexpert appraisal for each X_k, that is, the relationship of $\partial z/\partial X_k \big|_A$ to $\partial z/\partial X_k \big|_T$ does not vary for a given k. We classify this relationship into three mutually exclusive and collectively exhaustive cases based on the value of $\mu_k \equiv \left(\frac{\partial z}{\partial X_k} \big|_A \right) \Big/ \left(\frac{\partial z}{\partial X_k} \big|_T \right)$. First, suppose $\mu_k > 1$. This implies consumers sign the relationship between X_k and z correctly but perceive that X_k moves z more than it actually does. In this case, consumers *overshoot*. Second, suppose $\mu_k \in (0,1)$. This implies consumers sign the relationship between X_k and z correctly but perceive that X_k moves z *less* than it actually does. In this case, consumers *undershoot*. Third,

suppose $\mu_k < 0$. This implies consumers sign the relationship between X_k and z incorrectly –

that is, they perceive z rises with X_k when it actually falls, or falls with X_k when it actually

rises. In this case, consumers are said to entertain a *fallacy* about the X_k. Complete unawareness

of a surrogate indicator would be represented by the borderline value $\mu_k = 0$, while for expert

appraisers $\mu_k = 1$.

Table 1 summarizes the researcher's potential bias outcomes based on this classification.

For example, for a positively valued unobservable characteristic and positive surrogate indicator,

the estimate of $\partial P/\partial X_k\big|_D$ is positively biased when consumers overshoot. Intuitively, this is

because consumers assign more surrogate indicator value to the variable then merited by its

actual empirical relationship to the unobservable characteristic; so their intrinsic valuation of the

variable, as a component of overall valuation, is overestimated when the estimation considers the

actual empirical relationship instead of the perceived one. Note that while we may speak of the

biases in estimation conditional on each consumer conjecture, we normally are able to measure

neither the estimation bias nor the conjecture.

<center><Insert Table 1 about here></center>

The empirical conundrum created by consumers' inexpertise may be viewed through

another lens by estimating (7), which shows the actual empirical relationship between the X_k

and z. This relationship, as we have discussed, is generally not known to the non-expert

consumer. Thus the coefficients on the X_k are the $\partial z/\partial X_k\big|_T$ rather than the $\partial z/\partial X_k\big|_A$. In

practical terms, though estimation of (7) may indicate a good fit of z with the X_k, it is not

necessarily the case that consumers have in actuality obtained a good fix on z.

The measure of $\partial P/\partial z$ obtained from estimating (6) also reflects the conundrum. The coefficient varies with two effects that are not separately identified: the consumer's valuation of z, and the consumer's composite competence at using the surrogate indicators of z. Thus a small $\partial P/\partial z$ conflates consumer unawareness with respect to z with consumer apathy. It is possible, moreover, that $\partial P/\partial z$ takes the "wrong" sign, that is, negative for a characteristic that consumers value positively. This occurs when appraisal using available indicators is sufficiently inexpert and fallacious that consumers perceive an unobservable characteristic to be more present when it is in fact less present. Thus an unobservable characteristic desired by consumers could actually be valued negatively by the market.

Differences in appraisal expertise

Let us now consider the possibility that not all consumers are equally inexpert: some may be expert appraisers while others are less skilled. Generally, not all people will have the same exposures or experiences that enable them to learn. Even if they did, differences across individuals would lead to different learning with respect to the same exposure. The consequence is differences in knowledge and expertise across individuals.

To model this, let us begin by assuming that consumers differ only with respect to their expertise, and that they are identical with respect to their tastes for product attributes. That is, different consumers j will be characterized by different levels of $\partial z/\partial X_k\big|_{A(j)}$ for each k. This will tend to result in different levels $\partial P/\partial X_{k(j)}$ for each consumer; however, the direct log valuation components, $\partial P/\partial X_k\big|_D$, will be the same for all. Appraisal expertise may be defined

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in an overall sense based on the relative ability of different consumers in essence to fit (7) from

the X_k using their conjectures about the $\partial z / \partial X_k$. Specifically, consumer j' is "more expert"

than j'' if $\sum_k \left[\left(\partial z / \partial X_k |_{U(j')} \right)^2 \cdot \overline{X}_k \right] < \sum_k \left[\left(\partial z / \partial X_k |_{U(j'')} \right)^2 \cdot \overline{X}_k \right]$, where $\overline{X}_k = \sum_i X_{ki}$; that is, if her

weighted sum of squared conjectural error is lower.[5] Thus less-expert individuals, so defined,

are more prone to errors in distinguishing high-z brands from low-z brands.

The assumption of differences in expertise across consumers has implications for the

distribution of consumers across products. This may be seen by considering a simple example in

which there are two brands, H and L, and two consumers, j' and j''. Assume H exhibits higher

quality with respect to the unobserved characteristic, i.e., $z_H > z_L$. Suppose the two consumers

have identical conjectures with respect to all the $\partial z / \partial X_k$ except for one, and for that k' let

$\left| \partial z / \partial X_{k'} |_{U(j')} \right| < \left| \partial z / \partial X_{k'} |_{U(j'')} \right|$. Thus consumer j'' is less expert than j'. It follows that j'' is more

likely than j' to conclude erroneously that H is the low-quality product and L the high-quality

product. Thus, given any price pair for the two products, j'' is more likely to choose L, all else

being equal; that is, for a given price, j'' is more likely to conclude (erroneously) that L is the

better buy based on her erroneous appraisal of z_H and z_L. We can see that consumers who are

more expert at appraisal will tend to sort to the high-quality product, while inexpert consumers

sort to the low-quality product. Sorting of consumers need not be perfect; however, there will

generally be differences in the average expertise of consumers across product pools correlated

with the level of unobservable characteristic.

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[5] In fact, we expect that expertise in appraisal likely carries across all surrogate indicators, such that people who make erroneous conjectures about one $\partial z / \partial X_k$ will likely make larger errors about others. This is consistent with the literature, which views expertise as accruing at the level of the overall product (Alba and Hutchinson 1987). For the purposes of this paper, it is not necessary to introduce this complication into the modeling. However, the notion does provide motivation for thinking of expert and inexpert appraisers as constituting distinct market segments.

Consumer sorting based on expertise levels has important empirical measurement implications. Recall that the hedonic model requires homogeneous preferences. While this assumption has not been violated per se, the fact that consumers exhibit differences in expertise means that the manifestation of their preferences is heterogeneous. With preference heterogeneity, the hedonic relation taken over all consumers does not trace out a demand function (Bajari and Benkard 2005; Rosen 1974).[6] However, given sorting, it may be quite reasonable to posit consumer homogeneity (or a close approximation) *within product pools of a given quality level* such that the hedonic relation with respect to each pool traces out a demand function. If so, then the hedonic approach *may* be appropriately applied separately on product subsamples that vary, using the terminology of our model, as to the value of z.

Given the feasibility of hedonic regression on subsamples, it is possible to make inferences about consumers' conjectures relating to the surrogate indicators. Our simple model illustrates. Let us use subscript E to represent the relatively expert consumers that sort to the high-quality product, and I to represent the relative inexpert consumers that sort to the low-quality product. Estimation of (3) restricted to high-quality products provides a composite $\partial P / \partial X_{k(E)}$ for each k, while estimating the same equation for low-quality products provides $\partial P / \partial X_{k(I)}$. Using (8), we may write out the implicit components of the coefficients pertaining to experts and inexpert consumers

$$\partial P / \partial X_{k(E)} = \partial P / \partial X_k \big|_D + \partial P / \partial z_{(E)} \cdot \partial z / \partial X_k \big|_{A(E)} \qquad (9)$$

$$\partial P / \partial X_{k(I)} = \partial P / \partial X_k \big|_D + \partial P / \partial z_{(I)} \cdot \partial z / \partial X_k \big|_{A(I)} \qquad (10)$$

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[6] Rather, that relation depends on costs and a markup resulting from a complex relationship between the heterogeneous preferences and the characteristics of competing offerings, whence the hedonic regression becomes a reduced form in which the coefficients have no obvious interpretation in terms of economic primitives. See Pakes (2003).

where $\partial P/\partial z_{(E)}$ and $\partial P/\partial z_{(I)}$ represent, respectively, how experts and inexpert consumers collectively value z while $\partial z/\partial X_k\big|_{A(E)}$ and $\partial z/\partial X_k\big|_{A(I)}$ represent the surrogate indicator capability that each group attributes to X_k. Note that we are unable to estimate these components directly: z is a constant for the high- and low-quality subsamples, so we cannot include it in the equation. However, (9) and (10) do indicate that the difference in the coefficient estimates for the constant term provides an estimate of $\partial P/\partial z_{(E)} - \partial P/\partial z_{(I)}$.

Subtracting (9) from (10) yields the *relative bias in log valuation* of inexpert consumers for each X_k,

$$\partial P/\partial X_{k(I)} - \partial P/\partial X_{k(E)} = \left(\partial P/\partial z_{(I)} - \partial P/\partial z_{(E)}\right)dz/dX_k\big|_{A(I)} - \partial P/\partial z_{(E)} \cdot dz/dX_k\big|_{U(EI)} \quad (11)$$

This bias is the sum of two components: inexpert consumers' relative error in their log valuation of z, weighted by their surrogate indicator conjecture about X_k; and their relative error about the role of X_k as indicator, $dz/dX_k\big|_{U(EI)} \equiv dz/dX_k\big|_{A(E)} - dz/dX_k\big|_{A(I)}$, weighted by the experts' log valuation of z. Note that $dz/dX_k\big|_{U(EI)}$ represents a generalization of $dz/dX_k\big|_{U} \equiv dz/dX_k\big|_{T} - dz/dX_k\big|_{A}$ from the previous section, in which the conjectures of the relative experts who sort to the high-quality product replace the total information content represented by the subscript T. We observe that the intrinsic valuation of X_k plays no role in the bias; this follows from the presumption that all consumers have identical tastes for product attributes. Intuitively, the relative bias tells us how log valuations of X_k purely as a surrogate indicator differ for consumers sorting to low-quality versus high-quality products.

A corresponding *relative conjectural error*, $\mu_{k(EI)} \equiv \frac{\partial z}{\partial X_k}\big|_{A(I)} \Big/ \frac{\partial z}{\partial X_k}\big|_{A(E)}$, generalizes μ_k; here, overshooting, undershooting, and fallacy by inexpert consumers relative to the experts may

be defined, respectively, as $\mu_{k(EI)} > 1$, $\mu_{k(EI)} \in (0,1)$, and $\mu_{k(EI)} < 0$. Whereas inferences could

not drawn about μ_k, the sorting of consumers allows us to draw inferences about $\mu_{k(EI)}$, based

on (11). Table 2 summarizes. Inferences depend upon the sign of $\partial P / \partial X_{k(I)} - \partial P / \partial X_{k(E)}$, whether

the unobservable characteristic is positively or negatively valued, and whether X_k is a significant

positive or negative surrogate indicator with respect to the unobservable characteristic based on

estimation of (7). The table's results depend additionally on the maintained assumption that both

experts and inexpert consumers consistently and correctly value z as positive or negative; this

enables us to posit $\partial P / \partial z_{(E)} > \partial P / \partial z_{(I)} > 0$ for a positive z, and $\partial P / \partial z_{(E)} < \partial P / \partial z_{(I)} < 0$ for a

negative z. We also maintain the assumption that expert consumers are sufficiently expert that

they are not fallacious, though the inexpert consumers could be.

<Insert Table 2 about here>

Table 2 shows that the researcher may mainly distinguish only situations in which

inexpert consumers overshoot substantially from situations in which they do not. For example,

when a significant positive surrogate indicator of a positively valued unobservable characteristic

corresponds to a positive bias in inexpert consumers' log valuations, it is clear that inexpert

consumers assign more surrogate indicator value to the characteristic than is warranted. But

when these conditions correspond to a negative bias, it is impossible to distinguish whether the

conjectural error is characterized by fallacy, undershoot, or even a small overshoot. A negative

bias follows for modest overshooting because a negative first term may overwhelm a positive

second term in (11)[7]: intuitively, the inexpert consumers' failure to identify the positive

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[7] For this reason, a correctly signed bias term (i.e., the same sign as z when X_k is a significant positive indicator, the opposite sign when X_k is a significant negative indicator) is sufficient for identifying overshooting consumers, that

unobservable characteristic when it is present causes them to undervalue its presence in general. This drags down the surrogate indicator value of all observable characteristics. Meanwhile, in the case of a variable not being a significant surrogate indicator as revealed in the estimation of (7), the relative conjectural error is indeterminate: since we cannot reject the hypothesis that the observable characteristic in question is unhelpful as an indicator, we are unable to determine whether inexpert consumers have over- or under-relied upon it as such.

An application to the market for black cohosh

A topical exemplar of the uncertainty problem consumers face when a key product quality variable is unobservable, the market for the dietary supplement black cohosh provides the data we will use for demonstrating the method presented in the previous section. With overall sales of dietary supplements in the United States estimated at $28.7 billion in 2010 and continuing to grow rapidly,[8] research results relating to black cohosh and similar products have potentially far-reaching significance.

Background

A plant native to North America, black cohosh (Latin name *Actaea racemosa,* formerly *Cimicifuga racemosa*) was used historically by Native Americans for a number of medicinal purposes. Over the past 50 years it has gained popularity in Europe, and more recently in North

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is, the bias term need not be significantly different from zero. However, if X_k is insignificant, the relative conjectural error of consumers is indeterminate, regardless of the sign of X_k.

[8] See Mast (2011).

America, as an herbal supplement for treating menopausal symptoms. Randomized clinical trials studying the effects of black cohosh have produced mixed results, some showing benefit, and others not (Kronenberg and Fugh-Berman 2002; Fabricant and Farnsworth 2005; Borrelli and Ernst 2008). Yet, despite the uncertainty associated with the trial findings, black cohosh remains very popular, ranked recently as one of the top 10 dietary supplements based on retail sales in the United States (Cavaliere et al. 2009). Continued strong interest in this supplement suggests that consumers generally believe it to be effective in treating menopause.

As a dietary supplement, black cohosh is subject to regulation in the United States by the Food and Drug Administration (FDA) under the Dietary Supplement Health and Education Act (DSHEA). Following DSHEA's main premise, the rules that cover labeling and good manufacturing practices for dietary supplements more closely resemble those that govern foods than the FDA's rigorous drug regulations. Accordingly, supplements require no premarket clinical testing or approval. Since DSHEA was enacted in 1994, the number of products to which it has applied has grown from 4,000 to approximately 30,000. Over the same period, FDA funding for supplement oversight has declined. Consequently, the agency has recently faced severe constraints in its efforts to enforce its rules against supplement mislabeling and contamination (Wechsler 2007).

Mislabeling of black cohosh has been recently documented. In a laboratory study of 11 products labeled as pure black cohosh, Jiang et al. (2006) detected adulteration in four. Three of these products contained marker compounds for a lower-cost Asian *Actaea* species, but not those expected for American black cohosh. The fourth contained both Asian *Actaea* and American black cohosh. The medicinal uses of Asian *Actaea* differ from those of American black cohosh,

and the health consequences of substitution are not known (National Pharmacopoeia Committee 2005, p. 50).

Given lax product quality and truth-in-labeling regulation, it seems appropriate to view product authenticity as a relevant, unobservable quality variable over which consumers of black cohosh experience real uncertainty. This uncertainty and the consumer inference problem it creates are likely compounded by the lack of dispositive evidence concerning the effectiveness of even authentic black cohosh.

Data

We visited 20 stores in New York City and the lower Hudson River Valley and collected non-promotional retail prices for all black cohosh tablet, caplet, capsule, and softgel products sold in the stores.[9] We included only "single-herb" black cohosh, excluding multi-product formulations that combined black cohosh with other potentially active ingredients, such as vitamins or soy isoflavones. Some of the products sampled were sold at multiple stores, resulting in multiple price observations per product in certain cases. In total, 55 price observations were made representing 38 distinct products labeled as black cohosh.[10]

In addition to the price data, other publicly observable product information was obtained. For each distinct product, we collected all the information appearing on the label, including ingredients lists and the precise wording of all label verbiage. Using standard Internet search techniques (e.g., Google), we also found and collected online consumer ratings of the brands

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[9] Our use of list prices follows other hedonic studies (e.g., Gandal 1994; Roe et al. 2001). The limitations of using list prices instead of actual transacted prices, which were unable to observe for this study, are discussed in the concluding section.

[10] A distinct product consists of a specific brand with a certain number of units per package, a certain formulation (e.g., tablet, liquid-filled capsule, etc.), and a distinct set of ingredients.

represented.[11] All data on observable characteristics were collected during the summer and fall of 2007.

To measure product authenticity, we conducted a laboratory analysis of the 38 products, following the procedure described by Jiang et al. (2006, pp. 3243-3245). Specifically, we employed a combined method of high-performance liquid chromatography – photodiode array detection (HPLC-PDA) and selected ion monitoring liquid chromatography – mass spectrometry (SIM LC-MS). The method observes multiple ions in the products in order to evaluate whether the products contain black cohosh. The results of the authentication analysis were roughly consistent with Jiang et al.'s results. 25 out of the 38 products were found to contain black cohosh, while the other 13 did not. Thus, approximately 66% of products contained black cohosh in the current study, as compared to 73% analyzed by Jiang et al. For obvious reasons, we withhold identifying information on the products studied, though in what follows we do report average prices and regression results incorporating the authenticity data.

In all, in addition to PRICE (the retail price) and AUTHENTICITY (binary indicator of whether the product contained black cohosh or not), the following variables were populated for each observation:

1. NYC, a dummy variable indicating whether the store where the price was observed was located in New York City;

2. RETAILER BRAND, a dummy variable indicating whether the product is a retailer's brand (e.g., Whole Foods, Vitamin Shoppe);

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[11] Online retailers of dietary supplements, such as Amazon and drugstore.com, and dedicated review sites, such as Buzzillions.com, invite consumers to write product reviews. Typically any visitor to the site can write one. The review process is structured to allow the consumer both to offer a written comment and a numeric rating, usually on a 5-point scale. The comment and rating are then posted to the website for other visitors to view.

3.   INGREDIENTS, the number of commonly-perceived "active" ingredients listed on the label;

4.   VEGGIE, a dummy variable indicating whether the product is suitable for vegetarians, based on the ingredients or an explicit label affirmation;

5.   KOSHER, a dummy variable indicating whether the product is kosher, based on an explicit label affirmation;

6.   STANDARDIZED, a dummy variable indicating whether the label claims the product contains a standardized component or set of components, as determined by industry-recognized methods (a quality assurance measure);

7.   SIDE EFFECTS, a dummy variable indicating whether the label warns of side effects;

8.   SAFE, a dummy variable indicating whether the label contains the word "safe" or some derivative (e.g., "safely");

9.   RATED, a dummy variable indicating whether an online consumer rating could be located for the particular brand of black cohosh;

10.   SUM OF RATINGS, the total of the ratings located for the brand (with individual ratings normalized to a 1-point scale);

11.   TIME SUPPLY, the number of days of supplement supplied per package, calculated as the number of units (e.g., tablets) per package divided by the number of units per day in the recommended dosage (or the maximum number of units per day in those cases where a range was given);

12.   CERTIFIED, a dummy variable indicating whether the label contains the word "certified";

13.   GUARANTEED, a dummy variable indicating whether the label contains the word "guarantee" or some derivative;

14.   CLAIMS, a dummy variable indicating whether the label makes an affirmative therapeutic claim with respect to a specific symptom.

Table 3 displays descriptive statistics for our data.[12]

<Insert Table 3 about here>

Surrogate indicator estimation on the full sample

Measurement of inexpert consumers' relative conjectural errors requires two sets of estimates: full-sample estimates of the role of the observable product characteristics in indicating unobservable authenticity; and hedonic estimates on authentic and non-authentic product subsamples to obtain the log valuations of the observable characteristics by expert and inexpert consumers, respectively. To obtain the former, we estimated (7), including all variables #1-14 for the X_k. The results are shown in Table 4. As discussed in "Model and approach" section, these results show the true empirical relationship of the observables to unobserved authenticity: true positive indicators (e.g., KOSHER) take positive signs, while true negative indicators (e.g., STANDARIZED) take negative signs. The relationship that inexpert consumers infer between the observables and authenticity will tend to differ from what the results in Table 4 show.

< Insert Table 4 about here>

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[12] Note that while approximately 66% of distinct products in our sample were determined to be authentic, authentic products accounted for roughly 73% of our observations. This is because authentic products were slightly oversampled across retailers relative to non-authentic products.

Several of the observable characteristics we tracked have a significant relationship to authenticity. It is interesting to note that a number of label words that seem intended to reassure consumers about authenticity turn out to be significant negative indicators of actual authenticity: CERTIFIED, GUARANTEED, and CLAIMS (as well as STANDARDIZED) all take significant negative coefficients in the regression. There may be a number of possible marketing explanations for why these words appear on labels. However, their persistent presence seems to point to the inexpertise of a significant portion of consumers. After all, if consumers were all expert appraisers, they would figure out quickly that these words counter-indicate authenticity and would tend to steer clear of the associated products. This would then induce marketers to remove the words from their products' labels.

It is also interesting to note that our X_k, taken together, explain more than three-fifths of the total variation in authenticity. It is fair to say that the potential appears to exist for effective appraisal of black cohosh by knowledgeable consumers.

Hedonic estimation on quality-differentiated subsamples: inferences based on sorting

We now turn to the second component in our conjectural error measurement procedure: hedonic estimation on the authentic and non-authentic product subsamples. We estimated (3), including again all variables #1-14 for the X_k. The first two columns of Table 5 display the results of this estimation. A number of the explanatory variables are omitted from the regressions for either the authentic or non-authentic model because they take a constant value across the corresponding subsample, and so provide no variation as a basis for estimating a coefficient. Their omission from the regression only affects the size of the constant term, and so has no

relevance to the coefficients on included explanatory variables. However, it makes it impossible to compare constant terms between the models as a measure of the relative valuation of the unobservable characteristic, per our discussion in the "Model and approach" section above.

<Insert Table 5 about here>

There are stark differences in the coefficients estimated for the explanatory variables on the two subsamples. Under the assumption that the buyers of authentic and non-authentic black cohosh do not differ in their intrinsic valuation of observable characteristics, these differences represent differences in valuation of the observable characteristics purely as surrogate indicators. Given that consumers more capable at appraising black cohosh likely tend to sort to the authentic products, the coefficient differences may be characterized as representing the relative bias of the relatively inexpert consumers who buy the non-authentic products. We display this bias explicitly in the third column of Table 5.

We use our relative bias measures and the decomposition in (11) to determine the relative conjectural error of the inexpert consumers. We employ the classification in Table 2, taking the presumption that authenticity is a positively valued quality, and using the information in Table 4 on which variables are significant positive or significant negative surrogate indicators. The last column of Table 5 reports our findings.

With respect to most significant surrogate indicators, relatively inexpert consumers appear to undershoot – or else, entertain fallacies or modestly overshoot – in their conjectures. This suggests either unawareness or tentativeness about most of the indicators of authenticity. But there is one exception: inexpert consumers overshoot substantially with respect to drawing negative inferences about authenticity from the presence of specific therapeutic claims on the label. That is, while they correctly infer that therapeutic claims are a significant negative

indicator of authenticity, they place too much weight on them. We will discuss the possible implications of this finding in the next section.

Conclusion

In this paper we have proposed a method for measuring the conjectural errors that inexpert consumers make with respect to using observable characteristics as surrogate indicators of an unobservable product quality variable. The approach uses data on the quality variable – observable to researchers, though not to consumers – as a basis for creating subsamples for separate hedonic log-price regressions. Given the assumption that consumers sort between high- and low-quality products based on their product appraisal expertise, such regressions yield distinct marginal values accorded to observed characteristics by expert and inexpert consumers. Combining the estimates with data on the actual empirical relationship of the quality variable to the indicators enables the researcher to measure the conjectures of the expert and inexpert consumers, and the associated relative errors made by the latter.

We applied this method to data on observable characteristics of a set of brands of the dietary supplement black cohosh, paired to observations of consumer-unobservable product authenticity. We found that, whereas inexpert consumers probably err on the side of being too tentative in their use of most surrogate indicators, they devalued products making therapeutic claims on their labels more than experts did. Thus, while the presence of claims correlate negatively with product authenticity, suggesting that they are appropriately viewed as a negative indicator, inexpert consumers appear to have construed too much about authenticity from this

variable. Bogus supplement claims have received prominent treatment in the press,[13] and it is possible that their consequent salience causes some individuals, particularly those who are less skilled at appraising products, to focus too much on them in their assessment of supplement quality. These same individuals may suboptimally neglect other sources of information, including other product label cues.

From a managerial perspective, research along the lines of the methods demonstrated here may yield a number of useful applications. Performing hedonic analysis separately on expert and inexpert consumers may allow managers to develop targeted pricing strategies that account for differences in how these two groups value product characteristics as indicators of unobservable qualities. Such findings may also allow for targeted product and promotion strategies that emphasize product attributes of interest to each group. Observed differences in the conjectural errors with respect to surrogate indicators that inexpert consumers make relative to experts provide additional information for managers that may be useful in promotional targeting. In the market for black cohosh, for example, managers might conclude from our study's findings – perhaps tentatively, given its small sample – that a product targeted to less sophisticated consumers should tone down therapeutic label claims (e.g., "ends hot flashes within 48 hours"), whatever else the benefits of including such claims on the label might be. Products marketed with such claims to unsophisticated consumers would have to be priced lower, all else equal. Consistent with product labeling, advertisements of black cohosh products directed to inexpert individuals should perhaps also eschew emphasis on the product's therapeutic claims, while those directed to relatively sophisticated consumers might not. As discussed in the introduction, there are many marketing contexts in which researchers may gain access to relevant consumer-unobservable product characteristics across brands, allowing for the

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[13] See, for example, Gomstyn (2010).

techniques demonstrated in this paper to be applied quite broadly. Overall, our study highlights the value of accounting for consumer-unobservable characteristics in marketing research.

Further work needs to be done. The present study was limited by its small sample size and should therefore be considered largely as an initial proof of concept. In particular, the coefficient estimates associated with the two subsamples likely included a substantial amount of noise, and our interpretations of the differences and the associated conjectural errors should be weighted accordingly. The study was also limited by our reliance on list prices in place of transacted prices. For us to know definitively that consumers have valued a product at a certain price, we would need to witness actual transactions at that price. Undoubtedly, a significant share of transactions at the stores covered by our study occurred at list prices, but we do not know what share, nor do we know the discounted prices that applied to the remaining transactions. In using list prices, we effectively assume that discounting has been applied equally across all SKUs in the study, a characteristic that our study shares with other hedonic analyses that have used list prices (e.g., Gandal 1994; Roe et al. 2001). One objective for future research would be to test the application of the study's approach using scanner data. More generally, replication of our method in other contexts would be helpful in demonstrating its uses. Product markets with prominent experience and/or credence good qualities pose good candidates, particularly where important managerial or policy issues remain unresolved.

One example involving provocative policy issues that relate to marketing practices and consumer welfare is the market for illegal drugs. Public policy has focused on limiting supply through seizure, with mixed results. One consequence of supply-chain pressure has been that sellers "cut" their product with baser substances before selling it.[14] In regard to reductions in drug purity and their implications for drug policy evaluation, a number of questions need to be

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[14] For an extended discussion, see Letizia et al. (2009).

answered. To what extent do observable characteristics provide evidence of adulterated products? What observable characteristics are most influential in stimulating recognition of adulteration? Assuming some buyers are less sophisticated than others, what sorts of conjectural errors in drug purity evaluation do inexpert buyers make relative to experts? Do supply-chain pressure and consequent effects on drug purity have consequences for which type of buyer is predominantly purchasing the product?

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Table 1

Researcher's bias in estimating $\left.\partial P/\partial X_k\right|_D$

	$\mu_k < 1$	$\mu_k > 1$
$\partial P/\partial z$, $\left.\partial z/\partial X_k\right|_T$ same sign	Negative	Positive
$\partial P/\partial z$, $\left.\partial z/\partial X_k\right|_T$ opposite sign	Positive	Negative

Table 2

Inexpert Consumers' Relative Conjectural Error with Respect to X_k

	X_k is a significant positive indicator	X_k is a significant negative indicator	X_k is insignificant
$\partial P / \partial X_{k(I)} - \partial P / \partial X_{k(E)}$, z same sign	Large Overshoot	Fallacy, Undershoot, or Small Overshoot ("FUSO")	Indeterminate
$\partial P / \partial X_{k(I)} - \partial P / \partial X_{k(E)}$, z opposite sign	Fallacy, Undershoot, or Small Overshoot ("FUSO")	Large Overshoot	Indeterminate

Table 3
Descriptive Statistics

	Mean	St. Dev.	Min.	Max
Full sample (N = 55)				
PRICE	12.782	6.404	4.790	28.990
NYC	0.764	0.429	0.000	1.000
RETAILER BRAND	0.164	0.373	0.000	1.000
INGREDIENTS	1.018	0.135	1.000	2.000
VEGGIE	0.418	0.498	0.000	1.000
KOSHER	0.055	0.229	0.000	1.000
STANDARDIZED	0.745	0.440	0.000	1.000
SIDE EFFECTS	0.291	0.458	0.000	1.000
SAFE	0.182	0.389	0.000	1.000
RATED	0.400	0.494	0.000	1.000
TIME SUPPLY	47.267	39.550	2.250	240.000
CERTIFIED	0.091	0.290	0.000	1.000
GUARANTEED	0.345	0.480	0.000	1.000
CLAIMS	0.345	0.480	0.000	1.000
AUTHENTICITY	0.727	0.449	0.000	1.000
Subsample of online-rated products (N = 22)				
SUM OF RATINGS	9.277	7.298	0.800	15.980

See text for description of variables

Table 4
Full-Sample Regression Results - Indicators of Authenticity

Dependent variable: Authenticity

NYC	-0.2639**
	(0.1189)
RETAILER BRAND	-0.6625***
	(0.2222)
log of INGREDIENTS	-1.3011**
	(0.5383)
VEGGIE	-0.0586
	(0.1225)
KOSHER	0.6226**
	(0.2955)
STANDARDIZED	-0.6085***
	(0.1440)
SIDE EFFECTS	-0.2922
	(0.1925)
SAFE	0.0316
	(0.1694)
RATED	0.1294
	(0.1734)
SUM OF RATINGS	0.0265**
	(0.0124)
TIME SUPPLY	-0.0005
	(0.0018)
CERTIFIED	-0.3733*
	(0.2175)
GUARANTEED	-0.5175***
	(0.1607)
CLAIMS	-0.3639**
	(0.1648)
Constant	1.7898***
	(0.2286)
N	55
R^2	0.6051

Standard errors are in parentheses
***significant at 1%; **significant at 5%; *significant at 10%
See text for description of variables

Table 5

Hedonic Regression Results

and Estimates of Relative Bias in Log Valuation and Conjectural Error

Dependent variable: log of PRICE				
	(1)	(2)		
	Authentic Subsample (OLS)	Non-authentic Subsample (OLS)	Relative Bias of Inexpert Consumers	Relative Conjectural Error
NYC	-0.1671*	Omitted		
	(0.0968)			
RETAILER BRAND	-1.4214***	-1.3401*	0.0813	FUSO
	(0.3069)	(0.5354)		
log of INGREDIENTS	Omitted	Omitted		
VEGGIE	0.2003	0.5907	0.3904	Indeterminate
	(0.1600)	(0.3413)		
KOSHER	-0.0233	Omitted		
	(0.2418)			
STANDARDIZED	0.2868	Omitted		
	(0.1698)			
SIDE EFFECTS	-0.0347	0.8826	0.9173	Indeterminate
	(0.1799)	(0.7771)		
SAFE	0.6069**	-0.1791	-0.7860	Indeterminate
	(0.2873)	(0.8238)		
RATED	-1.0207***	Omitted		
	(0.2174)			
SUM OF RATINGS	0.0512***	-0.8145	-0.8657	FUSO
	(0.0143)	(0.4980)		
TIME SUPPLY	0.0135***	0.0089**	-0.0046	Indeterminate
	(0.0033)	(0.0028)		
CERTIFIED	0.1185	2.4236	2.3051	FUSO
	(0.2351)	(1.2730)		
GUARANTEED	-0.3631**	-0.0827	0.2804	FUSO
	(0.1729)	(0.4860)		
CLAIMS	-0.2532	-0.5029	-0.2497	Large overshoot
	(0.1819)	(0.4860)		
Constant	2.1782***	2.3967***		
	(0.2387)	(0.4189)		
N	40	15		
R^2	0.8196	0.7802		

Standard errors are in parentheses

***significant at 1%; **significant at 5%; *significant at 10%

FUSO=fallacy, undershoot, or small overshoot

See text for description of variables. Variables that took constant values within a subsample were omitted from the corresponding regression, as indicated.