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8 October 2010

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Abstract

Using the dietary supplement black cohosh to demonstrate our method, we employ data on a product characteristic unobservable to consumers to decompose the contribution to consumers' valuations of observable characteristics into surrogate indicator and direct components. Because consumers are not all "expert appraisers" of the unobservable characteristic, the measured relationship of indicators to the unobservable quality is generally not the one consumers perceive. Consequently, biases that depend upon the nature of consumers' ineptitude are introduced into the component estimation. The researcher's inference problem is solved by recognizing that consumers with greater appraisal expertise sort disproportionately to higher quality products. This enables feasible measurement of inept consumers' relative valuations and conjectures through separate hedonic estimation on high- and low-quality product subsamples. We find that, relative to experts, inept consumers likely underestimate the value of most observable characteristics in indicating black cohosh product authenticity; however they overweight online product ratings.

Keywords: hedonic analysis, surrogate indicators, asymmetric information, pricing strategy, product strategy.

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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 (see Brook 1998, pp. 225-6).

Standard hedonic analysis, which deals in the valuation of observable qualities, would tell us only that consumers value thickness in a vase. To know why, it is necessary to measure the unobservable characteristic (here, authenticity), which is not a common element of product valuation analyses.

This paper demonstrates a method of estimating, as two distinct valuation components, consumers' intrinsic valuation of observable characteristics and their valuation of those characteristics as surrogate indicators. It makes use of unique 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 medicinal herb believed to help with menopause symptoms. As a medication, black cohosh is properly characterized as a credence good, or product for which key 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. By incorporating instrumented (fitted) values for authenticity into our hedonic regression equation, we are able to take our analysis beyond the standard hedonic valuation of observable product characteristics, to gain insight into the extent to which these characteristics are valued as indicators.

An empirical conundrum is posed, however, by the fact that not all consumers are "expert appraisers" of key unobservable qualities. Two possibilities exist. First, consumers may suffer from various forms of unawareness.[1] They may not be aware of the need to appraise a certain unobservable quality; or they may be aware of it, but unaware that information at their disposal from observable characteristics could provide insight into it. Alternatively, consumers 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.[2] This second possibility – that consumers are aware, but are *inept* at appraisal – is the one that poses the problem.

Consider, again, the Ming Dynasty vase for which thickness is a surrogate indicator of authenticity. If all consumers were expert appraisers, then assuming we could observe authenticity, it would be possible to use the empirical relationship between thickness and authenticity to decompose the contribution of thickness to the price of the vase into intrinsic (e.g., durability) and surrogate indicator components. If, instead, all consumers were unaware that thickness could be used to diagnose the authenticity of a vase, or unaware that a vase's possible authenticity as a Ming Dynasty artifact should be taken into consideration, then there would likewise be no empirical problem. One would know for a fact that the contribution of thickness to the price of the vase was entirely based on the intrinsic value of thickness. But now suppose that consumers are aware that a vase with Chinese motifs might be a valuable artifact, and also aware (if vaguely) that thickness might help one determine authenticity, but not knowledgeable enough to accurately increment their forecasts of the likelihood that the vase is authentic per millimeter thickness of the item. If so, then the empirical relationship of thickness to authenticity would be misleading to determining the basis for how thickness is being valued by the market. This is because the relationship contains information not being used by the inept consumer. Thus a decomposition of the consumer's valuation of thickness based on this relationship leads to biased estimation of the components. Further, in such a case, it becomes difficult to interpret the strength of the empirical relationship of authenticity to market prices, as the relationship conflates the measurement of consumers' tastes for authenticity with their ineptitude at appraisal.

We struggle to provide some clarity regarding consumers' valuations and conjectures when quality is unobservable by classifying inept 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 empirical problem of extracting information about surrogate indicator use is partially overcome 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 conjectures of inept consumers relative to experts by separately performing hedonic analysis on high- and low-quality product pools. 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 (Salop and Stiglitz 1977, Nagler 1993, Gabaix and Laibson 2006, Armstrong and Chen 2009). 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 (e.g., lower price per unit quality) than those less skilled and more cost-encumbered. The present paper's innovation is 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. These methods may also be used in certain contexts to evaluate the effects of public policies (see concluding section).

The existing literature on 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 quality (e.g., Quester et al. 2000, West et al. 2002, Jo 2005, Johnson and Folkes 2007). Much of the research emphasis has been on the role of price as an indicator of quality; analyses of this have included experimental studies (e.g., Brucks et al. 2000, West et al. 2002) and some meta-analytic reviews (Rao and Monroe 1989, Völckner and Hofmann 2007). By and large, the studies are descriptive: none provides a methodology for using data on surrogate indicators and underlying qualities as a tool for making inferences about consumers' valuations and quality judgments.

Another strand of work, related to the literature on the influence of indicators, looks at the accuracy of consumer perceptions. In a set of analyses involving both durable and nondurable 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.

We proceed as follows. We lay out a model of unobservable characteristics and surrogate indicators, examine the empirical problem posed by inept consumer appraisal, and consider how consumer sorting addresses this problem. Next, we present results from empirical analysis of the market for black cohosh. Finally, we conclude.

MODEL

Unobservable Product Qualities

The standard hedonic approach posits a representative consumer who values a product as a bundle of characteristics. For our purposes, let us consider a product consisting of K observable characteristics, X_k, k=1,…,K, and one unobservable characteristic, z. Thus the utility the consumer obtains from consuming the product is given by

(1) $$U = U\left(X_1,...,X_K,z\right)$$

The corresponding hedonic regression equation specifies, for brand i,

(2) $$\log P_i = \alpha + \beta_1 X_{1i} + ... + \beta_K X_{Ki} + \xi_i$$

where X_{ki} is the value of the *k*th characteristic for brand *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 (2) 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

(3) $$z = z\left(X_1, ..., X_K\right)$$

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 $\partial z / \partial X_k < 0$, then X_k is a negative indicator of *z*. We may therefore decompose the slope coefficients β_k in (2) as:

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

That is, the effect of each observable characteristic on the 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.[3]

Now suppose we are able to privately observe *z*, so that *z* may be included along with the observable variables. Then (2) becomes

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

where η is the stochastic disturbance term for the augmented equation. Also, we may write a regression equation that determines the value of *z,* corresponding to (3),

$$z_i = a + b_1 X_{1i} + ... + b_K X_{Ki} + \varepsilon_i \tag{6}$$

where ε is a stochastic disturbance. The estimation of (5) poses problems: because *z* is not observed directly by consumers, it must be viewed as endogenously determined based on (6). In general, characteristics that consumers use to infer the value of *z* but that are not observed by the researcher will be correlated with variables that consumers value intrinsically and that are not observed by the researcher; that is, η is correlated with ε. Thus the coefficients in (5) are estimated with bias. To resolve this problem, it is necessary to instrument for *z* with a subset of the X_k. Importantly, this can only be accomplished if one can identify *ex ante* at least one observable characteristic, X_{k*}, that the consumer does not intrinsically value *at all*, hence $\beta_{k*} = 0$. This is needed to ensure that the exclusion criteria are met for identification of *z* in the instrumented version of (5).

Properly instrumenting for *z* with $\hat{z}$ yields

$$\log P_i = \tilde{\alpha}_D + \tilde{\lambda}\hat{z}_i + \tilde{\beta}_{1D} X_{1i} + ... + \tilde{\beta}_{KD} X_{Ki} + \tilde{\eta}_i \tag{7}$$

which may be efficiently estimated. In (7), the effect of the X_k on price through *z* is controlled for, so a decomposition has been effected. The coefficients on the X_k represent the direct effect of the X_k on 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 (2) and (7), we may obtain each component in (4).

Inept 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 (7) 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 (4) is re-written as

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

reflecting that the surrogate indicator influence of the X_k on 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 (7) 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 inept use of each surrogate indicator X_k. Put another way, estimation of (7) 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' ineptitude 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 ineptitude 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.

<Insert Table 1 about here>

The empirical conundrum created by consumers' ineptitude at appraisal may be viewed through another lens by estimating (6), 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 (6) 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 (7) 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 inept 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 inept: 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 appraisal expertise across individuals.

To model this, let us begin by assuming that consumers differ only with respect to their appraisal 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 valuation components, $\partial P / \partial X_k \big|_D$, will be the same for all. Appraisal expertise may be defined in an overall sense based on the relative ability of different consumers in essence to fit (6) from the X_k using their conjectures about the $\partial z / \partial X_k$. Specifically, consumer *j'* is "more expert at appraisal" than *j"* if $\sum_k \left[\left(\partial z / \partial X_k \big|_{U(j')} \right)^2 \cdot \bar{X}_k \right] < \sum_k \left[\left(\partial z / \partial X_k \big|_{U(j")} \right)^2 \cdot \bar{X}_k \right]$, where $\bar{X}_k = \sum_i X_{ki}$; that is, if her weighted sum of squared conjectural error is lower.[4] 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 inept consumers sort to the low-quality product. Sorting of consumers will not necessarily be perfect; however, there will generally be differences in the average expertise of consumers across product pools correlated with the level of unobservable characteristic.

Consumer sorting based on expertise levels has important empirical measurement implications, observable in our simple model. Let us use subscript *E* to represent the relatively expert consumers that sort to the high-quality product, and *I* to represent the relatively inept consumers that sort to the low-quality product. Estimation of (2) 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 inept consumers

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

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

where $\partial P/\partial z_{(E)}$ and $\partial P/\partial z_{(I)}$ represent, respectively, how experts and inept 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 value 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 valuation bias* of inept consumers for each X_k,

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

This bias is the sum of two components: inept consumers' relative error in valuing *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' 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 valuation bias tells us how 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 inept 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 does allow 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 the surrogate indicator X_k is a positive or negative one with respect to the unobservable characteristic. The table's results depend additionally on the maintained assumption that both experts and inept 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 inept consumers could be.

<Insert Table 2 about here>

Table 2 shows that the researcher may mainly distinguish only situations in which inept consumers overshoot substantially from situations in which they do not. For example, a positive surrogate indicator of a positively valued unobservable characteristic corresponds to a positive bias in inept consumers' valuations only when inept consumers assign substantially more surrogate indicator value to the characteristic than is warranted. Otherwise, the bias will be negative. Note that a negative valuation bias will follow even for modest overshooting, because a negative first term may overwhelm a positive second term in (11). Intuitively, the inept consumers' failure to identify the positive 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.

FINDINGS FROM THE MARKET FOR BLACK COHOSH

The market for black cohosh provides an opportunity to illustrate the use of unobservable product qualities in hedonic analysis and, in particular, to demonstrate the inferences that researchers may make based on consumer sorting.

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 North America, as an herbal supplement for treating menopausal symptoms. 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, as noted in National Pharmacopoeia Committee (2005, 50), the health consequences of substitution are not known.

Data

Our current laboratory analysis expands the sample of Jiang *et al*. (2006) to include a total of 38 distinct products labeled as black cohosh.[5] Following the procedure outlined in their study, [6] we employ 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.

We supplement our authenticity data with data on consumer-observable characteristics for the sampled products, which we collected as part of an earlier hedonic study of black cohosh that did not account for authenticity (Nagler *et al*., 2010). We visited 20 stores in New York City and the lower Hudson River Valley and collected non-promotional retail prices for black cohosh products sold in the stores. In total, 55 price observations were made representing the 38 laboratory-tested black cohosh products in the sample. 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 represented.[7] All data on observable characteristics were collected during the summer and fall of 2007.

In all, in addition to PRICE (the retail price), 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);
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.

We partition these variables into two groups, "group A" (#1-11) and "group B" (#12-14). Group A consists of characteristics hypothesized to have a direct effect on each product's price. Group B consists of characteristics hypothesized to affect consumers' valuations (hence prices) *only* through their influence on consumers' perceptions of the product's authenticity. For example, the word "safe" on the product label, we propose, conveys value to consumers that might result in a price premium because consumers perceive the product so-labeled to be safer, and consumers value safety. Meanwhile, "certified" conveys value to consumers only as a potential indicator that the product is more (or less) likely to be authentic.

Table 3 displays descriptive statistics for our data.[8]

<Insert Table 3 about here>

Estimation on the Full Sample

We begin by estimating the basic hedonic regression model (2) to show the total effect of observable product characteristics on price. For the X_k, we include all of the Group A variables (#1-11) listed above. Table 4 (first column) shows the results of this estimation. The high R-squared suggests we have captured a substantial portion of the variation in price with our included observable characteristics; most of these have a significant influence on the price. The results of the regression are largely consistent with those of the hedonic regressions estimated on a larger sample in our earlier paper (Nagler *et al.* 2010. We refer the reader to that paper for a detailed interpretation of the coefficients.)

< Insert Table 4 about here>

In the second column of Table 4 we present the results of estimating (7), the basic hedonic model augmented with authenticity. As discussed in the model section, authenticity must be treated as endogenous, therefore we must instrument for it in our regression. We do so using the Group B variables (#12-14) listed above. As these variables are hypothesized not to appear in (2), the system is fully identified, and we may proceed with estimation by two-stage least squares (2SLS).[9] The coefficients on the X_k in this regression, denoted β_{kD} in (7), yield the influence of each X_k on the log of price, purged of their influence on price through authenticity. Authenticity is insignificant in this regression, but this may be the consequence of multicollinearity as the model includes variables that likely are correlated with authenticity.

To understand the relationship of authenticity to observables, we estimate (6). Here, the X_k include all variables #1-14. The results are shown in Table 5. As discussed in the model section, these results show the true empirical relationship of the observables to unobserved authenticity. Thus, positive indicators (e.g., KOSHER) take positive signs, while negative indicators (e.g., STANDARIZED) take negative signs. Since consumers are not expert appraisers in general, the relationship that they infer between the observables and authenticity will tend to differ from what the results in Table 5 show.

< Insert Table 5 about here>

Several of the observable characteristics we tracked have a significant relationship to authenticity. It is interesting to note that, while authenticity would likely be positively valued by the market if it were observable, the signs of the coefficients on the X_k are not always the same in our estimation of (6) as they were in our estimation of (2). For example, STANDARDIZED is a significant positively-valued characteristic overall, but it is a significant negative indicator of authenticity, thus its effect on price through authenticity is negative. One may observe from Table 3 that purging STANDARDIZED of its negative influence on price as an indicator of authenticity increases the size of its overall positive price effect.

Perhaps more striking, 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 ineptitude either of a significant portion of consumers or of black cohosh marketers. After all, if consumers were 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 induce savvy 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 exists for fairly effective appraisal of black cohosh by knowledgeable consumers.

Subsample Estimation: Inferences Based on Sorting

To gain insight into the valuation biases and conjectural errors of inept consumers relative to more-expert consumers, we re-estimate (2) separately on the subsamples of authentic products and non-authentic products. Consistent with the first column of Table 4, we include all Group A variables.

The first two columns of Table 6 display the results of the 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 section.

<Insert Table 6 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 inept consumers who buy the non-authentic products. We display the bias explicitly in the third column of Table 6.

We use our relative bias measures and the decomposition in (11) to determine the relative conjectural error of the inept consumers. We employ the classification in Table 2, taking the presumption that authenticity is a positively valued quality, and using the information in Table 5 on which surrogate indicators are positive and which are negative. The last column of Table 6 reports our findings.

The results are very interesting. With respect to most surrogate indicators, the relatively inept 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: inept consumers overshoot substantially with respect to the sum of online ratings. That is, they place too much weight on the level and frequency of online ratings as an indicator of high-quality black cohosh products. We will discuss the possible implications of this finding in the next section.

CONCLUSIONS

The study presented in this paper has used data on a consumer-unobservable characteristic to cast light on consumer decision making under uncertainty. Our analysis suggests that the question of how consumers value products with key unobservable qualities is related not just to the issue of what information consumers have before and after purchase, but also to their expertise at using it. Consumers who are inept at appraisal may under- or over-weight observable characteristics in their attempts to ascertain unobservable qualities. These tendencies result in problems both for the consumer and the researcher. Consumers arrive at inaccurate determinations as to which products are high- and low-quality and their product valuations are correspondingly erroneous. And marketing researchers who use the empirical relationship between observable and unobservable qualities to reconstruct consumers' surrogate indicator valuations of observable characteristics arrive at biased estimates.

The problem for researchers seeking to extract relevant information about surrogate indicator use may be partially resolved by recognizing that consumers sort between high- and low-quality products based on their expertise levels. We illustrated this through a study of the black cohosh market in which we measured consumer-unobservable product authenticity as well as a range of consumer-observable product characteristics for a sample of brands. By applying hedonic estimation separately to authentic and non-authentic product samples, we measured expert and inept consumers' distinct valuations of observable characteristics. We also measured the relative conjectural errors made by inept consumers in using each observable characteristic as a surrogate indicator.

One important finding from this last element of the analysis was that, while inept consumers probably err on the side of being too tentative in their use of most surrogate indicators, they appear to construe too much about authenticity from small differences in the level and frequency of online product ratings. Online ratings and product commentary are widely touted as a source of helpful information on product quality, and it is possible that their consequent salience causes many individuals, particularly those who are less skilled at appraising products, to rely on them too heavily. These same individuals may suboptimally neglect other sources of information, such as the wording on product labels.

Our finding is consistent with the literature. Banerjee (1992, 1993) shows that decision-makers may rely excessively on others' opinions and actions, often substituting inferences from these for superior private information. Mayzlin (2006) proposes a model in which online communications that appear to be from consumers might have other sources (e.g., firms). She finds in this context that consumers nevertheless rely on anonymous online feedback, making it profitable for firms to pose as consumers and create promotional product commentary.

Our study generally highlights the value of accounting for consumer-unobservable characteristics in marketing research. While this study made use of unique data generated in a biochemical laboratory, data on unobservable characteristics may be 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.

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 non-expert 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 non-expert consumers make relative to experts provide additional information for managers that may be useful in targeting.

Further work needs to be done. The present study was limited by its small sample size and should therefore be considered exploratory. 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. Replication of our method in other contexts would be helpful in demonstrating its uses. Product markets with important experience and/or credence good qualities pose good candidates, particularly where important managerial or policy issues remain unresolved.

One example involving policy issues 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.[10] In regard to reductions in drug purity and their implications for drug policy evaluation, a number of questions need to be 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 inept buyers make relative to expert buyers? 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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FOOTNOTES

[1] 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), Liu (2008), and Li (2009).
[2] The archetype of this consumer is the typical guest on the popular public television show, Antiques Roadshow. The guest brings an artifact, which has been in her attic for decades, to the show, whereupon an antiques expert pronounces it to be extremely valuable, to the highly visible surprise of the guest. If the guest were herself an expert appraiser, she would not act dumbfounded upon learning of the artifact's true value. But neither is she completely unaware: some observable product characteristic has given her enough of an inkling that the artifact is valuable that she decided to bring it to the show for appraisal.
[33] People obtain indications about product quality 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).
[4] 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 those who make errors versus those who do not as having different traits (e.g., attentiveness, myopia, etc.). 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 inept appraisers as constituting distinct market segments.
[5] 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.
[6] For a detailed description, see Jiang *et al.* (2006), pp. 3243-5.
[7] 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.
[8] 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.
[9] GMM estimation is not used here due to its poor small sample properties. See Baum et al. (2003).
[10] For an extended discussion, see Letizia et al. (2009).

Table 1 Researcher's bias in estimating $\partial P/\partial X_k\big|_D$

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

Table 2 Inept Consumers' Relative Conjectural Error with Respect to X_k

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

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

Table 4 Hedonic Regression Results - Full Sample

Dependent variable: log of PRICE

	(1) Pure hedonic (OLS)	(2) Including AUTHENTICITY (2SLS)
NYC	-0.1706*	-0.0891
	(0.0096)	(0.1121)
RETAILER BRAND	-0.7438***	-0.6728***
	(0.1660)	(0.1619)
log of INGREDIENTS	0.4186	0.5991
	(0.4522)	(0.4374)
VEGGIE	0.2632**	0.2290**
	(0.0998)	(0.0951)
KOSHER	-0.1222	-0.2264
	(0.2474)	(0.2409)
STANDARDIZED	0.2930***	0.4176***
	(0.1077)	(0.1405)
SIDE EFFECTS	0.2235	0.2068
	(0.1406)	(0.1290)
SAFE	0.4288***	0.4303***
	(0.1497)	(0.1366)
RATED	-0.7378***	-0.7247***
	(0.1491)	(0.1364)
SUM OF RATINGS	0.0359***	0.0298***
	(0.0107)	(0.0109)
TIME SUPPLY	0.0073***	0.0073***
	(0.0015)	(0.0014)
AUTHENTICITY		0.2803
		(0.2261)
Constant	2.0323***	1.7008***
	(0.1416)	(0.2969)
N	55	55
R^2	0.6918	0.6719

Notes: Standard errors are in parentheses. ***,**, and * represent significance at the 1, 5, and 10 percent levels, respectively.

Table 5 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

Notes: Standard errors are in parentheses. ***,**, and * represent significance at the 1, 5, and 10 percent levels, respectively.

Table 6 Hedonic Regression Results - Subsamples and Estimates of Relative Valuation Bias and Conjectural Error

Dependent variable: log of PRICE

	(1) Authentic Subsample (OLS)	(2) Non-authentic Subsample (OLS)	Relative Bias of Inept Consumers	Relative Conjectural Error
NYC	-0.0994	Omitted		
	(0.0915)			
RETAILER BRAND	-1.1878***	-0.8215**	0.3663	FUSO
	(0.2849)	(0.3327)		
log of INGREDIENTS	Omitted	0.7597		
		(0.6150)		
VEGGIE	0.3811***	0.6035*	0.2224	FUSO
	(0.1308)	(0.3048)		
KOSHER	-0.1078	Omitted		
	(0.2218)			
STANDARDIZED	0.2339*	Omitted		
	(0.1249)			
SIDE EFFECTS	0.0260	1.7940*	1.768	FUSO
	(0.1585)	(0.8963)		
SAFE	0.7468***	0.2520	-0.4948	FUSO
	(0.2262)	(0.4003)		
RATED	-1.1484***	-2.5348*	-1.3864	FUSO
	(0.1912)	(1.1952)		
SUM OF RATINGS	0.0502***	0.8325*	0.7823	large overshoot
	(0.0110)	(0.4288)		
TIME SUPPLY	0.0134***	0.0089**	-0.0045	FUSO
	(0.0032)	(0.0025)		
Constant	1.8882***	1.8690***		
	(0.1564)	(0.2242)		
N	40	15		
R^2	0.7869	0.7802		

Notes: Standard errors are in parentheses. ***,**, and * represent significance at the 1, 5, and 10 percent levels, respectively. Variables that took constant values within a subsample were omitted from the corresponding regression, as indicated. FUSO = fallacy, undershoot, or small overshoot.