Latent Consideration Sets and Continuous Demand System Models

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Comments Welcome

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Abstract

This paper develops a theoretically consistent continuous demand system model that incorporates latent, probabilistic consideration sets and can be applied to consumption data for many goods. The model's empirical properties are illustrated with a recreation data set from the 1994 National Survey of Recreation and the Environment (NSRE). Parameter and welfare estimates suggest that the latent consideration set models fit the data better and generate qualitatively different policy inference than traditional models.

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1. Introduction

A standard assumption in applied demand analysis is that the consumer behaves as if she maximizes her utility with respect to *M* goods arbitrarily specified by the analyst. In applications employing highly aggregated commodity definitions, assuming the consumer has well-developed preferences and engages in optimizing behavior with respect to all *M* analyst-specified goods may be reasonable. Introspection suggests, however, that the assumption is more tenuous when commodities are defined at a more refined level.

In the discrete choice literature, the notion that only the commodities that are seriously considered by the individual should be treated as endogenous arguments of her utility function has generated considerable research attention (e.g., Shocker et al. [1991], Roberts and Nedungadi [1995]). A practical impediment to empirically implementing this insight, however, is the fact that observable choices do not fully reveal the consumer's "consideration set." To address this difficulty, discrete choice modelers have designed a variety of survey instruments to identify an individual's consideration set, but the validity and reliability of these survey approaches for ascertaining the individual's consideration set remains in doubt. Recognizing this limitation, Ben-Akiva and Boccara [1995] and Haab and Hicks [1997] build on a conceptual framework outlined by Manski [1977] and Swait and Ben-Akiva [1987] by developing discrete choice models of consumer behavior that incorporate consideration sets that are latent and probabilistic from the analyst's perspective. Although Ben-Akiva and Boccara and Haab and Hicks' empirical results suggest that latent consideration set models can generate improved statistically fits, produce more plausible behavioral predictions, and imply qualitatively different policy implications relative to traditional discrete choice models, their discrete choice models quickly become computationally intractable as the number of goods that an individual may consider grows large.

This paper uses Manski's framework to develop continuous demand system structures that incorporate latent, probabilistic consideration sets. Kuhn-Tucker demand system models (Wales and Woodland [1983], Phaneuf, Kling and Herriges [2000]) with latent consideration sets are developed that can be used in applications with potentially large numbers of goods. In contrast to Ben-Akiva and Boccara and Haab and Hicks' discrete choice applications, the latent consideration set models developed here do not exploit survey responses or exclusion restrictions in estimation. Rather, the econometric structure of continuous demand system models is such that the same economic determinants of choice (i.e., prices, quality attributes, and income) that influence the utility maximizing choice can also enter the consideration process without sacrificing model tractability. A notable advantage of structuring consumer behavior in this way is that the restrictive assumption embedded in traditional demand system models that economic factors influence consumer behavior at the extensive (discrete) and intensive (continuous) margins similarly can be relaxed without sacrificing the internal consistency of the model.

From an econometric perspective, the latent consideration set model proposed in this paper can be interpreted as a multivariate extension to the single equation censored regression demand models developed by Deaton and Irish [1984] as well as the univariate "spike" or double hurdle count data demand models developed by Gurmu and Trivedi [1996], Haab and McConnell [1996] and Shonkwiler and Shaw [1996]. By strategically employing a set of statistical independence assumptions and assuming that the model's structural parameters are equal across the target population, one can show that the model's likelihood function simplifies to the product of zero-augmented censored regression equations multiplied by a Jacobian of transformation. Following Chiang, Chib and Narasimhan [1999], the statistical independence assumptions can then be relaxed by assuming the coefficients are distributed randomly across the target population according to a multivariate probability density function that is known up to a vector of estimable parameters. Using the method of maximum simulated likelihood (e.g., Gourieroux and Monfort [1996]), estimates of all parameters entering the model can be recovered.

Although the model developed here can be used for modeling any number of quality differentiated goods (e.g., transportation mode, cereals, soft drinks) and answering numerous policy questions (valuing new goods, exact cost of living measurement), it is applied to an outdoor recreation data set from the 1994 National Survey of Recreation and the Environment (NSRE) and used to measure the Hicksian economic values arising from changes in recreation site quality and access. Because only recreators are included in the data, the estimation procedure follows Englin, Boxall, and Watson [1998] and consistently accounts for truncation at zero in total trip counts. Extending von Haefen, Phaneuf, and Parsons [forthcoming] (vHPP hereafter), fixed and random coefficient, additively separable Kuhn-Tucker demand system specifications with latent consideration sets are used in the analysis. Because these preference specifications assume environmental quality is a weak complement to trips (Mäler [1974]), they are attractive for measuring the use values arising from quality changes. A variation of vHPP's multi-stage Monte Carlo, Markov Chain simulation algorithm is developed to compute theoretically consistent welfare measures.

Using a Consistent Akaike Information Criteria (Schwartz [1978]), the empirical results strongly suggest that the latent consideration set models fit the data better than traditional demand system models. Moreover, a series of Vuong [1989] non-nested hypothesis tests further suggest that latent consideration set models statistically outperform the traditional models. Interestingly, the parameter estimates generally suggest that income is statistically significant in the consideration process but not in the conditional utility maximizing choice. This empirical finding suggests that income is an important determinant of choice at the extensive margin but less so at the intensive margin in this application. Sample mean welfare measures for the loss of a 40 mile reach of the lower Susquehanna River and the cleanup of eutrophic sites suggest that the latent consideration set models generate welfare estimates that are generally larger in absolute value but have greater variability than estimates from the traditional models. Although further research is necessary to confirm or refute these findings, they suggest that there may be a bias-variance tradeoff between the traditional approach of treating the consideration set as known and the approach pursued here of allowing it to be fixed or latent and probabilistic.

The remainder of the paper is structured as follows. The next section reviews the consideration set literature as it relates to the generic issue of choice set definition. Sections 3 and 4 then develop the econometric demand system model with latent consideration sets and procedures for generating welfare measures, respectively. Section 5 reviews the NSRE data used in the analysis, and section 6 presents the estimation results. Section 7 then discusses the welfare results, and Section 8 concludes with a discussion of the importance of consideration sets for applied demand analysis.

2. Choice Set Definition and Consideration Sets

Consideration sets are relevant for choice set definition, a fundamental issue arising in every applied demand analysis. Choice set definition deals with specifying the objects of choice that enter an individual's preference ordering and represent the endogenous arguments that the individual is assumed to optimize with respect to. In practice, defining an individual's choice set is influenced substantially by the analyst's judgment, the limitations imposed by the available data, and the nature of the policy questions to be addressed, but economic theory can also play a role. In particular, analysts can evaluate a proposed choice set definition by the appropriateness of its implicit separability and aggregation assumptions. In the context of developing the objects of choice in an outdoor recreation application for example, the analyst can evaluate a recreation site definition by whether the implicit geographic extent of the market has plausible implications for the separability of recreation preferences. Likewise, the Hicksian composite commodity theorem can be used to develop a reasonable level of temporal and/or spatial aggregation in the objects of choice. A significant and growing body of research in the discrete choice literature (e.g., Parsons and Needelman [1992], Parsons and Hauber [1998], Lupi and Feather [1998], Parsons, Plantinga, and Boyle [2000]) suggests that analyst judgments with respect to a choice set definition's implicit separability and aggregation assumptions can have important policy implications.

There is, however, an additional issue with choice set definition that has largely been ignored in the traditional demand systems literature but been the focus of much research in the discrete choice literature. Many researchers working in this area believe that when consumers are confronted with choices from a large set of quality differentiated goods, they may only seriously consider and choose from a subset of the available alternatives. From a psychological perspective, such mental behavior can be explained as a simplifying heuristic that individuals employ to mitigate the cognitive demands arising from difficult choices. An alternative, more economic explanation is that individuals have limited information about all available goods, rationally search for new information when the benefits of information acquisition exceed the costs, and at any point in time, have detailed information for only a subset of the available commodities (i.e., their "consideration sets"). Both psychological and economic interpretations seem plausible and may be relevant depending on the individual and her choice circumstances, but regardless of the interpretation, researchers who accept the cognitive notion of consideration sets argue that only their elements should be treated as endogenous arguments of an individual's utility function.

There is some empirical research supporting the existence of consideration sets (see Shocker et al. [1991] for a review), but because consideration sets are mental constructs that are not revealed by observable behavior, some researchers remain skeptical about their existence (Roberts and Nedungadi [1995]). Nevertheless, introspection suggests that the proposition that individuals employ consideration sets in difficult choice situations is plausible, and the significant amount of research in the fields of marketing (e.g., Gensch and Soofi [1995]), transportation (Horowitz [1991]), and more recently environmental economics (Peters, Adamowicz, and Boxall [1995] and Parsons, Massey, and Tomasi [2000]) devoted to the topic suggests that it is gaining academic standing. At the very least, developing choice set definitions that are consistent with the notion of consideration sets represents an alternative strategy that can serve as a robustness check for results derived from more traditional and equally arbitrary choice set definitions. A growing body of empirical research, moreover, suggests that models that incorporate consideration sets can statistically fit a given data set better and provide qualitatively different and more plausible inference than traditional models.[1]

For analysts interested in developing empirical models that account for consideration sets, an important practical question is how to do identify the objects of choice that enter each individual's consideration set from the universal set of relevant alternatives. Because observable choices do not reveal this information, researchers have employed a range of survey questions to elicit an individual's consideration set (e.g., Horowitz and Louviere [1995]). At present, no consensus on valid and reliable question formats have emerged, and it is doubtful that any survey instrument, however well-conceived, will generate enough information to identify the individual's consideration set with certainty.

Recognizing this, Ben-Akiva and Boccara [1995], and Haab and Hicks [1997] develop discrete choice econometric models that treat consideration sets as latent and probabilistic from the analyst's perspective. Their models build on a characterization of the consumer's choice process proposed by Manski [1977] and latter refined by Swait and Ben-Akiva [1987]. In

[1] See, e.g., the 1995 symposium on consideration sets in the *International Journal of Research in Marketing*.

Manski's original formulation, the probability that an individual will choose alternative *i* from C_M, the universal set of relevant alternatives of dimension *M*, can be decomposed as follows:

(1) $$P(i) = \sum_{C \subseteq C_M} P(i \mid C) P(C),$$

where $P(i)$ is the probability of selecting alternative *i*, $P(C)$ is the probability that the set C ($i \in C \subseteq C_M$) is the individual's consideration set, and $P(i \mid C)$ is the probability of selecting alternative *i* from the consideration set C. Two issues arise with the estimation of this representation of the consumer's choice process. Because the potential number of consideration sets can be large (i.e., 2^M), equation (1) can become computationally burdensome to derive as the number of goods grows large. Moreover, separately estimating $P(C)$ and $P(i \mid C)$ can be difficult in the context of discrete choice models where both $P(C)$ and $P(i \mid C)$ often have similar (logit or probit) econometric structures. In their application, Ben-Akiva and Boccara use respondent answers to survey questions about their consideration sets to help accomplish this task, but Haab and Hicks's data, like most data used in applied work, did not contain such survey responses. In the absence of this information Haab and Hicks partition the full set of observable determinants of choice into those that influence the consideration stage of the choice process (i.e., the $P(C)$ probability) and those that affect the conditional utility maximizing choice ($P(i \mid C)$). Although facilitating estimation of the model, these exclusion restrictions can be criticized as arbitrary.

The model developed in the following section can be interpreted as a variation of Ben-Akiva and Boccara and Haab and Hicks' latent consideration set models. However, in contrast to their models as well as virtually every existing model that incorporates the notion of consideration sets, it is applied to a continuous Kuhn-Tucker demand system that consistently accounts for interior and corner solutions. Introducing consideration sets into this alternative choice framework is attractive for at least two reasons. As demonstrated by the empirical application, the model can be applied to data sets with large numbers of goods. This feature makes the model attractive relative to discrete choice applications of consideration set models that have been limited to data sets with a relatively small numbers of alternatives (i.e., 10 or less). Moreover, although the empirical application described below does not exploit survey responses or exclusion restrictions in estimation, the parametric structure of the likelihood is such that the model can be estimated using standard techniques. This feature of the continuous demand system model allows the analyst to implement the suggestion of Swait and Ben-Akiva [1987] by having the same economic factors (i.e., prices, qualities, and income) influence the consideration process and the conditional utility maximizing choice. As discussed in the next section, a significant advantage of having these economic factors enter both dimensions of choice is that the tight link between the discrete and continuous dimensions of choice implicit in traditional continuous demand system models is partially relaxed without sacrificing the internal consistency of the behavioral model.

3. The Model

3.1 General Structure

As formulated originally by Wales and Woodland [1983], the traditional Kuhn-Tucker continuous demand system framework's central building block is the direct utility function, $U(\boldsymbol{x}, \boldsymbol{Q}, z, \boldsymbol{\beta}, \boldsymbol{\varepsilon})$, where $\boldsymbol{x}$ corresponds to the consumption levels of the M quality differentiated goods, $\boldsymbol{Q} = [\boldsymbol{q}_1, ..., \boldsymbol{q}_M]^{\mathsf{T}}$ is an $M \times K$ matrix of quality attributes for the M goods, z is an essential Hicksian composite good, $\boldsymbol{\beta}$ is an estimable parameter vector, and $\boldsymbol{\varepsilon}$ represents all of the remaining determinants of choice that are unobserved and random from the analyst's perspective. The rational individual is assumed to maximize $U(\boldsymbol{x}, \boldsymbol{Q}, z, \boldsymbol{\beta}, \boldsymbol{\varepsilon})$ with respect to her linear budget constraint, $\boldsymbol{p}^{\mathsf{T}}\boldsymbol{x} + p_z z = y$, and M non-negativity constraints, $\boldsymbol{x} \geq 0$. In addition to these constraints and the complementary-slackness conditions, the optimal consumption bundle is implicitly defined by the following M first order conditions:

(2) $$p_z \frac{\partial U(\boldsymbol{x},\boldsymbol{Q},z,\boldsymbol{\beta},\boldsymbol{\varepsilon})}{\partial x_i} \Big/ \frac{\partial U(\boldsymbol{x},\boldsymbol{Q},z,\boldsymbol{\beta},\boldsymbol{\varepsilon})}{\partial z} \le p_i, i = 1,\ldots,M$$

where the left hand side of (2) can be interpreted as good *i*'s "virtual price" (Neary and Roberts [1980]) or marginal willingness to pay for an additional unit. Placing some additional structure on how $\boldsymbol{\varepsilon}$ enters preferences and assuming and assuming that its elements can be treated as random draws from some probability density function, manipulations of these first order conditions and a sample of individuals observed choices can be used to recover estimates of the model's structural parameters within the maximum likelihood framework.

Equation (2) implies that the relationship between a good's virtual and market prices governs the individual's extensive margin choice – i.e., her discrete choice of whether to consume the good – as well as her intensive margin choice – her derived demand decision of how much to consume – in precisely the same fashion. This, in some sense, represents the beauty and appeal of the traditional Kuhn-Tucker framework, but it also places strong restrictions on the data generating process for consumption that may not hold empirically.

The latent consideration set framework represents an approach for partially relaxing this tight nexus without jeopardizing the model's theoretical consistency. The Kuhn-Tucker latent consideration set model works as follows. The direct utility function assumes the following general form:

(3) $$U(\tilde{x}_1,\ldots,\tilde{x}_M,\boldsymbol{Q},z,\boldsymbol{\beta},\boldsymbol{\varepsilon}),$$

where $\tilde{x}_i = 1_{f_i(\boldsymbol{p},\boldsymbol{Q},y,\boldsymbol{\beta}',\varepsilon_i')>0} x_i, i = 1,\ldots,M$. When the *i*th good is considered, the function $f_i(\boldsymbol{p},\boldsymbol{Q},y,\boldsymbol{\beta}',\varepsilon_i')$, which in general depends on market prices $\boldsymbol{p}$, quality attributes $\boldsymbol{Q}$**,** income y, a vector of estimable parameters $\boldsymbol{\beta}'$, and unobserved heterogeneity ε_i', is strictly positive and the indicator function $1_{f_i(\boldsymbol{p},\boldsymbol{Q},y,\boldsymbol{\beta}',\varepsilon_i')>0}$ equals one. In principle, $f_i(\cdot)$ could also be modeled as a function of responses to consideration set survey questions as in Ben-Akiva and Boccora [1995] or factors that the analyst assumes enter just the consideration process as in Haab in Hicks [1997]. These possibilities are not considered here in part because most consumption data does not contain auxiliary survey responses that are informative about an individual's consideration set and the exclusion restrictions are in some sense arbitrary and unnecessary in the subsequent empirical application.

The following intuitive (but not necessary) restrictions linking consumption of the *i*th good and its quality attributes are imposed on (3):

(4) $$\frac{\partial U(\tilde{x}_1,\ldots,\tilde{x}_M,\boldsymbol{Q},z,\boldsymbol{\beta},\boldsymbol{\varepsilon})}{\partial \boldsymbol{q}_i}=0 \text{ if } \tilde{x}_i=0,\forall i.$$

In the nonmarket valuation literature, (4) is commonly referred to as weak complementarity (Mäler [1974]). Note that the structure of preferences in (3) along with the assumption in (4) imply that a price and/or quality change that results in the expansion of the individual's consideration set will not in itself increase the consumer's utility. Only if the increase in the consideration set is concomitant with a change in consumption will the individual experience a welfare gain.

Three features of this representation of consumer preferences are worth emphasizing. First, prices, quality, and income are assumed to influence both the consideration process and the conditional utility maximizing choice, but depending on the functional forms of $f_i(\cdot)$ and the Kuhn-Tucker conditions implied by (3) and conditional on consideration, how they influence each of these dimensions may differ. Moreover, the structure of preferences in (3) suggests that the consideration process in some sense serves as additional constraints or hurdles on consumption.

In addition to the traditional hurdle requiring that the good's virtual and market prices must be equal (equation (2) above), the good must also be considered by the individual for it to be consumed, ($f_i(\cdot) > 0$). Thus if the ith good is not consumed, it is either the case $f_i(\cdot) \leq 0$ or that $f_i(\cdot) > 0$ and (2) is a strict inequality. Relative to the traditional demand system framework, this double hurdle structure is attractive because it allows a different structure represented by the consideration process to influence the extensive margin choice of whether to consume a good but not the intensive margin conditional derived demand choice. As a result, the tight nexus between the two dimensions of choice is relaxed without jeopardizing the internal consistency of the behavioral model. Finally, since the consideration process is treated here as observationally equivalent to a set of additional constraints on consumer choice, it should come as no surprise that relaxation of these constraints can not make the individual worse off. Since economic theory assumes that utility is strictly increasing in income and non-increasing in prices, the following additional restrictions on the structure of $f_i(\cdot)$ are employed:

(4) $$\frac{\partial f_i(\cdot)}{\partial y} \geq 0 \quad \& \quad \frac{\partial f_i(\cdot)}{\partial p_j} \leq 0, \forall i, j .$$

Moreover, because environmental quality explicitly enters the model, it is also intuitive to require that the consideration set is non-decreasing in quality improvements. Assuming all elements of $\boldsymbol{Q}$ are desirable,[2] the following assumption is employed in this paper:[3]

(5) $$\frac{\partial f_i(\cdot)}{\partial \boldsymbol{q}_j} \geq 0, \forall i, j .$$

[2] In many applications $\boldsymbol{Q}$ may contain undesirable characteristics, e.g., pollution levels in a water-based recreation context. In these cases, an improvement would involve a decrease in $\boldsymbol{Q}$.

[3] Note that the restrictions in (4) and (5) are sufficient but not necessary conditions for economic consistency. Alternative, less stringent, and more defensible conditions may be available to the analyst depending on the application.

As discussed in the previous section, identifying which of the two hurdles explains non-consumption is generally not possible, but the analyst can ascertain the relative probabilities of these outcomes conditional on a set of parametric functional form and distributional assumptions. The next subsections develop an empirical model that accomplish this task.

3.2 Structure of Preferences

The empirical application employs the following additively separable primal representation of consumer preferences:

$$\begin{gathered} U(\boldsymbol{x},\boldsymbol{Q},z,\boldsymbol{\beta},\boldsymbol{\varepsilon}) = \sum_{j}^{M} \Psi(\boldsymbol{s}_j,\boldsymbol{\varepsilon}) \ln(\phi(\boldsymbol{q}_j)\tilde{x}_j + \theta_j) + \frac{1}{\rho_z} z^{\rho_z} \\ \ln \Psi(\boldsymbol{s}_j,\boldsymbol{\varepsilon}) = (\delta + \varepsilon_\delta)^{\mathsf{T}} \boldsymbol{s}_j + \varepsilon_j, \forall j \\ \ln \phi(\boldsymbol{q}_j) = \gamma^{\mathsf{T}} \boldsymbol{q}_j, \forall j \\ \tilde{x}_j = 1_{\Phi + (\kappa+\varepsilon_\kappa)(\ln p_j - \gamma^{\mathsf{T}} \boldsymbol{q}_j) - (\lambda+\varepsilon_\lambda) y + \varepsilon' > 0}\, x_j, \forall j \end{gathered} \tag{6}$$

where $\boldsymbol{s}_j$ is a vector of individual specific demographic variables and site specific dummy variables, $\boldsymbol{\theta} = [\theta_1,...,\theta_M]^{\mathsf{T}} > \mathbf{0}$, $\rho_z \le 1, \delta$, γ, and $\Phi, \kappa,$ and λ are estimable parameters, ε_δ, ε_κ, and ε_λ represent unobserved heterogeneity that varies randomly across individuals in the population, and $\bar{\boldsymbol{\varepsilon}} = [\varepsilon_1,...,\varepsilon_M]$ and $\bar{\boldsymbol{\varepsilon}}' = [\varepsilon_1',...,\varepsilon_M']$ are unobserved heterogeneity that varies randomly across individuals and goods. Because the quality attributes of the differentiated goods enter through simple repackaging parameters (Grilliches [1964]), weak complementarity (i.e., equation (4) above) is satisfied. The preference specification in (6) is similar to the preference specification employed by vHPP except for the inclusion of the indicator functions designed to represent the consideration process. As discussed above, the analyst has some flexibility in specifying $f_i(\cdot)$ as long as the consideration is non-decreasing in income and quality and non-increasing in prices. Given these constraints and based on some preliminary exploratory analysis, the specification in (6) was chosen where $(\kappa + \varepsilon_\kappa)$ and $(\lambda + \varepsilon_\lambda)$ are censored at zero.

3.3 Estimation

Maximum simulated likelihood estimation techniques (e.g., Gourieroux and Monfort [1996]) are used to recover parameter estimates for the above model under the following set of parametric assumptions for the unobserved heterogeneity:

(a) $\varepsilon_j \sim iid\ Type\ I\ Extreme\ Value\ with\ inverse\ scale\ \mu, \forall j$

(b) $\varepsilon'_j \sim iid\ Logistic\ with\ normalized\ scale, \forall j$

(c) $Cov(\varepsilon_i, \varepsilon_j) = Cov(\varepsilon'_i, \varepsilon'_j) = 0, \forall i, j, i \neq j; Cov(\varepsilon_i, \varepsilon'_j) = 0, \forall i, j$

(d) $(\varepsilon_\delta, \varepsilon_\kappa^+, \varepsilon_\lambda^+) \sim Normal(0, \Sigma);\ \varepsilon_\nu = \begin{cases} \varepsilon_\nu^+ \text{ if } \varepsilon_\nu^+ \leq -\nu \\ -\nu \text{ otherwise} \end{cases}, \nu = \kappa, \lambda$

Using standard transformation of variables techniques, it can be shown that assumptions (a), (b), and (c) jointly imply that the likelihood function conditional on the random coefficients takes the form:

$$l(\boldsymbol{x}^* \mid \varepsilon_\delta, \varepsilon_\omega, \varepsilon_\lambda) = |\boldsymbol{J}| \prod_j \begin{bmatrix} (1 - 1_{x_j^* > 0}) \left[\pi_j(\varepsilon_\kappa, \varepsilon_\lambda) + (1 - \pi_j(\varepsilon_\kappa, \varepsilon_\lambda)) l_j(\varepsilon_\delta) \right] \\ + 1_{x_j^* > 0} (1 - \pi_j(\varepsilon_\kappa, \varepsilon_\lambda)) l_j(\varepsilon_\delta) \end{bmatrix} \tag{8}$$

where $1_{x_j^* > 0}$ is an indicator function equal to one when observed demand for the *j*th good, x_j^*, is strictly positive and $l_j(\varepsilon_\delta)$ is the conditional likelihood for the *j*th first order condition and takes the form:

$$l_j(\varepsilon_\delta) = \left[\frac{1}{\mu} \exp\left[\frac{-g_j(\varepsilon_\delta)}{\mu} \right] \right]^{1_{x_j^* > 0}} \exp\left[-\exp\left[\frac{-g_j(\varepsilon_\delta)}{\mu} \right] \right] \tag{9}$$

$$\begin{aligned} g_j(\varepsilon_\delta) = {} & -(\delta + \varepsilon_\delta)^\mathsf{T} \boldsymbol{s}_j + \ln p_j - \gamma^\mathsf{T} \boldsymbol{q} - (1 - \rho_z) \ln(y - \boldsymbol{p}^\mathsf{T} \boldsymbol{x}^*) + \\ & \ln(\phi(\boldsymbol{q}_j) x_j^* + \theta_j), \ \forall j \end{aligned} \tag{10}$$

$$\pi_j(\varepsilon_\kappa, \varepsilon_\lambda) = \frac{\exp(-(\kappa + \varepsilon_\kappa)(\ln p_j - \gamma^\mathsf{T} \boldsymbol{q}) - (\lambda + \varepsilon_\lambda) y - \Phi)}{1 + \exp(-(\kappa + \varepsilon_\kappa)(\ln p_j - \gamma^\mathsf{T} \boldsymbol{q}) - (\lambda + \varepsilon_\lambda) y - \Phi)}, \forall j, \tag{11}$$

and $\boldsymbol{J}$ is the Jacobian of transformation. Tedious algebra can be used to show that $l(\boldsymbol{x}^* \mid \varepsilon_\delta, \varepsilon_\omega, \varepsilon_\lambda)$ is consistent with Manski's latent consideration framework specified in equation (1) above, but the structure of (8) suggests that it simplifies to the product of independent marginal likelihoods. Each of these marginal likelihoods has an econometric structure that is similar to the single equation zero-augmented censored regression demand models of Deaton and Irish [1984] and the "spike" count data demand models (e.g., Gurmu and Trivedi [1996], Haab and McConnell [1996], Shonkwiler and Shaw [1996]) that have been widely used in the applied literature. This convenient decomposition arises not only from the restrictive covariance assumptions in (c) but also from the fact that $l_j(\varepsilon_\delta)$ does not depend on the prices and quality attributes of all elements entering the individual's consideration set. As (9) and (10) suggest, $l_j(\varepsilon_\delta)$ only depends on the price and quality of the *j*th good as well as the prices of the goods that are consumed in strictly positive quantities and *known with certainty* to be in the individual's consideration set.[4] This differs from the conditional likelihoods (i.e., the choice probabilities) arising with discrete choice models that depend on the price and quality attributes for *all* goods that enter the individual's choice set. This feature of the primal continuous demand system model explains why it can be applied to data sets with many goods.[5]

The unconditional likelihood of observing $\boldsymbol{x}^*$ is

(12) $$l(\boldsymbol{x}^*) = \int l(\boldsymbol{x}^* \mid \varepsilon_\delta, \varepsilon_\kappa, \varepsilon_\lambda) f(\varepsilon_\delta, \varepsilon_\kappa, \varepsilon_\lambda) d\varepsilon_\delta d\varepsilon_\kappa d\varepsilon_\lambda ,$$

where the integral is over the full support of $(\varepsilon_\delta, \varepsilon_\kappa, \varepsilon_\lambda)$. Given these assumptions and the structure of the conditional likelihood function, (12) has no closed form solution and cannot be

[4] Note that this attribute is independent of the additive separability assumption.
[5] It should be noted that deriving the likelihood function associated with dual continuous demand system models (Lee and Pitt [1986]) that incorporate latent consideration sets and allow for flexible cross-price effects would be confounded by the same difficulties associated with discrete choice models for applications with many goods. For small dimensional applications, however, deriving the likelihood function is possible.

evaluated using numerical integration techniques unless the dimension of $(\varepsilon_\delta, \varepsilon_\kappa, \varepsilon_\lambda)$ is small. However, simulation can be used to compute (12) to any arbitrary level of precision, and the simulated likelihood can then be fed into a maximum likelihood search routine to recover estimates of all structural parameters.

The estimation strategy used in this paper is similar in spirit to the strategies that are now widely used in the discrete choice literature (see Train [2003] for a recent review). Restrictive distributional assumptions (see (a), (b), and (c) above) are used to derive a tractable likelihood that has a closed form solution conditional on a vector of coefficients. Because the conditional likelihood can be computed cheaply, random coefficients and simulation can be used to introduce a more flexible and plausible error structure without jeopardizing econometric tractability. In this application, random coefficients are used to introduce heteroskedasticity and (positive) correlations in the unobserved determinants of choice across the first order conditions that implicitly define the conditional derived demands. Moreover, since no restrictions are placed on the variance-covariance matrix of $(\varepsilon_\delta, \varepsilon_\kappa, \varepsilon_\lambda)$ (i.e., the off-diagonal elements of Σ are estimated), the consideration process and conditional utility maximizing choice can be positively or negatively correlated for each good.

Like traditional demand system models that consistently account for interior and corner solutions, the latent consideration set model developed in this section can be interpreted as an endogenous regime switching model. However, a regime in the above model is defined not only by the weak inequality in (2) but also by the consideration process. This differentiates the latent consideration set model from the traditional model that defines regimes only by the inequality in (2). Thus, the latent consideration set model has 3^M regimes (do not consider, consider but do not consume, or consider and consume for each of the *M* goods) that the individual might rationally choose, whereas the traditional model has only 2^M (do not consume or consume for each of the M goods).

4. Welfare Calculation

4.1 Generic Issues

The approach used for constructing Hicksian welfare measures builds on the strategy suggested by vHPP. They develop a multi-stage, Monte Carlo, Markov Chain simulation algorithm that solves for the expected compensating surplus arising from changes in price and/or quality. Since their algorithm applies to situations where the consideration set is known and fixed, it must be extended to the present setting where the consideration set is latent and probabilistic.

Using standard notation, the Hicksian consumer surplus, CS^H, associated with a price and quality change from ($\boldsymbol{p}^0, \boldsymbol{Q}^0$) to ($\boldsymbol{p}^1, \boldsymbol{Q}^1$) is implicitly defined as:

$$V(\boldsymbol{p}^0, \boldsymbol{Q}^0, y, \boldsymbol{\beta}, \boldsymbol{\varepsilon}) = V(\boldsymbol{p}^1, \boldsymbol{Q}^1, y - CS^H, \boldsymbol{\beta}, \boldsymbol{\varepsilon}) . \tag{13}$$

vHPP identify three related issues that complicate recovering CS^H from traditional continuous demand system models. Unless preferences are homothetic or quasilinear in income, no closed form solution for the income reduction that equates utility across the two states exist, and thus iterative search procedures such as numerical bisection must be employed to solve for CS^H. Moreover, at each iteration of the search procedure, the analyst must solve for the consumer's utility conditional on a $(\boldsymbol{p}, \boldsymbol{Q}, y, \boldsymbol{\varepsilon})$ quadruplet. As vHPP argue, solving the consumer's problem analytically as in Phaneuf, Kling and Herriges [2000] quickly becomes computationally intractable as the dimension of the consideration set grows large, and thus numerical approaches must be used for this task. Finally, because $\boldsymbol{\varepsilon}$ is a random variable from the analyst's perspective, she cannot ascertain CS^H precisely. At best the analyst can recover an estimate of the central tendency of CS^H such as its expectation, $E(CS^H)$, which often requires simulation to construct.

All of these difficulties are present with models that incorporate latent consideration sets, but the difficulties associated with solving the consumer's problem conditional on a $(\boldsymbol{p},\boldsymbol{Q},y,\boldsymbol{\varepsilon})$ quadruplet are more complex because there are 3^M regimes that the individual might choose compared to 2^M for traditional models. As a result, the analyst must first determine which goods the individual considers and then conditionally the combination of interior and corner solutions from her consideration set that represents her optimal consumption bundle. Because the structure of the consideration process implies that the individual's consideration set is a function of prices, quality, and income, the analyst must resolve for the individual's consideration set whenever these values change. This fact suggests that the analyst must resolve for the individual's consideration set at every iteration of the search routine that solves for CS^H. Thus, the computationally challenge of welfare measurement arising from models with latent consideration sets is more formidable relative to traditional demand system models.

Similar to vHPP, the simulation-based approach to constructing Hicksian consumer surplus measures can be decomposed into three stages. Although the third stage is trivial (averaging the simulated welfare estimates), the first two are not and therefore discussed in detail in the next two sections.

4.2 First Stage – Simulating the Unobserved Heterogeneity Entering Consumer Preferences

Following von Haefen [2003], this paper employs an approach to constructing welfare measures sets that incorporates the implications of an individual's observed choice. In other words, $\boldsymbol{\varepsilon}$ is simulated such that the model perfectly predicts observed behavior at baseline conditions, and the structure of substitution implied by the model is used to predict how people respond to price, quality, and income changes. In the context of traditional demand system models, vHPP find that fewer simulations are necessary to achieve an arbitrary level of precision in the welfare estimates relative to more traditional welfare construction approaches that do not incorporate observed choice. These computational advantages carry over to the present context where consideration sets are latent and probabilistic.

Implementation of this approach requires that the analyst simulate from the joint distribution of the unobserved heterogeneity conditional on the individual's observed choice, i.e., $f(\boldsymbol{\varepsilon} \mid \boldsymbol{x}^*)$. The following decomposition suggests a convenient strategy for accomplishing this task:

$$f(\boldsymbol{\varepsilon} \mid \boldsymbol{x}^*) = f_1(\varepsilon_\delta, \varepsilon_\kappa, \varepsilon_\lambda \mid \boldsymbol{x}^*) f_2(\bar{\boldsymbol{\varepsilon}}' \mid \varepsilon_\delta, \varepsilon_\kappa, \varepsilon_\lambda, \boldsymbol{x}^*) f_3(\bar{\boldsymbol{\varepsilon}} \mid \bar{\boldsymbol{\varepsilon}}', \varepsilon_\delta, \varepsilon_\kappa, \varepsilon_\lambda, \boldsymbol{x}^*) . \tag{14}$$

Equation (14) states that the joint distribution of the unobserved heterogeneity conditional on $\boldsymbol{x}^*$ can be decomposed into the marginal distribution of the random coefficients multiplied by the distribution of $\bar{\boldsymbol{\varepsilon}}'$ conditional on the random coefficients and $\boldsymbol{x}^*$ and the distribution of $\bar{\boldsymbol{\varepsilon}}$ conditional on $\bar{\boldsymbol{\varepsilon}}'$, the random coefficients, and $\boldsymbol{x}^*$. This structure suggests a sequential simulation procedure where the analyst first simulates the random coefficients from $f_1(\varepsilon_\delta, \varepsilon_\kappa, \varepsilon_\lambda \mid \boldsymbol{x}^*)$ and then conditionally simulates $\bar{\boldsymbol{\varepsilon}}'$ from $f_2(\bar{\boldsymbol{\varepsilon}}' \mid \varepsilon_\delta, \varepsilon_\kappa, \varepsilon_\lambda, \boldsymbol{x}^*)$, and finally $\bar{\boldsymbol{\varepsilon}}$ from $f_3(\bar{\boldsymbol{\varepsilon}} \mid \bar{\boldsymbol{\varepsilon}}', \varepsilon_\delta, \varepsilon_\kappa, \varepsilon_\lambda, \boldsymbol{x}^*)$.

As discussed in von Haefen and vHPP, simulating from $f_1(\varepsilon_\delta, \varepsilon_\kappa, \varepsilon_\lambda \mid \boldsymbol{x}^*)$ can be accomplished by exploiting a Metropolis-Hastings simulation algorithm (Chib and Greenberg [1995]). Since the procedures involved in implementing the Metropolis-Hastings algorithm are fairly standard and outlined by vHPP in the context of traditional Kuhn-Tucker demand system models, the details of the algorithm tailored to the current application can be found in the appendix. It should be noted, however, that because the Metropolis-Hastings algorithm, like all Monte Carlo, Markov Chain simulators, generates simulations from the target distribution only after a sufficiently long burn-in period, the analyst should discard the first *T* simulations.

Moreover, to reduce the serial correlation in the Markov Chain of random parameters, the analyst should only use every *j*th simulation ($j > 1$) after the first T in subsequent steps.

The second step, however, involves complexities not fully addressed elsewhere. The approach for simulating $\vec{\varepsilon}'$ pursued in this paper involves a sequential procedure that can be interpreted as an extension to an approach suggested originally by von Haefen and Phaneuf [2003] for determining whether a non-consumer of a set of quality differentiated goods would consider consuming any of the goods under any circumstance. A feature of the approach used here is that it does not simulate $\vec{\varepsilon}'$ directly but instead simulates the individual's consideration set. Given the structure of the consideration process, it should be clear that simulating $\vec{\varepsilon}'$ and simulating the individual's consideration set are observationally equivalent conditional on prices, quality, and income.

The initial step in this process is to simulate the individual's consideration set under baseline conditions when the analyst observes a choice. Because commodities must be considered to be consumed, the analyst knows with certainty that all goods with interior solutions (i.e., strictly positive demands) are considered by the individual at baseline conditions. For goods with corner solutions, the analyst cannot identify precisely whether they are considered. However, the structure of the econometric model can inform the analyst about the likelihood of consideration conditional on observing a corner solution. In particular, the probability of an individual considering x_j^* when it is not consumed conditional on $(\varepsilon_\delta, \varepsilon_\kappa, \varepsilon_\lambda)$ is:

$$\Pr(x_j^* \text{ considered}|\varepsilon_\delta, \varepsilon_\kappa, \varepsilon_\lambda) = \frac{(1-\pi_j(\varepsilon_\kappa, \varepsilon_\lambda))l_j(\varepsilon_\delta \mid x_j^* = 0)}{\pi_j(\varepsilon_\kappa, \varepsilon_\lambda) + (1-\pi_j(\varepsilon_\kappa, \varepsilon_\lambda))l_j(\varepsilon_\delta \mid x_j^* = 0)}, \tag{13}$$

where $\pi_j(\varepsilon_\kappa,\varepsilon_\lambda)$ and $l_j(\varepsilon_\delta \mid x_j^* = 0)$ are evaluated at baseline prices, quality, and income. Simulating whether x_j is considered by the individual can be accomplished by comparing a uniform random draw, *U*, to (13), (i.e., x_j^* is considered if $U < \Pr(x_j^* \text{ considered}|\varepsilon_\delta,\varepsilon_\kappa,\varepsilon_\lambda))$.

Once the analyst has simulated the individual's consideration set at baseline conditions, she can then determine how the choice set changes in response to price, quality, and income changes. To see how this is accomplished, it is important to recognize that from a statistical perspective, the structure of the consideration set process implies that x_j is considered by the individual if a uniform random draw, say η_j, is greater than the threshold $\pi_j(\varepsilon_\kappa,\varepsilon_\lambda)$. Thus, the analyst knows that if x_j is considered at baseline conditions, $\eta_j > \pi_j(\varepsilon_\kappa,\varepsilon_\lambda)$ when $\pi_j(\varepsilon_\kappa,\varepsilon_\lambda)$ is evaluated at $(\boldsymbol{p}^0,\boldsymbol{Q}^0,y)$. By simulating $\boldsymbol{\eta} = [\eta_1,\ldots,\eta_M]^\top$ such that it is consistent with the simulated consideration set at baseline conditions, the analyst can ascertain how the choice set changes for any $(\boldsymbol{p},\boldsymbol{Q},y)$ triplet by comparing the simulated $\boldsymbol{\eta}$ vector with the corresponding $\pi_j(\varepsilon_\kappa,\varepsilon_\lambda)$ probabilities evaluated at any $(\boldsymbol{p},\boldsymbol{Q},y)$.

Operationally, the approach for ascertaining how the simulated choice set changes involves the following steps. Conditional on a simulated consideration set at baseline conditions, the analyst simulates the separate elements of $\boldsymbol{\eta}$ according to the following rule:

$$(14) \qquad \eta_j = \begin{cases} \pi_j(\varepsilon_\kappa,\varepsilon_\lambda)U & \text{if } x_j \text{ is not considered} \\ (1-\pi_j(\varepsilon_\kappa,\varepsilon_\lambda))U & \text{if } x_j \text{ is considered} \end{cases},$$

where *U* again is a uniform random draw and $\pi_j(\varepsilon_\kappa,\varepsilon_\lambda)$ is evaluated at $(\boldsymbol{p}^0,\boldsymbol{Q}^0,y)$. Given the simulated $\boldsymbol{\eta}$, the analyst need only compare each η_j to its corresponding $\pi_j(\varepsilon_\kappa,\varepsilon_\lambda)$ evaluated at any $(\boldsymbol{p},\boldsymbol{Q},y)$ triplet to determine how the individual's choice set has changed.

The third and final step for simulating the unobserved heterogeneity involves simulating $\bar{\boldsymbol{\varepsilon}}$ from $f_3(\bar{\boldsymbol{\varepsilon}} \mid \bar{\boldsymbol{\varepsilon}}', \varepsilon_\delta, \varepsilon_\kappa, \varepsilon_\lambda, \boldsymbol{x}^*)$. Assuming good *j* is consumed in strictly positive quantities, the structure of the behavioral model implies that $\varepsilon_j = g_j(\varepsilon_\delta)$ where $g_j(\varepsilon_\delta)$ is defined in equation (8). When x_j is not consumed but considered by the individual, then ε_j must be strictly less than $g_j(\varepsilon_\delta)$. Given the i.i.d. Type I Extreme Value distributional assumption, ε_j can be simulated via

(15) $$\varepsilon_j = -\ln(-\ln(\exp(-\exp(-g_j(\varepsilon_\delta)/\mu))U))\mu,$$

where μ is the scale parameter and *U* is another random draw from the uniform distribution. If x_j is not consumed or considered, the analyst infers nothing about the values that ε_j can take. In this case, ε_j is simulated from the Type I Extreme Value distribution with full support:

(16) $$\varepsilon_j = -\ln(-\ln U)\mu.$$

4.3 Second Stage – Solving for the Simulated Hicksian Consumer Surplus

The approach for solving for the Hicksian consumer surplus associated with a price and quality change used in this paper employs the same multi-layered numerical search routine employed by vHPP. At the top layer, a numerical bisection routine is used to solve for the income reduction that equates utility before and after the price and quality change. This task is complicated by the fact that the individual's consideration set can change when prices, quality, and income change. These changes in an individual's consideration set generate discontinuities in utility, and thus an income reduction that exactly equates utility before and after a price and quality change might not exist.

Figure 1 suggests the nature of the problem as well as a plausible resolution. Before the quality change, the individual achieves a utility level equal to $V(\boldsymbol{p}^0, \boldsymbol{Q}^0, y, \boldsymbol{\beta}, \boldsymbol{\varepsilon})$. Holding income constant, assume the individual is made better off with the price and quality change to ($\boldsymbol{p}^1, \boldsymbol{Q}^1$), and so an income reduction is necessary to equate utility before and after the price and quality change. Initially as income is taken away from the individual, her utility continuously declines. However, once the individual's adjusted income equals $\bar{y}$, any further reduction generates a discontinuous and potentially large drop in utility. This discontinuity arises because $\bar{y}$ represents a threshold at which the individual's consideration set contracts in a way that a good that is consumed in positive quantities at income levels at and above $\bar{y}$ is not considered and consumed at income levels below it. Figure 1 is drawn such that this discontinuity falls over a utility range that encompasses the baseline utility level, $V(\boldsymbol{p}^0, \boldsymbol{Q}^0, y, \boldsymbol{\beta}, \boldsymbol{\varepsilon})$. Thus, there is no income compensation that equates utility before and after the price and quality change in this example. However, Figure 1 suggests that if one defines CS^H as:

$$\begin{aligned} V(\boldsymbol{p}^0, \boldsymbol{Q}^0, y, \boldsymbol{\beta}, \boldsymbol{\varepsilon}) &\leq V(\boldsymbol{p}^1, \boldsymbol{Q}^1, y - CS^H + \Delta, \boldsymbol{\beta}, \boldsymbol{\varepsilon}) \\ V(\boldsymbol{p}^0, \boldsymbol{Q}^0, y, \boldsymbol{\beta}, \boldsymbol{\varepsilon}) &\geq V(\boldsymbol{p}^1, \boldsymbol{Q}^1, y - CS^H - \Delta, \boldsymbol{\beta}, \boldsymbol{\varepsilon}) \end{aligned}, \tag{17}$$

for any $\Delta > 0$, a unique welfare measure exists. This definition of the Hicksian consumer surplus is used in this paper.

To recover welfare estimates based on (17), a second numerical bisection routine that solves for the individual's utility conditional on a simulated consideration set and $(\boldsymbol{p}, \boldsymbol{Q}, y, \boldsymbol{\varepsilon})$ quadruplet is necessary. The approach pursued here borrows from vHPP's numerical bisection procedure designed for this same task with the only difference being that the consideration set defines the relevant goods in the current case whereas all goods are relevant in vHPP's setup. As described in vHPP, the routine exploits the fact that when preferences are additively separable, solving for the optimal consumption bundle reduces to a one-dimensional search for the optimal value for *z*, the essential Hicksian composite commodity. The steps of the algorithm are as follows:

1) At iteration *i*, set $z_a^i = (z_l^{i-1} + z_u^{i-1})/2$. To initialize the algorithm, set $z_l^0 = 0$ and $z_u^0 = y$.
2) Conditional on z_a^i, solve for $\boldsymbol{x}^i$ using
$$u_j(x_j) \le u_z(z)p_j, \forall j \in C$$
$$x_j \ge 0, \forall j \in C$$
$$x_j(u_j(x_j) - u_z(z)p_j) = 0, \forall j \in C$$
where $u_j(x_j)$ and $u_z(z)$ are the additively separable components of the indirect utility function that depend only on x_j and *z*, respectively.
3) Use the budget constraint (i.e., $z = y - \sum_{j \in C} p_j x_j$) and $\boldsymbol{x}^i$ to construct $\tilde{z}^i$.
4) If $\tilde{z}^i > z_a^i$, set $z_l^i = z_a^i$ & $z_u^i = z_u^{i-1}$. Otherwise, set $z_l^i = z_l^{i-1}$ & $z_u^i = z_a^i$.
5) Iterate until $abs(z_l^i - z_u^i) \le c$ where *c* is arbitrarily small.

Using the same arguments employed by vHPP, it is straightforward to show that the curvature properties of the direct utility function imply that the algorithm will solve for the consumer's optimal consumption bundle to any arbitrarily defined level of precision. Once these values are recovered, the analyst can solve for the individual's utility conditional on a $(\boldsymbol{p}, \boldsymbol{Q}, y, \boldsymbol{\varepsilon})$ quadruplet by plugging them into (6).

4.4 Empirical Implementation

Although the algorithm described above has more layers and details than the algorithm developed by vHPP, it remains relatively straightforward to code within a matrix programming language. Experience with the algorithm in an applied setting suggests, however, that, relative to traditional demand system models with fixed and known consideration sets, significantly more simulations are necessary to achieve an arbitrary level of precision in the welfare point estimates. Nevertheless, constructing consistent point and standard errors estimates for welfare measures from Kuhn-Tucker demand system models for models with latent and potentially large consideration sets remains well within the realm of current computational feasibility.

5. Data

The latent consideration set demand system model developed in the previous sections is applied to a subset of recreation data from the 1994 National Survey of Recreation and the Environment (NSRE). The 2,471 water-based trips taken by 157 residents of the lower Susquehanna River basin to lakes, rivers, and streams in the region are the focus of the analysis. The recreation data was linked to water quality chemistry data from a variety of sources so that benefit estimates for non-point source or diffuse pollution abatement could be derived. Although numerous studies in the environmental economics literature address point source (or end-of-pipe) pollution abatement, relatively few address non-point source pollution abatement, and thus the benefit estimates reported in this paper in principle can serve a valuable policy function. Elsewhere, von Haefen [1999, 2003] discusses the protocols used in assembling the final data set used in this analysis, and the interested reader should consult his work for further details. Table 1 defines and reports sample means for the variables used in estimation.

As discussed in Section 2, an important task in every applied demand analysis is choice set definition, and two important data constraints that were relevant in this application are worth mentioning before turning to the empirical results. First, the lower Susquehanna River basin is replete with lakes, rivers, and streams that in principle support some form of outdoor recreation. Given federal, state, and local environmental agencies limited budgets, water quality chemistries for all of these waterbodies was not available. These data limitations implied that a zonal or aggregated recreation site definition needed to be developed. To make the zonal sites as credible as possible, the Pennsylvania Department of Environmental Protection's delineation of the region into "sub-subbasin" watersheds (i.e., hydrological drainage regions of roughly 100 to 500 miles in size) were used to define their boundaries. As noted by the US Environmental Protection Agency's Office of Water [1998], a lake or river is "... in a real and figurative sense ... a reflection of its watershed," and thus it is logical to expect that receiving waters within a watershed will share common water quality attributes in addition to relatively close geographic proximity. Thus defining "composite" sites based on hydrological boundaries represents an intuitive approach that may be more defensible for policy purposes relative to those based on other delineations. Previous empirical analysis with this data by von Haefen [1999] suggests that per trip welfare measures from choice set definitions based on watershed boundaries have the desirable property of being less sensitive to the level of aggregation relative to those based on choice set definitions based on geopolitical criteria.

A second data limitation that significantly affected the definition of the objects of choice that may enter an individual's consideration set arose with the NSRE's survey instrument. In particular, the NSRE only elicited information on the number of trips an individual took to lakes, rivers, and streams within 100 miles of her home. As a result, each individual's geographic extent of the market was arbitrarily restricted to those sites located within 100 miles of her residence. Since individuals resided in different locations within the lower Susquehanna River basin (a 25-county region), each individual is assumed to formulate her consideration set from a universal set that may differ from all other respondents in the sample. Although the watershed-based site definition protocol implied that the region could be partitioned into 89 distinct zonal sites, only 68.960 on average fell within 100 miles of each respondent's home.

6. Estimation Results

Tables 2 and 3 report parameter estimates from traditional and latent consideration set Kuhn-Tucker demand system models, respectively. Estimates from fixed, uncorrelated random, and correlated random parameter specifications are reported to gauge the sensitivity of the estimates to more restrictive treatments of the unobserved heterogeneity entering consumer preferences.[6] Following Englin, Boxall, and Watson [1998], all of the estimation results reported in tables 2 and 3 are based on models that consistently account for truncation in the total trip counts arising from the fact that all individuals in the NSRE sample are recreators. This is accomplished by normalizing the conditional likelihood in (8) by the likelihood of positive consumption (i.e., one minus the likelihood of observing zero consumption for all quality differentiated sites).

In general, the common parameter estimates are similar across all six reported specifications. Individuals who have boated, fished, or swum in the past as well as females are more likely to recreate, and sites along the Susquehanna River and in federal, state and county parks are more likely to be visited *ceteris paribus*. For the environmental quality variables, the Lowdo parameter that captures low dissolved oxygen levels that inhibit most flora and fauna growth are negative as expected and similar in magnitude across all six specifications. Consistent with von Haefen's [2003] empirical findings, the quadratic trophic state index (TSI) specification consistently has the expected concave shape implying that beyond a threshold, decreases in TSI increase consumer utility. For the traditional models, the marginal value of a decrease in the TSI index is positive for values roughly greater than 32.5, but for the latent consideration set models the turning point is consistently less at roughly 29.5. Looking ahead, these differences in estimates suggest why similar reductions in the trophic states of waterbodies may generate larger welfare gains for the latent consideration set models relative to the traditional models. With respect to the ρ_z parameter, recall that economic theory requires that it be less than or equal to one. All six specifications were estimated with no restrictions placed on ρ_z, and likelihood ratio tests suggested that the null hypothesis that ρ_z equals one could not be rejected for significance

[6] For the correlated random parameter specifications, the covariance estimates of the random parameters are not reported but are available from the author upon request.

levels less than 0.0494 for all six models.[7] Therefore, ρ_z was restricted to equal zero for all models. Finally, the translating and scale parameters are consistently positive across the six models but differ in magnitude across the traditional and latent consideration set specifications.

Turning to the consideration set parameter estimates reported in table 3, one finds that the estimates have the expected sign and are generally statistically significant. Increases in a site's quality-adjusted price and reductions in income tend to decrease the likelihood that it will be considered, although the income effect is only statistically significant at roughly the 10 percent level in the correlated random parameter specification. Together, these estimates suggest that income may be more significant at the extensive site selection margin relative to the intensive derived demand margin in this data set. Traditional demand system models that place a tight nexus between these two dimensions of choice give the misleading impression that income effects are completely absent in this application.

One approach to evaluating the relative fits of these alternative specifications is to compare their ln-likelihood and Consistent Akaike Information Criteria (CAIC) (Schwartz [1978]) values. Consistently across the fixed, uncorrelated random, and correlated random parameter specifications, these values reported in table 4 suggest that the latent consideration specifications outperform the traditional specifications. Although the inclusion of uncorrelated or correlated random parameters in general increase the ln-likelihoods, comparisons of CAICs suggests that the more restrictive fixed parameter models are preferable statistically. A series of Vuong (1989) non-nested hypothesis tests are employed to further compare the traditional and latent consideration set specifications.[8] All nine of these tests reported in table 4 suggest that the

[7] The p-values from the likelihood ratio tests were 0.2196, 0.1300, and 0.0494, for the three traditional specifications in table 2 and 0.3238, 1.0000, and 1.0000 for the latent consideration set specifications in table 3, respectively.
[8] Using the Vuong non-nested hypothesis test in this way is conceptually similar to Greene's [1994] use of the test to compare single equation Poisson and negative binomial models with double hurdle Poisson and negative binomial models.

traditional and latent consideration set models are distinguishable and that the traditional models can be rejected in favor of the latent consideration set models. Finally, likelihood ratio tests of the hypothesis that all parameters are fixed (i.e., that the variances and covariances of the random parameters equal zero) are used to compare the fixed versus random parameter specifications. As Chen and Cosslett [1998] and Andrews [2001] discuss, the fact that the null hypothesis restricts the random parameters' standard errors to zero (their lower bound values) implies that the asymptotic distribution of the likelihood ratio test statistic is not the standard chi-squared distribution with degrees of freedom equal to the number of restrictions. Chen and Cosslett argue that the appropriate asymptotic distribution is a weighted average of chi-squared distributions that will imply critical values that are smaller than standard chi-squared critical values. The likelihood ratio p-values reported in table 4 are based on the standard chi-squared distribution with appropriate degrees of freedom. As Moeltner and Layton [2002] have pointed out, these p-values are too large and thus only informative when they clearly imply that the null hypothesis can be rejected at any reasonable significance level. Since all p-values reported in table 4 are less than 0.05, these tests are informative and suggest that the correlated random parameter specifications fit the data best. In combination with the CAIC values, these results suggest that the evidence is somewhat mixed with respect to the relative fits of the fixed and random parameter specifications.

7. Welfare Estimates

Two policy scenarios are used to evaluate the relative policy implications of the traditional and latent consideration set models. The first considers the loss of a 40 mile reach of the lower Susquehanna River from Columbia, PA to Havre de Grace, MD. This reach corresponds to three sites and contains three state parks supporting a wide range of recreational opportunities. 25 recreators in the sample took a total of 235 trips to the three sites that encompass the 40 mile stretch. The second policy scenario involves the cleanup of sites with low dissolved oxygen and high Trophic State Index (TSI) levels to safe standards as defined by the EPA. Welfare estimates from this scenario can inform policy makers of the potential benefits arising from the basin-wide cleanup of eutrophic sites, or receiving waters where phosphorous and nitrogen loadings from agricultural and silvicultural lands have sped up the photosynthetic process beyond their natural assimilative capacities. The EPA defines warm and cold water bodies with dissolved oxygen levels greater than 5.5 and 6.5 mg/l, respectively, and TSI levels less than 50 as unimpaired. This policy scenario therefore involves: 1) raising dissolved oxygen levels at impaired site such that the Lowdo variable equals zero at every site; and 2) lowering TSI levels to less than 50 at every site. 70 of the 157 recreators in the sample took a combined 347 trips to at least one of the 22 eutrophic sites.

Table 5 reports Hicksian consumer surplus point estimates and their 95 percent confidence intervals for both policy scenarios. Predicted changes in total trips as well as the baseline and predicted changes in the consideration sets are also reported. In general the results suggest that welfare measures are general larger in absolute value for the latent consideration set models relative to the traditional models. For the loss of the 40 mile reach and cleanup of eutrophic sites scenarios, the Hicksian consumer surplus point estimates for the latent consideration set models are larger by \$6.89 to \$7.78 and \$17.40 to \$30.53 in absolute value relative to the traditional models, respectively. In addition, the 95 percent confidence intervals for the latent consideration set models are much wider than the traditional model's confidence intervals. If one accepts the more general latent consideration set model as the true data generating process, these results combined suggest that there may be a bias-variance tradeoff between traditional models that assume the individual's consideration set is fixed and consists of all relevant goods and latent consideration set models that do not.

The change in total trips and baseline and change in consideration set size columns in table 5 illuminate why the latent consideration set models generate qualitatively different policy inference in this application. For the loss of the 40 mile reach scenario, both traditional and latent consideration set models predict the same loss in total trips (-1.833), an empirical result reflecting the limited amount of substitution resulting from the models' restrictive additive separability assumption. Thus the differences in welfare measures across the specifications arise because the parameter estimates for the latent consideration set models imply that the value of each lost trip is larger relative to the traditional models. For the cleanup of eutrophic sites scenario, table 5's results suggest that the latent consideration set models predict both a larger increase in total trips relative to the traditional models as well as significant expansion in the consideration set. Given the larger behavioral response, the finding that welfare measures are significantly larger in absolute value for the latent consideration set models is not surprising.

8. Conclusion

This paper has developed and empirically evaluated a Kuhn-Tucker continuous demand system model that incorporates latent, probabilistic consideration sets and can be applied to data sets with large numbers of goods. Under suitable assumptions, the econometric model is shown to have a convenient double hurdle structure that facilitates the introduction of more general error structures through random parameters. The empirical application suggests that the latent consideration set models fit the NSRE outdoor recreation data set better than traditional models, allow for differential income effects at the extensive margin of choice that are absent from traditional models, and generate qualitatively different policy inference for scenarios involving the loss of a river reach and a cleanup of eutrophic sites. Moreover, the relatively large confidence intervals for the welfare measures from latent consideration set models suggests that there may be a bias-variance tradeoff between the traditional approach in applied demand analysis of arbitrarily specifying the fixed elements of an individual's choice set and allowing for latent, probabilistic consideration sets.

In closing, it should be acknowledged that these empirical results are of course conditional on the NSRE data set and model specifications used here and therefore may not generalize to other applications of the latent consideration framework. Different preference specifications, distributional assumptions, and data sets might imply that the latent consideration framework does not improve statistical fit or alter policy implications significantly. Nevertheless, the results presented here suggest the tractability and potential gains arising from latent consideration set models, and thus researchers may wish to consider their use in future applied demand analyses.

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Technical Appendix – Simulating from $f_1(\varepsilon_\delta, \varepsilon_\kappa, \varepsilon_\lambda \mid \boldsymbol{x}^*)$

The Metropolis-Hastings Algorithm used to simulate from $f_1(\varepsilon_\delta, \varepsilon_\kappa, \varepsilon_\lambda \mid \boldsymbol{x}^*)$ employs the following steps:

1) At iteration *i*, simulate a candidate vector of unobserved heterogeneity, $(\tilde{\varepsilon}_\delta^i, \tilde{\varepsilon}_\kappa^i, \tilde{\varepsilon}_\lambda^i)$, from the normal distribution with location parameters $(\varepsilon_\delta^{i-1}, \varepsilon_\kappa^{i-1}, \varepsilon_\lambda^{i-1})$ and scale parameters ($\mathrm{r}^{i-1}\sigma_\delta, \mathrm{r}^{i-1}\sigma_\kappa, \mathrm{r}^{i-1}\sigma_\lambda$) where r^{i-1} is a constant. To initialize the process, set each element of $(\varepsilon_\delta^0, \varepsilon_\kappa^0, \varepsilon_\lambda^0)$ equal to zero and r^0 equal to 0.1.
2) Construct the following statistic:
$$\chi^i = \frac{N(\tilde{\varepsilon}_\delta^i, \tilde{\varepsilon}_\kappa^i, \tilde{\varepsilon}_\lambda^i \mid \Sigma) l(\boldsymbol{x}^* \mid \tilde{\varepsilon}_\delta^i, \tilde{\varepsilon}_\kappa^i, \tilde{\varepsilon}_\lambda^i)}{N(\varepsilon_\delta^{i-1}, \tilde{\varepsilon}_\kappa^{i-1}, \tilde{\varepsilon}_\lambda^{i-1} \mid \Sigma) l(\boldsymbol{x}^* \mid \varepsilon_\delta^{i-1}, \tilde{\varepsilon}_\kappa^{i-1}, \tilde{\varepsilon}_\lambda^{i-1})}$$
where $N(\cdot)$ is the multivariate probability density function for the normal distribution and $l(\cdot)$ is defined in equation (6). If $\chi^i \geq U$ where *U* is a uniform random draw, accept the candidate random parameters, i.e., $(\varepsilon_\delta^i, \varepsilon_\kappa^i, \varepsilon_\lambda^i) = (\tilde{\varepsilon}_\delta^i, \tilde{\varepsilon}_\kappa^i, \tilde{\varepsilon}_\lambda^i)$. Otherwise, set $(\varepsilon_\delta^i, \varepsilon_\kappa^i, \varepsilon_\lambda^i) = (\varepsilon_\delta^{i-1}, \varepsilon_\kappa^{i-1}, \varepsilon_\lambda^{i-1})$.
3) Gelman et al. (1995) argue that the Metropolis-Hastings algorithm for the normal distribution is most efficient if the acceptance rate of candidate parameters is between 0.23 and 0.44. Accordingly, the following updating rule for r^i is employed. If the proportion of accepted candidate parameters is less than 0.3, set $r^i = (1.1)r^{i-1}$. Otherwise, set $r^i = (0.9)r^{i-1}$.
4) Iterate.

After a burn-in period, this Monte Carlo, Markov Chain simulator generates draws from $f_1(\varepsilon_\delta, \varepsilon_\kappa, \varepsilon_\lambda \mid \boldsymbol{x}^*)$ that can be used to construct $E(CS^H)$.

Table 1
Variable Definitions & Sample Means

Variable	***Definition***	***Sample Mean***
Total Trips	Recreation trips to lakes, rivers, and streams within 100 miles of residence.	13.879 (19.427)
Total Sites Visited	Number of sites visited by each respondent.	2.325 (1.374)
Income	Household income in 1994 dollars.	$41,886 (16,668)
Travel Cost	Round trip travel cost (out-of-pocket expenses plus travel time valued at one-third the wage rate (Cesario[1976])) for each site entering each individual's choice set.	$56.06 (23.78)
WaterRec	= 1 if the individual participated in any boating, fishing, or swimming outdoor recreation during the past year, 0 otherwise.	0.879 (0.327)
Female	= 1 if the individual is female, 0 otherwise.	0.481 (0.499)
Susquehanna	= 1 if recreation site is located along the Susquehanna River.	0.136 (0.343)
Park	Percentage of visited recreation water bodies located within a federal, state, or county park.	0.250 (0.374)
Lowdo	Percentage of visited water bodies in the watershed/river reach with dissolved oxygen levels below the US EPA's threshold of impairment of 5.5 and 6.5 mg/l for warm and cold water bodies, respectively.	0.074 (0.222)
TSI	Average of Carlson's [1977] Trophic State Index levels for visited water resources in the watershed/river reach. These indexes were constructed from phosphorus and secchi disk water quality chemistry data.	22.49 (24.20)

Table 2
Parameter Estimates for Traditional Kuhn-Tucker Models[a,b]

	Fixed Parameters	*Uncorrelated Random Parameters*		*Correlated Random Parameters*	
Ln-Likelihood	-1,993.85	-1,982.68		-1,976.25	
Ψ_i *Parameters*		*Mean*	*Std. Er.*	*Mean*	*Std. Er.*
$\delta_{Constant}$	2.1292	2.3222	-	2.3067	-
	(8.168)	(8.500)		(7.212)	
$\delta_{WaterRec}$	0.5265	0.4680	0.3542	0.5103	0.4911
	(2.354)	(2.096)	(5.808)	(1.985)	(7.110)
δ_{Female}	-0.2766	-0.3307	0.0009	-0.2575	0.3815
	(-2.942)	(-3.215)	(0.160)	(-2.162)	(3.161)
$\zeta_{Susquehanna}$	0.7685	0.7092	0.0033	0.7423	0.4036
	(10.137)	(9.388)	(0.483)	(8.784)	(3.058)
ζ_{Park}	0.5848	0.5820	0.2229	0.5434	0.1344
	(5.582)	(5.161)	(1.477)	(4.556)	(1.321)
Quality Index Parameters					
γ_{Lowdo}	-0.2733	-0.3092		-0.3228	
	(-1.966)	(-2.255)		(-2.374)	
$\gamma_{TSI}/100$	4.0116	4.1020		4.1403	
	(5.519)	(5.762)		(5.960)	
$\gamma_{TSI^2}/10{,}000$	-6.0496	-6.2919		-6.4217	
	(-4.356)	(-4.653)		(-4.844)	
TSI Turning Point[c]	33.156	32.597		32.237	
(Standard Error)	(2.776)	(2.404)		(2.238)	
Rho Parameter					
ρ_z	1.0000	1.0000		1.0000	
	$(\cdot)$	$(\cdot)$		$(\cdot)$	
Translating Parameter					
$\ln\theta$	1.7834	1.8340		1.8447	
	(18.893)	(18.594)		(19.362)	
Scale Parameter					
μ	0.5856	0.5471		0.5338	
	(32.549)	(21.950)		(20.726)	

[a] Random parameter models estimated with 500 Halton draws.
[b] t-statistics based on robust standard errors in parentheses unless otherwise noted.
[c] The TSI turning points are thresholds at which additional increments to the TSI index negatively impact utility.

Table 3
Parameter Estimates for Kuhn-Tucker Models with Latent Consideration Sets[a,b]

	Fixed Parameters	*Uncorrelated Random Parameters*		*Correlated Random Parameters*	
Ln-Likelihood	-1,946.49	-1,934.01		-1,908.43	
Ψ_i *Parameters*		Mean	Std. Er.	Mean	Std. Er.
$\delta_{Constant}$	1.4719	1.6228	-	1.5643	-
	(4.206)	(4.616)		(4.265)	
$\delta_{WaterRec}$	0.7100	0.6196	0.4034	0.6976	0.6745
	(2.321)	(2.096)	(3.817)	(2.220)	(3.785)
δ_{Female}	-0.4008	-0.4461	0.0067	-0.4276	0.3201
	(-2.958)	(-3.158)	(0.512)	(-2.758)	(1.391)
$\zeta_{Susquehanna}$	1.0967	1.0316	0.0262	1.1955	0.6141
	(9.818)	(8.090)	(1.343)	(7.097)	(2.962)
ζ_{Park}	0.6544	0.7127	0.3436	0.9991	0.4170
	(4.477)	(5.040)	(1.507)	(4.621)	(1.870)
Quality Index Parameters					
γ_{Lowdo}	-0.3069	-0.2986		-0.2863	
	(-2.730)	(-2.619)		(-2.281)	
$\gamma_{TSI}/100$	3.7160	3.8011		3.6841	
	(7.049)	(6.924)		(6.190)	
$\gamma_{TSI^2}/10,000$	-6.3290	-6.4264		-6.1165	
	(-6.070)	(-5.914)		(-5.300)	
TSI Turning Point[c]	29.357	29.574		30.116	
(Standard Error)	(1.261)	(1.284)		(1.455)	
Rho Parameter					
ρ_z	1.0000	1.0000		1.0000	
	$(\cdot)$	$(\cdot)$		$(\cdot)$	
Translating Parameter					
$\ln\theta$	1.2081	1.2814		1.2629	
	(12.868)	(12.600)		(12.516)	
Scale Parameter					
μ	0.8277	0.7676		0.7342	
	(22.807)	(17.603)		(16.899)	
Consider. Set Parameters					
Φ	7.7018	10.4056	-	9.6250	-
	(8.210)	(3.818)		(3.132)	
κ	-2.7625	-3.7100	0.4780	-3.5979	0.6889
	(10.761)	(4.384)	(2.368)	(3.522)	(2.782)
$\lambda/10{,}000$	-0.2281	-0.3372	0.0824	-0.4236	0.1727
	(2.554)	(1.973)	(0.323)	(1.681)	(0.891)

[a] Random parameter models estimated with 500 Halton draws.
[b] t-statistics based on robust standard errors in parentheses unless otherwise noted.
[c] The TSI turning points are thresholds at which additional increments to the TSI index negatively impact utility.

Table 4
Statistical Comparisons of Alternative Models

	Traditional Model - Fixed	***Traditional Model - Uncorrelated***	***Traditional Model - Correlated***	***Latent Consid. Sets Model - Fixed***	***Latent Consid. Sets Model – Uncorrelated***	***Latent Consid. Sets Model - Correlated***
Traditional Model - Fixed	LL(-1993.85) CAIC(4048.27)					
Traditional Model – Uncorrelated	LR(←,0.0002)	LL(-1982.68) CAIC(4050.14)				
Traditional Model – Correlated	LR(←,0.0001)	LR(←,0.0456)	LL(-1976.25) CAIC(4073.63)			
Latent Consid. Sets Model – Fixed	V1(D,0.0000) V2(←,0.0000)	V1(D,0.0000) V2(←,0.0009)	V1(D,0.0000) V2(←,0.0119)	LL(-1946.49) CAIC(3971.70)		
Latent Consid. Sets Model – Uncorrelated	V1(D,0.0000) V2(←,0.0000)	V1(D,0.0000) V2(←,0.0000)	V1(D,0.0000) V2(←,0.0001)	LR(←,0.0003)	LL(-1934.01) CAIC(3983.08)	
Latent Consid. Sets Model – Correlated	V1(D,0.0001) V2(←,0.0000)	V1(D,0.0003) V2(←,0.0000)	V1(D,0.0001) V2(←,0.0000)	LR(←,0.0000)	LR(←,0.0000)	LL(-1908.43) CAIC(4022.77)

Key

LL(·) & CAIC(·)= Ln-Likelihood and Consistent Akaike Information Criteria, respectively.

V1(·,·) = Not statistically distinguishable (ND) or statistically distinguishable (D) in 1st stage of Vuong non-nested hypothesis test ($\alpha = .1$). P-value also reported.

V2(·,·) = If distinguishable in 1st stage, 2nd stage Vuong test results reported with arrow pointing to statistically prefered model ($\alpha = .1$). P-value also reported.

LR(·,·) = Likelihood ratio test with arrow pointing to restricted model if it could not be rejected, unrestricted model otherwise ($\alpha = .1$). P-value also reported.

All likelihood ratio tests employed the standard critical values from the chi-squared distribution with the appropriate degrees of freedom. Chen and Coslett (1998) have shown that these critical values are too large and thus lead on average to infrequent reject of the null hypothesis. Although the null hypotheses are consistently and strongly rejected in the above table, the p-values are likely overstated.

Table 5
Welfare Estimates

	Loss of 40 mile reach of lower Susquehanna River				*Cleanup of Eutrophic Sites*			
	Hicksian Consumer Surplus	*Change in Total Trips*	*Baseline Consideration Set Size*	*Change in Consideration Size*	*Hicksian Consumer Surplus*	*Change in Total Trips*	*Baseline Consideration Set Size*	*Change in Consideration Size*
Traditional Models[a]								
Fixed Parameters	-$18.89	-1.833	68.960	-2.543	$7.96	+0.540	68.960	0.000
	(-21.03,-16.80)[c]	(-1.83, -1.83)	(·,·)	(·,·)	(3.33,13.92)	(+0.18,+1.03)	(·,·)	(·,·)
Uncorrelated Random Parameters	-$18.29	-1.833	68.960	-2.543	$8.93	+0.648	68.960	0.000
	(-20.61,-16.11)	(-1.83, -1.83)	(·,·)	(·,·)	(4.30,15.26)	(+0.28,+1.17)	(·,·)	(·,·)
Correlated Random Parameters	-$17.66	-1.833	68.960	-2.543	$9.85	+0.685	68.960	0.000
	(-20.52,-16.19)	(-1.83,-1.83)	(·,·)	(·,·)	(4.41,20.28)	(+0.27,+1.26)	(·,·)	(·,·)
Latent Consideration Set Models[b]								
Fixed Parameters	-$26.20	-1.833	14.835	-0.698	$38.49	+1.252	14.835	+1.229
	(-28.88,-23.63)	(-1.83, -1.83)	(11.78,18.67)	(-0.84,-0.58)	(15.71,62.35)	(+0.58,+2.67)	(11.78,18.67)	(+0.74,+1.69)
Uncorrelated Random Parameters	-$25.18	-1.833	14.116	-0.670	$33.11	+1.075	14.116	+1.343
	(-28.01,-22.68)	(-1.83, -1.83)	(10.32,18.76)	(-0.86,-0.51)	(12.81,55.53)	(+0.57,+2.19)	(10.32,18.76)	(+0.74,+1.91)
Correlated Random Parameters	-$25.44	-1.833	20.428	-0.852	$27.25	+1.034	20.428	+1.080
	(-28.31,-22.87)	(-1.83,-1.83)	(15.49,27.36)	(-1.09,-0.66)	(10.33,65.26)	(+0.37,+4.00)	(15.49,27.36)	(+0.46,+1.49)

[a] 25 simulations were used to construct the point estimates for the fixed parameter traditional models. For the random parameter traditional models, a total of 2500 simulations were used. The first 500 were discarded as burn-in, and every 10th simulation thereafter was used to construct the point estimates. The sampling weights implied by the NSRE's county-stratified sampling design are used with all estimates.
[b] 1000 simulations were used to construct the point estimates for the fixed parameter latent consideration set models. For the random parameter latent consideration set models, a total of 10500 simulations were used. The first 500 were discarded as burn-in and every 10th simulation thereafter was used to construct the point estimates.
[c] 95 percent Krinsky-Robb (1986) confidence intervals generated with 1000 simulations reported in parentheses.

Figure 1
Welfare Measurement