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A Comparison of Welfare Estimates from Four Models for Linking Seasonal Recreational Trips to Multinomial Logit Models of Site Choice*

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We compare four methods of linking a site choice Random Utility Model to a seasonal trip model. The four approaches are those proposed by Morey et al. (1993, *Am J. Agric. Econom.* **75**, 578–592), Hausman et al. (1995, *J. Public Econom.* **56**, 1–30), Parsons and Kealy (1995, *J. Environ. Econom. Management* **29**, 357–367), and Feather et al. (1995, *J. Environ. Econom. Management* **29**, 214–227). We estimate the alternative models using a common data set and calculate a change in welfare for two policy scenarios across the models. We find that there is little practical difference between the approaches of Morey et al. and Hausman et al. They are nearly the same mathematically, and the welfare estimates in our empirical example are quite close. The approaches of Parsons and Kealy and Feather et al. generated welfare estimates that were substantially different from the previous two approaches as well as from each other. They also generated results that reveal the inconsistencies between their site choice and season trip models.

1. INTRODUCTION

The recent travel cost literature has focused considerable attention on using the multinomial logit model to study choice among recreation sites. However, the site choice model alone does not allow for prediction of the total number of trips taken over a recreation season. Several methods have been proposed for linking a site choice model and a seasonal participation model so that analysts can determine how a policy change will affect the total number of trips. Seasonal welfare change measures can then be calculated that include both site substitution effects (via the site choice model) and alterations in the total number of trips (via the participation model).

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The current published literature provides little evidence on whether seasonal welfare estimates are sensitive to the choice of trip model. In this paper, we compare four alternative models for linking site choice and trips. The models we compare have been proposed by Morey et al. [10], Hausman et al. [4], Parsons and Kealy [11], and Feather et al. [2].[1] We estimate the alternative models by using a common data set regarding fishing at reservoirs in Tennessee and consider welfare estimates for two different policy scenarios: removal of a fish consumption advisory and elimination of a site.

The models by Morey et al. (MRW) [10] and Hausman et al. (HLM) [4] give nearly identical seasonal welfare estimates in our empirical example. Both of these use the inclusive value index from the site choice model as an explanatory variable in determining seasonal trips. While these models are ostensibly developed from different theories, we find that they are nearly the same mathematically. This is surprising, insofar as these two models are rather widely portrayed as different approaches for handling the participation decision in random utility models of recreation demand.

Parsons and Kealy (PK) [11] and Feather et al. (FHT) [2] are related to one another but are quite different from MRW and HLM. PK and FHT split the inclusive value into separate terms for expected price and expected quality. They differ from one another in how the quality term is constructed. The seasonal trip model may be interpreted as a demand equation, and measures of welfare change may be derived by integrating the equation over the range of variation in the price index. When we use this welfare measure, we find that the sizes of the seasonal welfare estimates are inconsistent with the per-trip welfare estimates and that the sizes of the welfare estimates diverge considerably from the MRW and HLM estimates.

All four of the models above ‘‘integrate’’ a demand function of some sort to arrive at welfare.[2] Bockstael et al. (BHK) [1] have a different approach to welfare analysis. They suggest using the participation equation to predict the number of trips taken in the baseline and post-policy change situations. A per-trip welfare measure from the site choice model is then multiplied by the post-change number of trips (or average of the baseline and post change) to arrive at a seasonal welfare measure. BHK used a model like HLM’s in their analysis, but any of the trip models can be used in this way. When ‘‘BHK prediction’’ is applied, we find that all four models give similar results.

We begin with a discussion of the four models and follow that with our empirical comparison using the Tennessee data.

2. FOUR TRIP MODELS

2.1. *Basic Set-up*

Suppose that one has estimated a multinomial logit (nonnested or nested) model of choice among recreation sites, taking the number of trips as given. Let I be the

[1]The approach of Hausman et al. is a formalization of an empirical model developed over 10 years earlier by Bockstael et al. [1]. Their welfare analysis and interpretation, however, are different. Since we follow Hausman et al. on these matters, we refer to it as their model. We make comparisons with the approach of Bockstael et al. to welfare analysis later in the paper.

[2]Although the welfare measure proposed by MRW does not involve integration, it can be shown that the measure is equivalent to integration (see Tomasi and Lupi [16]) and our Appendix C.

expected value of the maximum utility for the model (the inclusive value index). Let I^0 be the inclusive value in the baseline state and I^1 be the inclusive value after some policy or event to be evaluated. If the marginal utility of income is assumed to be a constant, the expected loss or gain *per trip* is

$$W = (-1/\alpha)(I^1 - I^0), \tag{1}$$

where α is the coefficient of travel cost.

In the absence of any model for predicting total trips, the best one can do is to multiply W by the number of trips taken over the season in the baseline state, T^0, to arrive at a seasonal welfare estimate. One would expect, however, that the total seasonal trips would change in response to changes in the number and/or quality of the available sites. Recognizing this, researchers have specified trip models (or participation models) linked in some fashion to the underlying random utility model (RUM) of site choice.

MRW build the participation decision directly into the RUM. Theirs is known as the repeated logit model. The season is divided into some number of choice occasions, a time period within which a person can decide whether to participate or not, and if so, at which site. The repeated logit model typically is a nested model, with a go/don't go choice at the top level and site choice at the next lower level. The nested model has an expected maximum utility of D, where D is an inclusive value index similar to I, except that it includes a no-trip alternative along with the site alternatives. A change in D divided by the marginal utility of income gives the expected loss or gain on each choice occasion. If N is the number of choice occasions in a season, the overall welfare measure for the repeated logit model is

$$J^{\mathrm{MRW}} = (-1/\alpha)(D^1 - D^0)N. \tag{2}$$

BHK proposed an alternative approach to linking site choice and participation. They suggested regressing the number of trips taken on the inclusive value index for the site choice model, and using this equation to predict changes in trips. HLM modify the basic suggestion of BHK, using instead the index $S = -(I/\alpha)$ as a regressor, which merely rescales the coefficient estimate relative to just using I, as in BHK. More importantly, HLM interpret S as a price index. They then integrate the resulting "demand curve" for trips over changes in S to generate a consumer surplus-like seasonal welfare measure.[3] Letting $T = g(S, Z)$ denote their trip equation, the welfare measure is

$$J^{\mathrm{HLM}} = \int_{S_0}^{S_1} g(S, Z)\, dS, \tag{3}$$

where Z is a vector of covariates, and 0 and 1 reference the with and without conditions. HLM use a Poisson-based count model, so the welfare measure becomes $(1/\theta)\{\mathrm{Pred}(T^1) - \mathrm{Pred}(T^0)\}$, where θ is the coefficient on the price

[3] HLM claim that their model makes a utility theoretic link between the stages. However, a recent note by Smith [15] calls this into question, arguing that the theoretical link only works in cases where rather extreme assumptions are maintained.

index S in their demand equation and Pred(T) is the predicted value of T from the trip function.[4]

PK and FHT have some attributes in common with HLM. First, they seek to estimate a demand for trips as a function of a price index derived from the site choice model, and second, the resulting demand curve is integrated over the range of change in the price index to achieve a seasonal welfare measure. However, these two models depart from HLM by using a price index $P = \sum_i \Pr(i) p_i$, where p_i is the travel cost of visiting site i and $\Pr(i)$ is the probability of visiting this site, computed from the RUM model of site choice. Also included in the demand function is a quality index for which PK and FHT use different measures.

PK use the index $Q^{\mathrm{PK}} = \sum_i \Pr(i)\gamma x_i$, where x_i is the vector of nonprice attributes of site i, and γ is the associated vector of estimated coefficients from the RUM. The dot product of γ and x_i is a scalar. Defining the PK demand equation as $T = h(P, Q^{\mathrm{PK}}, Z)$, the welfare measure is

$$J^{\mathrm{PK}} = \int_{P_0}^{P_1} h\left(P, Q^{\mathrm{PK}^1}, Z\right) dP - \int_{P_0}^{P_1} h\left(P, Q^{\mathrm{PK}^0}, Z\right) dP, \tag{4}$$

where P is the price index, Q^{PK} is the quality index, and 0 and 1 reference the with and without conditions. The first term on the right-hand side is the total surplus with the change, and the second term is total surplus without the change. In a Poisson form this gives $(1/\eta)\{\mathrm{Pred}(T^1) - \mathrm{Pred}(T^0)\}$, where η is the coefficient on the price index P in $h(.)$.[5] FHT uses the same price index as PK, but it uses a vector of quality indices $Q^{\mathrm{FHT}} = \sum_i \Pr(i) x_i$. The FHT welfare measure is

$$J^{\mathrm{FHT}} = \int_{P_0}^{P_1} h\left(P, Q^{\mathrm{FHT}^1}, Z\right) dP - \int_{P_0}^{P_1} h\left(P, Q^{\mathrm{FHT}^0}, Z\right) dP. \tag{5}$$

As noted above, BHK have a different approach for welfare analysis. They suggested using the participation function to predict changes in the number of trips taken under the proposed policy. The per trip welfare measure W from Equation (1) would then be multiplied by the post-change number of trips or an average of the baseline and post-change number of trips to arrive at a seasonal welfare measure. This approach can be applied with any of the four models. Letting $\mathrm{Pred}(T^1)$ be the predicted number of post-change trips from a participation model and $\mathrm{Pred}(T^0)$ be the baseline or prechange number of trips, the BHK seasonal welfare measures are

$$W \cdot \mathrm{Pred}(T^1) \tag{6}$$

using the post-change trips, and

$$W \cdot \left[\mathrm{Pred}(T^1) + \mathrm{Pred}(T^0)\right]/2, \tag{7}$$

using the average of the post- and pre-change trips.

[4]Be aware that HLM inadvertently used the same symbol to denote the marginal utility of income in the site choice model (see their Equation 2.1.9, p. 9) and the coefficient on the price index in the trip model (their Equation 2.2.5, p. 11).

[5]Our Equation (4) is a corrected version of Parsons and Kealy's Equation (18).

2.2. *The MRW and HLM Models*

In all four approaches, the number of trips taken is modeled as a variant of the function

$$T = f(p, x, Z), \tag{8}$$

where p is a vector of travel costs to all of the sites faced by an individual, x is the vector of nonprice site attributes at all sites, and Z is a vector of other covariates. The MRW and HLM approaches both use the following special form of Equation (8):

$$T = g(I(p, x), Z). \tag{9}$$

$I(p, x)$ is the inclusive value index estimated in the site choice RUM. Recall that HLM use the welfare index $S = -(I/\alpha)$ as a regressor, but with a constant marginal utility of income α, this amounts to a simple rescaling of I and so is equivalent to Equation (9). Specifically, HLM's version of Equation (9), or $g(.)$ in Equation (3), is a count model with conditional mean

$$E[T \mid S, Z] = \exp[\theta S + \phi Z], \tag{10}$$

where $S = -I/\alpha$.

MRW model the utility of not recreating (let this be V_0) and use it to derive the participation probability per choice occasion (let this be π) in the RUM. To arrive at seasonal demand, this probability is multiplied by the number of choice occasions in the season. The participation probability is a function of V_0 and I. If we let δ be the coefficient on the inclusive value at the participation level, N be the number of choice occasions, and $V_0 = \psi Z$, the MRW logit form of Equation (9) is

$$E[T|I, Z] = N\pi = N \exp[\delta I]/(\exp[\delta I] + \exp[\psi Z]). \tag{11}$$

The nesting structure and implicit scaling of parameters in the MRW model are discussed in Appendix A.

As shown in Equations (11) and (10) then, HLM and MRW are both studying a scatter of data points relating the number of trips during the season to the inclusive value index. Econometrically, they differ only in their treatment of the data-generating process (functional form and error distribution) selected for the estimation of Equation (9).

Suppose that we accept HLM theory, but choose to specify our demand function $g(.)$ in Equation (3) as something other than the count model shown in Equation (10). Specifically, suppose we use the MRW form shown in Equation (11). This in no way departs from HLM theory. We merely use a functional form different from that chosen by HLM in their application. The form here is also discrete and quite plausible in the HLM context. In Appendix B we carry this newly specified model through the HLM welfare analysis and find that we get exactly the welfare measure proposed by MRW. That is, analyzing a MRW empirical form using HLM theory and welfare analysis gives us the same welfare measure as using MRW theory and welfare analysis. The "stories" told by the theorists to motivate their models are different, but they are equivalent mathematically when a common functional form is used.

Suppose now that we accept MRW theory but choose to approximate our demand function by using a HLM demand model. This is just the reverse of the analysis above. Again, when we carry the newly specified model through the MRW welfare analysis, we find that we get exactly the welfare measure proposed by HLM. These results are shown in Appendix C. With the exception of differences in functional form in their empirical analyses then, the MRW and HLM models are equivalent.

However, even the functional forms chosen by HLM and MRW are nearly the same, at least in a limiting sense. MRW use a binomial model, and HLM a Poisson model. Lindgren [9, pp. 168–169] has shown formally that the Poisson distribution is the limiting form of the binomial distribution as the number of choice occasions gets large. See Greene [4, pp. 72–73] and Hellerstein and Mendelsohn [6, pp. 607, 610–611] for similar statements. Lindgren shows (for large N) that

$$\exp(-\lambda)\lambda^T/T! \cong (N!/T!R!)(\lambda/N)^T(1-\lambda/N)^R, \tag{12}$$

where λ is the mean number of trips taken during the season and $R = N - T$. The left-hand side is the Poisson probability for observing T trips during the season and is the form used by HLM, where $\lambda = \exp[\theta S + \varphi Z]$, and again, $S = -I/\alpha$. The right-hand side is the binomial distribution and is in the form used by MRW, where $\lambda/N = \exp[\delta I]/\{\exp[\delta I] + \exp[\psi Z]\}$.

Lindgren argues that the Poisson distribution is a useful approximation for the binomial distribution when N is large and the probability of success (taking a trip on a given choice occasion) is small. He presents some numerical examples comparing the two distributions for cases ($\lambda = 1$, $N = 20$) and ($\lambda = 1$, $N = 10$). The distributions in these cases are nearly identical. In cases with large N and small trip-taking probability then, we would expect the HLM and MRW models to be nearly the same.

2.3. *The PK and FHT Models*

PK and FHT estimate different versions of Equation (8). As discussed above, the indices they use separate price and quality effects. They are not necessarily more general than the inclusive value approaches, however, since neither I nor $-I/\alpha$ can be decomposed into expected prices and expected quality indices. PK and FHT use the form of Equation (8),

$$T = h(P(p,x), Q(p,x), Z), \tag{13}$$

where $P(p,x)$ is the price index and $Q(p,x)$ is a quality index. $P(p,x) = \sum_i \Pr(i)p_i$ in both models. In PK, $Q(p,x) = \sum_i \Pr(i)\gamma x_i$, where x_i is the vector of nonprice attributes of site i, and γ is the associated vector of estimated coefficients from the RUM. The dot product of γ and x_i is a scalar. In FHT, Q is a vector of quality indices with elements $\sum_i \Pr(i)x_i$.

These models attempt to estimate the "demand curve" in Equation (13). Note that both the quality index and the price index include site attributes. Hence, changing site quality shifts demand via the quality index and changes price. The welfare measure for a change in quality at one or more sites is given in Equation

(4) for PK and in Equation (5) for FHT. In Poisson form PK and FHT give

$$E[T \mid I, Z] = \exp[\eta P + \tau Q^{\mathrm{PK}} + \omega Z], \tag{14}$$

and

$$E[T \mid I, Z] = \exp[\mu P + \rho Q^{\mathrm{FHT}} + \upsilon Z], \tag{15}$$

where $Q^{\mathrm{PK}} = \sum_i \Pr(i)\gamma x_i$ (scalar) and $Q^{\mathrm{FHT}} = \sum_i \Pr(i) x_i$ (vector).

All four models are presented in Table I in summary form for quick reference.

3. METHODS AND FINDINGS

3.1. *Model Specifications and Data*

We estimate all four models, using a common data set and a common specification for the site model. All models are estimated by full information maximum

TABLE I
Model Summaries

Model	Trip demand function	Seasonal welfare measure
MRW		
General	$T = \pi \cdot N$	$\int_{I^0}^{I^1} \pi N \, dI$
Logit form	$T = \dfrac{\exp \delta I}{\exp \delta I + \exp \Psi Z} \cdot N$	$-\dfrac{1}{\alpha}(D^1 - D^0)N$
HLM		
General	$T = g(S, Z)$	$\int_{s_0}^{s_1} g(S, Z) \, ds$
Poisson form	$T = \exp(\theta S + \phi Z)$	$\dfrac{1}{\theta}\{\mathrm{Pred}(T^1) - \mathrm{Pred}(T^0)\}$
PK		
General	$T = h(P, Q^{\mathrm{PK}}, Z)$	$\int_{p^0}^{p^1} h(P, Q^{\mathrm{PK}^1}, Z) \, dP - \int_{p^0}^{p^1} h(P, Q^{\mathrm{PK}^0}, Z) \, dP$
Poisson form	$T = \exp(\eta P + \tau Q^{\mathrm{PK}} + \omega Z)$	$\dfrac{1}{\eta}\{\mathrm{Pred}(T^1) - \mathrm{Pred}(T^0)\}$
FHT		
General	$T = h(P, Q^{\mathrm{FHT}}, Z)$	$\int_{p^0}^{p^1} h(P, Q^{\mathrm{FHT}^1} Z) \, dP - \int_{p^0}^{p^1} h(P, Q^{\mathrm{FHT}^0}, Z) \, dP$
Poisson form	$T = \exp(\mu P + \rho Q^{\mathrm{FHT}} + \nu Z)$	$\dfrac{1}{\mu}\{\mathrm{Pred}(T^1) - \mathrm{Pred}(T^0)\}$

Note. T, Number of trips in a season; π, probability of visiting a site on a given choice occasion; N, number of choice occasions in a season; I, site choice inclusive value; Z, individual characteristics; α, coefficient on travel plus time cost in the site choice model; D, ln{exp δI + exp $\psi\}/\delta$ (per-choice occasion utility); $S = -I/\alpha$ (site choice consumer surplus); $P = \sum_i \Pr(i) p_i$; $Q^{\mathrm{PK}} = \sum_i \Pr(i)\gamma x_i$ (scalar); $Q^{\mathrm{FHT}} = \sum_i \Pr(i) x_i$ (vector); $\Pr(i)$, probability of visiting site i; p_i, travel plus time cost of visiting site i; x_i, vector of site characteristics at site i; γ, non-price parameter estimates from site choice model; δ, ψ, θ, ϕ, η, τ, ω, μ, ρ, ν, parameters estimated in the trip demand function. 0 denotes without policy change; 1 denotes with policy change likelihood (FIML), with the site and trip models estimated simultaneously. This avoids the well-known problem of using generated regressors in two-staged approaches (Terza and Wilson [17]).

The data concern fishing in middle Tennessee (see Jakus et al. [7] for more details). The data were collected via a random-digit dial telephone survey in fall 1994. After deleting ineligible numbers, the response rate to the survey was 37%. Considering only reservoir anglers in middle Tennessee taking single-purpose trips, and after deletion for item nonresponse or otherwise unusable responses, we have a sample of 143 anglers.

The choice set for each angler consists of 14 reservoirs. The reservoirs are fairly homogeneous in offering a typical mix of warm-water lake species. However, two of the reservoirs had fish consumption advisories; at one reservoir the advisory warned anglers to eat no catfish, and at the other the advisory recommended limiting consumption of catfish to no more than 1.2 pounds per month. Advisories are included in the model as a dummy variable, taking a value of 1 if the site had an advisory. No effort to distinguish by type of advisory was made. Other site attributes included in the site choice model are the catch rate for all species of fish, expressed in number caught per angler per day, obtained by an average of self-reported catch and hours fished, and the number of boat ramps as a measure of access and a proxy for size. Finally, a site-specific dummy variable was included for Percy Priest. This site is much more developed than, and we felt it was different in character from the other sites in the choice set. The dummy variable is intended to capture this distinction.

The travel cost variable has an out-of-pocket component and an opportunity cost of time component. The first was constructed using a per-mile estimate of $0.30; the cost of time was set equal to the wage rate, calculated by taking annual household income divided by 2000 hours of work, and assuming an average driving speed of 50 m.p.h.

The site choice models will assume that the conditional indirect utility functions are linear, thereby imposing a constant marginal utility of income. Unobserved attributes of sites (the error terms) were assumed to be independently distributed. All of the trip models except MRW are estimated using a Poisson count model specification, including an overdispersion parameter (alpha). The MRW model was estimated as a two-level nested multinomial logit with go/don't go at the top level and site choice at the bottom.

3.2. *Estimation Results*

The estimation results are shown in Table II. The last column shows the parameter estimates from estimating the site choice model alone. In a sequential estimation all four models would have these parameters at the lower level. The difference between the FIML estimates of site choice for the various combined models that we report and the final column arises from the FIML procedure adjusting site choice parameters to assist in the fitting of the trips portion of the model.

All of the coefficient estimates on the site choice models have expected signs with statistical significance. The estimates are also quite similar across the four

TABLE II

Estimation Results for HLM, MRW, PK, and FHT

	HLM	MRW[a]	PK	FHT	Site choice only
Site choice					
Travel cost	−0.037	−0.035	−0.036	−0.036	−0.036
	(−42.12)	(−7.80)	(−42.09)	(−42.00)	(−42.02)
Catch rate	0.022	0.017	0.020	0.013	0.019
	(3.23)	(2.33)	(3.11)	(1.89)	(2.74)
Ramps	0.020	0.021	0.020	0.021	0.020
	(18.41)	(7.75)	(18.73)	(18.94)	(18.51)
Consumption advisory	−0.809	−0.804	−0.810	−0.850	−0.863
	(−6.88)	(−5.60)	(−7.02)	(−7.31)	(−7.33)
Percy Priest Int.	0.150	0.235	0.157	0.175	0.144
	(2.66)	(3.59)	(2.75)	(3.08)	(2.53)
Participation					
Intercept	1.738	2.135	3.296	3.059	
	(8.67)	(45.43)	(24.30)	(19.92)	
Inclusive value[b]	0.015	0.263			
	(5.44)	(7.84)			
Price index			−0.021	−0.024	
			(−6.62)	(−7.39)	
Attribute index			0.018		
			(0.59)		
Catch index				0.041	
				(2.96)	
Ramp index				0.003	
				(0.83)	
Advisory index				0.830	
				(2.07)	
Income ($1000)	0.008		0.005	0.004	
	(3.38)		(2.23)	(2.04)	
Alpha	0.178		0.171	0.164	
	(11.90)		(11.69)	(11.38)	

Note. The number in parentheses is the ratio of the coefficient to its asymptotic standard error.

[a] We estimated the MRW model under two different assumptions on season length: 184 days and 110 days. The latter is the maximum number of trips taken by a person in our sample. The results are nearly the same. We report the model using 184 days.

[b] Our MRW model uses I; our HLM model uses I/α.

models.[6] The trip demand models have expected signs with significant coefficients on many variables, but there are exceptions. The most notable is the coefficient of the advisory index in the FHT model, which has the wrong sign and is significant. Because the advisory index is just the sum of the probabilities of visiting the two sites with advisories and those two sites are close to population centers, it appears as though the index is serving at least in part as a proximity variable in the model. Also notable is the lack of significance on the quality index in the PK model.

[6] The MRW coefficient estimates are for β, not β^*. Recall that $\beta = \beta^*/\delta$, where δ is the scale parameter for the participation nest of the MRW model (see Appendix A).

TABLE III

Mean Per-Trip Welfare Estimates

	HLM	MRW	PK	FHT	Site choice only
Advisory removal scenario					
Mean (95% CI)	$1.77	$1.84	$1.77	$1.83	$1.86
	($1.37−$2.14)	($1.40−$2.22)	($1.36−$2.13)	($1.44−$2.18)	($1.45−$2.22)
Site loss scenario					
Mean (95% CI)	$6.63	$7.10	$6.68	$6.82	$6.63
	($5.97−$7.34)	($6.45−$7.78)	($6.04−$7.37)	($6.17−$7.58)	($5.99−$7.33)

Note. 95% confidence intervals were calculated using the Krinsky−Robb technique.

3.3. *Welfare Measures*

In Table III we show the welfare measures per trip for two policy scenarios: (1) removal of the two consumption advisories, and (2) elimination of the Percy Priest reservoir. The per-trip values are calculated using the site choice portion of each model. The estimates are sample means. The models give nearly identical results, reflecting the similarity of the basic site choice models noted above. We also report 95% confidence intervals for the estimates. These were computed using the simulation technique of Krinsky and Robb [8], with 5000 independent draws from our estimated variance-covariance matrix.

In Table IV we present seasonal surplus measures and estimated trip adjustments for the two scenarios. The estimates are sample means. WTP reports the welfare estimates for each of the four models, using Equations 2−5. BHK prediction uses the method suggested by BHK shown in Equation 7. Once again, we include confidence intervals, using Krinsky and Robb's technique with 5000 draws.

Notice the small adjustment in number of trips taken across all models in both scenarios. The estimated increase in number of trips due to elimination of the

TABLE IV

Mean Seasonal Welfare Estimates and Change in Trips

	HLM	MRW	PK	FHT
Advisory removal scenario				
Δ mean trips	0.32	0.19	0.07	(0.59)
Mean WTP	$21.55	$23.62	$3.41	($25.29)
(95% CI)	[$16.25−$26.73]	[$16.22− 30.25]	[$2.19−$5.01]	[($51.90)−$2.31]
BHK prediction	$21.58	$23.63	$24.09	$25.14
(95% CI)	[$16.28−$26.80]	[$16.76−$26.32]	[$18.40−$29.84]	[$19.12−$31.25]
Site loss scenario				
Δ mean trips	1.46	0.83	0.84	0.78
Mean WTP	$98.73	$103.95	$41.09	$33.27
(95% CI)	[$86.99−$112.80]	[$76.22−$132.83]	[$35.41−$47.81]	[$27.05−$39.67]
BHK prediction	$99.02	$104.03	$100.23	$100.21
(95% CI)	[$87.20−$113.25]	[$94.13−$114.97]	[$87.56−$113.91]	[$87.99−$114.64]

Note. 95% confidence intervals were calculated using the Krinsky−Robb technique.

consumption advisories is largest in the HLM model at 0.32 trips, a 2% mean rise. The site loss scenario gives somewhat larger adjustments, but given the significance of this site, even these seem small. Again, HLM gives the largest adjustment of 1.46 fewer trips, a 10% mean decline.

The HLM and MRW models give welfare measures that are quite close in both scenarios. Assuming the two welfare measures are independent and normally distributed, we find no statistical difference (95% level *t*-test) in these means.[7] In the advisory scenario, HLM gives $21.55 and MRW $23.62. In the site loss scenario, we have HLM at $98.73 and MRW at $103.95.

These results appear to confirm our argument in the previous section that these two models are practically the same. The differences in functional form here are apparently insufficient to generate much difference in welfare measures. Furthermore, however, given the small adjustment in the number of trips taken due to the changes in our scenarios, the amount of welfare being captured in the trip demand models may be a small fraction of the total and hence is hardly discernible in the welfare difference between the models.

The PK and FHT models, on the other hand, give statistically different results from MRW and HLM (95% level *t*-test). Recall that these models are unlike the inclusive value models of HLM and MRW in that they split the inclusive value into separate price and quality terms in the trip portion of the model. In our application, this structural difference generates substantial differences in welfare measurement, even for the presence of such small adjustments in trips.

In the advisory scenario, FHT actually give a negative change in welfare, −$25.29. This is due to the coefficient estimate on the advisory variable having a positive sign in the trip portion of the model. PK gives a seasonal welfare measure of $3.41, which has the expected sign but is substantially smaller than that found in the inclusive value models. In the site loss scenario for FHT and PK, we have losses of $41.09 and $33.27, less than half of what we found in HLM and MRW.

Notice that PK's seasonal value of $3.41 for the advisory scenario is about twice the per-choice occasion value at $1.77. This is surprising insofar as the average person in our sample takes over 12 trips. If the site and trip models were consistent, one would expect seasonal values at least as large as 12*$1.77. But, as PK point out in their original article, these models are not derived from a single utility theoretic structure. Hence these inconsistencies are possible. The FHT results show the same.

BHK prediction applied to all four models gives very similar results, and these are quite close to the standard HLM and MRW measures. This is not surprising, given the small adjustment in the number of trips reported by all models.

4. CONCLUSIONS

The HLM and MRW models are ostensibly derived from different theories. From a practical standpoint, however, we find that they are nearly equivalent. We show this mathematically and support the finding with empirical evidence, showing that the models give nearly identical welfare estimates for the same scenario in a

[7]See Poe et al. [12] for a discussion of alternative approaches to comparing the differences in means in formal statistical tests.

given data set. Given the mathematical similarity of HLM and MRW, we expect welfare estimates from these models to be close with most data sets. Differences are likely to emerge as the number of choice occasions becomes smaller and the probability of taking a trip on any given choice occasion becomes larger in the MRW model.

We also found that PK and FHT can give welfare estimates at the seasonal level that are inconsistent with the per-trip estimates. In our empirical application the seasonal estimates appeared to be too low when compared to the per-trip values. There is no reason to believe that this specific finding will hold up with other data sets. However, because these models do not constrain the two levels to be consistent, results that diverge are possible. This suggests caution when using these models. At the very least one should report seasonal welfare measures without trip adjustments $(T^0 * W)$ alongside the PK and FHT results as a validity check.

In closing, we call attention to two alternative modeling strategies for linking site choice and participation. The first is the Kuhn−Tucker model by Herriges et al. [6]. This is a more traditional demand system approach using modern econometric techniques to handle corner solutions. The model is utility theoretic, so consistency between stages is no issue. Indeed, there are no explicit ‘‘stages’’ in the model. The difficulty here is that the number of sites that can feasibly be estimated in this model is still quite limited. In time this may change. The second strategy is the two-stage budgeting model of Shonkwiler and Shaw [13]. This model looks similar to the conditional logit models discussed above. However, the aggregate demand function uses ‘‘total recreational travel, rather than total recreational visits’’ as the dependent variable in the participation stage (what they call the macro stage) of the model. This renders a model with a consistent aggregate price index and hence a utlitity theoretic link with site choice. It is worthwhile to follow the future development of both of these approaches.

APPENDIX A

The model underlying Equation (11) is the standard nested logit model of MRW. The model is nested at the participation level, with no-trip utility forming one nest (as a single alternative) and the site utilities (many alternatives) forming another. Following the notation in Equation (11), δ is the scale parameter in the participation model for the site nest. It follows from scaling in a RUM that the utility for any given site i has the form $V_i = \beta^* x_i/\delta$ and that $I = \ln \sum \beta^* x_i/\delta$. We let $\beta = \beta^*/\delta$. Using conventional MRW theory, the seasonal welfare measure for a policy change is

$$J^{\mathrm{MRW}} = N\big[\ln\big(\exp[\delta I^1] + \exp[\psi Z]\big) - \ln\big(\exp[\delta I^0] + \exp[\psi Z]\big)\big]/-\alpha^*, \quad (16)$$

where I^1 is the post-change and I^0 is the pre-change inclusive value. The element α^* is the travel cost coefficient in the vector β^*. It follows that $\alpha = \alpha^*/\delta$. Substituting $\alpha\delta$ for α^* we can write equation (16) as

$$J^{\mathrm{MRW}} = N\big[\ln\big(\exp[\delta I^1] + \exp[\psi Z]\big) - \ln\big(\exp[\delta I^0] + \exp[\psi Z]\big)\big]/-\alpha\delta. \quad (17)$$

Notice in Equation (2) that $D = \{\ln(\exp[\delta I] + \exp[\psi Z]\}/\delta$.

APPENDIX B

Suppose that we have estimated the logit demand function in Equation (11), using a standard repeated logit model. We are interested in the difference in the welfare measures this empirical model will yield if we use MRW versus HLM theory. If we use conventional MRW theory, the welfare measure for a policy change is

$$J^{\mathrm{MRW}} = N\left[\ln\left(\exp[\delta I^1] + \exp[\psi Z]\right) - \ln\left(\exp[\delta I^0] + \exp[\psi Z]\right)\right] / -\alpha\delta, \quad (18)$$

where I^1 is the post-change inclusive value, I^0 is the pre-change inclusive value, and $\alpha = \alpha^*/\delta$ (see Appendix A). What if we use HLM theory? In this case, in place of a Poisson demand function for $g(.)$ in Equation (3), we will use the estimated MRW logit function shown in Equation (11).

First, to put the new model in a form called for in HLM welfare analysis, rescale the model in Equation (11), using S instead of I. Since $S = -I/\alpha$, substitute $-\alpha S$ for I in Equation (11) and then substitute that expression into Equation (3) for $g(.)$. This gives

$$J^{\mathrm{HLM}_{\mathrm{logit}}} = N\int_{S^0}^{S^1} \exp[-\alpha\delta S]/(\exp[-\alpha\delta S] + \exp[\psi Z])\, dS. \quad (19)$$

Then, evaluating this integral gives

$$J^{\mathrm{HLM}_{\mathrm{logit}}} = N\left[\ln\left(\exp[-\alpha\delta S^1] + \exp[\psi Z]\right) - \ln\left(\exp[-\alpha\delta S^0] + \exp[\psi Z]\right)\right] / -\alpha\delta. \quad (20)$$

Since $I = -\alpha S$, this is equivalent to Equation (18). Hence, MRW and HLM theories give identical welfare measures if we start with the same logit functional form for the demand equations.

APPENDIX C

Suppose that we have estimated the Poisson demand function in Equation (10). We are interested in the difference in the welfare measures this empirical model will yield if we use HLM versus MRW theory. If we use conventional HLM theory, the welfare measure for a policy change is

$$J^{\mathrm{HLM}} = \frac{1}{\theta}\left[\exp(\theta S^1 + \phi Z) - \exp(\theta S^0 + \phi Z)\right]. \quad (21)$$

Now, reversing the analysis of Appendix B, suppose that we accept MRW theory. Instead of using a logit demand function, we now use the Poisson form of HLM shown in Equation (10).

Recall that MRW derive a per-choice occasion welfare measure and then multiply that value by N, the number of occasions in the season, to arrive at a seasonal measure. So, we first rewrite the model in Equation (10) in terms of per-choice occasion probabilities by dividing $\exp[\theta S + \varphi Z]$ by N. Then, we rescale the model, substituting $-I/\alpha$ for S. This gives a per-choice occasion probability of taking a trip of $\pi = \exp[-\theta I/\alpha + \varphi Z]/N$.

The per-choice occasion value of a change in trip utility is

$$j^{\mathrm{MRW}} = -\frac{1}{\alpha}\int_{I^0}^{I^1} \pi \, dI, \tag{22}$$

where I, the inclusive value, is the expected maximum utility of taking a trip in the HLM model (see Small and Rosen [14]). Lowercase j is used to denote the per-choice occasion, instead of seasonal, value. Substituting the Poisson expression for π in Equation (22) gives the per-choice occasion welfare measure,

$$j^{\mathrm{MRW}_{\text{poisson}}} = -\frac{1}{\alpha}\int_{I^0}^{I^1} \exp[-\theta I/\alpha + \phi Z]/N \, dI. \tag{23}$$

Evaluating this integral gives

$$j^{\mathrm{MRW}_{\text{poisson}}} = \frac{1}{\alpha}\frac{\alpha}{\theta}\frac{1}{N}\left[\exp\left(-\theta I^1/\alpha + \phi Z\right) - \exp\left(-\theta I^0/\alpha + \phi Z\right)\right]. \tag{24}$$

Multiplying this expression by N to put it in terms of a seasonal value and simplifying gives

$$J^{\mathrm{MRW}_{\text{poisson}}} = -\frac{1}{\theta}\left[\exp\left(-\theta I^1/\alpha + \phi Z\right) - \exp\left(-\theta I^0/\alpha + \phi Z\right)\right]. \tag{25}$$

Since $I = -\alpha S$, this is equivalent to Equation (21). Again, MRW and HLM theories give equivalent results if we start with the same functional form for demand.

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