

# Carnarvon Gorge: a comment on the sensitivity of consumer surplus estimation

Duangkamon Chotikapanich and William E. Griffiths\*

Beal's (1995) method of estimating the value of Carnarvon Gorge for recreational use is re-examined. When an inconsistency in her estimation procedure is corrected, the estimated value of Carnarvon Gorge for camping is found to be six times higher. The sensitivity of the estimate to the choice of functional form is examined, and standard errors and interval estimates for consumer surplus are provided. Comments are made about functional form choice and prediction in log-log models.

## 1. Introduction

In a recent article in the *Review of Marketing and Agricultural Economics*, Beal (1995) assesses the value of Carnarvon Gorge National Park for recreational use by estimating the consumer surplus associated with selected demand equations. She was kind enough to provide us with her data so that we could use her model as one of our examples in a paper we are writing on using Bayesian techniques for estimating areas in economics (Griffiths and Chotikapanich 1997). When we looked more closely at her article, we uncovered some contradictory assumptions in her estimation procedure, and we were struck by how sensitive consumer surplus estimates can be to functional form specification. In addition, there were some methodological issues which we thought could benefit from further discussion. These issues are (i) provision of standard errors for consumer surplus estimates, (ii) choice of functional form, and (iii) prediction in log-log models. Some of the points that we raise are not new in the field of consumer surplus estimation. Examples of studies which examine the sensitivity of consumer surplus estimation to functional form specification, statistical assumptions, and/or estimation technique, are Ziemer, Musser and Hill (1980), Kling (1988, 1989) and Smith (1988). Creel (1997) attempts to overcome the sensitivity

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\* Duangkamon Chotikapanich is at the School of Economics and Finance, Curtin University of Technology, Perth, Australia. William E. Griffiths is Professor of Econometrics at the Department of Econometrics at the University of New England, Armidale, NSW.

problem by using a flexible function form. The question of measuring reliability of consumer surplus estimates through asymptotic standard errors or bootstrapped finite sample standard errors has been considered by Adamowicz, Fletcher and Graham-Tomasi (1989), Kling and Sexton (1990) and Creel and Loomis (1991). Smith and Kaoru (1990) present an econometric synthesis of the results from numerous recreation demand models. Our main contributions are as follows. We point out that the 2-step, 2-equation estimation strategy used by Beal is internally inconsistent (see section 2). Another estimate of the value of Carnarvon Gorge for camping, obtained using an alternative more consistent estimation strategy, is provided (see section 2.1). We also indicate how a standard error for the consumer surplus estimate can be calculated (see section 2.2). The large discrepancy between the consumer surplus estimates from the two strategies made us wonder how sensitive such estimates are to the functional form specification. If policy decisions about Carnarvon Gorge National Park are going to be based on its perceived value for recreational use, then it is important to have an appreciation of the reliability of any estimate of value. We focus on two sources of uncertainty that make a consumer surplus estimate unreliable. One is uncertainty about functional form. The other is the sampling error that occurs because the parameters of a chosen functional form are estimated using just one random data set. The effect of functional form uncertainty is considered by estimating the consumer surplus implied by each of the functional forms tested by Beal (see section 3.1). In this same section, standard errors and associated confidence intervals provide information on uncertainty from parameter sampling error for a given functional form. Our contribution is not only in the empirical results which show the importance of the two sources of uncertainty, but also in the methods which can be utilised by other researchers employing the travel cost method for the valuation of national resources. In section 3.2, we give the maximised log-likelihood values for each function. These values are a better guide to functional form selection than the  $R^2$ s used by Beal. In the final section, we comment on prediction in log-log models; our comments help explain why Beal's equation seemed to give a biased prediction of total visits for a zero price.

## **2. An alternative consumer surplus estimate: Beal's estimation technique**

Beal estimates two demand functions, a camping demand function and a demand function for day visits. We restrict our discussion to the camping demand curve. The points we make are equally valid for the demand for day visits.

The origins of potential visitors to the park are divided into twelve geographical zones. Associated with travel to the park from each zone is a travel and time cost variable ( $TC_i$ ) that takes the place of price in a conventional demand equation. A demand equation for camp use is estimated by relating the  $i$ -th zone's average annual visitation rate per thousand population ( $V_i$ ) to travel cost, say,

$$V_i = f(TC_i) \quad i = 1, 2, \dots, 12 \quad (1)$$

The relationship between aggregate demand  $Q$  and the travel costs for each zone is given by

$$Q = \sum_{i=1}^{12} pop_i V_i = \sum_{i=1}^{12} pop_i f(TC_i) \quad (2)$$

where  $pop_i$  is the population of the  $i$ -th zone. Because it represents just one point on an aggregate demand curve, equation 2 by itself cannot be used to estimate consumer surplus. It describes the existing demand that relates to the existing range of zonal travel costs. The 'travel cost method' overcomes this problem by assuming that consumers of recreation react to changes in a hypothetical entry price ( $P$ ) in the same way as they would to changes in travel costs. If such is the case, augmenting the travel cost variable with an entry price variable yields the function

$$Q = \sum_{i=1}^{12} pop_i f(TC_i + P) \quad (3)$$

which can be used to trace out a complete demand function where aggregate demand  $Q$  is related to price  $P$ . The relevant consumer surplus measure in Beal's study is the area under this aggregate demand function.

The first point we make in this article is that Beal's specification for the aggregate demand function in equation 3 is algebraically inconsistent with her choice of the functional form for  $f(TC_i)$ . In addition, specifying equation 3 in an algebraically consistent way has a considerable effect on the estimate of consumer surplus. More explicitly, after some preliminary testing, Beal chooses the log-log equation

$$\ln(\hat{V}_i) = \hat{\beta}_0 + \hat{\beta}_1 \ln(TC_i) \quad (4)$$

for the visitation rate demand curve. The estimates obtained were  $\hat{\beta}_0 = 9.8426$  and  $\hat{\beta}_1 = -1.8743$ . Equation 1 becomes, therefore,

$$\hat{V}_i = \exp\{\hat{\beta}_0 + \hat{\beta}_1 \ln(TC_i)\} = e^{\hat{\beta}_0} (TC_i)^{\hat{\beta}_1} \quad (5)$$

and the corresponding aggregate demand curve, with the entry price variable  $P$  included, becomes

$$Q = e^{\hat{\beta}_0} \sum_{i=1}^{12} pop_i (TC_i + P)^{\hat{\beta}_1} \quad (6)$$

If equation 5 is the legitimate function to use for  $V_i$ , then, presumably, the relevant consumer surplus measure is the area under the aggregate demand function in equation 6. However, this was not the function utilised by Beal. Instead, she used equation 6 to predict values for  $Q$  for seven selected values of  $P$ . An eighth value was the observed value for  $Q$  when  $P = 0$ . These values of  $Q$  and  $P$  were used to estimate a number of alternative aggregate demand functions from which the linear function

$$\hat{Q} = 15764.7 - 252.09P \quad (7)$$

was chosen. Based on this estimated demand curve, the consumer surplus, which is the total area under the curve, was estimated as 492 931.

## 2.1 An alternative consumer surplus estimate

From the above section it can be seen that Beal chose to approximate the aggregate exponential demand function (equation 6) with the linear function (equation 7) and to use the latter to calculate the consumer surplus. An alternative way which is internally more consistent is to calculate the consumer surplus directly from the total area under the exponential demand function (equation 6). Figure 1 shows the two curves drawn from equations 6 and 7. It can be seen that the linear function is only a reasonable approximation for prices up to A\$20 and that, by using the linear function to approximate the exponential one, we largely underestimate the total area under the curve.

To calculate the area under the exponential curve (equation 6) we need to be aware that this exponential curve is asymptotic to the price axis. That is, as  $P \rightarrow \infty$ ,  $Q \rightarrow 0$ . The area under the curve is given by:

$$\begin{aligned} \hat{CS} &= e^{\hat{\beta}_0} \lim_{P^* \rightarrow \infty} \int_0^{P^*} \sum_i (pop_i) (TC_i + P)^{\hat{\beta}_1} dP \\ &= \left( \frac{e^{\hat{\beta}_0}}{\hat{\beta}_1 - 1} \right) \lim_{P^* \rightarrow \infty} \left[ \sum_i (pop_i) \left\{ (TC_i + P^*)^{\hat{\beta}_1+1} - TC_i^{\hat{\beta}_1+1} \right\} \right] \end{aligned}$$

Since  $\hat{\beta}_1$  is less than  $-1$ ,  $\lim_{P^* \rightarrow \infty} (TC_i + P^*)^{\hat{\beta}_1+1}$  is zero and the  $\hat{CS}$  becomes

$$\hat{CS} = \frac{-e^{\hat{\beta}_0}}{\hat{\beta}_1 + 1} \sum_i (pop_i) (TC_i)^{\hat{\beta}_1+1} \quad (8)$$

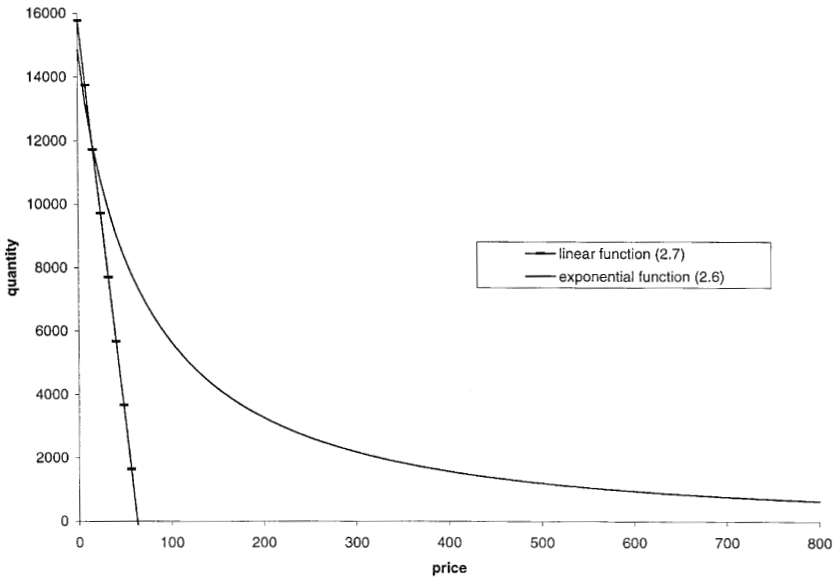


Figure 1 Demand curves

The consumer surplus calculated from this definition is 2 954 560. By using the linear function to approximate the exponential function the consumer surplus has been underestimated by as much as 6 times.

### 2.2 Standard error for the consumer surplus

When estimating any quantity it is important to have some idea of the reliability of that estimate. One indicator of reliability is provided by the standard error and a consequent interval estimate. An approximate standard error for the consumer surplus estimate can be obtained from the square root of the asymptotic variance which is given by (Judge *et al.* 1988, p. 542):

$$\text{var}(\hat{CS}) = \left(\frac{\partial(CS)}{\partial\beta_0}\right)^2 \text{var}(\hat{\beta}_0) + \left(\frac{\partial(CS)}{\partial\beta_1}\right)^2 \text{var}(\hat{\beta}_1) + 2\left(\frac{\partial(CS)}{\partial\beta_0}\right)\left(\frac{\partial(CS)}{\partial\beta_1}\right)\text{cov}(\hat{\beta}_0, \hat{\beta}_1) \tag{9}$$

For the consumer surplus defined in equation 8, the derivatives are

$$\frac{\partial(CS)}{\partial\beta_0} = \frac{-e^{\beta_0}}{\beta_1 + 1} \sum_i (pop_i)(TC_i)^{\beta_1+1}$$

$$\frac{\partial(CS)}{\partial\beta_1} = \frac{e^{\beta_0}}{(\beta_1 + 1)^2} \sum_i (pop_i)(TC_i)^{\beta_1+1} - \frac{e^{\beta_0}}{(\beta_1 + 1)} \sum_i (pop_i)(TC_i)^{\beta_1+1} \ln(TC_i)$$

Using  $\hat{v}\text{ar}(\hat{\beta}_0) = 1.1005$ ,  $\hat{v}\text{ar}(\hat{\beta}_1) = 0.0377$ ,  $\hat{c}\text{ov}(\hat{\beta}_0, \hat{\beta}_1) = -0.2016$  and evaluating the derivatives at  $\hat{\beta}_0$  and  $\hat{\beta}_1$ , the standard error calculated for the consumer surplus (equation 8) is 792 214. This value, along with the estimated consumer surplus gives a 95 per cent confidence interval as (1 189 507, 4 719 613). This very wide interval shows there is considerable uncertainty associated with our consumer surplus estimate.

### 3. Sensitivity of consumer surplus estimation

The enormous difference between the estimate of consumer surplus from Beal's linear aggregate demand function and the estimate implied by her visitation rate function raises questions about the sensitivity of consumer surplus estimation to functional form specification. In this section, we look at the consumer surplus implied by the other five functional forms of the demand function that were considered by Beal. For each of the functional forms, we provide the point estimate, the standard error and the 95 per cent interval estimate of the consumer surplus. A comparison of these results reveals the critical nature of functional form selection. Also, for a goodness-of-fit comparison, we give values of the maximised log-likelihoods under an assumption of normally distributed errors. Since the six functional forms do not have the same dependent variable, Beal's comparison using  $R^2$ 's is not valid; the maximised log-likelihood provides a better basis for comparison.

#### 3.1 Consumer surplus estimates and their standard errors

From equations 1 and 2, a general expression for consumer surplus is

$$CS = \int_0^{P^*} \sum_i (p_i o p_i) f(TC_i + P) dP \quad (10)$$

where  $P^*$  is that price for which  $Q = 0$  in equation 3. If the demand function in equation 3 is asymptotic to the price axis, then it is necessary to take the limit of equation 10 as  $P^* \rightarrow \infty$ .

Table 1 reports the point estimates, their standard errors and corresponding 95 per cent interval estimates of consumer surplus obtained from the different functional forms. These results were obtained by evaluating equations 10 and 9 for each of the functional forms. These evaluations were not trivial and involved some novel mathematical derivations. Details can be found in an earlier version of this article (Chotikapanich and Griffiths 1996). The interval estimates are derived assuming, in each case, that  $\hat{C}S$  has a limiting distribution that is normal. It should be noted that the demand curve for equation 4 in table 1 is asymptotic to the price axis, and, as price approaches infinity, the curve does not approach the axis quickly enough for the area to

**Table 1** Point and interval estimates of consumer surplus for different functional forms

Functional form	$\hat{CS}$ (se( $\hat{CS}$ ))	95% interval estimate
equation 1 $V = \beta_0 + \beta_1 TC$	4 105 566 (5 933 944)	(- 7 524 965) - (15 736 100)
equation 2 $V = \beta_0 + \beta_1 \ln TC$	1 002 818 (1 742 918)	(- 2 413 301) - (4 418 937)
equation 3 $\ln V = \beta_0 + \beta_1 TC$	2 875 357 (983 023)	(948 632) - (4 802 082)
equation 4 $1/V = \beta_0 + \beta_1 TC$	$\infty$	$\infty$
equation 5 $V = \beta_0 + \beta_1(1/TC)$	442 324 (1 442 770)	(- 2 385 506) - (3 270 153)
equation 6 $\ln V = \beta_0 + \beta_1 \ln TC$	2 954 560 (792 214)	(1 401 821) - (4 507 299)

be finite. The most striking thing about the entries in table 1 is that the estimated  $CS$ 's obtained from the different functional forms vary considerably, from 442 324 to 4 105 566. Also, from the large standard errors and the wide 95 per cent interval estimates, we see that all consumer surplus estimates are very unreliable, even if the underlying functional form is known. This is particularly the case for equations 1, 2 and 5 in table 1 where the 95 per cent interval estimates contain meaningless negative ranges. In the sampling theory approach to inference (as distinct from Bayesian inference), there does not appear to be any simple way of incorporating prior information to ensure that interval estimates include only a positive range. Also, it appears that a small degree of uncertainty or unreliability in the estimation of the parameters  $\beta_0$  and  $\beta_1$  can lead to a large degree of uncertainty in the estimation of  $CS$ . Very few of Beal's estimates for  $\beta_0$  and  $\beta_1$  are not significantly different from zero, yet three out of five of the  $CS$  estimates derived from them have standard errors that are bigger than the estimates themselves. It is clear that any valuation of the Carnarvon Gorge National Park on the basis of consumer surplus estimation is particularly tenuous.

### 3.2 Comparing functional forms

As mentioned earlier, the use of  $R^2$  as a criterion for model selection is questionable for models with different dependent variables. An alternative, which makes comparisons in terms of comparable units of measurement, is the value of the maximised log-likelihood function. We are not suggesting

that choosing the model that has the largest maximised log-likelihood is a foolproof model selection criterion. Such a procedure is subject to sampling error and does not consider whether the data ‘significantly’ favour one model over another (see, for example, Box and Cox 1964 and Fisher and McAleer 1981). However, as a descriptive goodness-of-fit measure, it is preferable to  $R^2$ . To give an expression for the maximised log-likelihood consider the equation:

$$g_1(V) = \beta_0 + \beta_1 g_2(TC) + e$$

where it is assumed that  $e$  is an independent normal random variable with mean zero and variance  $\sigma^2$ , and  $g_1(V)$  and  $g_2(TC)$  are functions of  $V$  and  $TC$ , respectively. For example, for equation 2 in table 1,  $g_1(V) = \ln V$  and  $g_2(TC) = TC$ . After substituting maximum likelihood estimators for  $\beta_0$ ,  $\beta_1$  and  $\sigma^2$  into the log-likelihood function, this function becomes

$$L = -\frac{n}{2}[\ln(2\pi) + 1 - \ln(n)] - \frac{n}{2}\ln(SSE) + \sum \ln\left(\left|\frac{\partial g_1(V)}{\partial V}\right|\right)$$

where  $n$  = total number of observations,  $SSE$  = sum of squared errors, and  $|\partial g_1(V)/\partial V|$  is the Jacobian of the transformation from  $g_1(V)$  to  $V$ . It is the presence of this last term that makes a ranking of models on the basis of  $L$  possibly different from a ranking of models on the basis of  $R^2$ .

Table 2 reports the values of the log-likelihood function, along with the  $R^2$ s from Beal’s article. Based on these values of the maximised log-likelihood functions, equation 6 in table 1 is the best equation, a choice that is consistent with that of Beal. However, the ranking of the other models has changed. Because the relative magnitudes of the log-likelihood values provide a guide to the relative relevance of each functional form, they also provide an indication of the relative importance of each of the consumer surplus estimates in table 1. However, without using the Bayesian paradigm (see, for example, Geweke 1998), it is difficult to quantify this ‘relative importance’.

**Table 2** Values of  $R^2$  and log-likelihood function

Functional form	$R^2$	$L$
eqn 1: $V = \beta_0 + \beta_1 TC$	0.23	-34.1261
eqn 2: $V = \beta_0 + \beta_1 \ln TC$	0.56	-30.7955
eqn 3: $\ln V = \beta_0 + \beta_1 TC$	0.62	-14.1678
eqn 4: $1/V = \beta_0 + \beta_1 TC$	0.86	-13.5402
eqn 5: $V = \beta_0 + \beta_1(1/TC)$	0.83	-25.0763
eqn 6: $\ln V = \beta_0 + \beta_1 \ln TC$	0.90	-5.9777



#### 4. Prediction in log-log models

One last point of interest is the characteristics of prediction in log-log models and their implications for consumer surplus estimation. As mentioned in section 2, Beal uses a 2-stage procedure where, to begin the second stage, eight values of  $P_j$  ( $j = 1, 2, \dots, 8$ ) are used to compute eight visitation-rate predictions for each of the twelve zones ( $i = 1, 2, \dots, 12$ )

$$\hat{V}_{ij} = \exp\{\hat{\beta}_0 + \hat{\beta}_1 \ln(TC_i + P_j)\} \quad (11)$$

These values are then used to compute 8 demand predictions.

$$\hat{Q}_j = \sum_i pop_i \hat{V}_{ij}$$

She notes that the result obtained from this predictor for  $P_j = 0$  is 14 843. This value largely underestimates the true value of 17 000. A possible reason for this outcome is that the predictor  $\hat{V}_{ij}$  is *not* an unbiased predictor. Consider the zonal demand function  $\ln V_i = \beta_0 + \beta_1 \ln TC_i + e_i$  where we assume  $e_i \sim N(0, \sigma^2)$  and hence

$$\begin{aligned} \ln(V_i) &\sim N[(\beta_0 + \beta_1 \ln(TC_i)), \sigma^2] \\ V_i &\sim \text{LogN}[(\beta_0 + \beta_1 \ln(TC_i)), \sigma^2] \end{aligned}$$

From the properties of lognormal distributions (Aitchison and Brown 1966), the mean of  $V_i$  is

$$E(V_i) = \exp\left\{(\beta_0 + \beta_1 \ln(TC_i)) + \frac{1}{2}\sigma^2\right\}$$

Thus, an unbiased predictor for  $V_{ij}$  is

$$\tilde{V}_{ij} = \exp\left\{(\beta_0 + \beta_1 \ln(TC_i + P_j)) + \frac{1}{2}\sigma^2\right\} \quad (12)$$

When  $\beta_0$ ,  $\beta_1$  and  $\sigma^2$  are replaced by their estimators,  $\tilde{V}_{ij}$  no longer retains its unbiasedness property, but it is still likely to be a better predictor than  $\hat{V}_{ij}$ . Table 3 shows the new values of  $\tilde{Q}_j$  obtained using the feasible version of  $\tilde{V}_{ij}$ , alongside those obtained by Beal. Note that the actual number of visits demanded  $Q_j$  at zero additional entry fee ( $P_j = 0$ ) is 17 000. The new prediction for  $Q_j$  is very accurate with a value of  $\tilde{Q}_j = 17 003$ . If a new linear function is estimated on the basis of those new values of  $\tilde{Q}_j$ , the estimated consumer surplus is 697 771. This value emphasises once more how sensitive consumer surplus estimation can be to choice of methodology.

**Table 3** Alternative predictions from the log-log model

$P$	$\bar{Q}$	Beal's $\hat{Q}$
0	17 003	17 000 <sup>a</sup>
5	15 735	13 736
8	15 068	13 156
10	14 656	12 769
12	14 267	12 456
15	13 723	11 981
18	13 219	11 540
20	12 904	11 265
CS	697 771	492 931

Note: <sup>a</sup> Observed value.

#### 4.1 Stochastic considerations in consumer surplus estimation

The possible use of properties of the log-normal distribution to predict quantity for Beal's second stage of estimation raises questions about whether such properties should be used for the more algebraically consistent procedure that we proposed. The underlying issue here is how to treat the stochastic error term  $e$  in the visitation rate demand function  $\ln V_i = \beta_0 + \beta_1 \ln TC_i + e_i$ . One approach is to ignore it. This is the approach taken by Beal and by us so far. Another approach is to carry it through to the aggregate demand function and consider the estimation of consumer surplus on the basis of the average or expected demand function. In this case the function becomes

$$Q = \sum_i pop_i \exp\{\beta_0 + \beta_1 \ln(TC_i + P) + e_i\} \quad (13)$$

And, if we assume  $e_i \sim N(0, \sigma^2)$ , then the expected aggregate demand function is

$$E(Q) = \sum_i pop_i \exp\left\{\beta_0 + \beta_1 \ln(TC_i + P) + \frac{1}{2}\sigma^2\right\} \quad (14)$$

Consumer surplus is obtained by integrating  $E(Q)$  in equation 14 between 0 and  $P^*$  and taking the limit of the integral as  $P^* \rightarrow \infty$ .

A third approach is to first obtain consumer surplus by integrating  $Q$  in equation 13 between 0 and  $P^*$  and taking the limit as  $P^* \rightarrow \infty$ . The resulting CS depends on the error term  $e_i$ . Taking the expected value of this result gives an expected or average CS. The two approaches are conceptually different. One measures CS as the area under the 'average' demand curve. The other recognises that different errors lead to different demand curves that lead to different consumer surpluses, and then takes the average CS.

Despite this conceptual difference, for the model we are considering, both approaches lead to the same result, namely:

$$\hat{CS} = \frac{-e^{(\beta_0 + \frac{1}{2}\sigma^2)}}{\beta_1 + 1} \sum_i pop_i TC_i^{\beta_1 + 1}$$

To derive the standard error of a CS estimate based on this expression would involve partial derivatives of CS with respect to  $\beta_0$ ,  $\beta_1$  and  $\sigma^2$  as well as the variance of  $\hat{\sigma}^2$ . Related issues have been considered by Bockstael and Strand (1987).

## 5. Conclusion

It is evident from the results in this article that estimating consumer surplus can be tricky. The results can be very sensitive to demand function specification and to the chosen estimation methodology. In addition to correcting and explaining some of Beal's results, the purpose of this article was to expose the sensitivity and to suggest ways in which the methodology could be improved by computing standard errors and developing consumer surplus estimates which are internally consistent with visitation rate equations. There are two general observations that we would also like to make.

One likely reason for the sensitivity of Beal's results to model specification, and the impreciseness of the consumer surplus estimates as reflected in the width of interval estimates, is the small number of observations. With only twelve observations it is difficult to estimate most things accurately. In Beal's case, however, the twelve observations were obtained via an aggregation of individual responses. The effect of such an aggregation may have been a loss of information. A possible direction for the future that might yield better, more reliable estimates is through the development and estimation of models that utilise single observations on individuals rather than observations that are computed by aggregating information. Also, it would be good to get consumer surplus estimates and reliability measures that are not dependent on functional form selection. We are now to investigate a Bayesian approach that may yield some success along this lines.

Another fundamental difficulty associated with estimating consumer surplus from models of the type considered here is the need to extrapolate the demand function beyond the region of the observed sample. The problem is well depicted in figure 1. While any number of functions may fit the data reasonably well up to a price of A\$20, which is the maximum considered by Beal, it is the behaviour of the function beyond this point that is critical for the estimation of consumer surplus. If the data contain no information on

this behaviour, the most critical part of the estimation procedure is fraught with uncertainty. While this uncertainty is reflected by the sensitivity of the consumer surplus estimates to functional form specification, it is not reflected in the width of an interval estimate for a given functional form. The fact that these interval estimates are very wide means that estimation of consumer surplus is subject to a great deal of uncertainty even if we have perfect knowledge of the correct functional form. However, as mentioned in the previous paragraph, it may be possible to correct this problem with a larger number of observations.

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